INVESTIGATION OF NOVEL CONTROL STRATEGIES FOR PROMOTING MOTOR LEARNING IN THE UPPER LIMB WITH A HAPTIC COMPUTER EXERCISE SYSTEM IN ABLE-BODIED ADULTS AND THOSE WITH MOTOR IMPAIRMENTS

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PhD 2017

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Abstract

Motor impairments caused by stroke and cerebral palsy (CP) are common and often affect the function of the upper limb, which to be restored requires rehabilitation. As positive outcome is correlated to how early and intensive therapy is and since the resources of the healthcare providers are limited, robotic devices have been introduced to provide adjunctive therapy. The algorithms that control the manner those devices apply forces to the impaired limb are called haptic control algorithms (HCA) and to this date there has not been conclusive evidence as to what the behaviour of these algorithms should be. One type of HCAs is error augmentation (EA) which is a rather understudied but promising approach. This work presents to the literature two novel control strategies of the EA type that incorporate adaptive features namely Error Augmenting Adaptive(EA) and Error Augmenting Proportional (EA). Those two algorithms were implemented for and deployed to a single point of attachment robotic rehabilitation system.

The effectiveness in inducing motor learning of the developed algorithms was evaluated in a trial with able-bodied participants and compared against a third more established assistive HCA namely Assistance As Needed (AAN) and a control condition (no forces). Four groups (one per condition) practised reaching movements with a speed and accuracy requirement using their non-dominant arm to interact with the robot under a visual rotation of a 100^{o}. To assess learning kinematic measures were collected to measure their performance on reaching and circle-drawing movements. Also, bilateral transfer to the arm that did not receive practice was assessed. Changes in the participants' valence, arousal and dominance were assessed with a Self-Assessment Manikin questionnaire.

All groups learned to move their non-dominant arm under a visual perturbation showing comparable improvements in all key measures ($p<0.05$). Passive movements and EAP led to greater improvement in movement smoothness ($p<0.05$) and resulted in more retention of the improvements after a washout block ($p<0.05$) was introduced. Conversely, EAA showed a better effect on improving mean velocity ($p<0.05$). All groups performed similarly in terms of improving movement error and duration but EAA and AAN achieved peak performance faster ($p<0.05$). Similar improvements were measured on the arm that did not receive any training which were fully retained post-washout indicating that bilateral transfer occurred and led to better retention ($p<0.05$).

The findings of this work indicate that different attributes can be exploited from the developed HCAs to induce motor learning and improve different aspects of the movement suggesting that multimodal training protocols tailored to the needs of the patient are the way forward. Also, this work showed that bilateral transfer training has great potential in upper limb rehabilitation and the positive effects of the different HCAs on the arm that received practice transfer to the one that did not receive training. It is recommended that the findings of this work to be further investigated in experimental therapy protocols for those who suffer from neurological impairments such stroke and CP.

List of publications

Alexoulis-Chrysovergis, A. C., Weightman, A., Hodson-Tole, E. and Deconinck, F. J. A. (2013) 'Error augmented robotic rehabilitation of the upper limb a review.' *In Neurotechnix 2013 - Proceedings of the International Congress on Neurotechnology, Electronics and Informatics*, pp. 167–178.

Weightman, A., Alexoulis-Chrysovergis, A. C. and Olsen, S. (2014) 'What should we consider when designing rehabilitation robots for the upper limb of the neurologically impaired ?' *Proceedings of the Australasian Conference on Robotics and Automation*.

Weightman, A., Alexoulis-Chrysovergis, A. C., Cooper, G., Hodson-Tole, E. and Deconick, F. (2015) 'Novel rehabilitation robotic control strategies for promoting motor learning in the upper limb of the neurologically impaired.' *In Society for Research in Rehabilitation Summer Meeting*.

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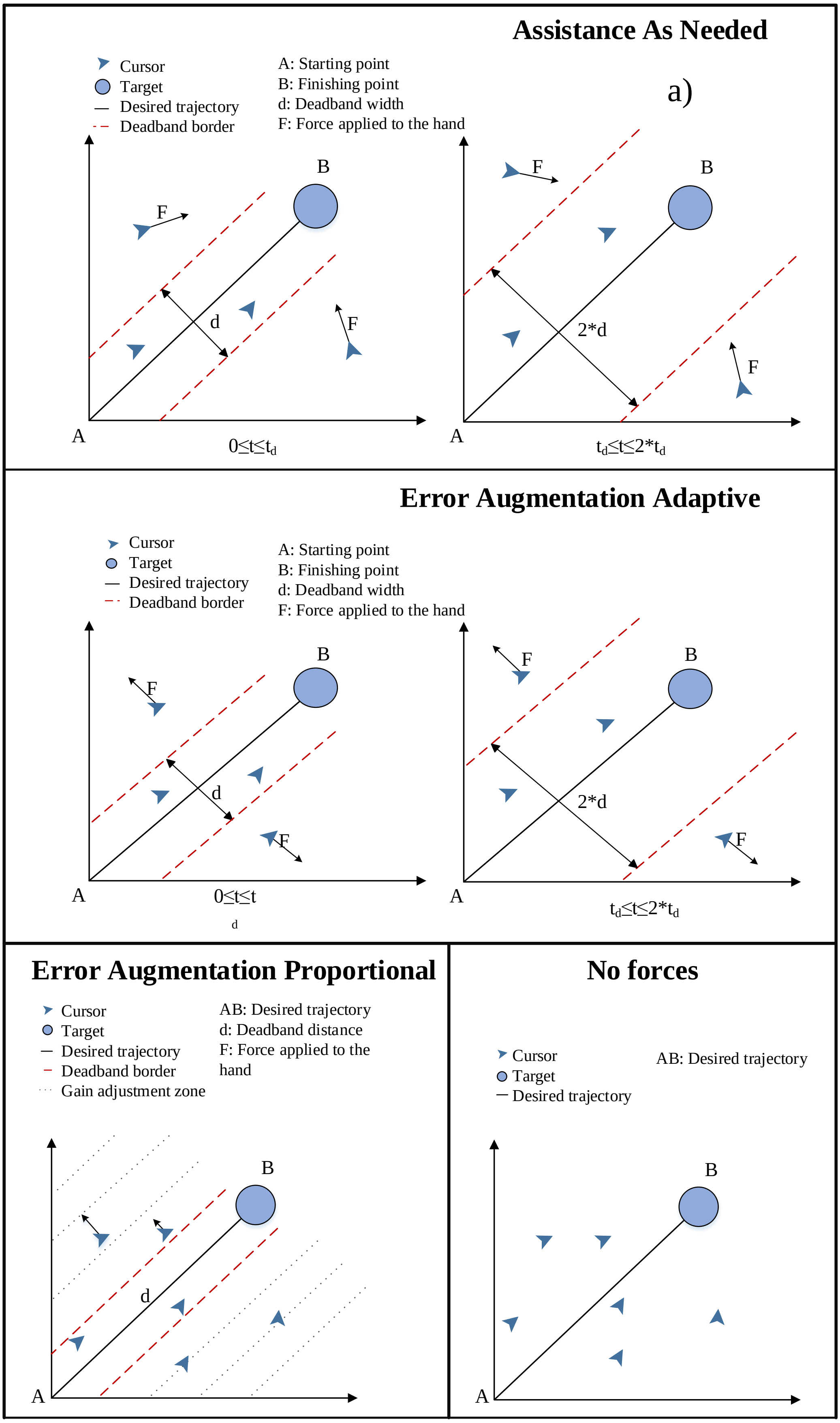
List of abbreviations

AAN	Assistance As Needed
ADL	Activities of Daily Living
ANOVA	Analysis Of Variance
AR	Augmented Reality
BTT	Bilateral Transfer Training
BTXA	Botulinum toxin type A
CCW	Counter-Clockwise
CIMT	Constraint Induced Movement Therapy
CNS	Central Nervous System
CP	Cerebral Palsy
cRIO	compact Reconfigurable Input Output
DA	Dominant Arm
DK	Development Kit
DOF	Degrees Of Freedom
EA	Error Augmentation

EAA	Error Augmented Adaptive
EAP	Error Augmented Proportional
EHI	Edinburgh Handedness Inventory
EMG	Electromyogram
F/T	Force/Torque
FMA	Fugl-Meyer Assessment
FPGA	Field Programmable Gate Array
FPS	Frames Per Second
FWD	Forward
GLM	General Linear Models
GMFM	Gross Motor Function Measure
GUI	Graphical User Interface
HCA	Haptic Control Algorithm
I/O	Input/Output
IC	Integrated Circuit
ICF	International Classification of Functioning
LMM	Linear Mixed Models
MAS	Modified Ashworth Scale
MPC	Maximum Permissible Current
MR	Magnetic Rotary
MS	Multiple Sclerosis
MT	Motion Tracking
NDA	Non-Dominant Arm
PC	Personal Computer
PCB	Printed Circuit Board
PID	Proportional Integral Derivative
PWM	Pulse Width Modulation
RCT	Randomised Control Trial
RT	Real-time
SAM	Self-Assessment Manikin
TCP/IP	Transmission Control Protocol/Internet Protocol
TDMS	Technical Data Management Streaming
WHO	World Health Organization
WMFT	Wolf Motor Function Test

Overview of HCAs under Investigation



1 Introduction to research

Neurological impairments such as stroke and cerebral palsy often result in upper limb impairments. To treat those impairments, the patients, rely on rehabilitation therapy provided by rehabilitation experts such as physiotherapists. Improvement in the function of the impaired patients is correlated to how early they receive therapy and the intensity of that therapy (Masiero et al., 2011). As a result of the breakthroughs in medicine and technology, life expectancy has increased globally and is projected to increase even more so, over the next century (United Nations, Department of Economic and Social Affairs, 2013). Due to the ageing of the population the prevalence of chronic diseases has increased significantly, stretching the capabilities of the healthcare providers and in turn resulting in reduced access to their services by the patients.

To overcome the aforementioned limitations, the scientific community introduced robotic devices in order to provide adjunctive therapy to the patient's limb either in the clinical or in the home environment and as a result a new field of research was established, rehabilitation robotics. The paradigm introduced with rehabilitation robotics is similar to the conventional therapy where the patient practices therapeutic movements; however, in this case the patients are interacting with the rehabilitation robot through their impaired limb. As the patients are performing movements the robot is applying forces to their limb to either assist or challenge their movements. The manner that these forces should be applied to maximise the rehabilitation outcome (Haptic Control Algorithms) is still an active topic of research as the research community has not yet concluded on the merits of a single approach (Marchal-Crespo and Reinkensmeyer, 2009).

This project introduces new haptic control algorithms whose conception and development is informed by the existing literature (Alexoulis-Chrysovergis et al., 2013). To develop and deploy these algorithms a rehabilitation robot developed by researchers at the University of Leeds, was used whose designs were made available to the researcher. Some of the designs of the rehabilitation robot had errors and certain components were outdated as such the project started with updating its design followed by the manufacturing and assembly process. Furthermore, all the necessary software was developed to control the rehabilitation robot as well as a gaming environment to be used as an interface of the user with the robot.

Thesis overview:

Chapter 2: This chapter introduces the reader to the literature relevant to the field of error augmentation in the form of a literature survey. Subsequently the aim of this project is presented along with the objectives set to meet that aim. Finally, the conceptual design informed by the literature survey of three haptic control algorithms is presented in the end of the chapter. Namely, three algorithms were to be developed namely assistance as needed (AAN), error augmenting adaptive (EAA) and error augmenting proportional (EAP).

Chapter 3: This chapter presents the reader with the all the software development undertaken to actuate the rehabilitation robot, interface it with the user and ultimately implement the conceptualised haptic control algorithms. Furthermore, the testing undertaken to ensure that the operation of the system is within the set parameters, is presented.

Chapter 4: The effectiveness of the developed haptic control algorithms on promoting motor learning was tested in a trial with healthy participants. Informed by the existing literature a trial protocol was designed. This pilot trial had two main objectives, the first one was to test the effectiveness of the trial protocol in successfully measuring motor changes in motor learning. The second part of the trial was to test whether the rate that a haptic control algorithm evaluates the performance of the user and adapts accordingly, affects motor learning. Informed by the findings of the pilot trial the protocol and the analysis methodology were updated and implemented in an investigatory trial. The aim of this trial was to collect kinematic and psychological data in order to evaluate the effect of the developed haptic control algorithms. The final part of this chapter presents the protocol used in the main trial of this body of work.

Chapter 5: In this chapter the findings of the statistical analysis which compared the effect of AAN on the motor learning of healthy adults against a Control group that did not receive any forces by the rehabilitation robot, are presented.

Chapter 6: In this chapter the findings of the statistical analysis which compared the effect of EAA on the motor learning of healthy adults against a Control group that did not receive any forces by the rehabilitation robot, are presented.

Chapter 7: In this chapter the findings of the statistical analysis which compared the effect of EAP on the motor learning of healthy adults against a Control group that did not receive any forces by the rehabilitation robot are presented.

Chapter 8: In this chapter the findings of the statistical analysis are presented which compared all developed haptic control algorithms against each other and the movements without any forces applied by the robot (control condition). This chapter is primarily focused on identifying differences between the developed HCAs, on how they affect motor learning in adults and on how they affect their psychological state.

Chapter 9: This is the final chapter of this work where the conclusions of this programme of work are drawn and suggestions for future work are presented.

2 Literature review

2.1 Upper limb motor impairment caused by neurological conditions

Pathophysiology of any disease is defined as the manner that the normal physiology is altered by a disease, injury or a syndrome (Nair and Peate, 2012). Long term neurological conditions such as stroke and multiple sclerosis are common in the UK affecting an estimated 10 million adults in Britain (Turner-Stokes et al., 2008). Long term neurological conditions (LTNC) result from disease, injury or damage to the body's nervous system (i.e. brain, central nervous system) and affect the individual and their family for the rest of their lives (Agrawal and Mitchell, 2005). Such neurological conditions can be categorised as: a) Progressive conditions, such as multiple sclerosis (MS) and Parkinson's; b) Suddenly acquired conditions such as brain injury and stroke; c) Stable/intermittent conditions such as epilepsy and cerebral palsy (CP) (Jackson et al., 2013).

Symptoms in neurological disorders vary according to the affected area of the central nervous system and the type of damage/deficiency (pathology). An overview of the functions of certain regions of the brain is provided in Figure 2-1. A common effect of neurological conditions is that they often lead to motor impairment and thus the patients experience difficulty in controlling the movement of their otherwise healthy extremities. Motor impairments can be distinguished according to the number of extremities involved. As such in monoplegia only one limb is affected (involved), in diplegia two, in triplegia three and in quadriplegia all four limbs are affected (World Health Organization (WHO), 2001). In the cases where only one hemisphere of the brain is affected, impairments are located in just one side of the body (hemiplegia). Often in literature, the term hemiparesis is used instead of hemiplegia to define partial paralysis or weakness in one side of the body. A further classification of motor impairments is according to whether the impairment is located on the upper extremities or the lower extremities (upper or lower limb impairments).

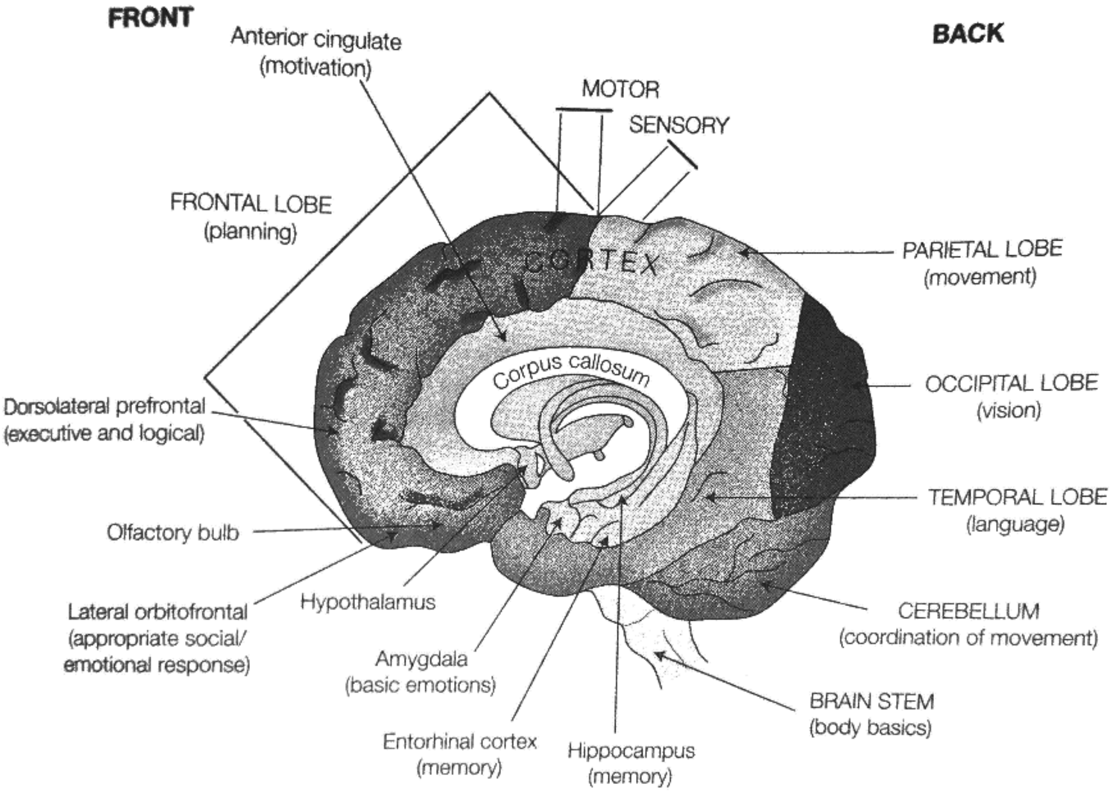


Figure 2-1: Structures of the brain and their functions. Source:(Utley and Astill, 2008)

As different conditions have different causes and demonstrate different pathophysiology only two conditions, namely stroke and cerebral palsy, which share similar symptoms related to neuromuscular control, will be reviewed as they are two of the most common causes of upper limb impairment in adults and children, respectively. Moreover, this programme of work is focused on impairments on the upper limb therefore only such impairments are considered in this review.

2.2 Common causes of neurological impairment

2.2.1 Physiopathology of stroke and its effects on upper limb function

Stroke is defined as a neurological deficit attributed to an acute focal injury in the central nervous system (CNS) by a vascular cause such as, an ischemic stroke (cerebral infarction) or a haemorrhagic stroke (Sacco et al., 2013). Ischemic strokes are caused when blood supply to a region of the brain is obstructed, typically due to thrombosis (blood clot), and as a result the affected area is not oxygenated resulting in necrosis (death) of the brain cells. On the other hand, haemorrhagic stroke is caused by either a leak of a blood vessel or a rapture of an aneurysm (swelling- area where blood is concentrated) (Heiss and Hossmann, 2009). This results in accumulation of blood in the affected area of the brain which leads to an increase in pressure that subsequently damages the specific region of the brain.

Symptoms in stroke patients vary according to the part of the brain that has been affected as well as according to the severity of the damage inflicted. As such stroke can affect the patients' i) mental status (e.g. lethargy, confusion, loss of memory), ii) motor function (e.g. limb impairments), iii) sensation (e.g. hyperesthesia, anaesthesia), iv) vision and audition (e.g. loss of vision/hearing ,visual/auditory impairments such as: double vision and dizziness), v) language (e.g. disturbance of language function i.e. aphasia resulting in difficulties in speaking or difficulties in speaking (e.g. motor output difficulty)) and in understanding language (e.g. receptive aphasia), vi) swallowing (difficulty to swallow/aphagia) (Massey, 2014).

Stroke is a leading cause of adult disability in the UK, with an estimated 1.1 million stroke patients under recovery in England and 110000 new stroke incidences annually (Scarborough et al., 2009). The most common effect of stroke is motor impairment, affecting 80% of the total stroke population (Langhorne et al., 2009) while 67% of stroke patients suffer from upper limb impairment (Liao et al., 2012). The latter, affects the volitional movement of the upper limb causing weakness (paresis), spasticity and loss of selective muscle control (Kelly-Hayes et al., 1998). Lance et al. define movement spasticity as a velocity dependent hypersensitivity of stretch reflex (Lance, 1990). As a result movement accuracy, velocity and smoothness of the impaired limb is affected (Elizabeth B. Brokaw et al., 2011). Consequently, the ability of the patients to perform activities of daily living (ADL) is hindered and as a result they become dependent on others (Rønning and Guldvog, 1998), depressed and they often display reduced social participation (Cooper et al., 2015).

2.2.2 Physiopathology of cerebral palsy and how it affects upper limb function

In Europe, cerebral palsy (CP) is the most common cause of severe disability among children. A study by Surman et al, 2006 which collected and examined registers of children with CP in the UK between 1986 and 1996, concluded that for every 1000 children born, 2 would be affected by CP (Surman et al., 2006). CP is an umbrella term used to describe a group of disorders of the development of movement and posture. As a result, the patients exhibit limited activity and often suffer from disturbances in sensation, cognition, communication, perception and/or behaviour, and/or suffer from seizure disorder. The cause of CP is attributed to non-progressive disturbances that occur during the development of the foetal or infant brain. (Bax et al., 2005)

CP can have different manifestations and impact on each patient. Four out of five children with CP suffer from upper limb impairment that affects arm and hand, which demonstrate weakness, spasticity and reduced muscle tone usually associated with spasticity, dystonia or disuse. As a result, the affected individuals face difficulties with reaching, pointing, grasping and manipulating objects (Boyd et al., 2001).

2.3 Assessment of motor impairment in upper limbs after stroke and Cerebral Palsy-Outcome measures

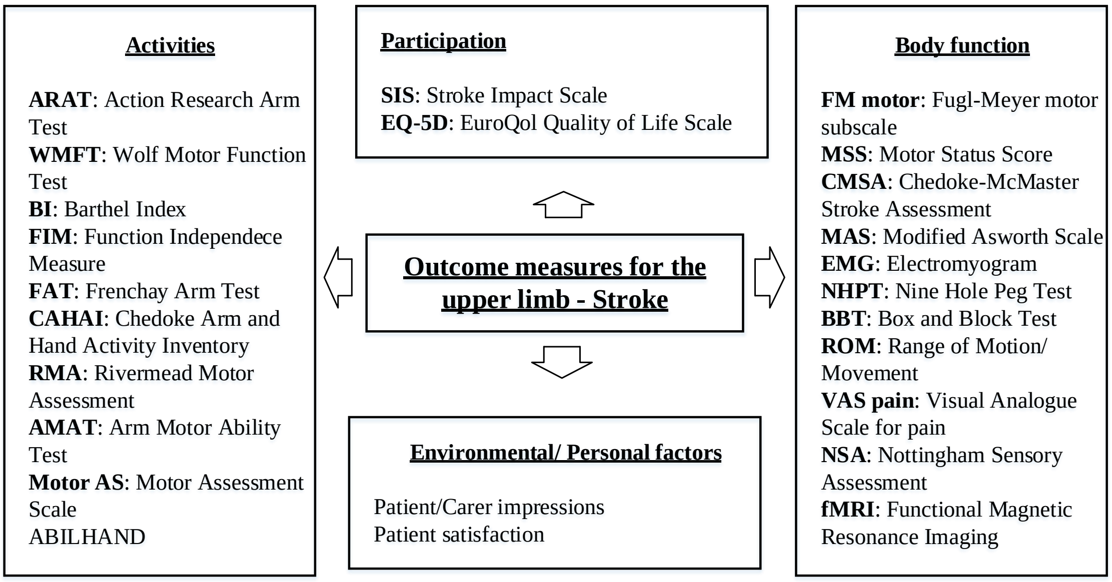
2.3.1 Standard clinical measures for assessing upper limb impairment

In 2001 the World Health Organisation (WHO) published the International Classification of Functioning (ICF), Disability and Health Framework. With the ICF the WHO aimed to standardise the language and framework describing health and health-related states (World Health Organization (WHO), 2001). Since the publication of the ICF there has been an increasing interest to link outcome measures used in rehabilitation to the classification suggested by this framework. Indicative of that are the findings of the overview of reviews paper on upper extremity outcome measures after stroke (Alt Murphy et al., 2015) where the authors report that all thirteen identified review papers used the ICF to classify outcome measures.

ICF consists of two parts, with each part being divided into two main categories. The first part regarding functioning and disability, is divided in a) Body Functions and Structures and b) Activity and Participation. The second part is about Contextual Factors and it is further divided into a) Environmental Factors and d) Personal Factors (World Health Organization (WHO), 2001). An overview of the ICF classification can be found in Table 2-1. It is out of the scope of this report to describe in detail the different clinical measures being used for assessing upper limb impairment after stroke and CP. However, Figure 2-2 and Figure 2-3 provide an overview of well-established clinical measures for assessing upper limb impairment after stroke (Sivan et al., 2011) and CP (Levitt, 2010; Schiariti et al., 2014) , respectively.

Table 2-1: ICF overview. Adapted from (World Health Organization (WHO), 2001; Jette, 2006)

	Part 1: Functioning and Disability		**Part 2: Contextual factors**	
Components	Body Functions *(physiological functions of body systems)* and Structures *(anatomical parts of the body, organs, limbs etc.)*	Activities *(execution of task or action)* and Participation *(involvement in a life situation)*	Environmental Factors *(Individual (e.g. home, work etc.) and Societal (e.g. organizations, services)*	Personal Factors *(the particular background of an individual's life and living)*
Domains	Body functions Body structures	Life areas (tasks, actions)	External influences of functioning and disability	Internal influences of function and disability
Constructs	Change in body functions (physiological) Change in body functions (anatomical)	Capacity executing tasks in a standard environment Performance executing tasks in the current environment	Facilitating or hindering impact of features of the physical, social, and attitudinal world	Impact of attributes of the person



Activities

ARAT: Action Research Arm Test
WMFT: Wolf Motor Function Test
BI: Barthel Index
FIM: Function Independece Measure
FAT: Frenchay Arm Test
CAHAI: Chedoke Arm and Hand Activity Inventory
RMA: Rivermead Motor Assessment
AMAT: Arm Motor Ability Test
Motor AS: Motor Assessment Scale
ABILHAND

Participation

SIS: Stroke Impact Scale
EQ-5D: EuroQol Quality of Life Scale

Outcome measures for the upper limb - Stroke

Environmental/ Personal factors

Patient/Carer impressions
Patient satisfaction

Body function

FM motor: Fugl-Meyer motor subscale
MSS: Motor Status Score
CMSA: Chedoke-McMaster Stroke Assessment
MAS: Modified Asworth Scale
EMG: Electromyogram
NHPT: Nine Hole Peg Test
BBT: Box and Block Test
ROM: Range of Motion/ Movement
VAS pain: Visual Analogue Scale for pain
NSA: Nottingham Sensory Assessment
fMRI: Functional Magnetic Resonance Imaging

Figure 2-2: Clinical measure scales for upper limb impairment after stroke. Adapted from (Sivan et al., 2011)

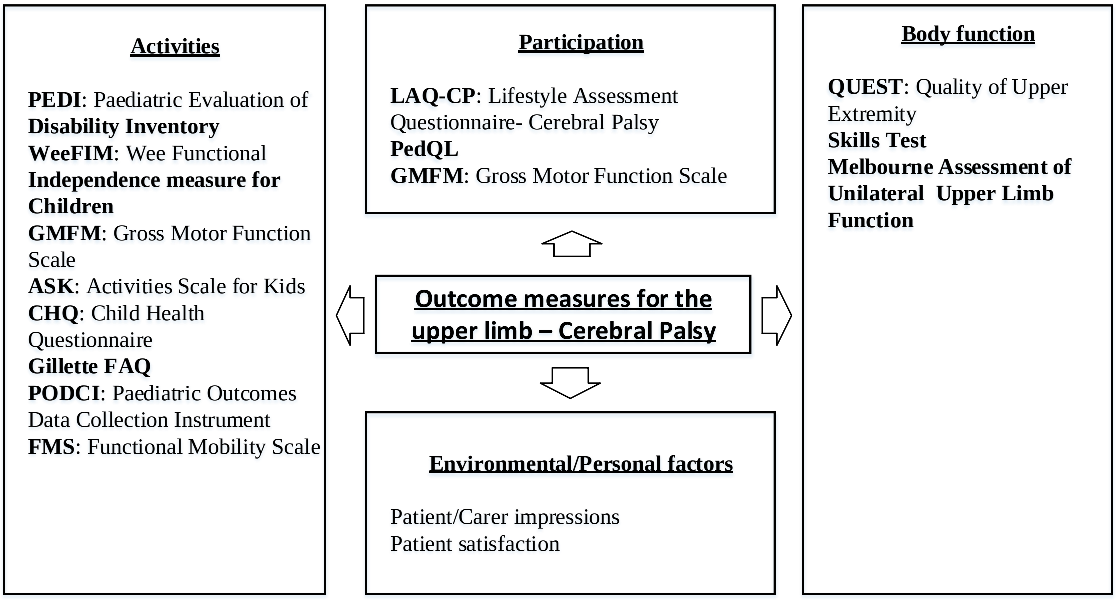


Figure 2-3: Clinical measure scales for upper limb impairment after CP. Adapted from (Levitt, 2010; Schiariti et al., 2014)

2.3.2 Kinematic measures for assessment of upper limb function

Standard clinical measures have been established as valid and reliable evaluation methods of the abilities of the affected individuals. However, such measures have limited sensitivity to assess discrete differences in performance because of their scalar nature (Bosecker et al., 2010). Furthermore, they often rely on the ability of the individual practitioner to assess upper limb function (Krebs et al., 2014). Motion analysis on the other hand is a reliable and objective method for movement quantification (Butler et al., 2010; Colombo et al., 2014; Duret et al., 2016).

Kinematic measures, which are derived from motion analysis, have been extensively used in rehabilitation robotics research for assessing upper limb function (Subramanian et al., 2010; Chen and Howard, 2014). Kinematic measures are fundamental for assessing human movement as they can more accurately analyse movements (Alt Murphy et al., 2015) and as such they have been increasingly popular in robotic rehabilitation studies alongside standard clinical scales (Santisteban et al., 2016). Additionally, there have been successful attempts (Bosecker et al., 2010; Krebs et al., 2014) to correlate kinematic measures with clinical scales such as Fugl-Meyer (Fugl-Meyer et al., 1974) and Modified Ashworth Scale (Ashworth, 1964), advances that may potentially lead to the assessment of human upper limb function only by the use of kinematic measures.

A popular manner of performing kinematic assessment is by using marker-based motion tracking systems (Alt Murphy et al., 2015). Such systems utilise a set of markers placed onto the subject. Detectors are used to triangulate the position of the markers and hence derive the coordinates of each marker relative to the reference system (De Vito et al., 2014). Such systems are usually divided in passive and active marker systems. Passive marker systems such as the VICON™ by Motion Systems, Ltd., Oxford, England are utilising passive reflective markers and a carefully positioned array of infra-red cameras (Hingtgen et al., 2006). In active marker systems such as the NDI Measurement Sciences© Optotrack Certus™ (NDI Measurement Sciences, 2016) the markers emit infra-red light which is then captured by the detectors.

Another approach is to utilise inertial sensors (a combination of accelerometers, gyroscopes and magnetometers) which accurately measure the velocity, orientation and gravitational forces of an object (Leuenberger et al., 2016). By attaching an array of inertial sensors into known locations of the arm and by using reconstruction software these systems can track the movement of the arm without the need of an external reference (Pérez et al., 2010).

Finally, kinematic data can be collected by utilising the sensors of a rehabilitation robot in real time. In the case of an exoskeleton for example, which is coupled to the arm movement, the embedded sensors on the actuators report their respective position to the system. By using inverse kinematics, a method very common in robotics, one can track the movement of the arm accurately in real time (Sivan et al., 2011).

The kinematic assessment is usually performed while the participants perform reaching movements without receiving external forces (unconstrained movements). Those movements resemble movements performed during exercise. As such, by measuring changes in kinematic parameters the therapists can identify the outcome of therapy. Several studies have also introduced an unpractised task to the assessment protocol (Dipietro et al., 2007; Bosecker et al., 2010; Celik and O'Malley, 2010) where the participants are asked to draw circles using their arms. This circle-drawing task allows to evaluate whether improvement in the practised task transfers to other unpractised tasks (Casellato et al., 2012). Furthermore, such a task requires coordination of both the shoulder and elbow and as such allows the evaluation of synergetic movements (Krabben et al., 2011). Figure 2-4 shows how different kinematic measures link to symptoms caused by stroke.

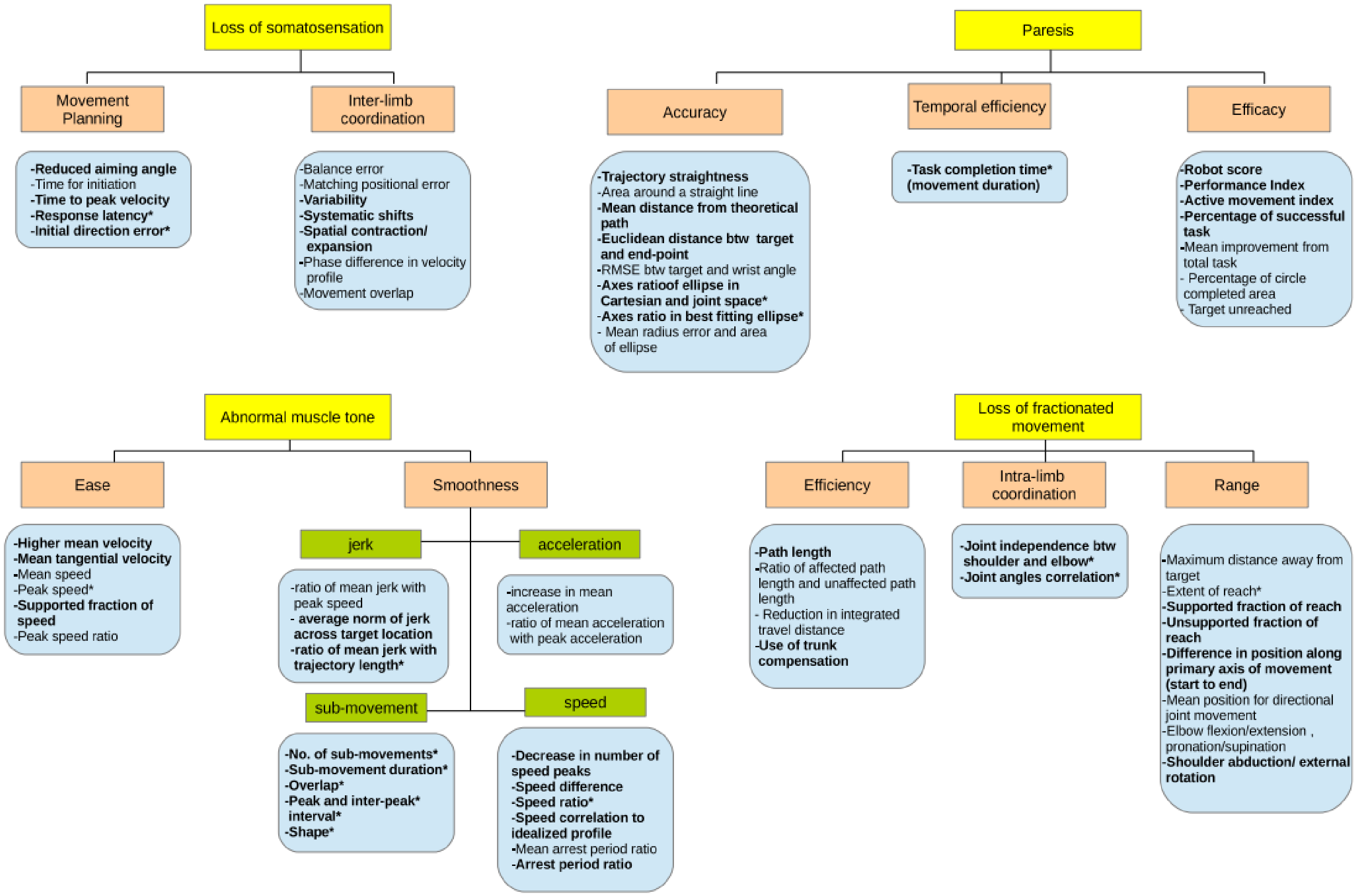


Figure 2-4: Kinematic assessment measures and how they relate to stroke symptoms. Source: (Nordin, S. Q. Xie, et al., 2014)

By reviewing the literature, a number of kinematic assessment parameters (measures) were identified that have been used in conventional as well as in robotic rehabilitation:

a) <u>Time to perform a movement (duration)</u>:

The time to perform a certain movement is measured (Finley et al., 2005). For example, in a reaching task the time to reach from target A to target B is measured (Figure 2-5). The movement of the impaired limb is characterised by extended movement time (Cirstea and Levin, 2000; Balasubramanian et al., 2009) which is often reduced when improvement in function occurs (Chang et al., 2007; Frascarelli et al., 2009) hence making duration of movement a good measure of functional recovery. This metric is relative to the task and performance can either be established through comparison with a Control group or through comparison with a baseline measurement.

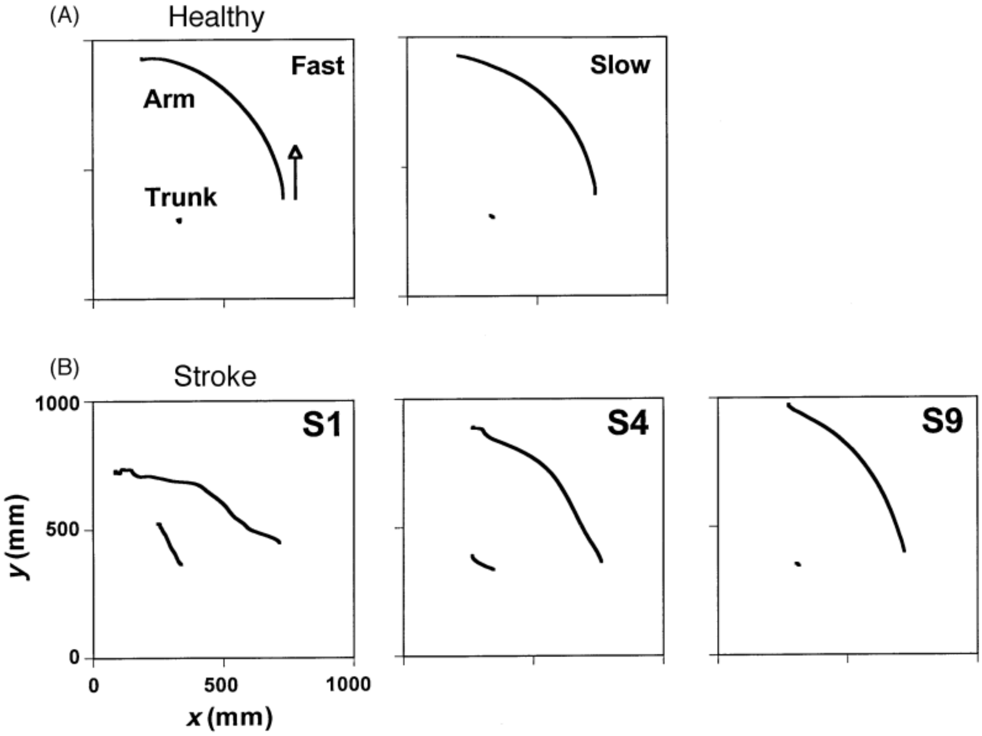


Figure 2-5: Different arm movements for A) a healthy participant and B) three stroke subjects. Source: (Cirstea and Levin, 2000). The healthy participant perform accurate movements regardless of the speed of the movement. On the other hand the impaired participants despite performing slower movements their movements are inaccurate.

b) Movement accuracy:

This is a measure of the error/deviation of movement from a theoretical or predefined desired trajectory usually measured in millimetres (Colombo et al., 2010). Several studies (Hingtgen et al., 2006; Novakovic and Sanguineti, 2011; Preston et al., 2014) indicate that movement of an impaired limb is less accurate when compared with that of a healthy individual. Furthermore, there is evidence that improvements in accuracy are correlated with the patient’s recovery (Colombo et al., 2005). Movement accuracy is usually measured in millimetres.

c) Movement velocity:

The velocity profile of the movement of an impaired limb is not smooth with high peaks in velocity (Krakauer, 2005). On other hand, for healthy individuals the velocity profiles, for example in a reaching task, are smooth and bell-shaped similar to the velocity profile displayed in Figure 2-6c. As such acquiring the velocity profile can provide good insight on the performance of the impaired limb (Colombo et al., 2005, 2010).

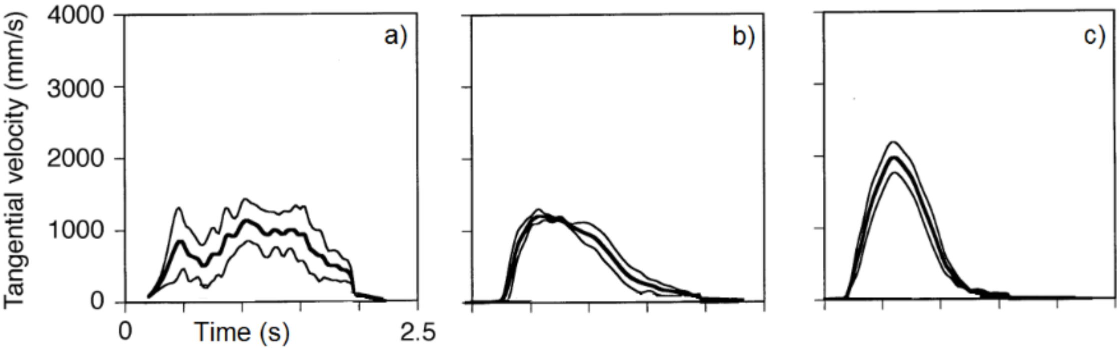


Figure 2-6: Thick lines represent tangential velocity profiles of a curved movement for three different stroke patients with different levels of impairment with a) being the more severe and c) the least severe. Source: (Cirstea and Levin, 2000)

Additionally, mean and/or peak velocity of a certain movement are measured. Several studies have measured significant improvements in both metrics (Rohrer et al., 2002;

Colombo et al., 2005) for stroke patients after receiving therapy (Figure 2-7). Furthermore, there is a direct correlation between the outcome of clinical scales such as FMA and MSS (Figure 2-2) and the outcome of studies that utilise both peak and mean velocity metrics (Nordin, S. Xie, et al., 2014).

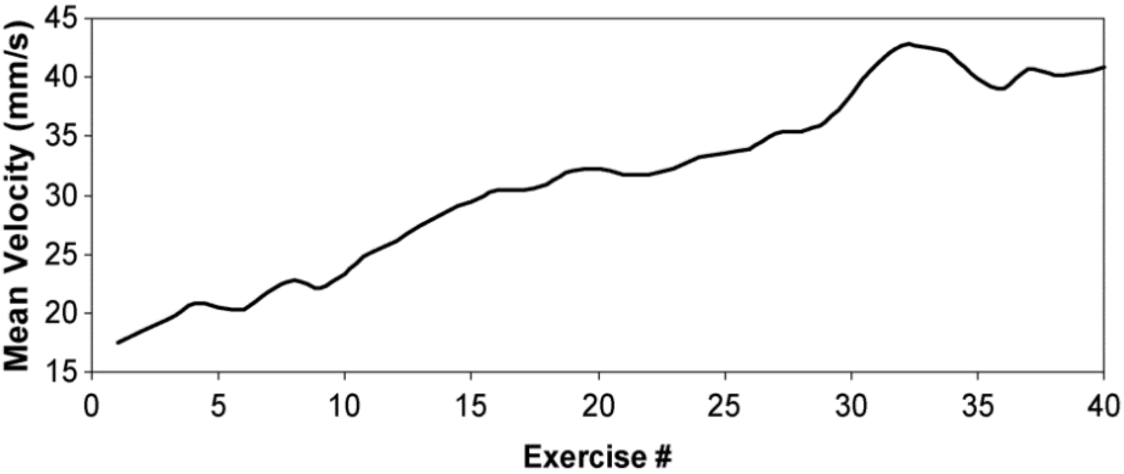


Figure 2-7: Mean velocity measurement for a stroke patient during the course of rehabilitation therapy. Source: (Colombo et al., 2005)

d) **Movement smoothness**:

The movements of those with a neurological impairment such as stroke or CP are not smooth as they appear to be divided into a series of discrete sub-movements. There is evidence that improvement in the motor performance correlates to more unified, less spastic movements (Rohrer et al., 2002), hence making smoothness a good measure of upper limb function (Yoo and Kim, 2015).

A common measure of smoothness is calculating the deviation from the minimum jerk (Equation*(1)*), which is the third time derivative (Equation *(2)*) of the position, along the trajectory of the movement (Wang et al., 2010; Kadivar, Sullivan, et al., 2011). This measure has been extensively used as a measure of performance in conventional therapy (Rohrer et al., 2004) as well as in robotic therapy (Colombo et al., 2005).

$$Smoothness = \int_{t_i}^{t_j} \dddot{x}(t)^2 \, dt$$

(1) Minimum jerk for movement smoothness

Where:

$$\dddot{x}(t) = \frac{d^3x(t)}{dt^3}$$

(2) The equation for jerk

Normalised jerk (Equation *(3*)) is also a common metric in rehabilitation (Chang et al., 2007; Peter R Culmer et al., 2009; Celik and O'Malley, 2010). Jerk is being normalised regarding the duration and length of the movement hence allowing the comparison of different trajectories (Preston et al., 2014).

$$Normalised\ jerk = \sqrt{{}^{1}\!/_{2} \int_{t_i}^{t_j} \dddot{x}(t)^2 * (duration^5/length^2)dt}$$

(3) Normalised jerk

e) <u>Movement synergy</u>:

Synergy patterns are defined as the coupling of joints or muscles in certain movements (Kung et al., 2010). Patients suffering from neurological impairments appear to have abnormal movement synergies on the affected limb (van Roon et al., 2005; Lang et al., 2013). By collecting kinematic data these synergies can be visualized and evaluated and thus be used to assess improvement and/or to provide specialized rehabilitation (Safavynia et al., 2011).

A measure of movement synergy was proposed for reaching movements by (Balasubramanian et al., 2009) and is presented in Equation *(4*). In this equation N is the number of samples of data in the reaching movement and d(i) is the perpendicular distance between the arm’s endpoint and the straight line joining the initial position with the target position (Colombo et al., 2010).

$$Movement\ synergy = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(d(i))^2}$$

(4) Calculation of movement synergy for a reaching movement

f) <u>Active range of motion</u>:

Active range of motion is a well-established measure used in the clinical environment (Beebe and Lang, 2009; Posteraro et al., 2010). Reduced joint range is a characteristic orthopaedic deformity of the paretic limb (Butler et al., 2000). An example of reaching trajectories pre- and post-intervention for a stroke patient can be seen in Figure 2-8. By acquiring goniometric measurements during active movement of a joint, potential limitations of its motion can be identified (Gajdosik and Bohannon, 1987). As such the range of motion is measured to determine the muscle shrinkage and joint movement reduction as well as any improvement caused by rehabilitation (Ostensjø et al., 2004).

Figure 2-8 demonstrates a good example of improvement in the range of motion for a stroke patient. The trajectories of the endpoint during reaching movements are displayed pre-and post-intervention. The patient was unable to reach the most distal targets pre-intervention while managing successfully to reach all targets after receiving rehabilitation therapy.

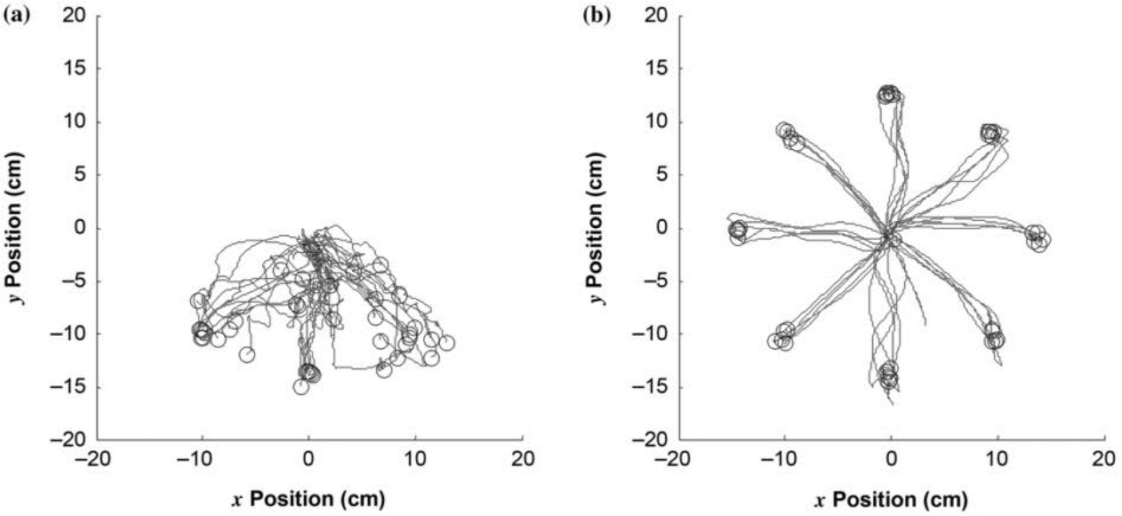


Figure 2-8: Movement trajectories towards eight targets pre- a) and b) post-intervention for a stroke patient. The patient was incapable of reaching the targets on the top half of the workspace at the beginning of training. (Finley et al., 2005)

g) **Movement circularity**:

Circularity (or roundness) is a measure of how circular a trajectory is. If circular movements are imperfect they result to elliptic trajectories instead. To measure circularity an ellipse is fitted to the participants' movement trajectory (Figure 2-9). By calculating the eccentricity of the fitted ellipse, which is defined as the ratio between the lengths of the minor axis and the major axis, a measure of the circularity of the trajectory is acquired. A value of 1 in circularity represents a perfectly circular trajectory. The smaller its value the less circular the trajectory is.

The most common method amongst the reviewed studies (Dipietro et al., 2007; Krabben et al., 2011) for determining movement circularity was the one suggested by (Oliveira et al., 1996) which uses principal component analysis to fit an ellipse to a given dataset. In Figure 2-9 two attempted circular trajectories by a stroke patient's paretic limb are shown pre-and post-intervention in a study contacted by Dipietro et al., 2009. It is clear that the post-intervention movement is more circular than the pre-intervention.

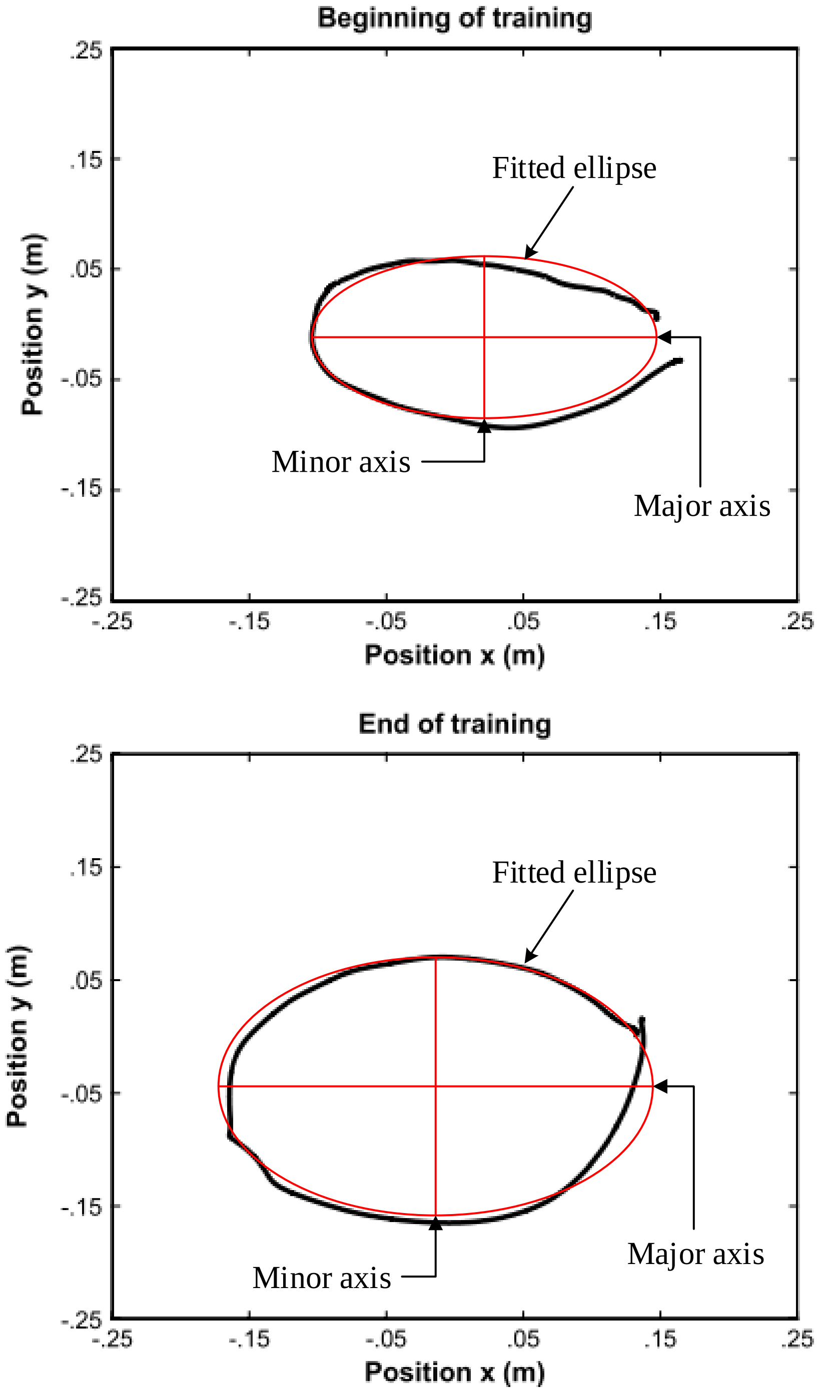


Figure 2-9: Movement circularity of a stroke patient pre-and post-intervention. Adapted from: (Dipietro et al., 2009)

2.4 Conventional methods for upper limb rehabilitation after neurological impairment

2.4.1 Stroke rehabilitation of the upper limb

It has been shown by several studies that in the incidence of a stroke early and intensive therapy has a better outcome in upper limb function when compared to later intervention (Kwakkel et al., 2007; French et al., 2009). A review paper by Langhorne et al., 2009 identified 13 different theoretical approaches of intervention with examples being motor learning, bilateral training, constraint-induced therapy and electrical stimulation. An overview of the intervention modalities as reviewed by Langhorne et al. is provided in Table 2-2.

Table 2-2: Intervention modalities for upper limb rehabilitation following stroke (Langhorne et al. 2009)

Approach	Description
Mixed approaches	Utilises treatment components that originate in various theoretical approaches
Motor learning	Assumes neurologically impaired people learn in the same way as healthy people; focus on context-specific cognitive learning by use of feedback and practice
Neurophysiological approaches	Various therapeutic approaches based on neurophysiological knowledge and theories, most commonly used is the Bobath approach
Bilateral training	Involves use of both upper limbs to perform identical activities simultaneously but independently
Biofeedback: force and position feedback	On a force platform, special force sensors measure the weight under each foot and the position or movement of the body's centre of pressure; information (feedback) about the distribution of weight between the legs and about movement of the centre of pressure can be given to the patient by use of visual or auditory feedback
Constraint-induced movement therapy	Involves restraint of the intact limb, in combination with a large number of repetitions of task-specific training
Electromyographic biofeedback	Involves the use of instrumentation applied to muscles with external electrodes to capture motor unit electrical potentials; the instrumentation converts the potentials into audio or visual information
Electrostimulation	Electrostimulation can be delivered to the peripheral neuromuscular system by external or internal electrodes, at a range of frequencies, intensities, and patterns of delivery
High-Intensity Therapy	Increased amount of focused therapy or interventions compared with a reference group
Mental Practice with Motor Imagery	Cognitive rehearsal of a physical action; aims to improve goal-orientated movement or stabilisation of a given movement
Repetitive task training	Active motor sequence performed repetitively within a single training session, aimed towards a clear functional goal
Robotics	Robotic devices enable high-intensity, repetitive, task-specific, and interactive treatment of the upper limb independent of a therapist
Splinting or orthosis	Splints or orthoses are external, removable devices that are used to meet several clinical aims: a decrease in spasticity and pain, improvement in functional movement, and prevention of contracture, over-stretching, and oedema

2.4.2 Treatment of upper limb impairment in children with Cerebral Palsy

There has been a plethora of proposed interventions to treat upper limb impairment in children with CP which are summarised in Table 2-3. Despite the efforts of the scientific community to repair the damage to the affected brain, there has not been significant evidence of success of any of the approaches published so far (Rosenbaum, 2003; Goldstein, 2004). However, a more recent study (Novak et al., 2013) has found more substantial evidence of improvement in certain parameters (motor function, spasticity) of some modalities such as bimanual training, constraint induced movement training, occupational therapy, home rehabilitation interventions and approaches based on motor learning theory.

Table 2-3: Intervention modalities for treatment of the upper limb in children with CP (Boyd et al. 2001)

Treatment Modality	**Content**
Behavioural and environmental treatments	Physiotherapy (e.g. constrain induced therapy) Occupational therapy Neurodevelopmental treatment Motor learning Conductive Education Strength training
Peripheral splinting and casting	Serial plaster casting Rigid bivalve casts Dynamic splints (polypropylene) Lycra UPSuit garments
Electrophysical agents	Neuromuscular Electrical Stimulation (NMES) Electromyography (EMG) biofeedback
Pharmacological - focal	Phenol Botulinum toxin type A (BTXA)
Pharmacological- generalized spasticity management	Continuous Intrathecal Baclofen (CITB)
Surgery	Selective Dorsal Rhizotomy (SDR) Upper limb surgery for function Surgery for deformity correction and cosmesis BTXA and surgery

2.4.3 Brain plasticity, motor learning and motor rehabilitation

Some of the approaches in rehabilitation such as injections with Botulinum toxin type A (BTXA) and strength training are aiming to address the symptoms of the neurological conditions rather than the cause (BTXA is used to treat spasticity and strength training is used to address muscle weakness caused by disuse). Other approaches that aim to cure the cause of the impairment are based in the neuroplasticity theory.

Neuroplasticity assumes that the nervous system can restructure itself to dynamically adapt to new environmental, developmental and experiential conditions (Levitt, 2010). There is evidence that the brain can dynamically restructure itself in order for unaffected areas of the brain to assume the function of an affected area (Bach-y-Rita, 1990). Furthermore, development in brain imaging technologies has allowed the scientific community to show that brain cells can actually regenerate (neurogenesis) (Johansson, 2000).

Motor learning is the active field of study regarding how a movement is learned and retained (Schmidt and Lee, 2005). Schmidt and Lee, 2005 define motor learning as "a set of (internal) processes associated with experience or practice leading to relatively permanent changes in one's ability for skilled behaviour". Learning is measured by the change in one's capability to perform a motor task due to practice (Utley and Astill, 2008). Rehabilitation based on the motor learning theory aims to induce brain plasticity and hence recovery in the function of an impaired limb by using the principles of motor learning. As such, patients can learn (in the case of CP) or re-learn (in the case of stroke) how to use their impaired limb.

Krakauer et al., 2006 identified five modalities for the upper limb rehabilitation of stroke patients, based on the principles of motor learning, namely arm ability training, constraint induced movement therapy (CIMT), electromyogram-triggered neuromuscular stimulation, interactive robotic therapy and virtual reality based rehabilitation (haptic simulation) (Table

2-2, Table 2-3). A brief overview of the first three is provided below while a more detailed review of robotic rehabilitation is provided in Section 2.5.

Arm ability training (AAT): is method introduced by (Platz et al., 2001). AAT is focused on stroke patients with mild arm paresis and already improved arm function and muscle tone that are slow and uncoordinated in performing certain tasks. Such training emphasized on the accuracy and the speed of the performed tasks by introducing repetitive training of certain movements with a variation in the difficulty of the task. In the same paper by (Platz et al., 2001) the authors performed a randomised control trial comparing AAT with conventional therapy and found superior improvement for the AAT group in activities of daily living (ADL) which was retained a year after therapy stopped.

Constrained-induced movement therapy (CIMT): the healthy arm is constrained in a mitt or a cast for the waking hours while providing focused repetitive training to the impaired arm (Gordon, 2006). CIMT aims to reduce the dependence of the subjects to their healthy arm and as a result to maximise potential improvement of the impaired. A systematic review on randomised control trials (RCT) using CIMT to treat stroke patients (Hakkennes and Keating, 2005) identified fourteen relevant studies. The same review concluded that CIMT may have positive effects on improving upper limb function in stroke patients when compared to alternative or no treatment. However, a Cochrane literature review on the effect of CIMT in children with hemiplegic CP (Hoare et al., 2007) identified only three relevant studies, only one of which was an RCT. This review reported positive outcome of CIMT. However due to the small number of included studies and the lack of methodological quality in some, the authors recommended CIMT only for experimental treatment until more evidence is gathered.

Electromyogram (EMG)-triggered neuromuscular stimulation: in this approach sensors that record the electrical activity of the muscles (EMG) are attached to the limb. Voluntary movements, usually focused on specific muscles, are initiated and when the EMG signal reaches a certain level an electrical pulse is applied to the target-muscle(s) (neuromuscular stimulation) to initiate an involuntary contraction of the respective muscle(s) the predefined movement (Krakauer, 2006). Such approaches are based on the theory supporting that proprioceptive feedback (body's sensation of movement) is fundamental for motor learning to occur (Cauraugh and Kim, 2002). Several studies have reported improvement in the hand and arm function of patients suffering from stroke (Bolton et al., 2004; IJzerman et al., 2009) and CP (Kerr et al., 2004).

Since the publication of the review paper by Krakauer et al., 2006 another rehabilitation method was suggested based on the motor learning theory namely, bilateral transfer. Bilateral transfer occurs when a skill practised with one limb transfers to the other that did not receive any prior training (Ausenda and Carnovali, 2011). Bilateral transfer based therapy (BTT) is performed in the opposite manner than the CIMT as all the training is undertaken with the healthy limb with the intention to improve the function of the impaired. BTT is not to be confused with bimanual training as the latter requires coordinated movements of both limbs (Park et al., 2011).

There is limited evidence for the efficacy of BTT however, promising results were observed in two Randomised Control Trials (RCTs) performed by (Ausenda and Carnovali, 2011) and (Ausenda, 2014) where stroke patients that received training with their non-affected arm improved their ability to perform functional movements with their impaired limb while the Control group that did not receive any training did not show any improvement. Furthermore, an RCT by (Iosa et al., 2013) showed that more transfer occurs when the higher skilled hand received therapy. The possible implications of the findings of the studies in upper limb rehabilitation are great as they could potentially allow access to different training modalities for patients with severe impairments that prevented them to perform certain exercises such as reaching movements.

2.5 Robotic rehabilitation for the upper limb after stroke and Cerebral Palsy

Although conventional therapy has been beneficial for upper limb impairments, it is labour intensive for the practitioner and it requires frequent visits to/by the rehabilitation experts which are often limited by difficulty of access as well as financial constraints of the healthcare providers (Krebs et al., 1998). To overcome the aforementioned limitations a new paradigm was introduced in literature (Prior and Warner, 1990) where rehabilitation would be provided under the supervision of a clinician but the exercise would be provided by a powered device (robot). These devices can be used as an adjunct to conventional therapy hence allowing the patient more access to beneficial therapy.

Various approaches for robotic rehabilitation of the upper limb have been presented in literature over the years (Krebs et al., 2009; Waldner et al., 2009; Fasoli et al., 2012; Holt et al., 2013), but the concept behind most of these systems remains fundamentally the same. A robotic manipulandum is attached or held by the patient’s affected limb, the patient is asked to perform predefined tasks while interacting with a computer interface (Figure 2-10). The system provides one or more different types of feedback to the user namely, visual, audio, audio-visual or haptic, usually through a computer game environment. A haptic control algorithm (HCA) controls the systems response to the user’s movement utilising information collected by a setup of different sensors such as encoders, accelerometers, dynamometers and electromyography (EMG) signals.

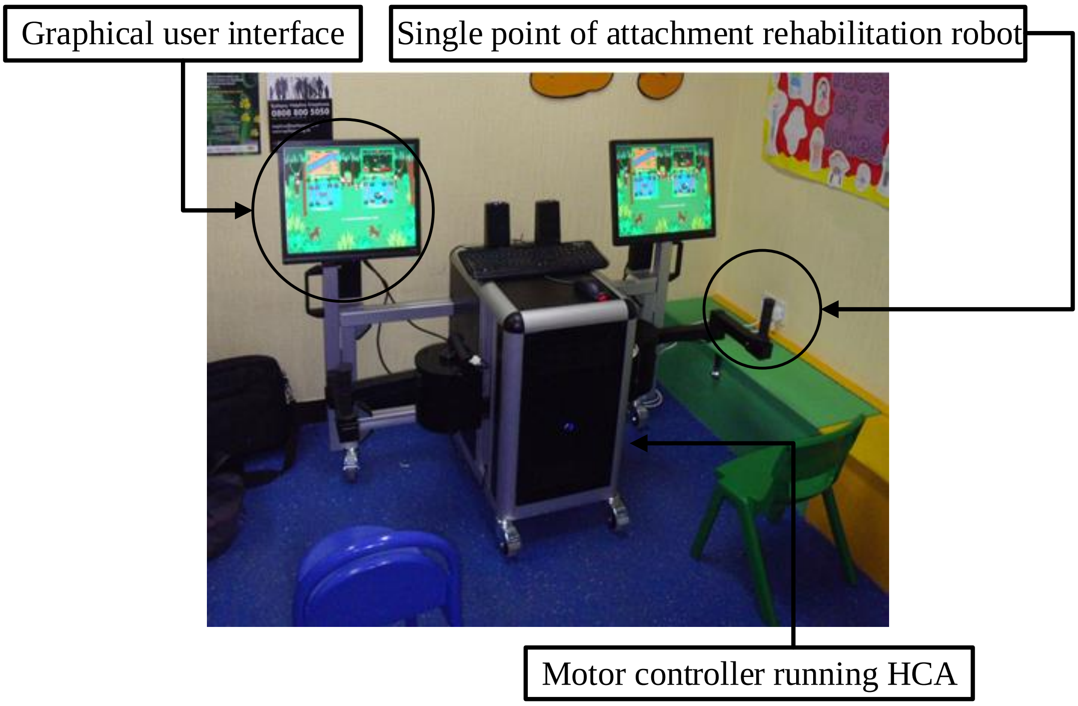


Figure 2-10: Example of typical robotic system for upper limb rehabilitation. Adapted from (Holt et al., 2013)

In order to set a simple framework for developing robotic rehabilitation systems (Iosa et al., 2016) recently suggested that such systems should comply with the following three laws: “1) A robot for neurorehabilitation may not injure a patient or allow a patient to come to harm, 2) A robot must obey the orders given it by therapists, except where such orders would conflict with the First Law, 3) A robot must adapt its behaviour to patients’ abilities in a transparent manner as long as this does not conflict with the First or Second Law”, (Iosa et al., 2016). As rehabilitation robotics become more popular and more systems reach commercialisation, a good framework surrounding those systems is required. Whether the aforementioned framework will be adopted by the scientific community is yet to be seen.

2.5.1 Existing robotic devices for upper limb rehabilitation after stroke and Cerebral Palsy

Numerous designs of robotic devices for upper limb rehabilitation have been introduced in literature. One way to distinguish these devices is according to the type of actuators they are utilising (Gopura et al., 2009). As such there are systems actuated by electric motors (Krebs and Hogan, 2006), hydraulically (Stienen et al., 2007) and pneumatically (Secoli et al., 2011) actuated systems (Figure 2-11).

Electric motors are the most commonly used actuators in upper limb rehabilitation as they provide relatively higher power and are easy to actuate and control. On the other hand pneumatic actuators are lighter and have lower impedance (Caldwell et al., 2007), but they are hard to control because of their non-linear nature (Lo and Xie, 2012). Additionally, in pneumatic systems the actuators despite being small and lightweight, the whole system is relatively large due to the compressor that is required to provide them with pressurised air thus making pneumatic actuated robots more suitable for applications where the system is stationary such as the clinical environment (Morales et al., 2011; Maciejasz et al., 2014). Finally, hydraulic actuators provide high torques, are very precise and responsive, but they have been rather underutilized in upper limb robotic rehabilitation (Umemura et al., 2009; Maciejasz et al., 2014). This is most likely due to the fact that such systems require frequent maintenance, they are prone to oil spillages and have large space requirements for their deployment. (Gopura, 2011)

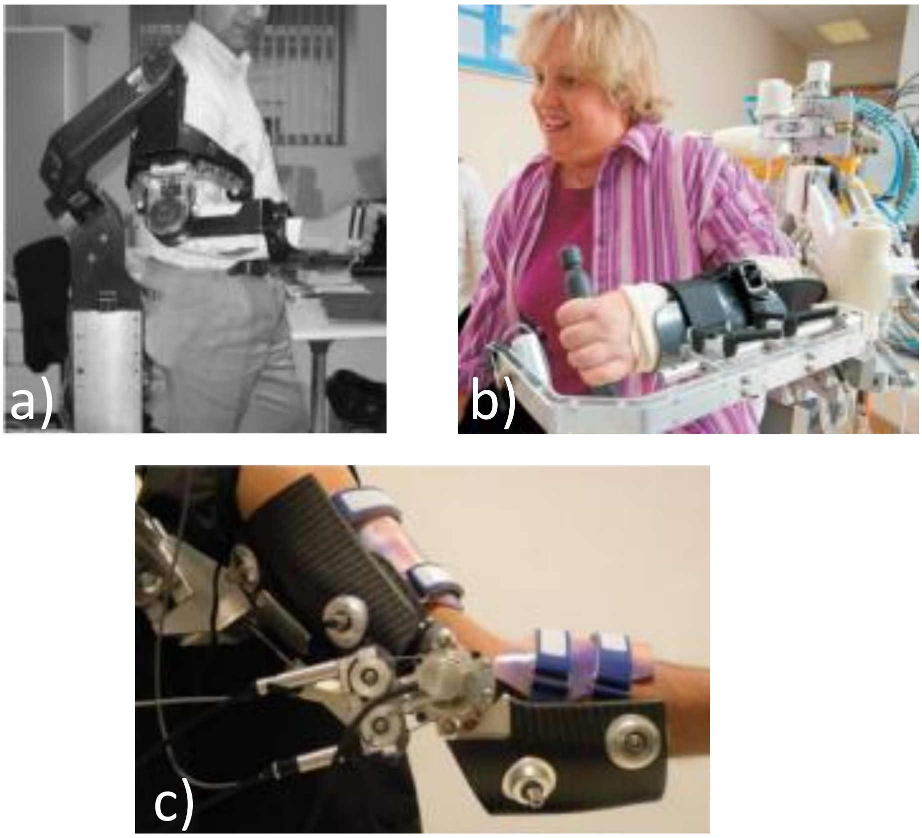


Figure 2-11: Image a) The PERCRO-L-Exos electrically actuated exoskeleton, Image b) The Pneu-WREX pneumatically actuated exoskeleton, The NEUROExos hydraulically actuated exoskeleton Images retrieved by: a) (Frisoli et al., 2009), b) (Wolbrecht et al., 2010), c) (Lenzi et al., 2011)

Nevertheless, the most common way of distinguishing robotic systems for upper limb rehabilitation is according to the number of points at which these devices apply forces to the user’s limb. As such there are single point of attachment devices, multiple point of attachment devices (Culmer et al., 2010) and exoskeletons (Maciejasz et al., 2014). Characteristic examples of such systems are displayed in Figure 2-12. A special case of rehabilitation robots are bimanual robots. Such robots can fall under either of the aforementioned categories with the only difference being that two robots are used in order to allow interaction with two arms.

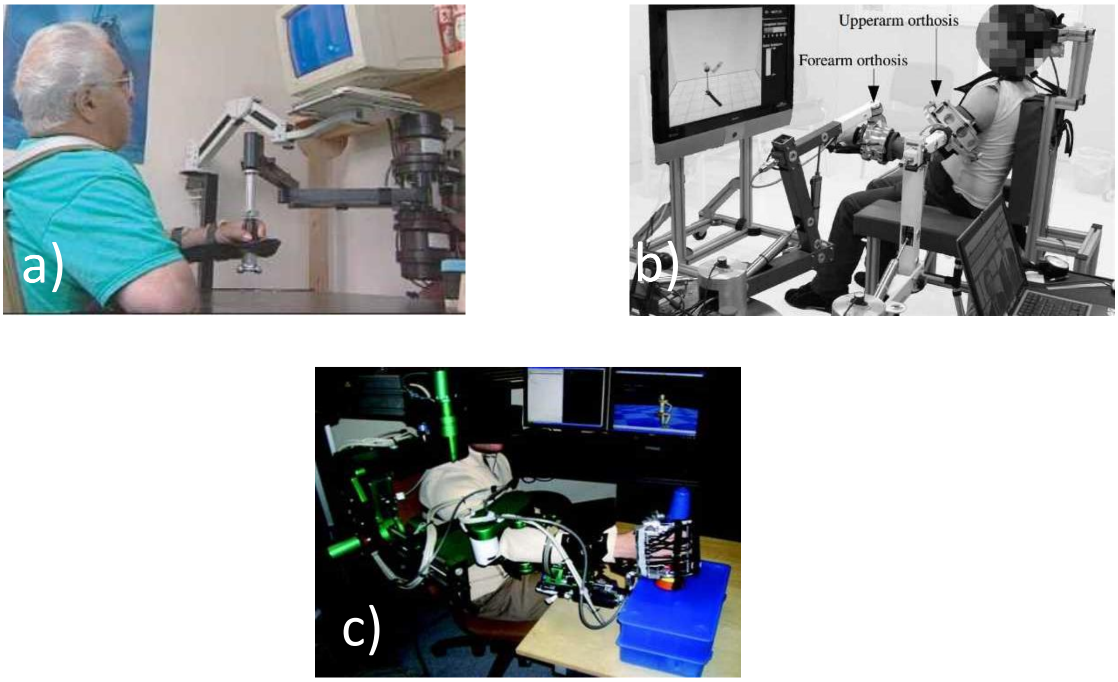


Figure 2-12: Image a) the MITmanus a single point of attachment system, Image b) The iPAM, a dual (multiple) point of attachment system, Image c) the ARMin III exoskeleton robot. Source: a)(Marchal-Crespo and Reinkensmeyer, 2009),b)(P R Culmer et al., 2009) *c)(Elizabeth B. Brokaw et al., 2011)*

2.5.1.1 *Single point of attachment systems*

The most common design of single point of attachment systems are end effector systems (endpoint). These systems use a single distal attachment point on the forearm usually in the means of an orthosis (Loureiro et al., 2011). The main advantages of such systems are that they are usually more simple to manufacture and control thus making them less expensive. Some of these devices (Weightman et al., 2011; Holt et al., 2013) are portable and with a small footprint therefore they are ideal for home rehabilitation applications. Nonetheless, such systems can only control the position of the hand and not the corresponding position of the elbow and shoulder consequently allowing configurations that may potentially injure the arm (Babaiasl et al., 2015).

A recent review by Maciejaz et al., 2014, identified that the majority of the single point of attachment systems that were reviewed, allowed movement in three dimensions. However, several systems have been developed that only allow movement on two dimensions. Such systems, while being very simple and cost-effective, when combined with effective control algorithms can be comparably effective to the three dimensional single point of attachment systems (Loureiro et al., 2011).

2.5.1.2 *Multiple point of attachment systems and exoskeletons*

These systems can control the full kinematics of the human arm. They allow the control of posture during the movement and control the synergies between the joints by allowing or prohibiting certain configurations (Gopura et al., 2016). Furthermore, because of their ability to precisely follow the movement of the human arm they provide very accurate means to collect kinematic measures in real-time. Conversely, these systems are usually large, utilise multiple actuators, are more complicated to design and control and as a result are more expensive. For all the aforementioned reasons such systems are more suitable for the clinical environment such as hospitals and rehabilitation centres and less suitable to be used in home rehabilitation applications (Lo and Xie, 2012; Maciejasz et al., 2014).

2.5.1.3 *Bimanual training robots*

Bimanual robots (Figure 2-13) can fall under any of the abovementioned categories with the only difference being in their configuration. Such systems utilise two rehabilitation robots to provide bi-lateral training. They also allow a control scheme where the movement of the healthy limb is mirrored by the impaired (Song and Guo, 2012). One of the most advocated benefits of bimanual robots is that they allow practice of tasks which require the coordination of both limbs that simulate movements that the patients would have to perform in their activities of daily living (Li et al., 2013). There has been evidence suggesting bilateral training promotes better movement coordination compared to unilateral training (Sheng et al., 2015).

In addition, the second rehabilitation robot can be used to provide haptic guidance by a rehabilitation expert (Trlep et al., 2011) which can allow for tailored training schemes where the therapist assesses which movements would benefit the patient and demonstrate them while the patient tries to match the therapists' movements with the robot assisting or perturbing those movements (Abdollahi et al., 2014)

Figure 2-13: Example of a bimanual robot consisting of two single point of attachment robots. Source: (Li et al., 2009)

2.5.2 Feedback in upper limb rehabilitation

As stated in the beginning of this section the main paradigm of rehabilitation robotics involves providing feedback to the user through a computer interface. Feedback provided by the system has been shown to be an important factor affecting the outcome of the rehabilitation process regardless of the training method (Levin et al., 2010). Feedback when selected appropriately can be motivating to the user and as a result reduce abandonment (Perry and Andureu, 2010) and also provide the user with useful information about their improvement.

Feedback, is commonly distinguished according to its source to either intrinsic or extrinsic (van Vliet and Wulf, 2006). Intrinsic feedback results from the sensory information generated by an individual's own movement while extrinsic or augmented feedback is information provided by external sources (Ryan and Deci, 2000; Molier et al., 2010). The latter can be provided in different forms to stimulate the different senses. As such, there is auditory, visual and haptic feedback (Sigrist et al., 2013). There has been evidence that extrinsic feedback can improve motor function, promote motor learning and increase retention of an acquired skill in stroke patients (van Vliet and Wulf, 2006) and children with CP (Burtner et al., 2014). However, the positive effect of extrinsic feedback on improving upper limb function is influenced by the type of feedback, the stage of the trial that is provided and the information it communicates to the user. An overview of the parameters that influence extrinsic feedback is shown in Figure 2-14.

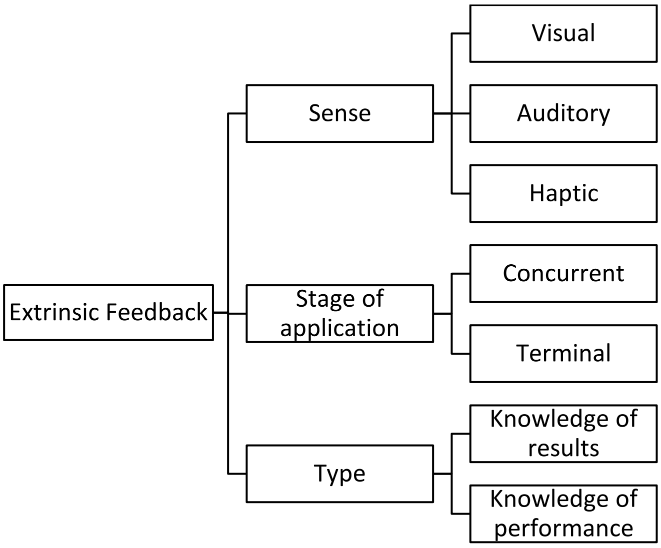


Figure 2-14: Different parameters of extrinsic feedback on upper limb rehabilitation

2.5.2.1 ***Type of feedback in terms of sensory information***

Robotic rehabilitation is often based in the interaction of the patient with the rehabilitation robot within a virtual computer environment, similar to a computer game. The virtual environment is providing extrinsic sensory feedback to the patients in order to provide them with information about different parameters of the task. This information can include a visual representation position of the patients' arm relative to the virtual workspace, trajectories that need to be followed, auditory cues for initiation of tasks. In the context of this report as a simplification the word feedback is used instead of extrinsic feedback.

Visual feedback is the most commonly used type of feedback either being used alone or combined with auditory feedback. Visual feedback is displayed on a computer screen or in a virtual reality environment. Some recent studies have also explored the effects of visual feedback when provided through an augmented reality environment. There has been evidence of the benefits of visual feedback when provided in a carefully selected manner (Molier et al., 2010; Parker, 2011; Patton et al., 2013).

Auditory feedback has been a rather understudied source of feedback (Sigrist et al., 2013). Recently there has been evidence presented in literature that auditory feedback promotes brain plasticity through mechanisms that are fundamental for the recovery from neurological injury (Rosati et al., 2013). Yet, the effect of auditory feedback may differ according to the side of the brain that has been affected (Robertson et al., 2009). Robertson et al. in their study with stroke patients with hemiparesis investigated the effect of auditory feedback according to the affected hemisphere. The results of their study indicated that although the group with damage on the right hemisphere improved in terms of kinematic outcomes the group with damage on the left hemisphere deteriorated (Robertson et al., 2009).

Over the years, different definitions have been proposed for haptic feedback each definition usually related to the application. In the context of this programme of work the definition provided by Sigrist et al, 2013 seems to be appropriate as such "haptic feedback is defined as any kind of haptic perception that teaches the necessary features that guide the subject toward, and not necessarily through, the desired motion" (Sigrist et al., 2013). Haptic feedback has been found to enhance participation and cooperation and promote motor learning (Sigrist et al., 2013; Santis et al., 2014).

2.5.2.2 *Stage of trial where feedback should be provided*

Equally significant to the type of augmented feedback provided to the subject is the timing where feedback should be provided. There is still an open debate in the scientific community on whether feedback should be provided during the trial (concurrent feedback) or after its completion (terminal feedback). Concurrent feedback has been shown to have a positive effect on motor learning and skill acquisition. However, it has been observed that when only real-time concurrent feedback was provided the performance has reduced on follow-up retention tests (Park et al., 2000). This has been attributed to the fact that the patients become highly dependent on the feedback provided (Sigrist et al., 2013) .

It has been suggested that concurrent feedback may only be useful in the early stages of a training scheme where the patient needs assistance in understanding the task needed to be performed and that it should be switched off in the subsequent trials (Park et al., 2000). An alternative is to only provide feedback at the end of a trial. This has been shown to reduce dependency but not eliminate it. As such, trials where no feedback is provided are required in order to strengthen the internal movement representation. (Sigrist et al., 2013)

2.5.3 Control strategies that promote motor learning in upper limb

Haptic Control Algorithms (HCAs) are algorithms that control a powered haptic system's (rehabilitation robot) response, according to the user's input. In rehabilitation robotics numerous control strategies have been introduced utilising different HCAs. Marchal-Crespo & Reinkensmeyer, 2009 performed a review on the control strategies used on robotic rehabilitation both for gait and upper limb. In their paper they categorised the HCAs used in robotic rehabilitation into three main categories namely, assistive, challenge-based and haptic simulation (Marchal-Crespo and Reinkensmeyer, 2009) control strategies as shown in Figure 2-15. Since the publication of this review paper in 2009 this has been the most accepted manner of distinguishing the different HCAs used in upper limb rehabilitation robotics.

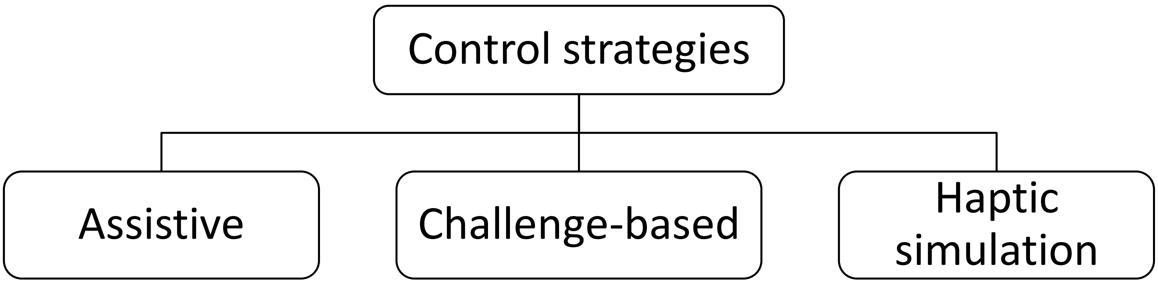


Figure 2-15: Categorisation of control strategies for upper-limb robotic rehabilitation as suggested by (Marchal-Crespo and Reinkensmeyer, 2009)

According to Marchal-Crespo and Reikensmeyer, strategies that utilise assistive haptic control help the user to move their limb to perform the desired movement. Challenge-based algorithms introduce a “challenge factor” to the movement. Finally, haptic simulation strategies involve practising of movements respective to activities of daily living (ADL) in a virtual environment.

In a more recent systematic literature review on training modalities for upper limb robotic rehabilitation after stroke by Basteris et al., 2014 the authors stated that the commonly used terms for the classification of training modalities in the field were not specific allowing ambiguity in their definition. As such an alternate classification of HCAs was proposed by the authors based, not only on the features of the training modality (e.g. assistive, resistive etc.), but also on the manner that it is implemented. A brief overview of the Basteris classification of HCAs is provided in Table 2-4. In the same review the authors mentioned that the proposed classification of training modalities failed to describe a particular implementation of HCA that induces challenges to the movement by augmenting movement errors.

Whether the classification proposed by Basteris et al. will be adopted by the scientific community is yet to be seen nevertheless, certain adjustments are needed in order to describe all existing training modalities such as error augmentation and allow for the description of future ones. For the purpose of this review the classification introduced by Marchal-Crespo & Reikensmeyer will be used as it not only is the more established within the scientific community but also because it is based on a simplistic approach that successfully describes all the current training modalities.

Table 2-4: Basteris classification of HCAs for upper limb rehabilitation and the relation of the categories with the classification by Marchal-Crespo & Reinkensmeyer, 2009. (Basteris et al. 2014)

Basteris classification		**Description by Marchal-Crespo & Reinkesmeyer**
Feature	**Specification**	
Passive, passive mirrored	The device follows a pre-programmed trajectory/force profile toward a desired trajectory. In the case of passive mirrored therapy, the unimpaired limb guides the affected limb.	Assistive non-adaptive
Moving attractor	Similar to passive with the only difference being that assistance varies according to different parameters	Assistive adaptive
Triggered assistance	Assistive forces (similar to passive) are applied only after a threshold in performance is reached e.g. certain delay in performing the movement	Assistive adaptive (performance based)
Assistive force constant	Constant forces towards the target or weight support (gravity compensation)	Assistive Counterbalancing
EMG-proportional	EMG signals activate the robot's actuators to perform the desired movement	EMG-based assistance
Pushing force (in case of delay)	Force is applied towards the movement direction only when a delay occurs with regard to a desirable motion pattern	Assistive adaptive (performance based)
Spring-damper guidance	Elastic or viscoelastic force fields that keep movement from deviating laterally from the desired trajectory	Passive (haptic wall)
Tunnels	Similar to spring-damper systems but forces are applied only if certain threshold in error (lateral deviation from the desired trajectory) is reached.	Assistive adaptive (performance based)
Spring against movement	Forces are applied in the direction opposite of that of the movement in the form of an elastic force field.	Challenge based - Resistive
Damper against movement	Forces are applied against the direction movement based on the velocity	Challenge based – Resistive/Viscous force fields
Not clear	In some cases, the authors do not report the manner of implementation of the HCA but only state its purpose i.e. assistive algorithm, resistive algorithm	N/A

2.5.3.1 *Control strategies that assist movement*

Assistive control strategies have been extensively studied in literature for the rehabilitation of stroke patients while a limited number of studies have explored the effects of assistive HCAs on the rehabilitation of the upper limb of children with CP (Bayón et al., 2016). Basteris et al. in their systematic review paper on training modalities for robotic stroke rehabilitation of the upper limb identified that from 126 groups of subjects (group sizes unclear) who participated in the reviewed studies 91 received assistive training either exclusively or in conjunction with other modalities. On the other hand, a mere 22 groups received resistive therapy. (Basteris et al., 2014). Similar to “active assist” exercise provided by clinical therapists (Marchal-Crespo and Reinkensmeyer, 2009), such strategies were initially developed to assist more severely impaired patients who due to their impairment could not complete the desired task (Wang, 2012). Such algorithms have been claimed to promote brain plasticity by introducing novel sensorimotor stimulation, augmenting effort and by provoking repetitive movement. (Marchal-Crespo and Reinkensmeyer, 2009)

Several adaptations of assistive strategies have been proposed by the different research groups. These strategies usually fall under two categories; non-adaptive and adaptive assistive strategies, respectively. Non-adaptive assistive strategies apply a constant force to the impaired limb to assist movement (Kirihara et al., 2010), while adaptive strategies provide different levels of assistance based on predefined factors such as performance (Posteraro et al., 2010). There is evidence supporting that when moving under the effect of assistive force in robotic rehabilitation participants tend to incorporate these forces in their motor plan in order to reduce the voluntary control while keeping the error low (Emken et al., 2007). Furthermore, such strategies have been shown to have a better effect on improving outcome in ADLs when compared to conventional therapy (Chang and Kim, 2013).

To minimise reduced effort (slacking) several studies have introduced a forgetting factor to their systems. This was implemented in either a non-adaptive manner (forces switch off after a set or random number of movements) or in an adaptive manner where performance is evaluated at a certain amount of time/movements and assistance is adjusted accordingly. If performance is improved assistance is reduced to challenge the participants (assistance as needed) (Guidali et al., 2011). Adaptive algorithms such as the assistance as needed (AAN) aim to provide tailored rehabilitation by providing the minimum level of assistance for the patient to perform the intended movement (Xu et al., 2011; Carmichael and Liu, 2012; Pehlivan et al., 2016). There is evidence showing that algorithms such as AAN are better in promoting motor recovery over passive movements (Krebs et al., 2009) and have been shown to improve upper limb function in children with CP (Fasoli et al., 2008; Bayón et al., 2016).

2.5.3.2 *Control strategies that induce a challenge factor to the movement*

Challenge based control strategies aim to perform in an opposite manner to the assistive by making movements more demanding. Implementations of such strategies include resisting movement by applying opposing forces (Stienen et al., 2009; Conroy et al., 2011), introducing new environments to the movement such as resisting movement (Lum et al., 2002; Stienen et al., 2009) , introducing viscous force fields (Sanguineti et al., 2009; Masia et al., 2011) and by enhancing error (Rozario and Housman, 2009; Shirzad and Van der Loos, 2012).

There is sufficient evidence to suggest that training which requires higher effort from the paretic limb can improve motor function (Patten et al., 2006; Marchal-Crespo and Reinkensmeyer, 2009). In addition, in the case of resistive forces, movement oscillations are dampened hence promoting less spastic, smoother movements (Stienen and Kooij, 2007; Basteris et al., 2014). In a study by Patton et al. (2006), stroke patients had to perform reaching movements within a curl force field where forces were applied orthogonally to the velocity of the movement forming a clockwise or anti-clockwise pattern. In this study improvement in terms of path errors occurred only in the directions where error was amplified by the applied forces (Patton, Stoykov, et al., 2006). Interestingly a literature review by (Proietti et al., 2016) on control strategies developed for exoskeletons did not identify any studies that implemented challenge-based algorithms.

2.5.3.3 *Error-augmentation in upper-limb robotic rehabilitation*

Error augmenting (EA) strategies are challenge-based strategies which perform in an opposite manner to the assistive (error reducing strategies). In the case of error augmentation movement error is increased either haptically or visually. In haptic error augmentation, forces are applied in such a manner that movement is perturbed in the direction away from the desired trajectory. It must be noted that some implementations of haptic EA forces are applied away from the desired target with a force proportional to the distance from a desired target (Lee and Choi, 2010; Givon-Mayo and Simons, 2014). Although, such algorithms are technically resistive according to the classification by (Marchal-Crespo and Reinkensmeyer, 2009) they are often considered as EA (Israely and Carmeli, 2015) because they aim to increase movement errors and not just resist movement. Conversely, in visual error augmentation, the visual representation of the arm’s position is shifted away from its actual position in the workspace. Haptic error augmentation is more relevant to robotic therapy, as it utilises the force generating capabilities of such systems which is the focus of this project. For this reason; visual error augmentation will not be discussed further in this report. However, the interested reader can find information about its effectiveness on motor learning in a literature review paper by (Alexoulis-Chrysovergis et al., 2013).

Error augmenting strategies are based on the recent evidence that motor adaptation relies on sensory error prediction or motor correction (Tseng et al., 2007) as such it is an error driven process. It is assumed that by performing movements in an error rich environment the potential for error correction and therefore opportunities for brain plasticity are greater. Furthermore, error augmentation introduces a challenging training environment that provokes the patients by keeping them interested and concentrated on the task, which are significant factors that influence motor learning (Emken et al., 2007; Shirzad and Van Der Loos, 2013) as well as reduce abandonment (Shirzad and Van der Loos, 2012).

To further investigate the potential of error augmentation a literature review was performed investigating its use in the robotic rehabilitation of the upper limb (Alexoulis-Chrysovergis et al., 2013). The review was not condition-specific in order to gather as much information on the effects of this modality to the rehabilitation of the upper limb. The results of the review were published as a review paper which can be found in Appendix B.

From the thirteen studies that were reviewed, six explored the effects of EA on stroke participants and four on only able-bodied. Interestingly, none of the reviewed studies explored the effect of EA on children with CP which is further confirmed by a more recent review on robotic therapy interventions for children with CP which did not identify any EA interventions for children with CP (Bayón et al., 2016). Most of the reviewed studies reported positive outcomes, such as improvement of kinematic measures (Cesqui et al., 2008; Rozario et al., 2009) in stroke patients and improvement in the optimal path control for patients with primary dystonia (Casellato et al., 2012). Furthermore, one of the studies identified potential benefits of EA forces in being more effective in improving large movement errors of the movements of stroke patients when compared to assistive forces (Patton, Stoykov, et al., 2006). However, there is very limited existing literature to support this finding.

A study by (Cesqui et al., 2008) compared the effects of EA against those of an assistive HCA. Fifteen stroke patients were divided into two groups and performed centre-out reaching movements towards targets placed in a circular configuration using a robotic manipulandum. The first group trained for two weeks with an error augmenting HCA that applied forces to the perpendicular direction away from the desired path with an amplitude proportional to the distance away from that path. After a two-week washout period (no robotic training) the participants trained with an assistive HCA that provided assistive forces when the participants were not able to complete a movement. The second group undertook the same protocol with the only difference being that its participants first received assistive training and then EA. Interestingly, the authors of the study concluded that patients with less severe upper limb impairment benefited more from the EA HCA while the more severely impaired benefited more from the assistive HCA. This is an intuitive finding as a severely impaired participant would benefit more from an assistive HCA as it would allow them to perform movements that they could not perform otherwise while an EA HCA would further impede those movements and vice versa. The implications of this study are great as it showed that an EA HCA had comparable effect on motor learning to an assistive HCA but also that different control strategies may be suitable for different impairments and in different stages of the recovery.

The study by (Lee and Choi, 2010) which evaluated the effectiveness of an error augmenting HCA in a trial with able-bodied participants (N=60) reported different findings. The participants were randomly assigned into one of four intervention groups and performed tracking movements using a single point of attachment rehabilitation robot under one training condition. Those were an assistive HCA, an error-augmenting HCA in the form of resistive forces in the opposite direction of the vector pointing towards the target and an amplitude proportional to the distance between the robot’s endpoint and the target, random direction and amplitude forces, and a control condition where no forces were exerted by the robot. The study considered one measure for the analysis of the results that is the mean error (distance from the target). In the assessment following the training stage of the trial the assistive condition was the one that reduced the error the most, while the error augmenting HCA was the one had the least effect. Nonetheless, an interesting finding of this study was that the in retention tests the group that received training with the EA HCA performed better than the one that practised with the assistive HCA. This suggest that assistive HCAs are better at inducing short term improvements but EA can provide longer lasting effects i.e. more retention. That is an interesting finding however, it must be taken with caution as the study is of limited methodological quality mostly due to the fact that the authors only report the findings of the analysis for one kinematic measure and as such it is difficult to draw conclusions as to what would be the effect of the different training modalities in other aspects of the movement such as duration, velocity and smoothness an issue that should be addressed in later repeatability studies.

Furthermore, only few studies have investigated the effectiveness of haptic error augmentation when combined with adaptive features (visual or haptic) in conditions such as stroke (Abdollahi et al., 2014) and multiple sclerosis (Squeri et al., 2007; Vergaro et al., 2010) and provide evidence of the potential of such control strategies. Such approaches include machine learning (Patton, Kovic, et al., 2006; Shirzad and Van Der Loos, 2013) and performing a tracking task where the participant was asked to follow a therapist’s movement while the system is applying forces proportionally and in the direction of the error between the position of the therapist’s arm and the patient’s arm (F Abdollahi et al., 2011; Abdollahi et al., 2014).

The study by (Patton, Kovic, et al., 2006) introduced a machine learning algorithm which in the course of an “algorithm learning stage” within a session the robot applied random intermittent forces on the participants' movement in order for the system to learn the average forces that are required to move the subjects' arm to a certain position. To perform EA, the opposite vector of these forces was applied in the learning stage of the session. To test the effectiveness of that HCA on the rehabilitation of those suffering from stroke the authors performed a clinical trial. This trial had two intervention groups that trained on performing reaching movements with the robot either applying EA forces or no forces (Control group). The participants' movements improved only in the directions with initial high errors. Both groups performed similarly in the kinematic measures but the treatment group showed a marginal but statistically significant improvement in the Fugl-Meyer Assessment (FMA) scale ((1.6 points, $p<0.06$).

A more recent study by (Givon-Mayo and Simons, 2014) with stroke participants (N=7) explored the effects of a velocity oriented EA approach. A healthy bell-shaped velocity profile was established by measuring movements of able-bodied subjects. The stroke participants were asked to perform a reaching task while following the optimal velocity profile and the system calculated the deviation (error) of the participants' movement velocity from that profile. If participants 'movement velocity deviated from the desired velocity profile a force was applied in the opposite direction of the movement in order to augment errors in movement velocity. As such for a high velocity movement the system would be opposing movement and hence reduce velocity while for a low velocity it would do the opposite. The study populations were divided in two groups with one being the treatment group (n=4) performing reaching movements while manipulating a single point of attachment rehabilitation robot under error augmenting forces and the other being the Control group (n=3) that did the same but without any forces. The authors reported that the treatment group improved movement smoothness as velocity profiles changed in the course of the trial to resemble more the optimal profile than the Control group did. Also, the treatment group showed greater improvement in the Modified Ashworth Scale (MAS) (Figure 2-2) scale (≥40% improvement for treatment group, <12% for the Control group). Given the very small population the authors advise caution and suggest that trial with refined protocol and bigger population needs to be contacted to further explore this finding.

It appears that studies in error augmentation for robotic rehabilitation suffer from low methodological quality as many studies found in literature are pilot/exploratory studies with small sample sizes and designs that allow bias (Israely and Carmeli, 2015). An exception to this was the Random Control Trial (RCT) study by (Abdollahi et al., 2014) where a crossover protocol was implemented. RCTs are considered to be of greater methodological quality (Dobkin, 2004). More, specifically, in the study by (Abdollahi et al., 2014) the same group of stroke patients received practice with a combination of visual and haptic EA and after a washout period of one week where no practice was received the participants undertook the same protocol but without any visual or haptic EA. The participants were randomly assigned to one of two groups. Each group underwent the same practice with the only difference being that one group was firstly trained with EA and after a washout period trained with the control condition while the other group did the opposite.

The participants were asked to move the robot's endpoint to match the movements of a cursor controlled by a therapist. The adaptive features of this approach were provided by the therapist who was adjusting the movements to tailor the training according to the needs of each participant. EA forces were proportional in magnitude to the distance from the participants' hand to the that of the therapist and were applied in the opposite direction providing a resistive force. The authors reported that EA had a greater effect than the control condition with a better score in the FM and the Wolf Motor Function Test (WMFT) clinical scales (Figure 2-2) indicating improvements in motor function while no kinematic measures were evaluated. Despite the positive outcome such rehabilitation approaches can be considered more of an enhancement to the traditional rehabilitation therapy rather than robotic rehabilitation approaches as they rely heavily on the presence and actions of a therapist hence not taking into advantage the main benefits of robotic therapy which places the therapist in a supervisory role overseeing the therapy of multiple patients in parallel rather than one at a time.

Moreover, by studying the literature one can find limited evidence of studies investigating the effects of adaptive EA training. Most studies, adjust the magnitude of error amplification/the difficulty of the task by multiplying a fixed gain to the instantaneous error which is the same across all participants (Rozario et al., 2009; Abdollahi et al., 2014; Givon-Mayo and Simons, 2014). Another approach that aims to provide for more individualised training, is the use of machine learning to assess the forces that are required to disturb movement the most efficiently for each individual (Patton, Kovic, et al., 2006) or predict what amount of difficulty the patients would desire to increase their motivation (Shirzad and Van der Loos, 2015). However, in order to train the algorithm for each individual the participant is required to perform many movements (200) before the actual therapy begins. As a result precious therapy time is been lost and therefore such approaches make impractical the adjustment of difficulty more than once in a session.

Within the limited number of studies exploring the effects of EA on motor learning there is sufficient evidence to demonstrate that they can be beneficial for upper limb rehabilitation. Nevertheless, currently it is difficult to conclude what those benefits are and how EA compares against more established approaches such as assistive HCAs and free movements. The study by (Cesqui et al., 2008) indicated that the benefits on improving upper limb impairments of assistive and error augmented HCAs can be specific to the severity of the impairment. The logical question arising from this finding is if a single HCA with performance-based adaptive features could be more beneficial for a wider range of impairment severities than a non-adaptive HCA and if so, does the type of the HCA have an effect on the outcome. To the author’s knowledge there has not been an attempt to answer this question as a comparison between performance-based adaptive assistive HCAs and their error-augmented counterparts has not yet been made. Furthermore, to this day the search for an optimal haptic control algorithm to promote motor learning on those with impairments still remains unanswered (Marchal-Crespo and Reinkensmeyer, 2009) leaving open the question of whether all possible strategies have been explored.

2.6 Aim and objectives

2.6.1 Aim

The aim of this work was to develop novel haptic control algorithms utilising a single point of attachment haptic device and evaluate how they affect motor learning primarily in able-bodied adults with the intention to transfer the findings to the stroke and cerebral palsy populations.

2.6.2 Objectives

1. Perform a literature review on upper limb robotic rehabilitation approaches for impairments caused by stroke and cerebral palsy to identify haptic control algorithm methodologies and trends in research.

2. Further develop an existing single point of attachment upper limb rehabilitation device.

3. Design simulation and development environments that can be used for the development and testing of haptic control algorithms.

4. Develop a computer game environment to interface the single point of attachment rehabilitation device with the end user.

5. Develop assistive and challenge based novel haptic control algorithms for upper limb rehabilitation.

6. Design and perform an appropriate trial to evaluate the effect of the developed haptic control algorithms in the motor learning of able-bodied adults.

7. Analyse kinematic data collected in the trial in order to evaluate the effectiveness on motor learning of each of the haptic control algorithms and compare them against each other.

2.6.3 Study Hypotheses

During the selection and development as well as the testing of the haptic control algorithms certain hypotheses were made. These are as follows:

1. Error augmented robotic rehabilitation would be better at inducing motor learning to the upper limb compared to assisted or free movements.
2. Adaptive HCAs would better induce motor learning to the upper limb when compared to free movements.
3. Training with one limb will induce bilateral transfer to the other. Error augmenting adaptive HCAs would be more effective in inducing bilateral transfer.
4. Training with adaptive error augmenting HCAs would result to increased engagement and satisfaction to the users.

2.7 Selection of algorithms for investigation

From the findings of the literature review presented in this chapter it appears that only few studies have investigated the effectiveness of haptic error augmentation when combined with adaptive features in conditions such as stroke (Farnaz Abdollahi et al., 2011) and multiple sclerosis (Vergaro et al., 2010; Shirzad and Van Der Loos, 2013). Nevertheless, these studies provide promising evidence of the potential of this type of control strategies. Such approaches include machine learning (Patton and Mussa-Ivaldi, 2004; Shirzad and Van Der Loos, 2013) and performing a tracking task where the participant is asked to follow a therapist's movement while the system is applying forces proportionally and in the direction of the error between the position of the therapist's arm and the patient's arm (Farnaz Abdollahi et al., 2011).

The results of the literature survey indicated a lack of extensive study of error augmenting HCAs with adaptive features that are informed by the theory of motor learning. Two novel HCAs were selected for further study namely, error augmentation adaptive (EAA) and error augmentation proportional (EAP). Furthermore, to compare the effectiveness of the developed HCAs relative to other (more established) HCAs an assistive HCA was to be developed. This assistive algorithm was selected to be an implementation of a well-established adaptive HCA namely assistance as needed (AAN). As current evidence in literature supports that active engagement is positively correlated with brain plasticity in robotic therapy (Blank et al., 2014) all of the developed HCAs had adaptive features that assess the participants' performance and adjust accordingly to challenge them. As findings on motor learning of the able-bodied transfer to the impaired population (Krakauer, 2006), the effectiveness of the developed haptic control algorithms is evaluated in a trial with healthy participants and compared against established modalities of training such as AAN and free movements. It must be noted that as this body of work focuses on point to point planar movements while following a desired trajectory, movement error is defined as the perpendicular distance away from the trajectory that is required to be followed.

The following subsections present the conceptual design of the aforementioned HCAs.

2.7.1 Error Augmentation Adaptive

Error Augmentation Adaptive (EAA) is introducing a challenge factor to the movement by applying forces to increase movement error in an adaptive manner. In the context of this work the error is defined as the perpendicular distance from a desired trajectory. In a reaching task where the user is asked to move the robot's endpoint across a straight line trajectory from point A to point B the robot provides forces in the perpendicular trajectory away from the desired path Figure 2-16. An adjustable band (deadband) is placed around the desired trajectory within which no forces are applied by the robot. The user's performance is evaluated over a specific period of time t_d (or a set number of movements) as a running average. When time elapses equal to t_d the system reads the running average of error up to that point. Consequently, based on the value of this average the system makes a decision to adjust the deadband zone accordingly that is, as performance improves the deadband becomes narrower in order to make the task more difficult and vice versa.

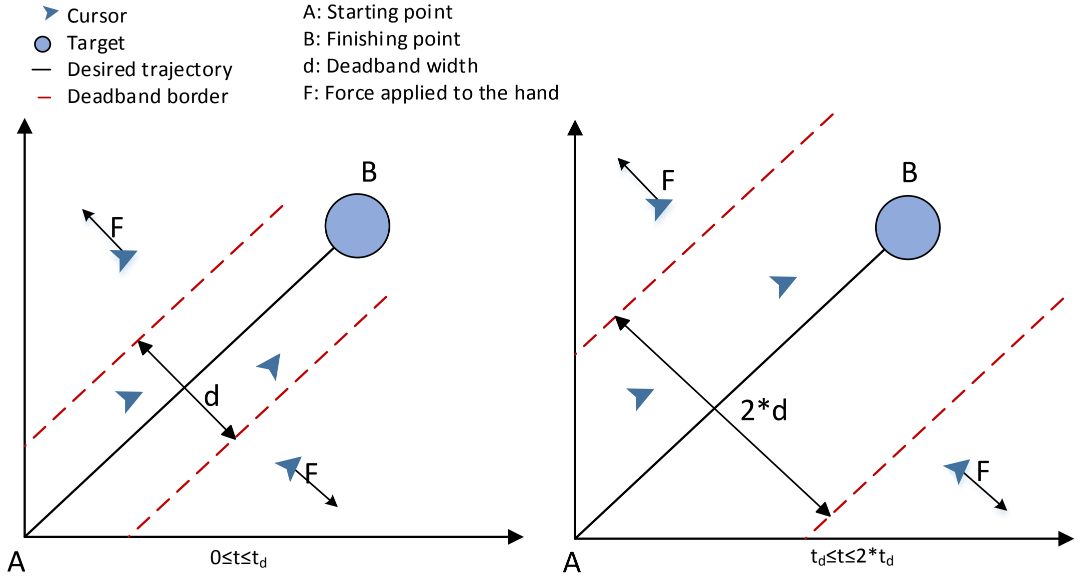


Figure 2-16: Both figures show typical scenarios for different values of mean performance. The figure on the left demonstrates initial conditions while the one on the right shows how the system adapts if an improvement in the user's performance has occurred

This HCA is utilising haptic tunnels (but inversed) that have been extensively used with assistive adaptive HCAs (Basteris et al., 2014) and combines them with error augmentation. Other adaptive EA algorithms (Patton, Kovic, et al., 2006; Shirzad and Van Der Loos, 2013) require a lengthy learning phase at the beginning of the training session to adjust the difficulty of the movements according to the ability of the user hence making multiple adjustments within the same session impractical. Therefore, such HCAs do not take into account changes in the performance of the user within the session due to learning or even fatigue. The aim of this novel HCA is to provide challenge proportional to the performance by incrementally adapting to the patient's performance. Several studies have demonstrated (Colombo et al., 2012; Chemuturi et al., 2013) that challenging tasks have a better effect on inducing motor learning. Still, there is evidence suggesting that incremental changes in the conditions (in this case incrementally increasing or decreasing the perturbation) of practise have a better potential in inducing motor learning (Bastian, 2008).

2.7.2 Error Augmentation Proportional

Error Augmentation Proportional (EAP) is a challenge-based HCA that makes movements more difficult by applying forces towards the perpendicular direction away from the desired trajectory. Similar to the Error Augmentation Adaptive (EAA) HCA a zone within which no forces are applied (deadband) is positioned around the desired trajectory of movement. When the user moves the robots handle (endpoint) outside from the deadband then the robot applies a force in the perpendicular direction away from the desired trajectory. The further away from the deadband the more intense the perturbation is; as such the more challenging the movement becomes.

Figure 2-17 provides an example of a reaching movement from A to B for different positions of the endpoint (cursor) with respect to the workspace (marker 1-6). When inside the deadband (zone defined by red dashed lines) no forces are applied by the robot (markers 1,2). The area around the deadband is divided into zones of adjustable width. Within those zones forces are applied in the perpendicular direction away from the desired trajectory. The furthest the zone the greater the forces. For example, in the positions represented by markers 3 and 4 the user will experience the same force amplitude but in different directions. On the other hand, in positions represented by markers 4-6 the user will experience forces in the same direction but of different amplitudes (force in marker 6 > force in position 5 > force in position 4).

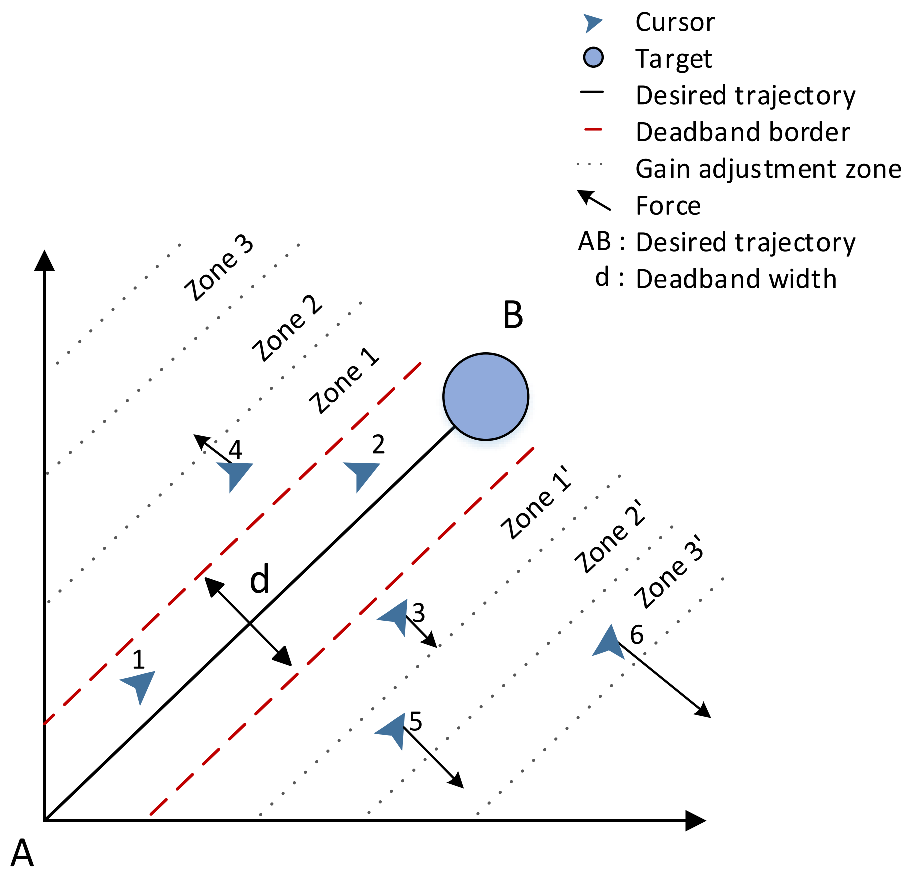


Figure 2-17: When the participants moves within the deadband no forces are applied. When movement deviates from the deadband forces are applied in a perpendicular direction away from the desired trajectory. The greater the distance from the perpendicular error the greater the intensity of the perturbation.

This HCA aims to increase effort and hence learning by introducing a penalty system. There is evidence supporting that humans adapt their movements to reduce effort (Todorov, 2004). This algorithm, exploits that feature of the human motor control system to guide the participants through the trajectories of reduced effort to promote desired trajectories. Inaccurate movements are penalised with higher perturbation making them more difficult to perform. Consequently, the participants can develop one of two strategies; either concentrate to attempt high accuracy movements or concentrate while resisting perturbing forces. If the force amplitudes are carefully mapped to the zones, the therapist can provide haptic trajectories that provide a compromise between accuracy and magnitude of perturbation hence training the internal system of the patients to move through these areas. As the participant improves those "optimal" zones can be adjusted accordingly to be closer to the desired trajectory etc..

Error augmentation proportional is based on an HCA developed by (Cesqui et al., 2008) where EA forces are proportional to movement error multiplied by a fixed gain but unlike this algorithm EAP allows for customisation of the forces to meet the requirements of the therapy as not only the different zones are adjustable in width but they can be assigned to a specific gain or response (magnitude of perturbation) within those zones (Figure 2-18). As such it is not bound by a linear relationship between error and magnitude of perturbation and other magnitude relationships can be achieved (Figure 2-19). Finally, in contrast to the algorithm introduced by (Cesqui et al., 2008) EAP allows for a deadband i.e. a zone where no forces are applied to allow movement for accurate but not perfect movements not to be penalised which in turn will decrease training fatigue when the participant achieved the error goal that was set for them. Furthermore, the use of a deadband allows the patients to have more control over their movements a feature that has been suggested to increase outcome (Tropea et al., 2013)

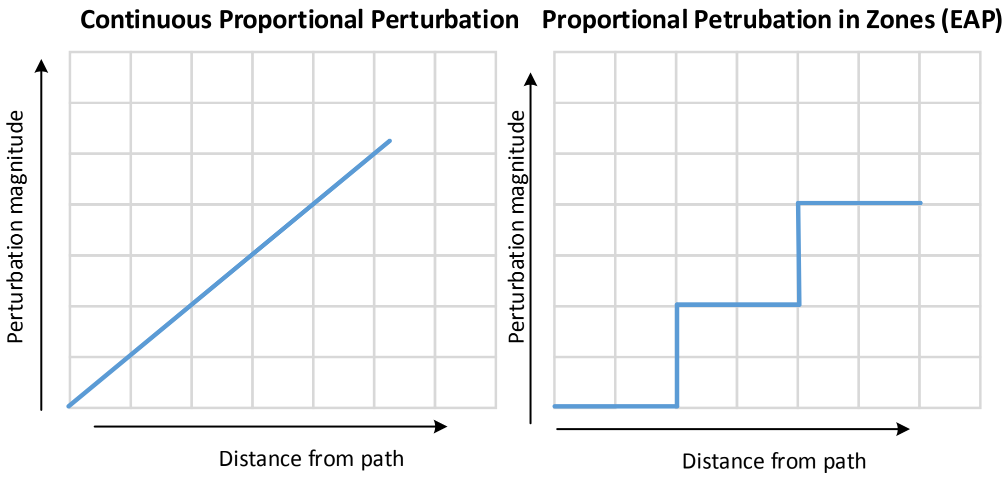


Figure 2-18: Perturbation magnitude in continuous proportional EA and proportional perturbation in zones

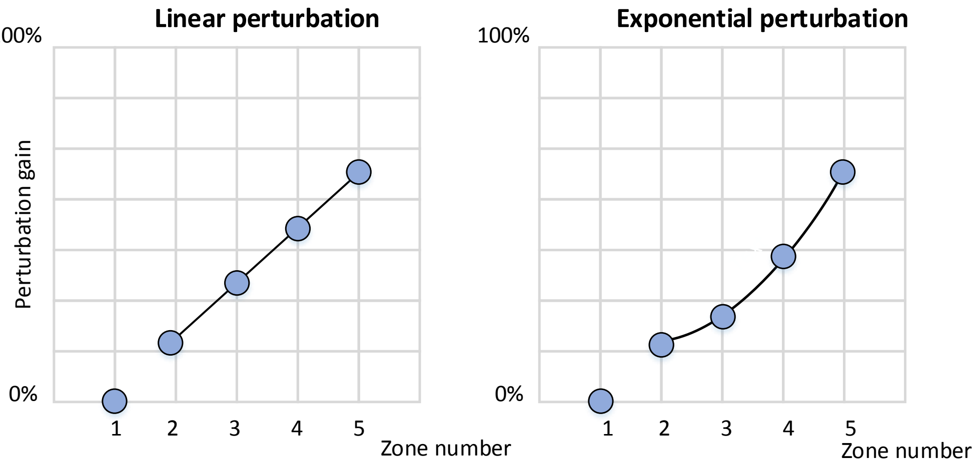


Figure 2-19:By adjusting the perturbation gains for each zone different patterns can be achieved to adjust the difficulty of the task at different distances from the desired trajectory (In the figure zone 1 is the nearest to the desired trajectory while zone 5 is the furthest). Zone 1 acts as deadband i.e. a zone where no forces are applied.

2.7.3 Assistance As Needed

Assistance as needed (AAN) is an assistive adaptive HCA. AAN provides forces towards the target of the movement. A neutral zone (deadband) is fitted around both sides of the desired trajectory within which no forces are applied. Performance in the form of tracking error away from the desired trajectory is measured over a period of time t_d. When t_d has elapsed the average error is calculated and the walls of the deadband are adjusted to become narrower (more assistance) when error is high and to become wider (less assistance) when error is low. Active assistive type algorithms are the most studied category of HCAs (Basteris et al., 2014). AAN algorithms have been shown to improve upper limb function (Kahn et al., 2004) while making movements faster, smoother and more accurate (Sanguineti et al., 2009).

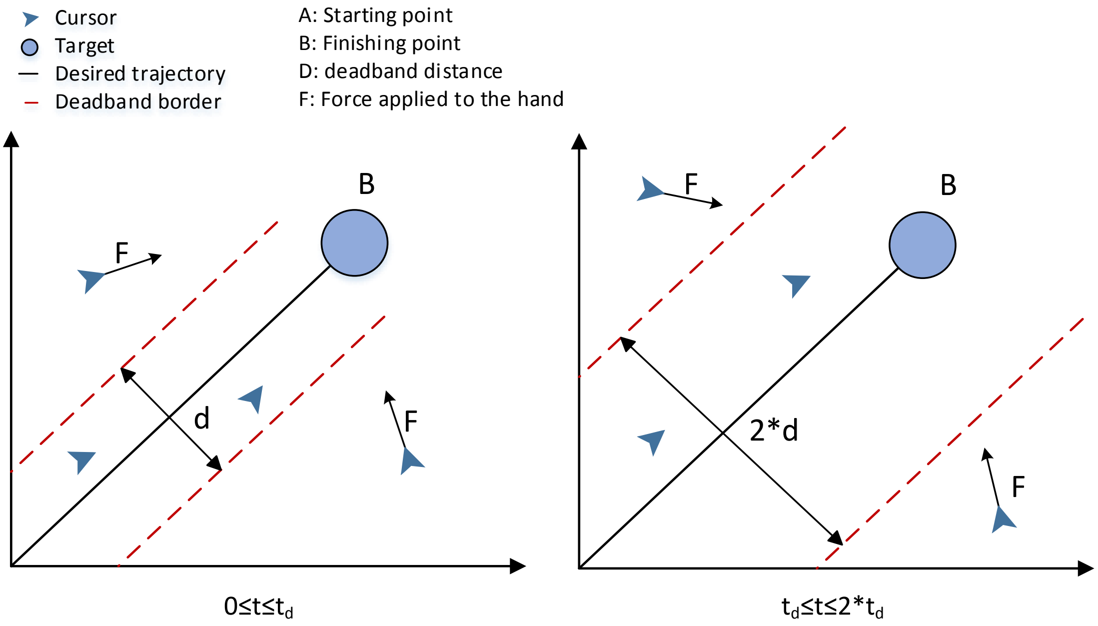


Figure 2-20: Both figures show typical scenarios for different values of mean performance. The figure on the left demonstrates initial conditions while the figure on the right shows how the system adapts if an improvement in the user's performance has occurred

3 Development of the robotic rehabilitation system

3.1 Introduction

The literature survey presented in Chapter 2 identified that error augmentation has potential in improving arm function on patients who suffer from neurological impairments. At the end of the chapter the concept behind the three haptic control algorithms considered in this thesis was introduced, namely Error Augmenting Adaptive (EAA), Error Augmenting Proportional (EAP) and Assistance As Needed (AAN). This chapter discusses the development of the hardware and software required to implement the aforementioned HCAs.

The platform that these HCAs were to be developed for and deployed on, was a single point of attachment planar rehabilitation robot initially developed in the University of Leeds. The hardware designs of the aforementioned robot were made available to our research team. However, an attempt was made to further improve certain aspects of the robot such as an update of the electronic components and some changes in the original designs of the rehabilitation robot which are described in detail in Appendix A. Furthermore, it must be noted that all software developed for the purposes of this project was not based on the previous design. This chapter presents the details of the software development component of this work including the algorithmic implementation of the HCAs discussed in Section 2.7.

3.2 Overview of the rehabilitation robot

The rehabilitation robot used in this project was a single point of attachment rehabilitation robot originally developed by researchers at the University of Leeds for studying the effects of the robotic therapy to the rehabilitation of children with CP (Holt et al., 2013). A description of the original system can be found in (Holt et al., 2013; Sivan, 2014). The rehabilitation robot was developed as a low-cost solution that aimed to be more accessible to the public when compared to the more expensive rehabilitation systems such as the MIT-MANUS (MacClellan and Bradham, 2005). It consisted of a two link planar robotic manipulator with two degrees of freedom (DoF) as shown in Figure 3-1 and Figure 3-2. Each link was actuated by a DC motor with magnetic rotary encoders to determine position.

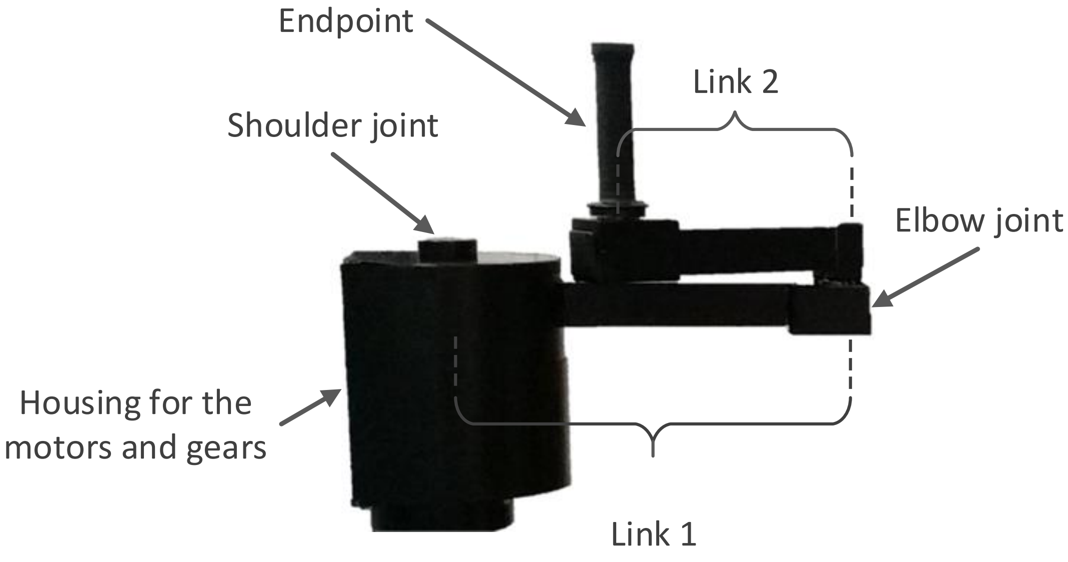


Figure 3-1: The two degree of freedom rehabilitation robot

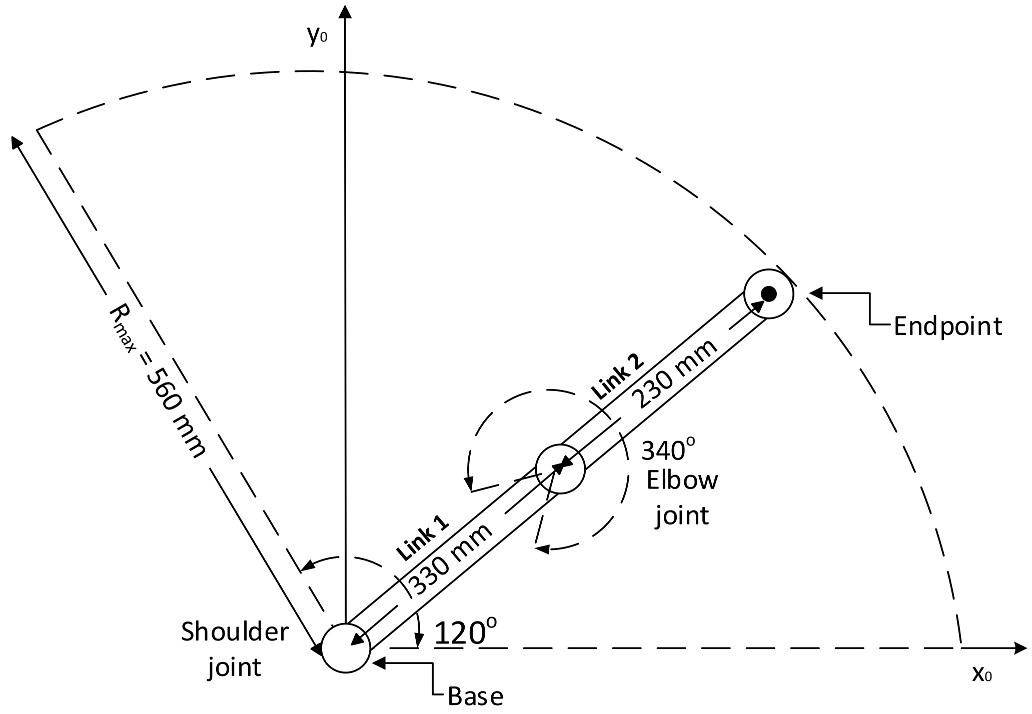


Figure 3-2: Overview of the workspace of the rehabilitation robot and dimensions.

To control the robot a National Instruments compact Reconfigurable Input Output (cRIO) was used. The cRIO is a reconfigurable industrial controller, which combines a real-time (RT) processor and a Field Programmable Gate Array (FPGA). The processor was running a real time operating system, namely the NI Linux Real-Time Operating system that allows the deterministic execution of high-level operations such as communications, control, data logging and others. The FPGA can be programmed by the user to perform high-speed low-level operations such as high-speed control, data processing and others. The cRIO was attached to a chassis that allowed several hot-swappable input/output (I/O) modules to be interfaced and to connect to a PC via crossover Ethernet to allow two-way communication. An overview of the electronic components of the system can be found in Table 3-1 and a basic connection diagram is provided in Figure 3-3.

Table 3-1: List of components and expansion modules that were used with the cRIO system

Module	Model	Quantity
Real-Time Controller 533 MHz processor, 256 MB DDR2 RAM, 2 GB Storage	cRIO-9022	1
8-Slot, Virtex-5 LX110 CompactRIO Reconfigurable Chassis	cRIO-9118	1
Full H-Bridge Brushed DC Servo Drive Module	NI 9505	2
±10 V, Analog Output, 25 kS/s/ch, 16 Ch Module	NI 9264	1
±10 V, Simultaneous Analog Input, 100 kS/s, 4 Ch Module	NI 9215	1

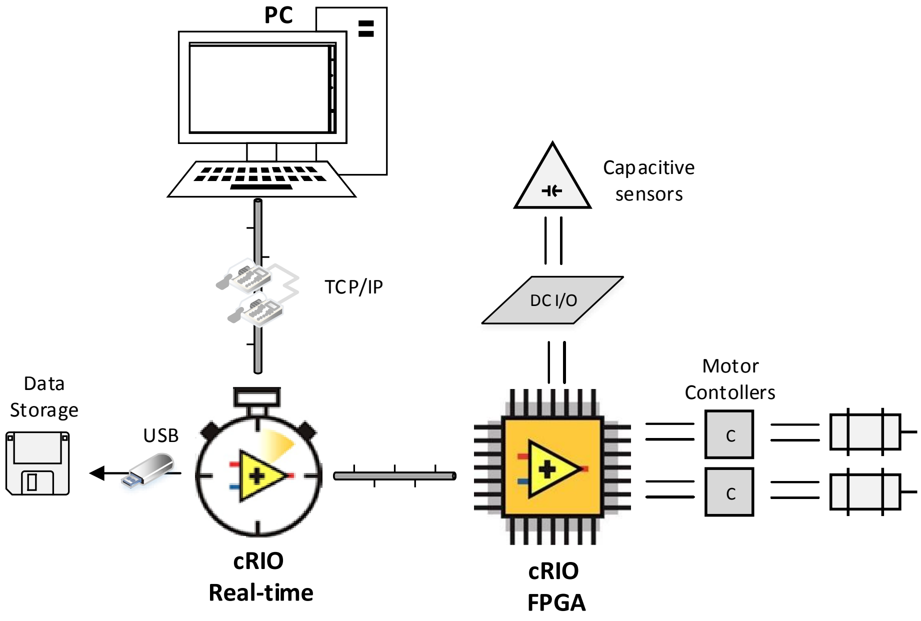


Figure 3-3: The robotic rehabilitation system overview and basic connection diagram.

Each of the two links of the rehabilitation robot is actuated by a brushed direct current motor (Maxon Motor Worldwide, part number 148867) with a maximum output of 150 Watts (Figure 3-4b). Each motor was fitted with a 15:1 ratio gearhead (Maxon Motor Worldwide, part number 203116) as shown in Figure 3-4a. The gear-motor combination had a nominal speed of 458 rpm and a nominal torque of 2443 mNm. Finally, a three channel (A, B, Index) magnetic rotary encoder (Maxon Motor Worldwide, part number 225787) as shown in Figure 3-4c was attached to each of the motors.

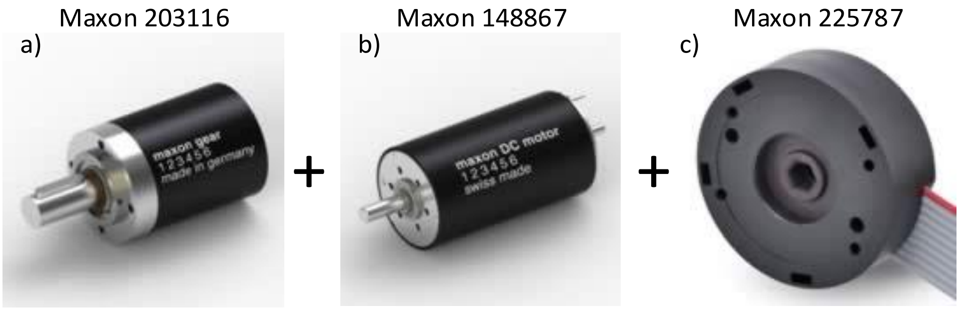
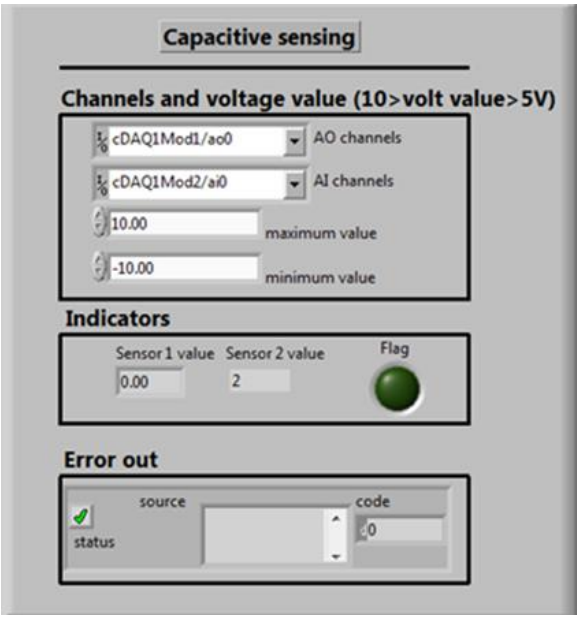


Figure 3-4: The actuator used was comprised of a) a gearhead, b) a DC motor and c) an encoder (Maxon Motor Worldwide, 2014).

Furthermore, as a safety mechanism, the system incorporated a capacitive sensor inside the handle of the device. The system detected changes in capacitance when a hand was in proximity to the sensor. As such, the robot would apply forces only when the users were holding the handle. Three the Atmel™ AT42QT1011 capacitive sensors were used mounted on a custom-designed Printed Circuit Board (PCB). This allowed sensing to be performed through multiple inputs for redundancy purposes in case a single sensor malfunctioned. The AT42QT1011 is a single channel capacitance sensing integrated circuit (IC). The specific IC was selected because it did not incorporate the Max on-duration feature, a common feature among the capacitive sensing IC's which recalibrates the sensor when it is activated for a certain period of time (Atmel, 2013).

Finally, the sensor board was interfaced with the cRIO. The supply voltage needed for the sensors operation was provided by the NI 9264 analogue output module and two of the sensors' inputs were connected to the NI 9215 analogue input module. A program was developed in LabVIEW (Figure 3-5) so that the sensors' output would perform as a switch that would output a signal only when one or both sensors were activated (Figure 3-6).


Capacitive sensing

Channels and voltage value (10>volt value>5V)

AO channels: cDAQ1Mod1/ao0
AI channels: cDAQ1Mod2/ai0
maximum value: 10.00
minimum value: -10.00

Indicators

Sensor 1 value: 0.00
Sensor 2 value: 2
Flag

Error out

status
source
code: 0

Figure 3-5: The user interface for the capacitive sensor program

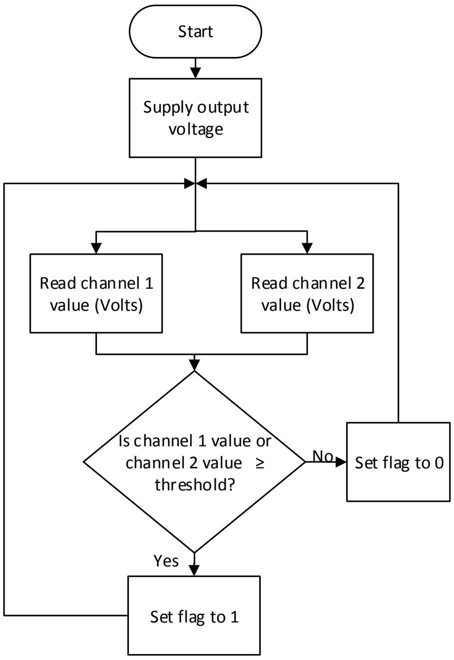


Figure 3-6: Flowchart for the capacitive sensor program

3.3 Software development for the rehabilitation robot

As described in the previous section the rehabilitation system was comprised of three sub-systems namely the FPGA and Real-time system of the cRIO and a gaming personal computer (PC). As such, the software development was divided accordingly to three main parts. The FPGA portion of the system was used to handle the low-level sensing and motor control. Furthermore, the real-time controller of the cRIO was used to handle the high-level motor control i.e. the haptic control algorithm, the data storage and communications. Finally, a graphic environment in the form of a computer game was developed for the computer, which received input from the cRIO through a TCP/IP Ethernet connection (Figure 3-7).

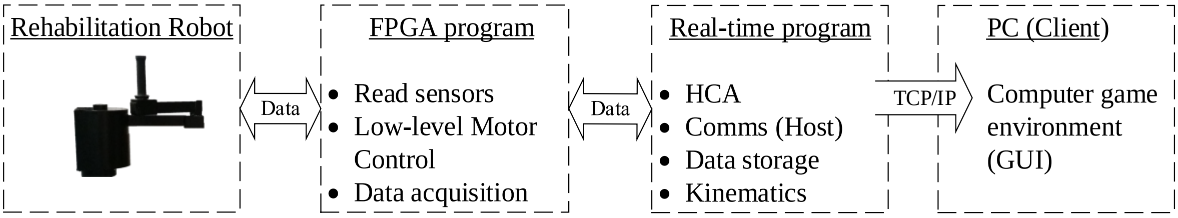


Figure 3-7: The system architecture

3.3.1 Field-Programmable Gate Array software development

3.3.1.1 *Field-Programmable Gate Array software overview*

The cRIO's FPGA was used to handle all the low-level operations of the system such as performing data acquisition for the motors encoders, implementing pulse-width modulation (PWM) and also implementing proportional integral derivative (PID) controllers for the motors. The FPGA is capable of executing multiple loops in parallel up to the maximum frequency supported by the cRIO which was 40 MHz.

The FPGA portion of the architecture consisted of two sets of identical loops, one for each motor, as well as an additional loop that handled the input and output of the capacitive sensors (Figure 3-8). The loop that is responsible for the operation of the capacitive sensor was described in Section 3.2 and a flowchart of the code is displayed in Figure 3-6. The design of the FPGA program for controlling the motors was based on the NI program for position control for NI 9505 as described in (National Instruments, 2010). Figure 3-10 provides a flowchart of the FPGA programs for controlling one motor.

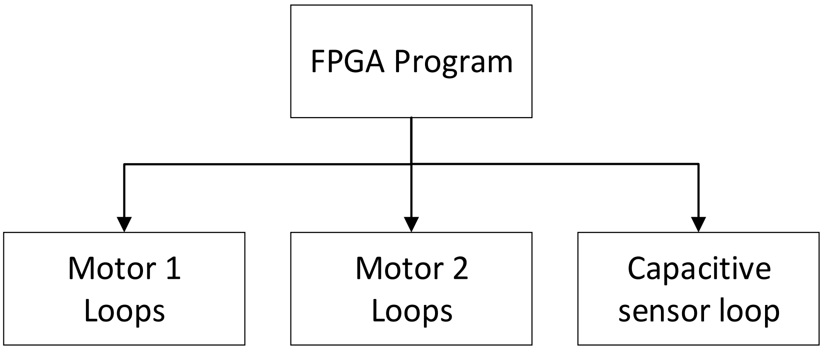


Figure 3-8: The main components of the FPGA program

The encoder loop, received input in the form of square waves generated from each channel of the motor's encoder and decoded them in order to calculate the motors rotation as shown in Figure 3-9. Subsequently the rotational information was fed in to the input of the position loop, which used a PID controller to reach the requested setpoint (position control). The output of the position loop was used as an input by the current loop to act as the setpoint for a PID controller that also received a sample measurement from the current sense loop as its input (torque control). The output of the loop served as the duty cycle for the pulse width modulation (PWM). The PWM pulse had a maximum duty cycle of 20 kHz. Finally, the PWM loop implemented the PWM that was then outputted to the controller embedded in the NI 9505 and subsequently to the motor. Additionally, an error-monitoring loop monitored the system for overvoltage ($V_{supply} > 40V$) or undervoltage ($V_{supply} < 8V$) supply to the motors and also to monitor whether the motor terminal was directly connected to the power supply or the ground as well as to monitor for overheating within the module (Temperature > 115 ^{o}C).

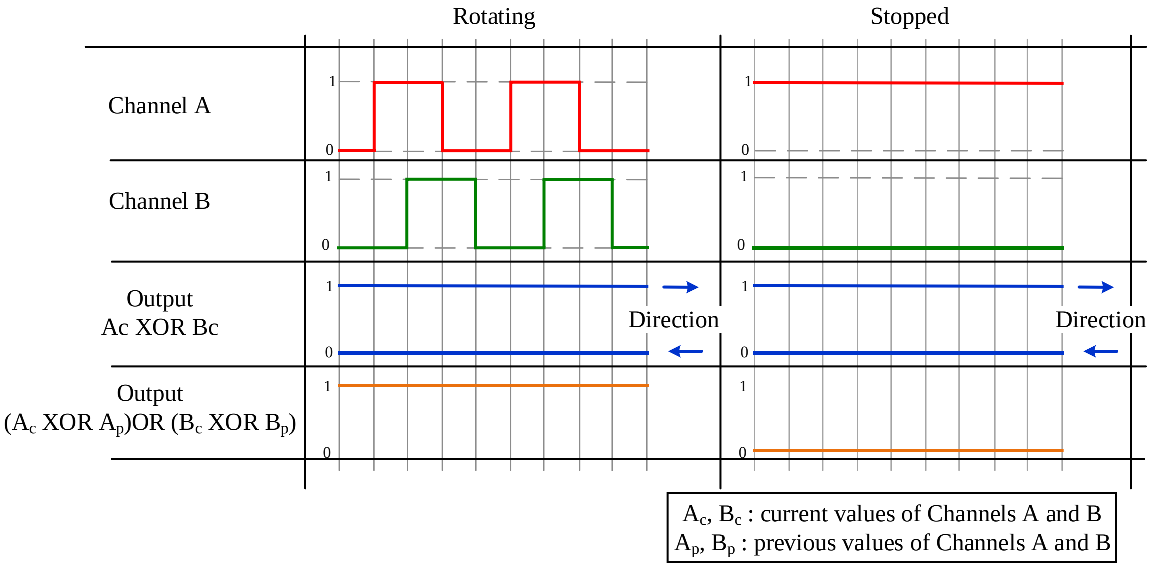


Figure 3-9: The outputs of the encoder channels when the encoder shaft is rotating and when it is not. By applying digital logic to the encoder's outputs the rotation of the encoder shaft can be quantified as well as the direction of its rotation.

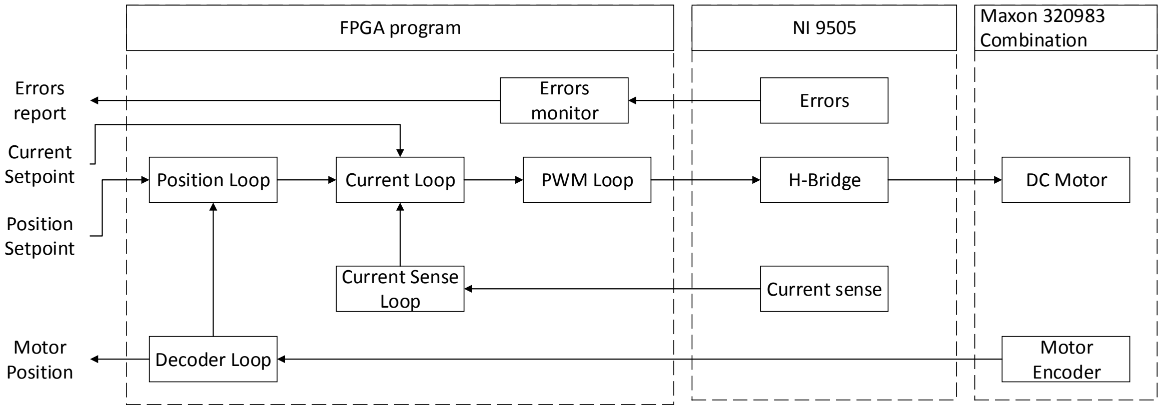


Figure 3-10: The FPGA program for position control of a single motor and the corresponding inputs and outputs (Figure adapted from (National Instruments Corp., 2010))

3.3.1.2 ***Pulse-Width Modulation generation and current measurement***

The rehabilitation robot in its current configuration does not have force-sensing capabilities. As such, a current controller was used to control the torque of the robot's motors and subsequently to control the forces exerted by the robot's endpoint. The NI 9505 has an embedded current sensor that measures the current supplied to the motor at any time. The current sensing circuit used by the NI 9505 relies on two resistors (R1 and R2) each connected to one end of the motor Figure 3-11. The potential difference (p.d.) across each of the resistors is measured and the difference between their voltages is calculated. The output of this operation is in turn amplified and converted to a 12-bit digital signal. The sign of the output signifies the motor’s direction of rotation. (National Instruments Corp., 2012).

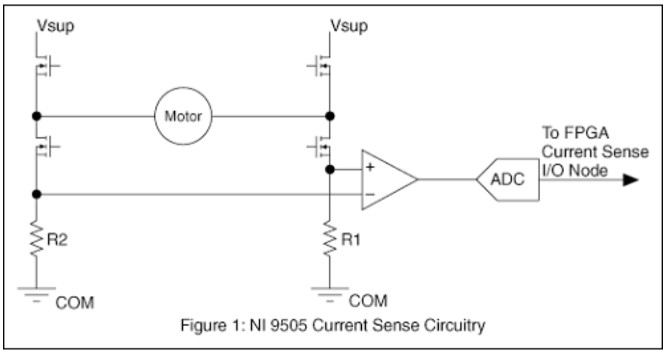
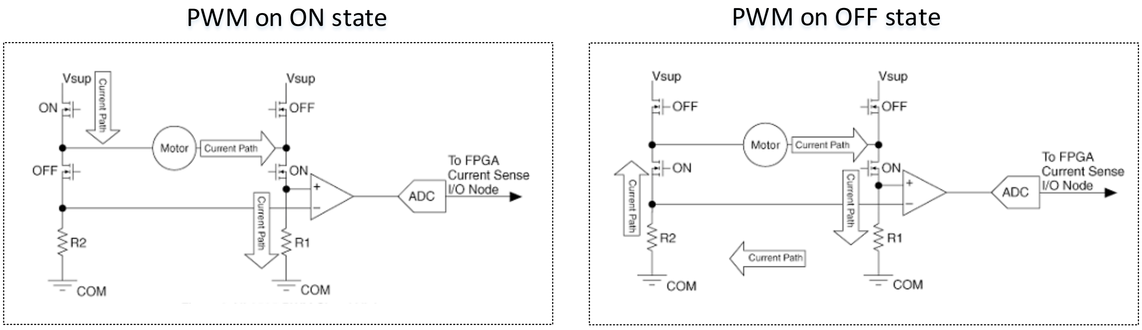


Figure 3-11: The current sensing circuit of the NI 9505. Source: (National Instruments Corp., 2012)

During the off state of the PWM, current flows through both resistors on the NI 9505 as shown in Figure 3-12. This affects the output of the sensor giving incorrect readings. As such, current has to be sampled during the on state of the PWM where current is flowing through only one of the resistors.


PWM on ON state

PWM on OFF state

Figure 3-12: The current sensing circuit for both states of the PWM. Source: (National Instruments Corp., 2012)

Furthermore, during the on state of the PWM the current does not remain constant due to the motors inductance but it increases until the voltage drops again incrementally to its minimum value during the off state of the PWM as shown in Figure 3-13. To acquire a reliable measurement, the current had to be sampled at the same point of the on state of the PWM and as the middle of the current pulse provides an average value this point was deemed suitable for sampling the current.

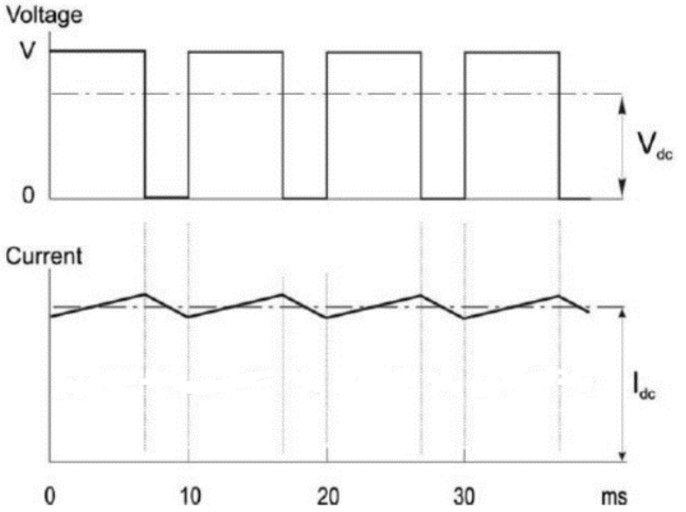


Figure 3-13: Voltage and current for a DC motor where a PWM is applied at its input. Source:(Hughes and Drury, 2013)

On the FPGA program, the current sense loop was triggered by the PWM loop to sample current in the midpoint of the on portion of the PWM. To compensate for delays that are inherent to the system and for the delay between sampling the current measurement and reading its value, the current measurement was triggered before the midpoint of the PWM so that the reading was received at the midpoint of the PWM pulse. To calculate the point of the PWM that the current sensing had to be triggered in order for the current measurement to be acquired in the specified time i.e. the midpoint of the On portion of the PWM Equation (5) was used (National Instruments Corp., 2009).

$$t_{cur\_sense\_trig} = T + 395\ ns - \frac{t_{PWM_{On}}}{2} - \frac{6}{f_{clk}} \qquad (5)$$

Where:

$t_{cur_{\_sens\_trig}}(s)$ *is the time between the falling edge of the PWM pulse until the current measurement to be acquired*

$395ns$ *ns is the compensation for accumulated delays within the system*

$t_{PWM_{On}}$*(s) is the requested time for the On portion of the PWM*

f_{clk}*(Hz) is the frequency of the FPGA clock (40MHz)*

To test the implementation of the current measuring loop an LEM© PR30 current probe was used to acquire current measurements of the system's motors under stall load (fixtures cancelled forces produced by motors) for different specified maximum permissible current requests and to compare them against the measurement received by the current sense loop. The output of the current probe overlaid with the PWM pulse is displayed in Figure 3-14. For a comparable measurement to be acquired the same process was followed as in the current sense measurement reading. The current was sampled at the midpoint of the on part of the PWM pulse (Figure 3-15). As such, a range of measurements was collected for current values between 1-6 A with a step size of 0.5A. The results of the experiment shown in Figure 3-16 indicated that there was a close correlation between the two measuring methods (Mean error= 0.08A, standard deviation = 0.07A) indicating that reliable measurements could indeed be acquired using the current sense circuit within the NI 9505.

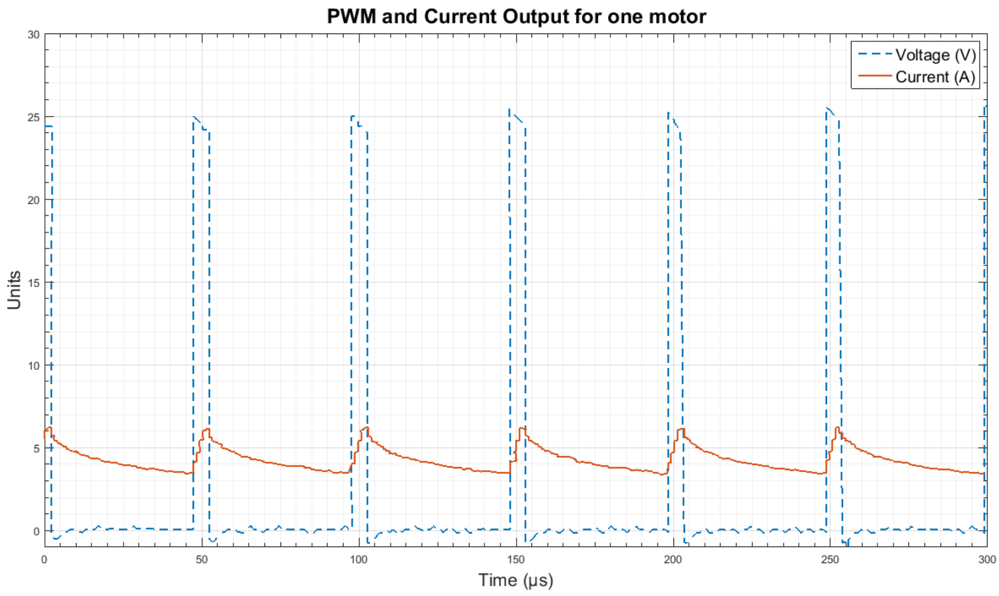


Figure 3-14: An example of the output of the PWM loop on Channel 2 and the current passing through the motors Channel 1 (conversion ratio is 100mv/A) on static load for a requested current of 5.5A

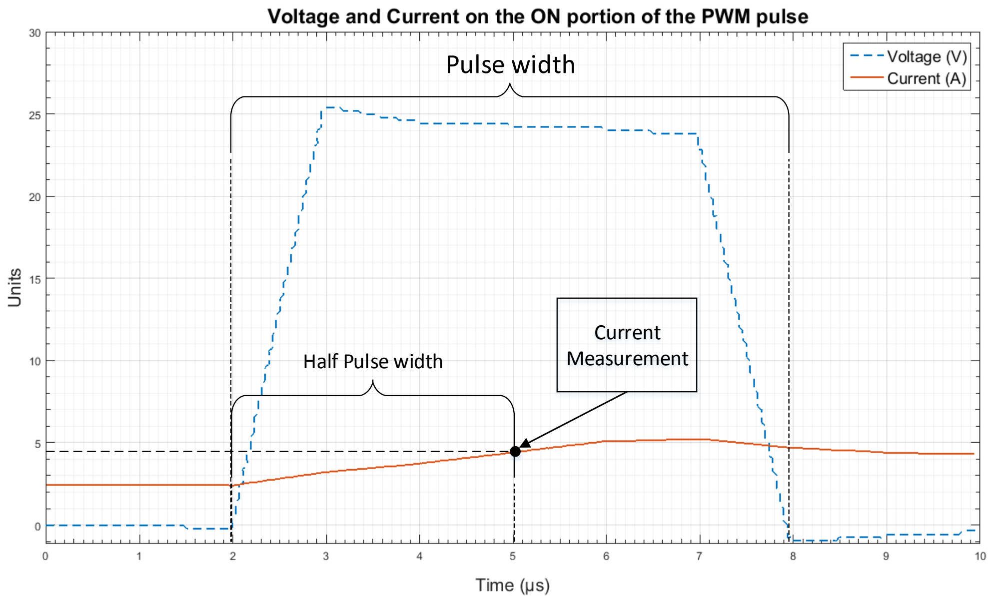


Figure 3-15: Current from the current probe is measured at the midpoint of the On state of the PWM pulse

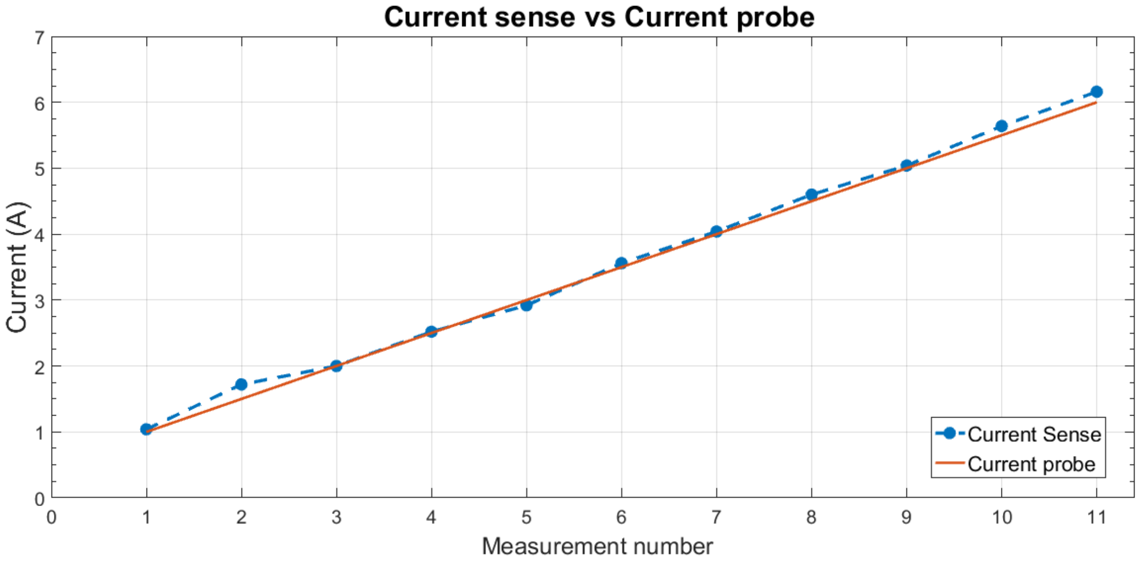


Figure 3-16: Measurement comparison between the current measurements received by the current sense loop and the measurement of the current probe. (Mean error = 0.08 A, Standard deviation from expected value = 0.07A)

3.3.1.3 ***Proportional-Integral-Derivative controller tuning***

As mentioned in Section 3.3.1.1 the system utilised two PID controllers per motor to perform position and torque control, respectively. PID controllers are feedback controllers whose performance is determined by three parameters namely the proportional (K_p) the integral (K_i) and the derivative (K_d) gains as shown in Figure 3-17 (McKerrow, 1991). By changing these parameters, the response of the controller can be adjusted to a given input in order to provide the desired output. Over the years several methods have been proposed for calculating suitable values for the PID parameters. An established approach to online tuning is the method developed by Zeigler-Nichols (Ziegler and Nichols, 1942) and its different variations presented over the years (Astrom and Hagglund, 2001). As such methods were developed for industrial operations they are not always accurate especially if error is introduced into the system.

In industry, a common manner of tuning PID controllers is the manual tuning of the different parameters to achieve the desired output based on empirical rules (Johnson and Moradi, 2005) as shown in Table 3-2.

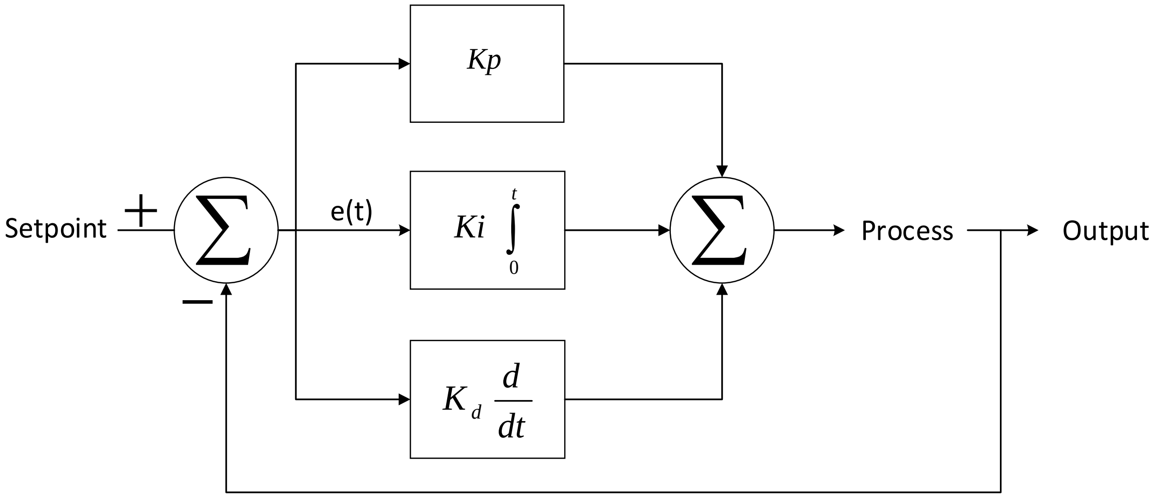


Figure 3-17: Basic PID controller flowchart.

Table 3-2: Tuning rules for the different parameters of the PID controller. Adapted from (Li et al., 2006)

Gain	*Rise time*	*Overshoot*	*Settling Time*	*Steady-State Error*	*Stability*
↑K_p	↓	↑	↑ *(Small)*	↓	↓
↑ *Ki*	↓ *(Small)*	↑	↑	↓ *(Large)*	↓
↑ *Kd*	↓ *(Small)*	↓	↓	*Negligible*	↑

Potentially there is an infinite number of parameter values that could provide the desired output. As such a combination of the Ziegler-Nichols method and manual tuning was used to select appropriate values (tune) the individual controllers. The Ziegler-Nichols method was used to obtain initial values for the PID gains followed by manual adjustment of the different parameters to achieve the desired performance. To define acceptable performance of the controllers a critically damped response was set as the desired output, a stable system with a response to a step input that has low rising time, overshoot, and low steady state error. As the selected tuning approach usually requires a very large number of iterations to achieve the required output it would not be possible to include all the different measurements however, two examples of the tuning process (one for each joint) are provided in Figure 3-18 and Figure 3-19 where the response of the position controller to a step input of 5^{o} with zero step time for four different sets of settings of the PID gains, is displayed.

An example of the aforementioned process is shown in Figure 3-18 in the responses where a PD controller (responses where $K_i = 0$) is implemented for the shoulder joint with $K_p = 100$. By changing the K_d a critically damped response was achieved at $K_d = 1000$ (response in blue) with a faster rising and settling time and low steady-state error. Furthermore, the response of the elbow joint (Figure 3-19) for the gain combination of the position controller shows that the responses in blue, green and cyan are overdamped and hence have slower rising times. Conversely, the response in red had a much shorter rising time while producing low overshoot and steady state error hence this set of gains was more suitable for the purposes of the application.

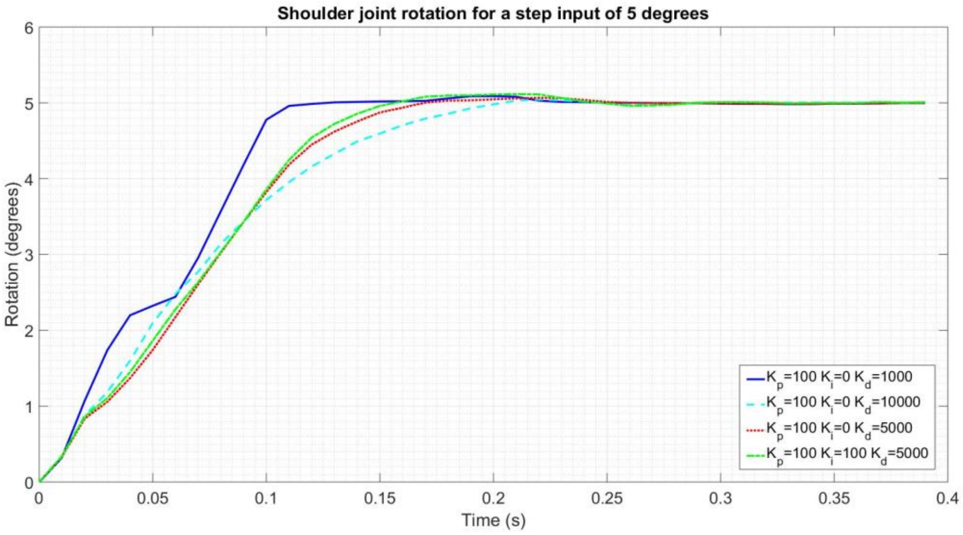


Figure 3-18: The output of the controller for the shoulder joint for different combinations of the PID controller gains for a step input of 5^{o}.

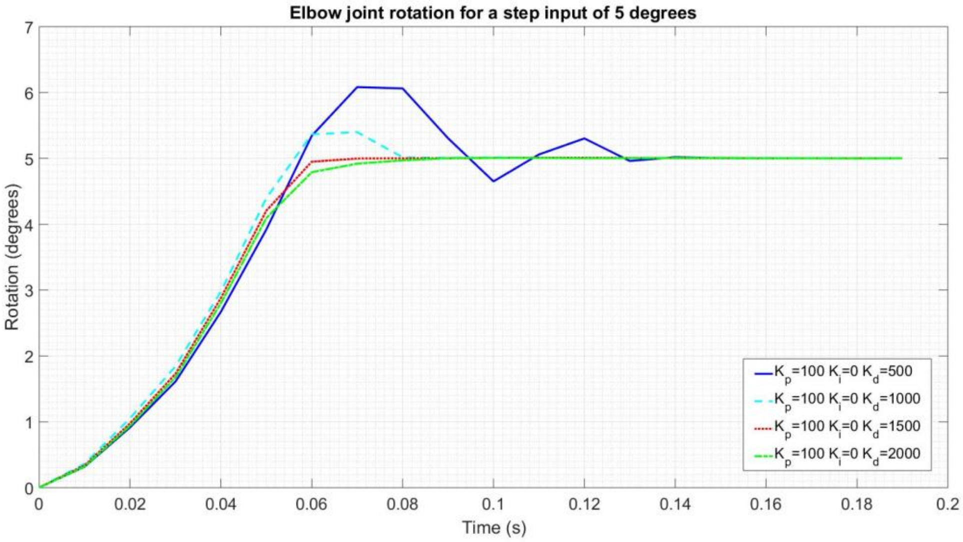


Figure 3-19: The output of the controller for the elbow joint for different combinations of the PID controller gains for a step input (setpoint) of 5°

As the systems movement is dynamic with the movement of each joint affecting the response of the other, the response of the controllers was tested for all of the four possible combinations of movements between the two joints as displayed in Figure 3-20. It must be noted that due to the different positioning of the motors the clock-wise movement is defined as positive rotation of the shoulder and negative for the elbow. From these plots it can be seen that the response of the two joints is similar for all combinations of movements. The elbow joint reaching steady state after just above 0.05 seconds and the shoulder joint just below 0.2 seconds while the overshoot in all combinations was kept below 10% of the setpoint.

Table 3-3: Possible combinations of rotation between the two joints.

Combination	*Shoulder joint*	*Elbow joint*
1	CW	CW
2i	CW	CCW
3	CCW	CW
4	CCW	CCW

CW: Clock-wise, CCW: Counter clock-wise

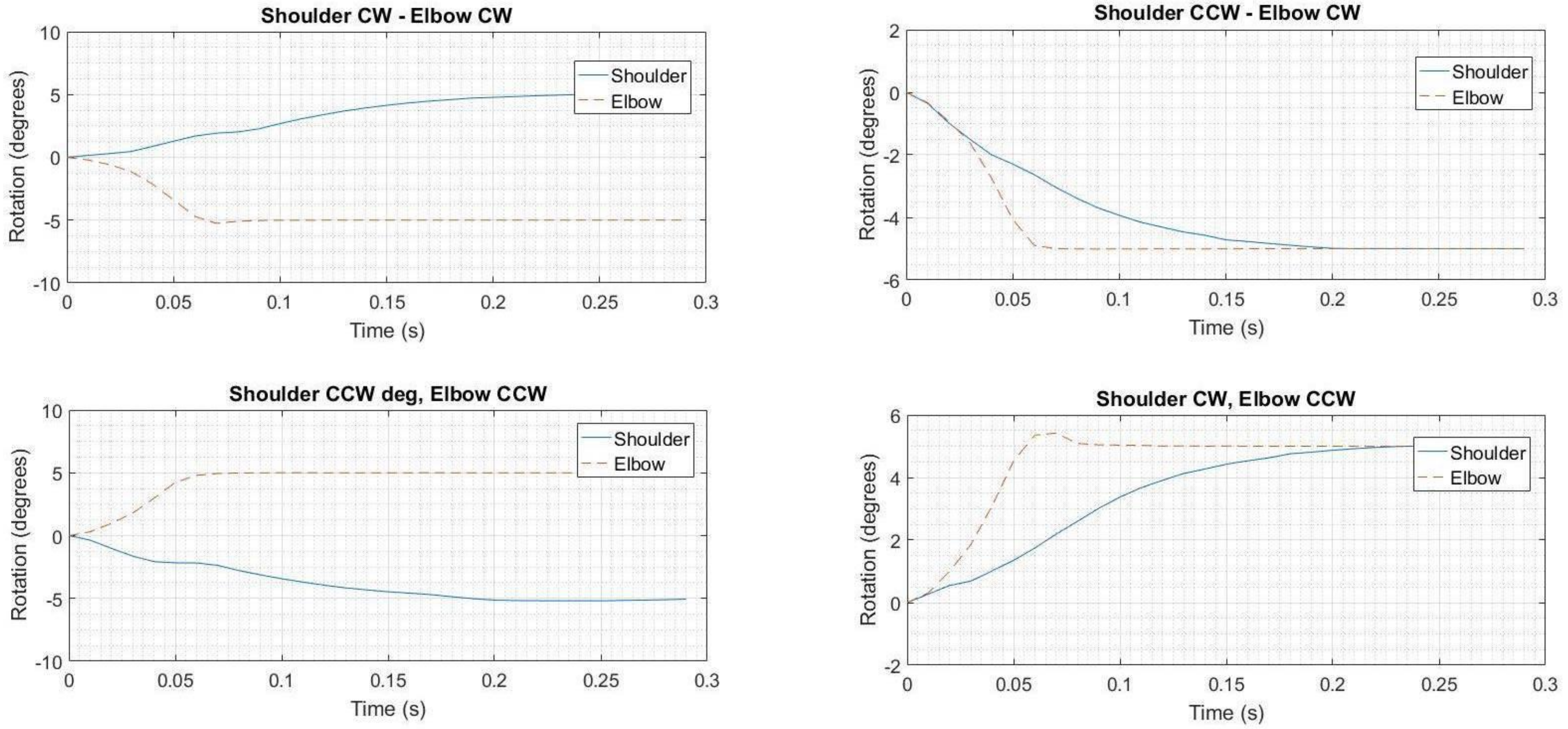


Figure 3-20: Combined joint movement for different combinations of a step input of ±5 degrees

3.3.2 Real-time software development

The real-time (RT) portion of the architecture was responsible for the high-level operation of the system by reacting to inputs received by the FPGA program and controlling its outputs. Furthermore, the RT program performed data acquisition and handled the communications between the cRIO and the client PC portion of the architecture. The flowchart of the RT program is displayed in Figure 3-21.

To ensure the deterministic operation of the crucial functions of the program, data storage was designed to run independently from the other operations. To do so a producer-consumer architecture was used which is ideal for one-way asynchronous parallel operations (Lin et al., 2013). In this architecture, two loops run in parallel with one loop serving as the producer feeding data into a data buffer (queue) which in turn was accessed by the consumer loop. According to the principle of operation of queues, the received data were being accessed by the consumer loop in the sequence they entered the queue, resulting to a lossless communication between the two loops.

The real-time program had a two-way communication with the FPGA. It read the raw position of the motors as it had been outputted by the decoder loop on the FPGA program and converted it to angular position. The angular position for each motor was fed into the forward kinematics function and the position of the endpoint was calculated. The positions of the targets were provided to the program as an input the function target_selec that comprised of a state machine architecture, which switched between the different targets as they were reached and outputted the coordinates of the active target and the previously active target. The aforementioned positions served as the starting (previously active target) and ending point (active target) of the desired path.

The coordinates of the active target as well as the ones of the endpoint were used as inputs by the HCA portion of the code that calculated the setpoint of the motors in order for the system to achieve the desired behaviour. Inverse kinematics were used to calculate the rotational position in degrees of the joints in order for the robot to move to the given setpoint. The angular position of the setpoint measured in degrees was then converted to raw angular position and then transmitted to the FPGA program to be used as the setpoint for the respective position loops.

Finally, the real-time program transmitted two streams of data: one locally through a buffer to the consumer loop, and one over transmission control protocol/internet protocol (TCP/IP) to the client computer that was responsible for displaying the graphical user interface. The streams contained information concerning the number (ID) of the target that was active, the set of movements, the endpoint position, the distance from the desired trajectory and time. The consumer loop received the data buffer and accessed its elements in the same sequence they have initially entered the buffer and without any loses. The de-buffered data were then stored in a technical data management streaming (TDMS) file which was appended with every iteration of the loop to include the next set of data. The NI TDMS file format was developed by National Instruments and it was optimised for storing measurement data to hard drives using LabVIEW and NI hardware (National Instruments Corp., 2015).

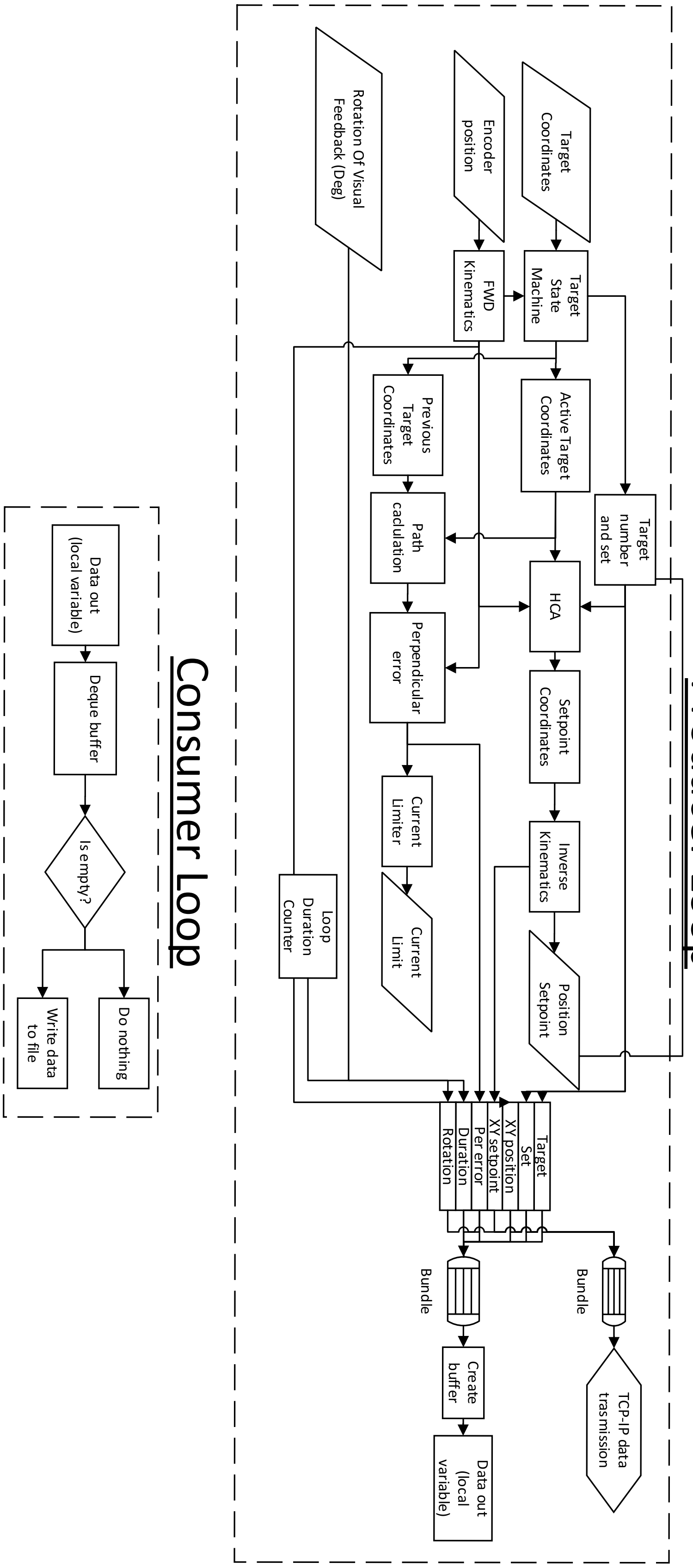


Figure 3-21: The RT program. The consumer loop runs with a constant frequency of 100Hz (deterministic) while the producer loop runs unbound to accommodate for delays of the storage process.

3.3.2.1 *Forward and inverse kinematics for the rehabilitation robot*

Kinematic analysis of a robotic manipulator provides the spatial relationships of the links, the solid mechanical object between two joints, in order to calculate the position of the end-effector (direct kinematics) or given the position of the end-effector provides the tools in order to calculate the respective angles of the joints for the manipulator to reach this position (inverse kinematics) (McKerrow, 1991).

By utilizing information from the motor encoders of the robotic device and by using forward (FWD) kinematics the position of the end effector can be calculated. That position can be used to inform a virtual environment about the actual position of the robot in space, for example the cursor position providing information about the corresponding position of the joystick to the virtual environment workspace. On the other hand, inverse kinematics are crucial for robot control. For a given target, the desired position of the end effector is known. Inverse kinematics provide information on what the joint angles should be in order for the end effector to reach that position. By comparing the actual joint angles with the desired an error signal is generated that can be used for robot control.

This section describes a trigonometric approach to calculate the forward and inverse kinematics for the robotic manipulator utilised in this project as well as their programmatic implementation in LabVIEW. The derivation of the equations of the forward and inverse kinematics for the two-degree of freedom planar manipulator is provided in Appendix A.

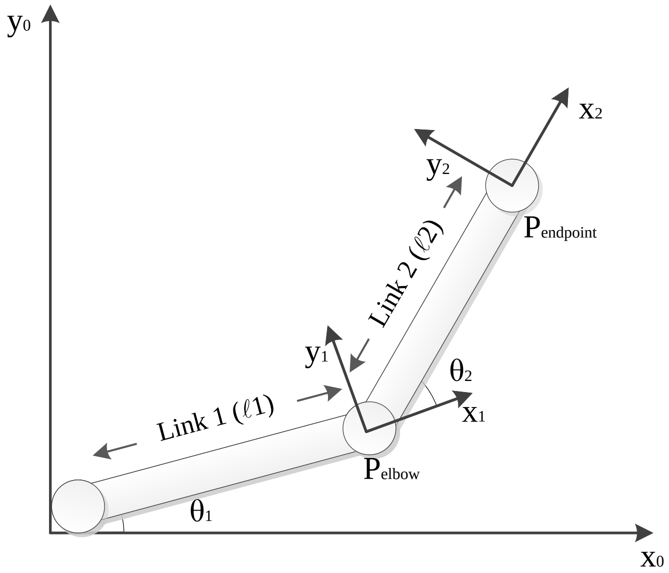


Figure 3-22: The two link manipulator for a given position of the end-effector

The vector of the Cartesian coordinates (forward kinematics) of the endpoint of the two degrees of freedom (DOF) planar rehabilitation robot with rotational joints given joint angles θ_1 and θ_2 (*Figure 3-22*) is provided below in Equation (6).

$$p_{endpoint} = \begin{bmatrix} x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} l_1 \cos(\theta_1) + l_2 \cos(\theta_1 + \theta_2) \\ l_1 \sin(\theta_1) + l_2 \sin(\theta_1 + \theta_2) \end{bmatrix}$$ *(6) vector for endpoint coordinates*

And the vector of coordinates of the elbow joint given a rotation θ_1 of the shoulder joint is given by Equation (7)

$$p_{elbow} = \begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} l_1 \cos(\theta_1) \\ l_1 \sin(\theta_1) \end{bmatrix}$$ *(7) vector for the elbow coordinates*

3.3.2.2 *Inverse kinematics*

$$\theta_2 = \pm atan2(sin\theta_2, cos\theta_2)$$ *(8) Angular position of the elbow joint*

Where: $cos\theta_2 = \left(\frac{x_e^2 + y_e^2 - l_1^2 - l_2^2}{2 l_1 l_2}\right)$ and $\sin\theta_2 = \sqrt{1 - cos^2\theta_2}$

And

$$\theta_1 = atan2(p_y, p_x) - atan2(l_2 sin\theta_2, l_1 + l_2 cos\theta_2)$$

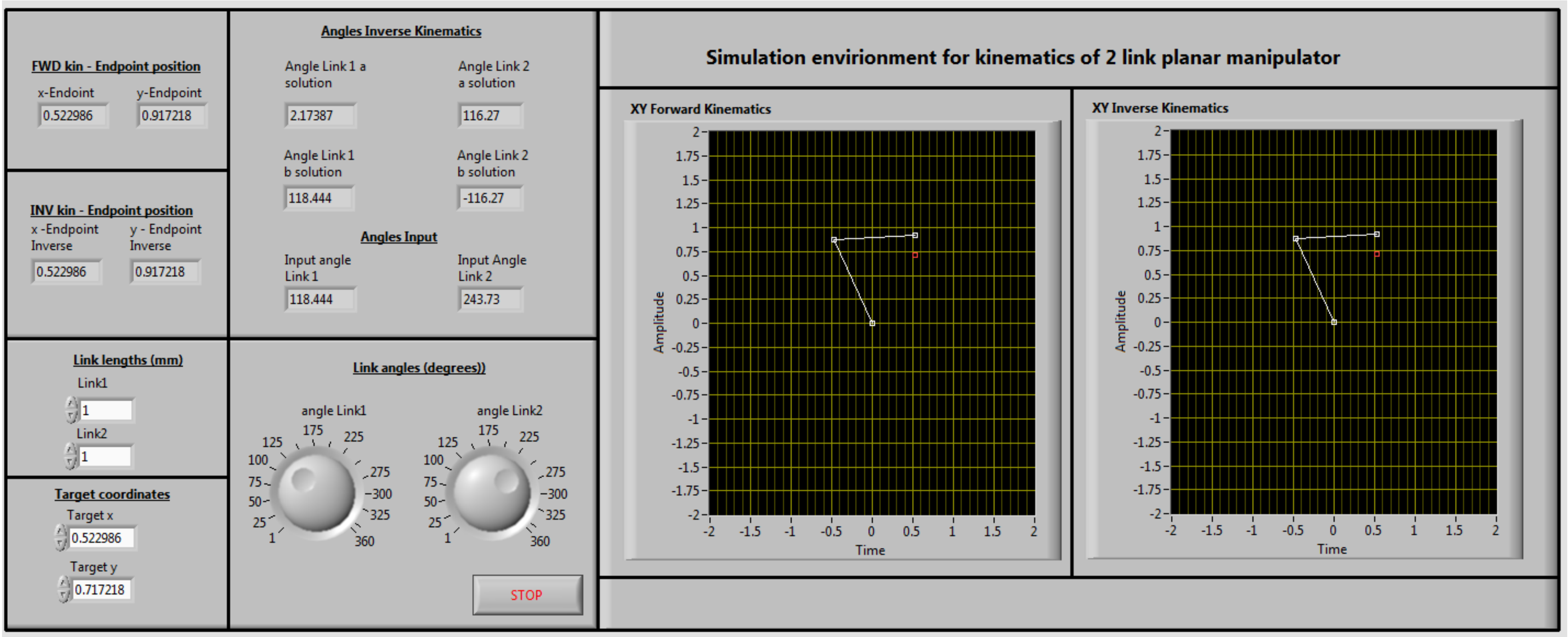
(9)Angular position of the shoulder joint

From the previous equations it is evident that θ_2 has two solutions; one for the positive result and for the two solutions of θ_2 there will be two respective solutions for θ_1. This is known as redundancy in robotics and it means that there are two possible configurations for the manipulator's endpoint to reach a certain position (McKerrow, 1991). As for the specific application, there were no limitations on the design of the robot to indicate which angles should be selected and as such, either of the two sets of solutions is valid.

A detail analysis of how the kinematic equations were derived is provided in Appendix A.

3.3.2.3 *Simulation of the robot's kinematics*

A kinematic model was programmatically implemented in order to create a simulation environment for the motion of the robotic manipulandum. The program accepted as an input the lengths of the links as well as their respective angles and displayed their position on the plane. The program could also accept as an input the position of the end-effector, calculate, and display the angles at which the respective links are positioned. Furthermore, the system provided a visual representation of the manipulator's kinematics as well as a target whose position can be adjusted accordingly. In Figure 3-23 the simulation environment setup to verify the kinematic algorithms is shown. The angles of the links are inputted in the system, the forward kinematics are calculated and displayed and that output is connected to the input of the inverse kinematics algorithm whose results are then visualized.



FWD kin - Endpoint position

x-Endoint: 0.522986

y-Endpoint: 0.917218

INV kin - Endpoint position

x -Endpoint Inverse: 0.522986

y - Endpoint Inverse: 0.917218

Link lengths (mm)

Link1: 1

Link2: 1

Target coordinates

Target x: 0.522986

Target y: 0.717218

Angles Inverse Kinematics

Angle Link 1 a solution: 2.17387

Angle Link 2 a solution: 116.27

Angle Link 1 b solution: 118.444

Angle Link 2 b solution: -116.27

Angles Input

Input angle Link 1: 118.444

Input Angle Link 2: 243.73

Figure 3-23: Kinematics Simulation Environment. In this picture the environment is set on verification mode where it accepts as an input the sizes and relative angles of the robot's links and the forward and inverse kinematics are calculated and visualized.

3.3.2.4 *Workspace translations*

Multiple movement translations occurred at the system. Firstly, there was a translation of angular movement to linear movement as described by the forward kinematics in the previous section. The workspace where the endpoint of the robot moved that is, the physical workspace of the robot, was also translated to a virtual workspace on the computer screen.

The gearhead of the Maxon© motors had a 15:1 gear reduction ratio. The movement of each motor was then transmitted to a set of gears with a 2:1 ratio (Figure 3-24). To convert the raw rotational data collected by the decoder loop into angular displacement the following formula was used

$$Rotation\ Angle = Encoder\ reading \times \frac{360}{gr_1 \times gr_2 \times cor \times 1024} \qquad (10)$$

where gr_1 =91:6 was the reduction on the gearhead and gr_2 = 2:1 is the reduction on the subsequent gears, 1024 is the number of pulses the motors encoder outputted per rotation and cor = 4 was used to correct for the fact that the encoder loop was measuring four pulses per unit of rotation. Once the angular displacement was calculated the FWD kinematics were calculated. As the encoders used are incremental, they do not measure position in an absolute manner, as such the position had to be reset to the same starting point before using the rehabilitation robot. The starting point was defined as the one where the robotic arm was fully extended while the shoulder joint was used on the rightmost position.

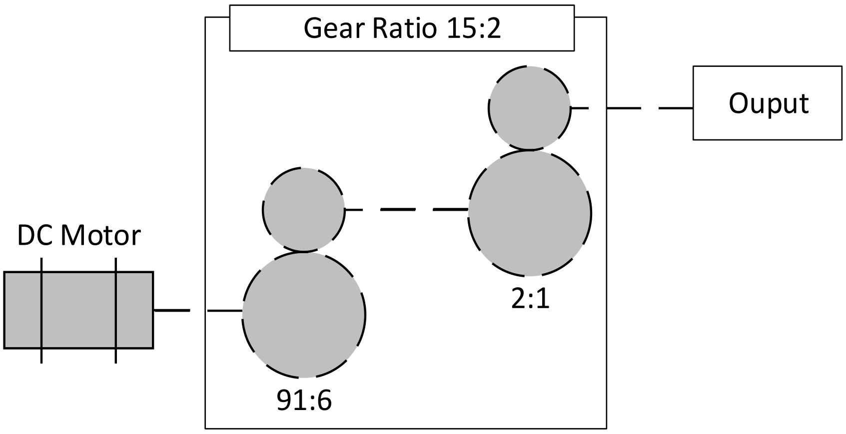


Figure 3-24: Gear ratio from motors to the robot's links

As the centre of the user's workspace (Figure 3-25) was selected to be the point C (x_c,y_c), where the shoulder joint was at the middle of its range and the elbow joint was at a 90^o angle with the first link. Given a square workspace of size L by L, its centre coordinates C (x_c,y_c) and an endpoint position of E(x_a,y_a) the workspace is defined by the following algorithm:

$$x = \begin{cases} L, \ x > L \\ x_e - x_c + \frac{L}{2}, 0 \leq x \leq L \\ 0, \ x < 0 \end{cases} \quad , \quad \mathrm{y} = \begin{cases} L, \ y > L \\ y_e - y_c + \frac{L}{2}, 0 \leq y \leq L \\ 0, \ y < 0 \end{cases} \qquad (11)$$

A final translation occurs from the actual coordinate system of the robot to a virtual coordinate system on the computer screen (Figure 3-25). Given a square virtual workspace of N by N pixels and an actual workspace size of L by L meters the translation ratio is calculated as r_t = L/N. As such, the coordinates of the endpoint on the virtual environment are calculated as follows:

$$x_v = r_t x \ , \ y_v = r_t y \qquad (12)$$

$$Where: x, y \ actual \ coordinates \ of \ endpoint \ and \ r_t = \frac{L}{N} \ translation \ ratio$$

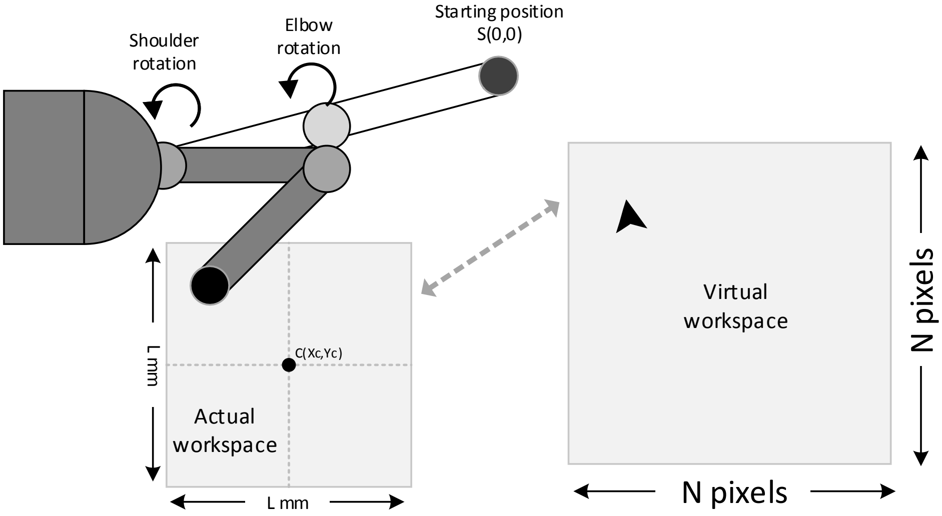


Figure 3-25: Linear movement of the robot's endpoint translates to rotational movement of the robot's joints. By analysing the signal from the motors encoders, the angular displacement is calculated and by using FWD kinematics the position of the endpoint is calculated. Finally, the movement in the actual workspace is translated into movement in the virtual workspace of the computer screen.

3.3.2.5 *Target selection state machine*

As previously mentioned the user is meant to interact with the system in order to follow trajectories towards alternating targets while the robot is providing forces according to an HCA. To ensure a robust deterministic operation of the cRIO in general and the RT program in particular, the cRIO portion of the system was designed not to rely on from the non-deterministic portion of the system i.e. from the Windows™ PC running the GUI. As such only one-way communication was established between the RT and the PC with the RT being the host and the PC the client.

To overcome this limitation two instances of the computer game were developed. One running on the cRIO (master) and one on the client PC (slave) with the first controlling the latter through TCP/IP. As such, the RT instance of the game was able to inform the system and the HCA about the position of the targets, the trajectories needed to be followed and when a target was reached and a new one was activated i.e. there was a change in the trajectory needed to be followed. The PC instance of the game served as graphical user interface that allowed visualisation of the virtual environment created with the RT program. To do so, a virtual model of the environment was created.

The position of the targets was provided to the system as a table in the initiation of the program. In its latest version, the system could interact with a maximum of sixteen targets. At any instance, there was only one target that was marked as active indicating the end position of the movement. The straight-line trajectory was calculated connecting the previously active target and the currently active target. The program outputted the coordinates of the active and the previously active target. A state machine was created to switch between the different targets and activate them once the previous target had been reached. To trigger the change in states i.e. for the next target to be activated, the endpoint of the robot needed to be within a virtual circle which was drawn around the coordinates of the target. The radius of the virtual circle was adjustable allowing the sensitivity of the system to be fully customisable.

As described in the previous section a 16x2 table containing the x-y coordinates of the targets was used as an input to the system. The file was only read by the program once at its initiation and as a result the target coordinates could not be changed during the execution of the program. Furthermore, a 16x1-index table was used with each line having a unique value from 1-16. This index table served as a reference to each line of the table with the coordinates.

Initially, there were sixteen identical states; one for each target, with the only difference being that each state would read a different line of the index table. As such, the first state would read the first line, the second the second line etc. In this manner, different coordinates would be accessed according to the respective index for the coordinate table. For example, if the active state was the first one and the value of the first line of the index table was five, then the fifth line of the coordinate table would be accessed. Once the target was successfully reached by the robot’s endpoint, the program would move on to the second state where the value of the second line of the index table would have been accessed and as such the corresponding line of the coordinate table etc.

All the states followed each other in a consecutive manner (state 1 was followed by state 2 etc.). When the last target at the index was reached and before the transition to the first, the system had the capability of randomly reordering (shuffle) the values of the table of index in order to randomise the sequence the different targets would appear. The randomisation of the target sequence within each set of sixteen transitions could be turned on or off according to the needs of the application. Finally, during the transition from last to first state a counter is increased by one to serve as counter of sets (a full set is sixteen movements).

The subroutine outputted constantly the coordinates of both the current target and the previous target, the set number and the value of the index table corresponding to the active target in order to be used by the other subroutines of the program such as the HCA subroutine and the communications subroutine.

3.3.3 Haptic control algorithms

A significant aspect of the system was the HCA portion of the program. The HCA controlled the direction and the intensity of the forces applied to the user’s hand. The HCAs developed fell under one of two categories namely assistive and challenge-based. To manipulate the direction of the forces position control was used. As such, by knowing the position of the endpoint and the virtual target and by applying geometrical operations the coordinates of the setpoint were calculated which then were transformed in angles by using inverse kinematics (Figure 3-26). Those angles were then used as an input by the position loop of the FPGA.

Also as a means of controlling the torque outputted by the system and hence the intensity of forces the setpoint of the current was also altered when needed.

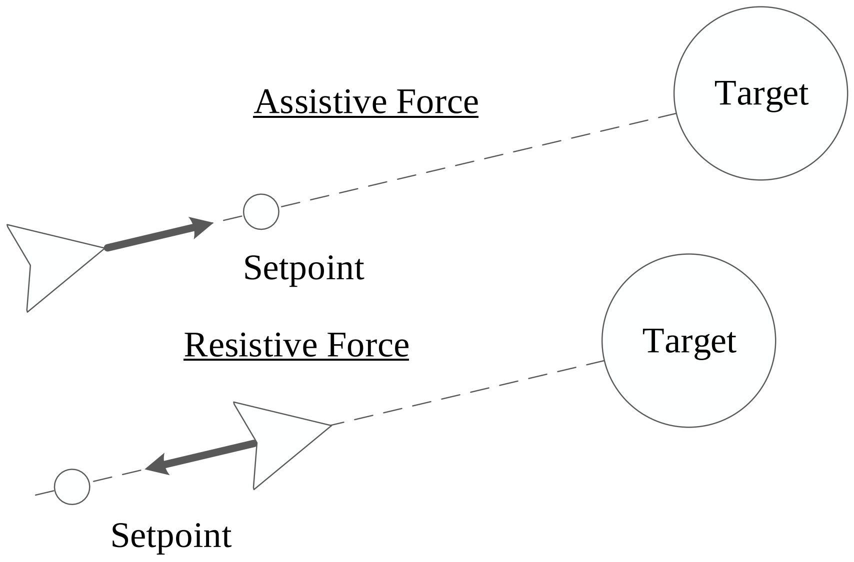


Figure 3-26: By placing the setpoint at different positions, the user experiences different forces as the robot is trying to reach the setpoint

3.3.3.1 *Assistive Haptic Control Algorithms*

Assistive forces can be applied by the robot either a) towards the perpendicular direction from the endpoint of the robot towards the desired trajectory, or b) in the direction from the endpoint towards the desired trajectory or c) in all the directions pointing towards any point on the desired trajectory that is closer to the target from the point of intersection between the desired trajectory and the perpendicular line to the desired trajectory passing through the coordinates of the endpoint (Figure 3-27).

For the user to experience an assistive force, the setpoint provided to the position controller should be placed between the position of the endpoint and the target or the desired trajectory and to be moving accordingly as the endpoint comes closer to the target. To do so the assistive HCA received as an input the coordinates of the endpoint and the current target as well as the previously active target. As desired trajectory was defined the straight line connecting the previously active target A with the currently active target B (active: next to be reached). Furthermore, the perpendicular line from the endpoint position to the line containing the AB was drawn and the point of intersection was I. Finally, a third line was drawn connecting E and A. As such the orthogonal triangle EIB was formed.

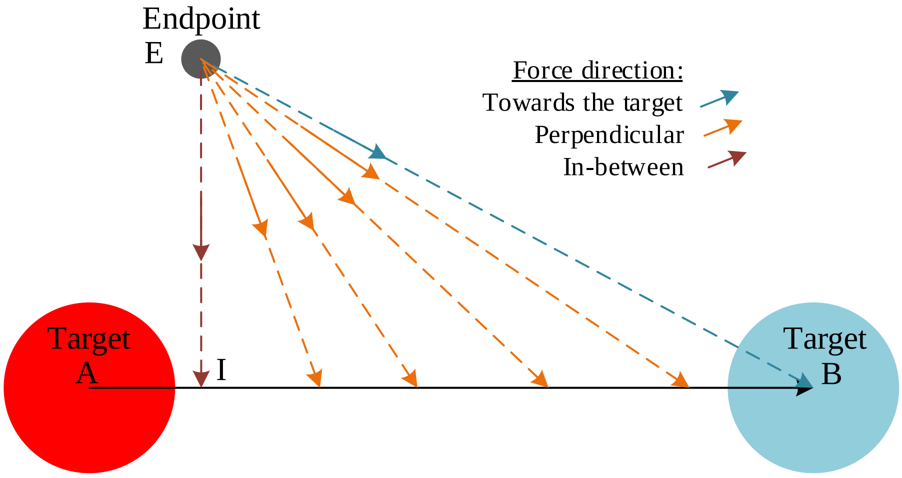


Figure 3-27: Assistive forces can be generated towards the desired trajectory, the target or any angle between the two.

A built-in function to LabVIEW namely, IMAQ GetPointsOnLine was used to output an array containing different points of a line given the coordinates of its starting point and end point. The GetPointsOnLine was used on the lines EB and EI to provide a set of potential setpoints on the direction of each of lines. An index was used to access the element at a given percentage of the length of the array/line. Furthermore, by getting the coordinates of the points on the two lines a third line was drawn connecting them. Again, the GetpointsOnLine function was used to get the individual points forming the line. By indexing the created array, the setpoint on the in-between line can be moved accordingly to get different angles from the robot’s endpoint towards the desired trajectory. (Figure 3-28)

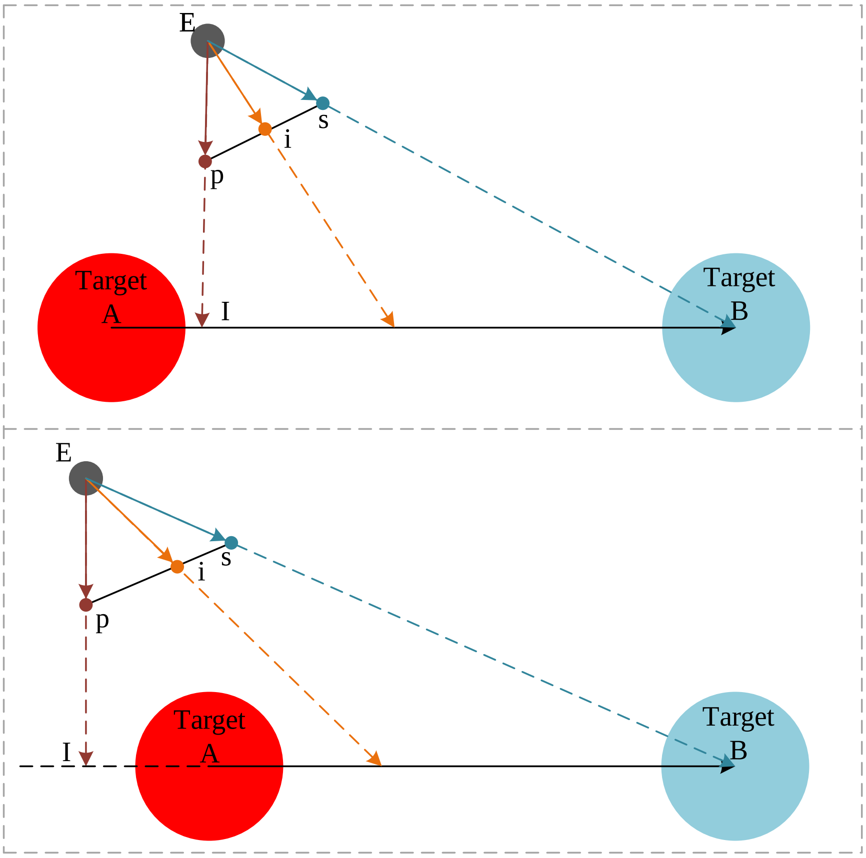


Figure 3-28: Two different scenarios for setpoint calculation given the position of the endpoint E. The user can select which direction the forces will be applied towards by selecting p, i or s as the setpoint of the position controller.

3.3.3.2 ***Error augmenting Haptic Control Algorithms***

For the purposes of this work, error is defined as the perpendicular distance from the position endpoint to the desired trajectory. As such, an error-augmenting algorithm would provide forces on the perpendicular direction away from the desired trajectory. To do so the IMAQ VI Perpendicular line was used. This function calculates the perpendicular line to a reference line crossing a given point and outputs the points and the distance from that line.

A virtual circle was drawn around the position of the endpoint. There were two points where the perpendicular line intersected the circle (Figure 3-29). If the setpoint was placed on the outermost point of intersection, then the user would experience a force that has a direction perpendicular and away from the desired trajectory. As such, this solution was used to set the coordinates of the setpoint. In addition, from the main environment the user could alter the size of the virtual circle and as such how far from the endpoint the setpoint would be.

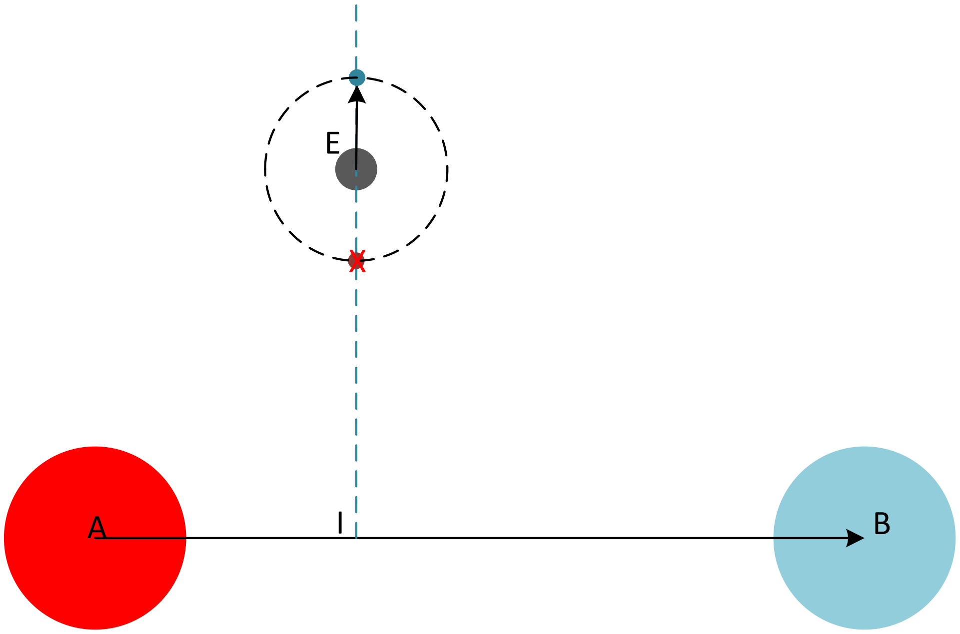


Figure 3-29: There are two points of intersection of the perpendicular line and the virtual circle. The distance from the desired trajectory of the solutions is calculated and the furthermost point is selected as the setpoint.

Calculating the setpoint for error augmentation

To calculate the points of intersection of a circle and a line the following algorithm is used:

The points of intersection between a line that's defined by two points A(x_1,y_1) and B(x_2,y_2) and a circle $(x-a)^2+(y-b)^2 = r^2$ is given by Equations (13) and (14) respectively (Weisstein, 2015). The derivation of these equations is provided in detail in Appendix A.

$$X_{1,2} = \frac{Dd_y \pm s(d_y)d_x\sqrt{r^2d_r^2 - D^2}}{d_r^2} \qquad (13)$$

$$Y_{1,2} = \frac{-Dd_x \pm s|d_y|\sqrt{r^2d_r^2 - D^2}}{d_r^2} \qquad (14)$$

Where:

$$s(x) = \begin{cases} -1 \; for \; x < 0 \\ 1 \; for \; x \geq 0 \end{cases} \qquad (15)$$

As such the two points of intersection between the perpendicular line and the circle around the endpoint are C(x_1,y_1) and D(x_2,y_2). To select the appropriate solution, the distances between the two points and the target B are calculated and compared as shown in Figure 3-30. The solution that results in the greatest distance is selected as the endpoint as it will always be on the outermost section of the circle.

Given B(x_3,y_3) the coordinates of the target the distances from C and D are calculated

$$\overrightarrow{CB} = \sqrt{(x_1 - x_3)^2 + (y_1 - y_3)^2} \qquad (16)$$

$$\overrightarrow{DB} = \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2} \qquad (17)$$

$$\text{Is } \overrightarrow{CB} > \overrightarrow{DB} \text{ ? } \begin{cases} Yes, Setpoint \; is \; C \\ No, \; Setpoint \; is \; D \end{cases} \qquad (18)$$

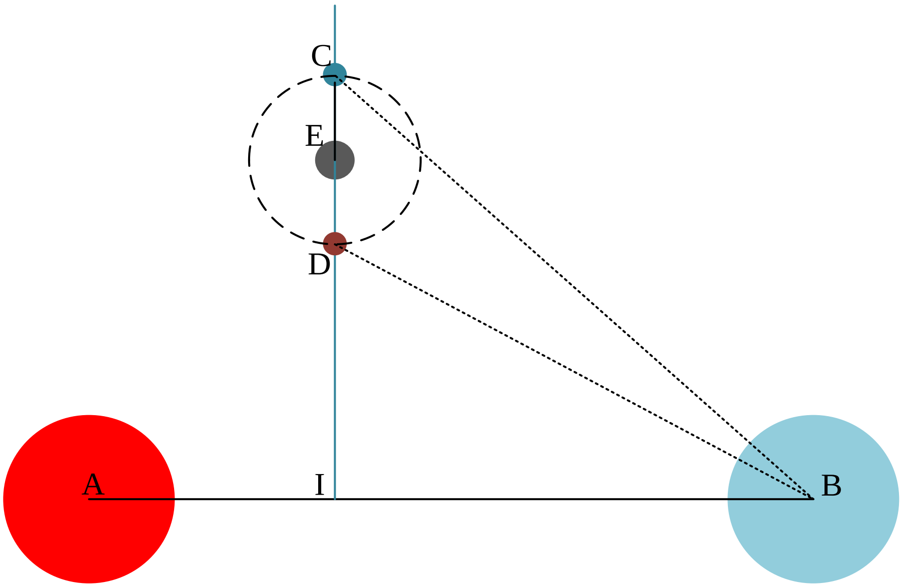


Figure 3-30: The points of intersection between the perpendicular line and the circle with the endpoint coordinates as a centre. The controller's setpoint is selected as the solution that is the furthest away from the active target B.

3.3.3.3 *Performance based adaptation*

One required feature of the different HCAs was the ability to adapt to the user’s movement according to their performance and as a result make the task easier or more difficult. For example, in the case of an assistive HCA the system would provide less assistance as the user’s performance was improving and vice-versa, and in the case of a challenge-based HCA the system would be making the movement more challenging as the user’s performance improved.

In the context of the project, performance was defined as tracking error that is, the perpendicular distance from the desired trajectory. Different types of adaptation were considered and implemented in the system for further experimentation. In total, there were three rules of adaptation developed. They were all based on haptic tunnels which are zones within the robot’s workspace where no forces are applied. By manipulating the width of the zones, the user’s movements would become easier or more difficult to perform.

3.3.3.3.1 Adaptation in set zones

A zone where no forces are applied to the user’s hand (deadband) was created. The zone was parallel and surrounded the desired trajectory and its walls were placed in equal distances from it. The possible distances away from the desired trajectory were divided in ten different bands namely, error bands. Once the mean value of error was calculated the system evaluated within which error band the performance fell under and would adjust the walls of the deadband according to the respective HCA. There were ten possible widths of the deadband with the first (width 1) being the narrower and the last (width 10) being the widest. For example, for an assistive HCA if tracking error was low (band 1) in the next iteration (after time = T had elapsed) the participants were assigned to a wider (width 10) deadband to receive less assistance by the rehabilitation robot. On the other hand, in a challenge-based algorithm if tracking error was low (band 3) after time T had elapsed the user was assigned to a narrower deadband (zone 2) to make the movement more challenging (Figure 3-40).

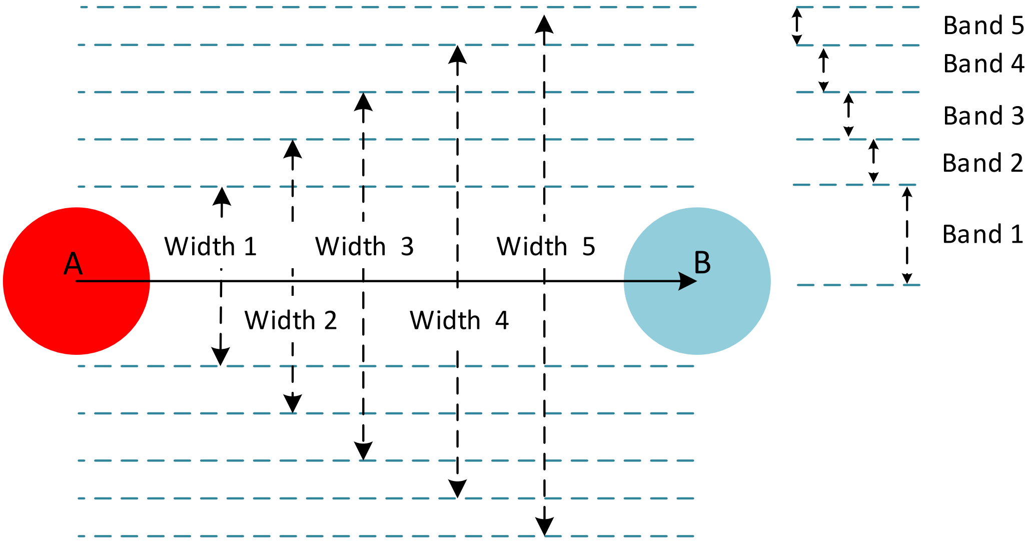


Figure 3-31: An example of the adaptation in zone for 5 zones. After the mean error is calculated and assigned to an error band the width of the deadband is adjusted according to the respective HCA to either assist or challenge the movement...

Table 3-4: Deadband widths for the respective error zone according to the HCA. Width 1 is the narrower and Width 10 is the widest.

Error Band	*Assistive HCA deadband width*	*Challenge-based HCA deadband width*
Band 1	Width 10	Width 1
Band 2	Width 9	Width 2
Band 3	Width 8	Width 3
Band 4	Width 7	Width 4
Band 5	Width 6	Width 5
Band 6	Width 5	Width 6
Band 7	Width 4	Width 7
Band 8	Width 3	Width 8
Band 9	Width 2	Width 9
Band 10	Width 1	Width 10

3.3.3.3.2 Infinite zones

Similar to the set zone adaptation the infinite-zone adaptation used a deadband parallel to the desired trajectory with its walls at equal distances from it. The tracking error was again measured over time T. Once T had elapsed, the average tracking error ε_t was calculated. The width of the zones was then adjusted according to the following Equation (19).

$$Deadband\ width = 2(\varepsilon_t + \alpha\beta W) \qquad (19)$$

Where ε_t = perpendicular error, $0 < \alpha < 0.5$, W = workspace width,

$$\beta = \begin{cases} +1, Assistive\ HCA \\ -1, Challenge - based\ HCA \end{cases}$$

The variable b was used to modify the behaviour of the program to suit the respective HCA. As such, b had a positive value for an assistive HCA and a negative value for a challenge-based HCA. The purpose of this was to challenge the user by adjusting the deadband accordingly in such a manner that less assistance or more challenge would be provided to the user in small increments according to the participants' previously measured performance. The idea behind this approach was that as the task became incrementally more difficult the users would be constantly challenged to improve further their performance.

3.3.3.3.3 Incremental adaptation

This approach also used a deadband with an adjustable width. On the initiation of the program the system was assigned to an initial value of error ε_0 around which a zone was formed with its boarders being ± a percentage of the of value ε_0. As such, there was an upper border and a lower border. The deadband width (d_w) was twice the size of the initial error. Conversely, error was measured for a period of time T to calculate current error ($\varepsilon_{c)}$ and then the system adjusted the deadband width according to the HCA.

An overview of this method of adaptation is provided in Figure 3-32. If error fell within the zone, the width of the deadband remained unchanged. In the case of an assistive HCA if error exceeded the upper limit of the zone (more error) the deadband width was adjusted to be twice the value of the zone’s lower band to provide more assistance. In the case error was under the lower limit of the zone the deadband was adjusted to be twice the size of the upper limit of the zone. In the case of a challenge-based HCA the exact opposite would happen i.e. when error exceeded the upper limit then the deadband was adjusted to be twice the width of the lower band of the zone and when error was below the lower limit the deadband width was set to twice the value of the lower limit.

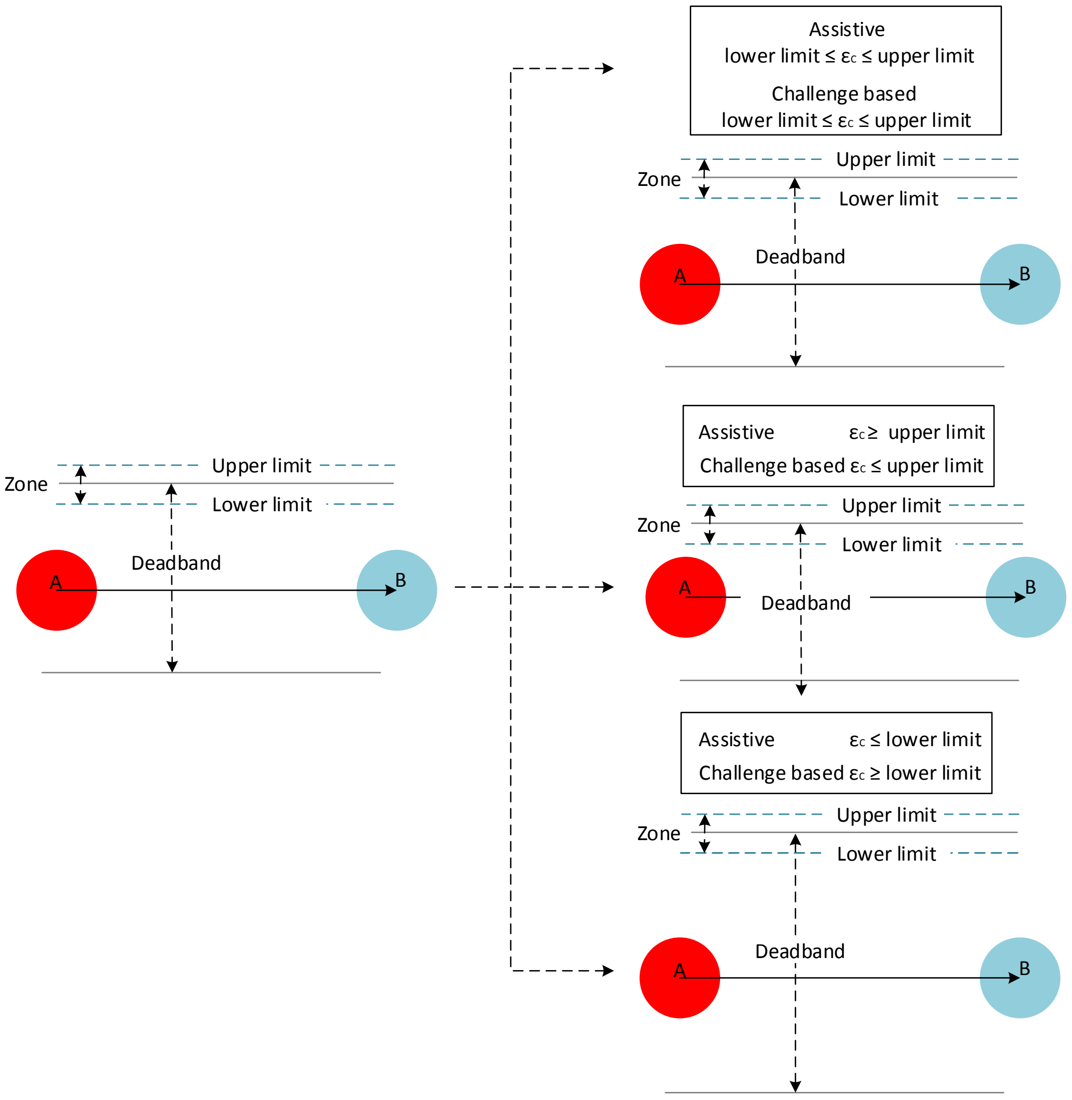


Figure 3-32: The deadband width becomes wider or narrower in small increments.

3.3.3.4 *Proportional forces*

As discussed in Section 2.7.2 EAP is a special case of performance based adaptation as it does not assess the user's performance over a set period of time and adjusts accordingly like the EAA and AAN HCAs do. On the contrary, it measures the instant performance of the user by measuring the perpendicular distance from the robot's endpoint to the desired trajectory and adjusts the magnitude of the forces accordingly. As mentioned previously (Section 3.3.1.2) the rehabilitation robot does not have force measuring capabilities. As such, forces exerted by the robot are controlled indirectly by controlling the maximum permissible torque on the robot's motors by adjusting the maximum permissible current (MPC). An attempt to map the different values of MPC to the maximum permissible forces on the robot's endpoint is presented in Section 3.4.2.

Nevertheless, to achieve the proportional forces behaviour required by the EAP the robot's workspace is divided in eleven zones on each side the desired trajectory. The first zone is defined by the line of the desired trajectory and line a parallel (l_1) to it at a distance d_1. The walls of the second zone are defined by l_2 on one side and the parallel line l_2 at a distance away from the desired trajectory d_2 and so on for all other zones. The zones and zone widths are mirrored for the other side of the desired trajectory. Within, each zone the value of maximum permissible current can be adjusted. The system checks whether the robot's endpoint is within a certain zone and adjust the maximum permissible current accordingly.

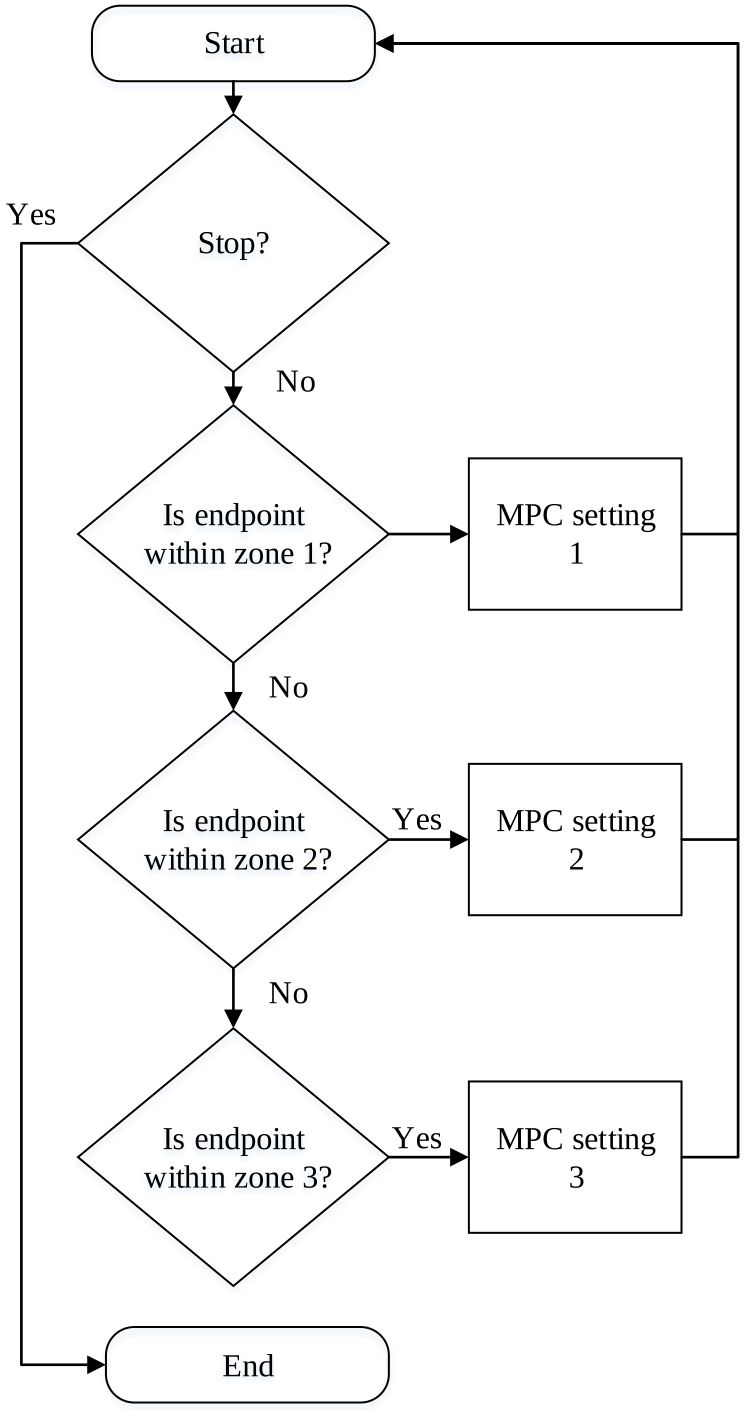


Figure 3-33: Example for the proportional force algorithm for three zones.

3.3.4 Computer game environment development

In order to encourage the user to perform therapeutic movements while interacting with the rehabilitation device in a natural and comprehensive manner, a graphical user interface (GUI) in the form of a computer game was developed. So that incompatibilities with the other components of the system such us the cRIO to be avoided, the computer game was also developed with National Instruments™ LabVIEW. Static games appear to induce more effort in stroke patients as opposed to dynamic and they appear to be preferred by the target population (Simkins et al., 2012). Furthermore, games in robotic rehabilitation are required to set clear tasks because such approaches have been beneficial for increasing motivation and to be challenging to increase engagement (Weightman et al., 2014). As such the main design considerations of the computer environment were simplicity and re-configurability as well as the ability to create different paths for the participants to follow. Finally, for the purposes of this study the computer environment needed to replicate configurations commonly used in literature in order to be used in the evaluation trial of the HCAs.

The requirements for the software as they were set out in the design phase of this project are summarized below:

Game environment requirements

a) To be compatible with the cRIO system *and hence the rehabilitation robot*
b) To accept as an input x-y coordinates *to allow the translation of the robot's endpoint planar movement into a virtual movement*
c) To display the current position of the manipulandum with an indicator - *to serve as feedback of robot's endpoint position*
d) To display multiple targets varying in number and size which could be displayed in adjustable positions on the screen – *to generate targets in the virtual environment for the user to reach in the physical environment*
e) To provide feedback when the indicator reaches a target – *provide feedback to the user about an achieved goal*
f) To be easily reconfigurable. This means, to allow easy configuration of parameters within the environment such as the colour of the indicator, targets and background,

the number and position and size of targets, and the sensitivity of when the indicator reaches the target – *to allow experimentation with different settings and setups*.

3.3.4.1 ***Development of a game environment for upper-limb rehabilitation***

The program accepts as an input the Cartesian coordinates of the manipulandum’s endpoint transmitted over TCP/IP from the real-time program and it displays its relevant position to the workspace with an indicator. As such by adjusting gains within the software, the actual movement of the robot can be translated into a movement in the virtual environment. For example, a 20 cm reaching movement in the real workspace can be displayed in a 2 cm movement in the virtual environment if a gain of 0.1 is used for the conversion.

Moreover, multiple circle-shaped targets are displayed whose coordinates are read from the same file provided to the real-time controller file allowing an infinite number of combinations of the targets positions. These targets are displayed on the virtual environment but correspond to a position on the workspace of the robot (Figure 3-34). Likewise, the straight-line trajectory that connects two consecutive targets is displayed. When the indicator reaches a target, the system provides feedback to the user by changing the colour of the target to white.

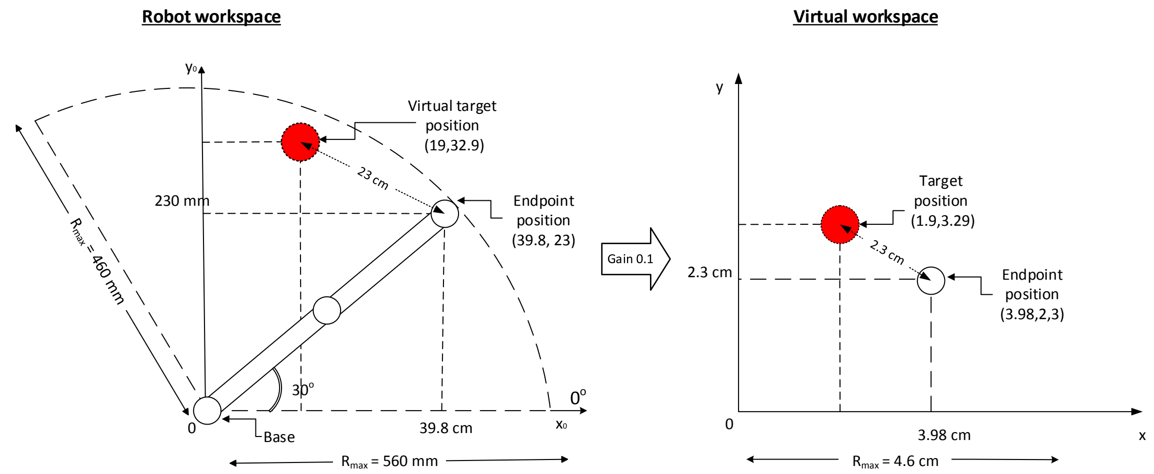
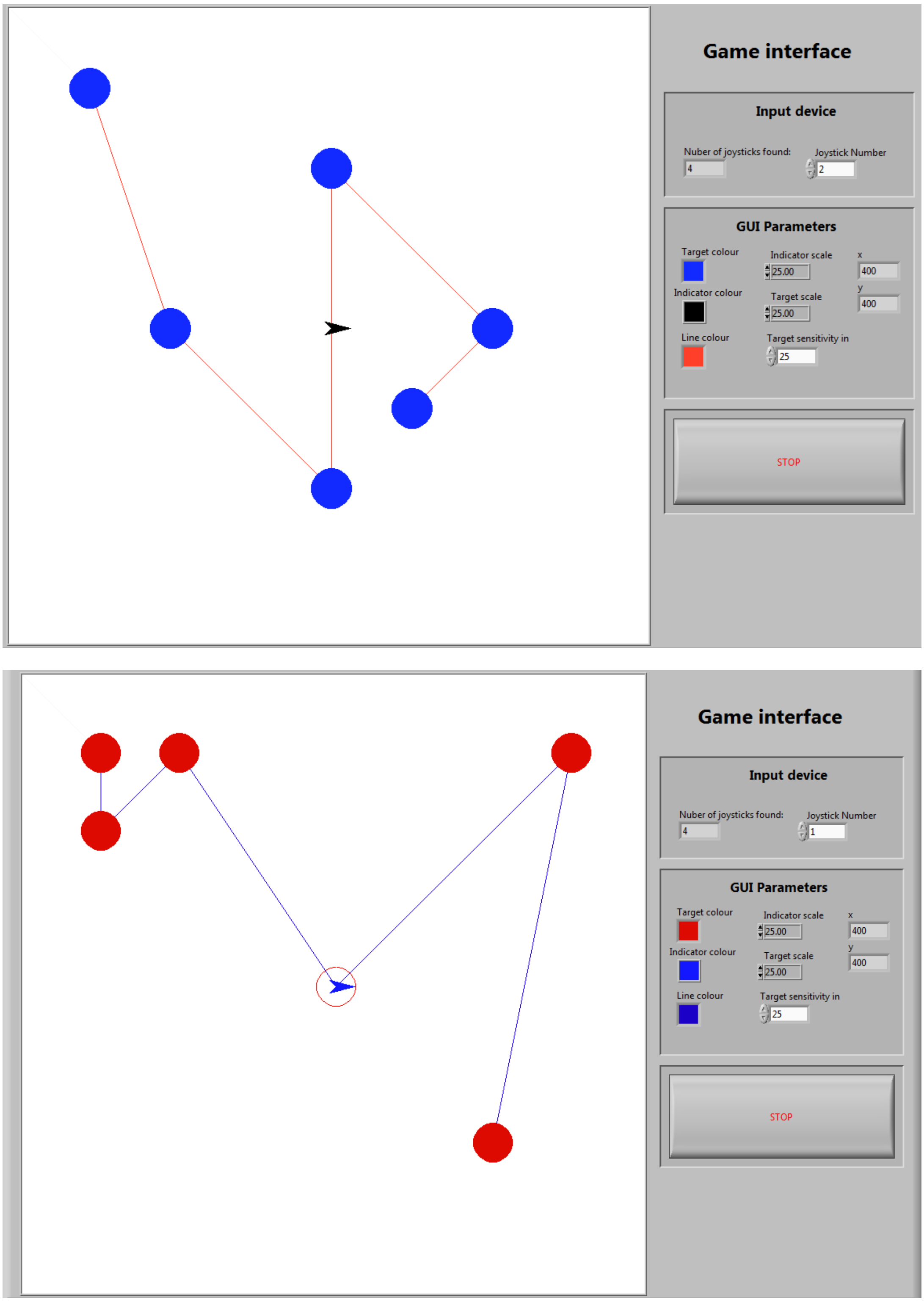


Figure 3-34: By adjusting gains within the environment, the movement in the actual space can be visualised in a smaller movement in the virtual (game environment) workspace.

Additionally, the sizes and colours of the targets, lines and indicator as well as the sensitivity of when the indicator was considered to have reached the target; were fully adjustable within the environment. Likewise, with small modifications to the code infinite number of targets could be added as well as to change the background into a different colour or image. Additionally, the size of the workspace could be changed and adjusted to any size of screen. However, during this project a square 800x800 pixel virtual workspace was used. Finally, to inform the participants about the initiation and the ending of a task messages would appear at the beginning of task providing instructions and at the end congratulating the participants accompanied by the sound of an applauding crowd.



Game interface

Input device

Nuber of joysticks found: 4

Joystick Number: 2

GUI Parameters

Target colour: 🟦

Indicator colour: ⬛

Line colour: 🟥

Indicator scale: 25.00

Target scale: 25.00

Target sensitivity in: 25

x: 400

y: 400

Game interface

Input device

Nuber of joysticks found: 4

Joystick Number: 1

GUI Parameters

Target colour: 🟥

Indicator colour: 🟦

Line colour: 🟦

Indicator scale: 25.00

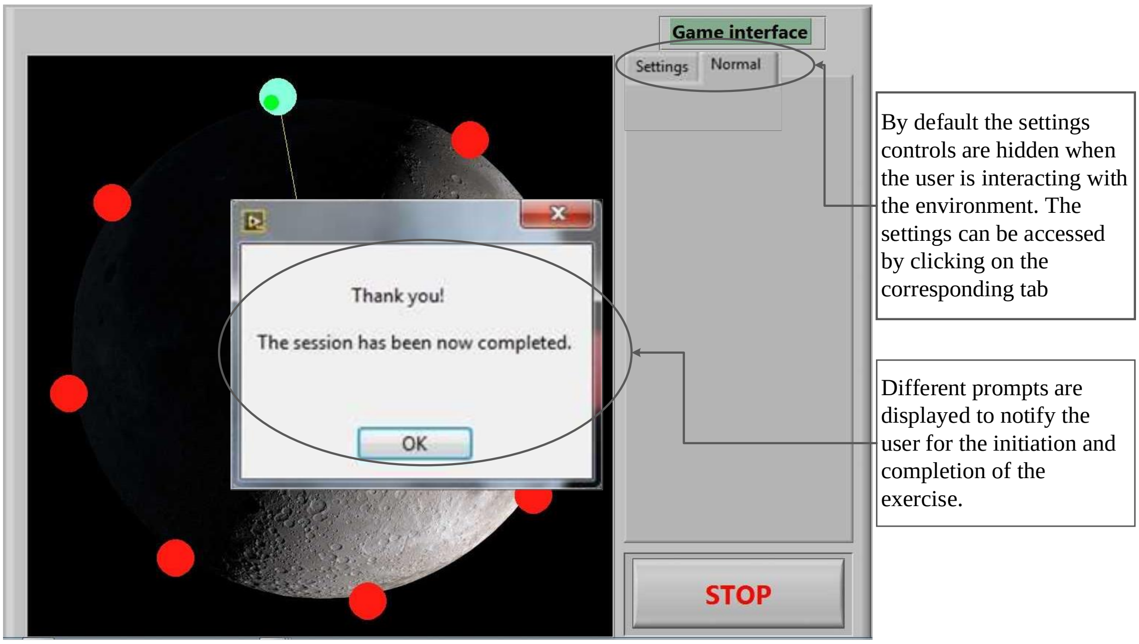
Target scale: 25.00

Target sensitivity in: 25

x: 400

y: 400

Figure 3-35: Different variations of the game by changing parameters within the environment



Thank you!

The session has been now completed.

By default the settings controls are hidden when the user is interacting with the environment. The settings can be accessed by clicking on the corresponding tab

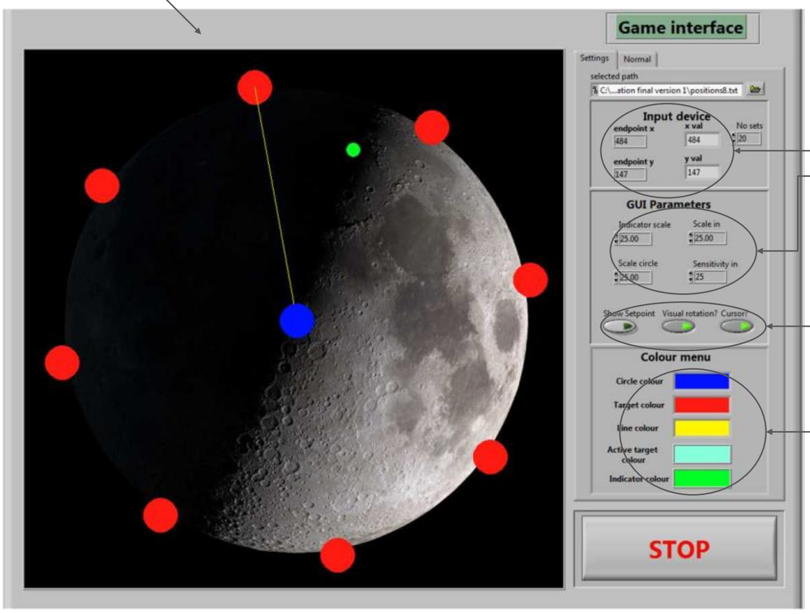
Different prompts are displayed to notify the user for the initiation and completion of the exercise.

Figure 3-36: The user experience of the game's GUI. Settings are hidden away from the user but always accessible for the developer/researcher.

The background image can also be changed but not during the operation of the program

Indicators of the position of the relatiive position of the endpoint and the setpoint

Controllers that adjust the displayed size of the indicator and targets as well as the size of the are that the system considers that a target has been successfully reached



selected path: C:\...ation final version 1\positions8.txt

endpoint x: 484
x val: 484
No sets: 20
endpoint y: 147
y val: 147

Indicator scale: 25.00
Scale in: 25.00
Scale circle: 25.00
Sensitivity in: 25

Show Setpoint
Visual rotation?
Cursor?

Circle colour: 🟦
Target colour: 🟥
Line colour: 🟨
Active target colour: 🟩
Indicator colour: 🟩

Controllers
1) Display the setpoint visualisation (on/off)
2) Rotate the virtual feedback (on/off)
3) Change the cursor type (On: circular, Off: arrow)

Controllers that adjust the colours of different components of the environment

Figure 3-37: The GUI of the game in developer mode. When used the system would hide the settings menu by appearing empty in order to avoid distracting the user

The computer where the game was deployed on was a Windows™ 7 64-bit system with an Intel i5-3470 dual core CPU, 8 GB of DDR3 RAM and an AMD™ Radeon HD 7400 graphics card attached to a HannsG HW173A 17” LCD TFT monitor with a resolution of 1440x900 pixels and a maximum refresh rate of 60 Hz. The main program of the computer game consisted of one loop which was not time-bounded so as the computer would run it as quickly as possible. According to (Funkhouser and Séquin, 1993) the frame rate of rendered game should be kept constantly above a certain level so as the experience is not affected. Furthermore, (Claypool and Claypool, 2007) state that the frame rate affects the performance of the user in gaming applications. To test whether the program could maintain a high frame rate a benchmark was undertaken counting the frame rate of the game while it was being played.

The performance of the program was satisfactory as the frame rate remained well above 40 frames per second (fps) with a maximum frame rate of 333 fps. As the subroutine that is responsible for the visual rotation is more expensive in processing power a drop on the average fps was expected when the subroutine was executed (rotation on). Indeed, the program had an average of 159 fps with the rotation turned off and an average of 105 fps when rotation was enabled (Figure 3-38, Figure 3-39). However, as the computer monitor that was used had a maximum refresh rate of 60 Hz (60 fps) the average frame rate that the computer game produced did not affect the experience of the user.

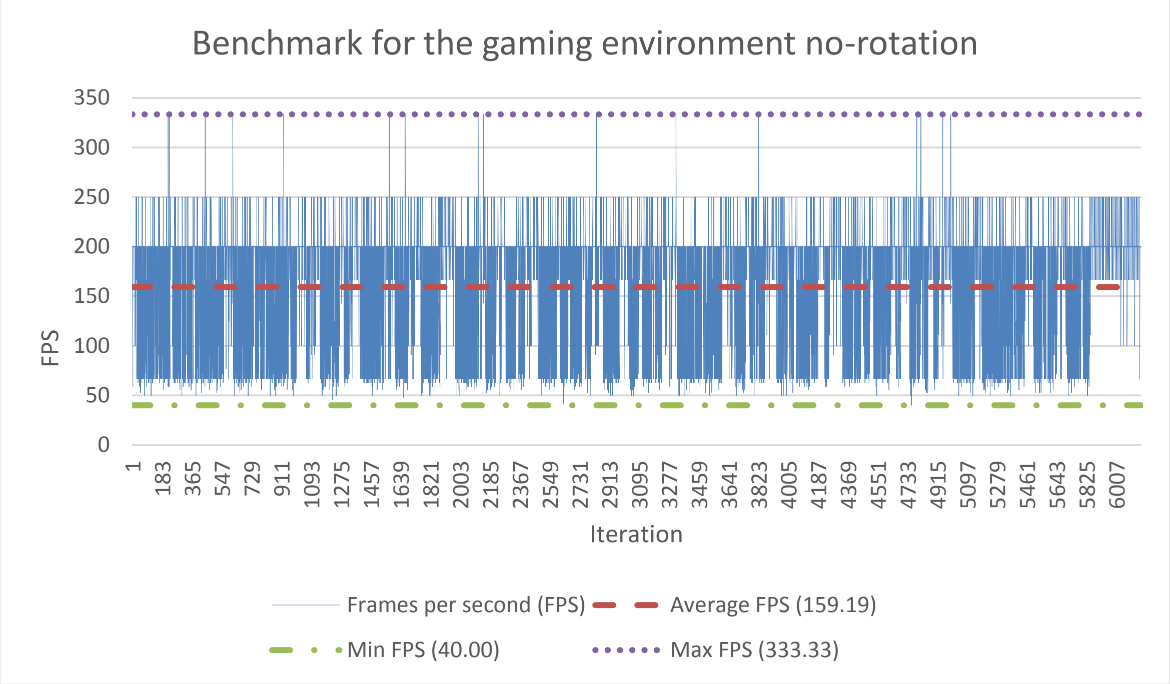


Figure 3-38: Frame rate per iteration with visual rotation turned off.

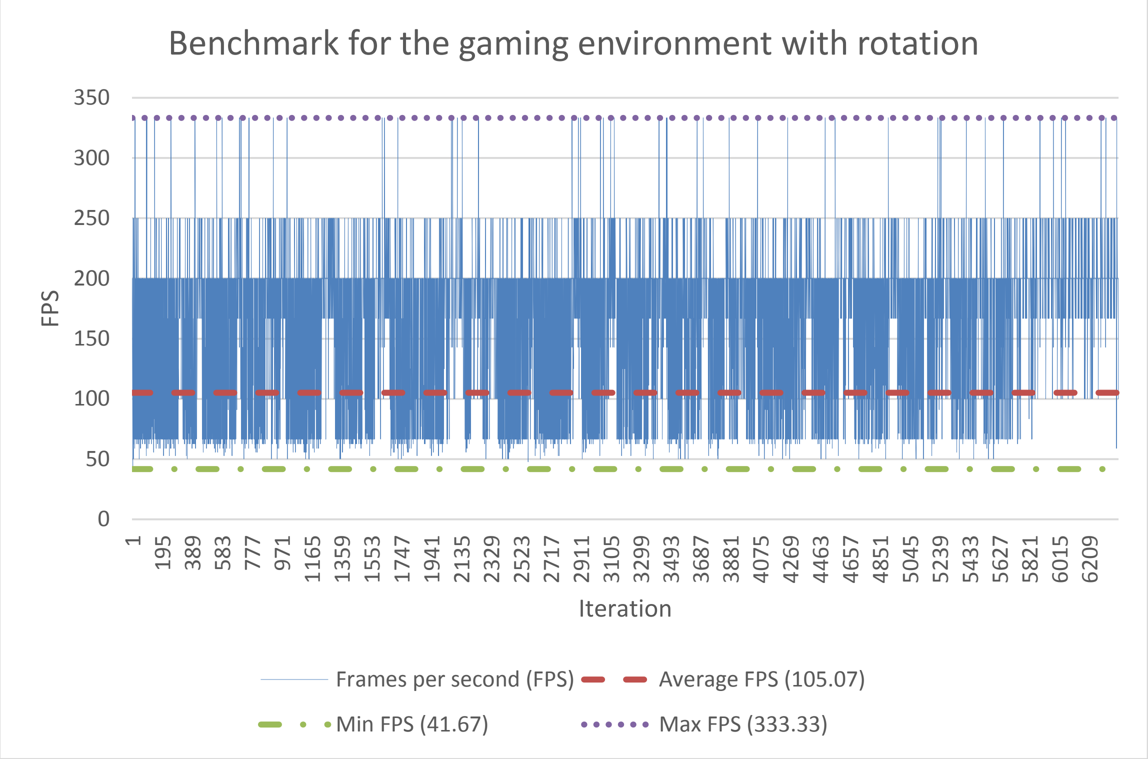


Figure 3-39: Frame rate per iteration with visual rotation turned on.

3.4 System verification tests

This section provided an overview of the different tests that were carried out in order to ensure that the system operated as expected. The first test presented in Section 3.4.1 aimed to verify the accuracy of the system's position controller by comparing data acquired by the robot's sensors against the data acquired by a motion tracking system. The second test aimed to map the forces generated by the robot, as the robot in its current configuration has no embedded force sensors it can only measure torque generated by the motors indirectly as a factor of the current drawn.

3.4.1 Evaluation of the accuracy of the position controller

To evaluate the performance of the position controller as well as the stability and reliability of the system to accurately perform movements on the Cartesian plane, an experiment was devised and executed. This experiment compared positional information collected by the robotic system against data acquired by a motion tracking system. The aim of the trial was to establish to what extent the positional controller and the kinematic model used by the system was sufficiently accurate. As such, the experiment was focused on identifying two important factors; the accuracy of the system to perform required movements and the repeatability of the results in different trials and how those two were affected by different settings of the controller.

3.4.1.1 *Experiment questions*

The questions that this experiment aimed to answer are summarised below:

1) How accurately the system is measuring angular displacement of each joint of the robot?
2) Are movements repeatable (repeatability test)?
3) How the systems accuracy is affected by the maximum allowable torque/current?

3.4.1.2 *Methodology of kinematics evaluation experiment*

Kinematic data acquired by the encoders of the robot were compared against data acquired by the Xsens Motion Tracking (MT) development kit (DK), a motion tracking system that utilises miniature three-dimensional inertial measurement units (MTw). Each of the units has embedded an array of sensors including 3D accelerometers, gyroscopes, magnetometers and a barometer. Also, each unit has a processor for handling the data acquisition, wireless communication etc. The MTw SDK is using an array of MTw sensors in order to analyse complicated movements of articulated objects. (Xsens Technologies B.V., 2013).

Table 3-5: Specifications of the sensors embedded in the Xsens MT units

	Angular Velocity	**Acceleration**	**Magnetic Field**	**Pressure**
Dimensions	3 axes	3 axes	3 axes	-
Full Scale	±1200 deg/s	±160 deg/s	± 1.5 Gauss	300-1100 mBar
Linearity	0.1 % of FS	0.2 % of FS	0.2 % of FS	0.05% of FS
Bias Stability	20 deg/hr		-	100 Pa/year
Noise	0.05 deg/s/√Hz	0.003 deg/s/√Hz	0.15 Gauss/√Hz	0.85 Pa/√Hz
Alignment error	0.1 deg	0.1 deg	0.1 deg	-
Internal Sampling rate	1800 Hz	1800 Hz	120 Hz	-
Bandwidth (analogue)	-120 Hz	-140 Hz	10-60 Hz	-

The robot was programmed to move its endpoint in order to reach eight targets placed on a circle and at equal distances from each other. The robot started from the centre of the circle and moved towards each of the targets and back to the centre. As data acquisition for the rehabilitation robot and the motion tracking systems was not synchronised, the robot was programmed to move in a quasi-static manner. As such, the robot's endpoint moved to the different targets (Figure 3-40) and remained at each position for a short period of time

(100ms). This was done to introduce discrete data points at the position where the robot reached the target which in turn assisted the process for the post-hoc manual synchronisation of the signal. Four different iterations of the same experiment were undertaken. The robot moved multiple times between the targets to ensure repeatability of the results. In addition, both systems were collecting data with a frequency of 100 Hz.

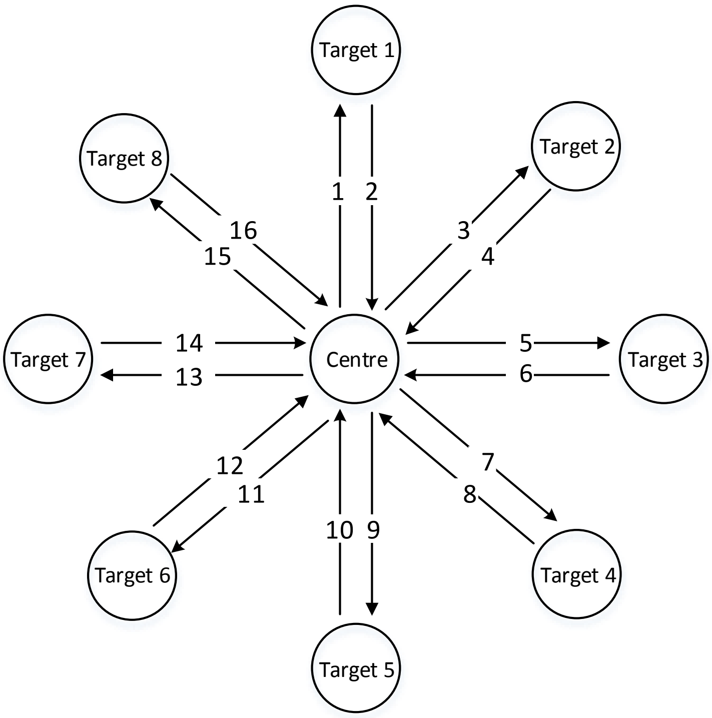


Figure 3-40: The robot's endpoint cycled between the different targets starting from the centre. To distinguish between the movements an individual number was assigned to each movement direction.

As the Xsens used accelerometers and inertial measurements to determine movement only the relative angle of the rotational movement could be measured by measuring the change in yaw of the robot's links. Three sensors were used in total and their placement configuration is shown in Figure 3-41. One sensor was placed on the robot's shoulder joint to provide a reference measurement for a static point. A second was placed on the robot's elbow joint to measure the rotation of the first link. The third sensor was placed on the robot's endpoint to measure the rotation of the second link (rotation of 2nd link = rotation measured on endpoint – rotation of 1st link).

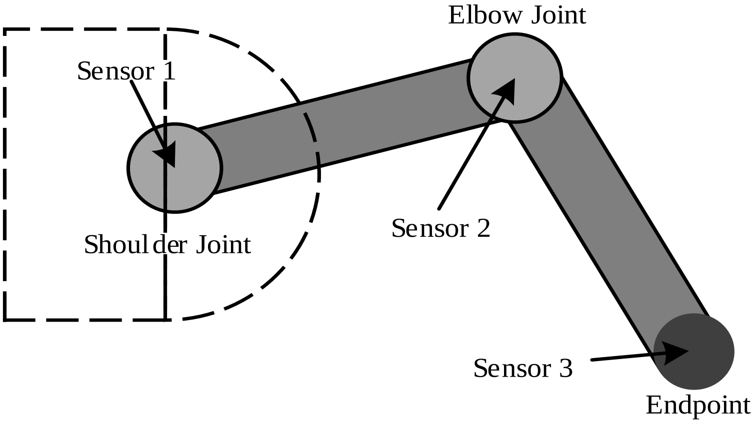


Figure 3-41: Three MTw sensors were placed in three different locations to measure the rotation of the two joints.

The MTw provided two manners of calculating the rotation across the vertical axis. One involved the use of the inertial sensor in the MTw which is measuring angular velocity. In this case velocity is integrated against time using the trapezoidal rule for integration (Brian H. Hahn, 2013) to calculate the angular displacement. Also, the MTw utilises a Kalman filter to fuse data acquired from the embedded sensors (gyroscopes, accelerometers and magnetometers) to compute 3D orientation (Xsens Technologies B.V., 2013). More specifically, to calculate the heading (Yaw) the sensors operate similar to a magnetic compass providing measurement with reference to earth's magnetic North. Table 3-6 provides information on the sensitivity characteristics of the characteristics of the MTw sensors.

Table 3-6: Orientation performance for the MTw sensors (Source: (Xsens Technologies B.V., 2013))

Dynamic range	**All angles in 3D**
Angular resolution	**<0.05 degrees**
Static accuracy (Roll/Pitch)	**1 degree**
Static accuracy (Heading)	**1 degree**
Dynamic Accuracy	**2 degrees RMS**

The experiment consisted of four trials in total with different settings. In all trials the robot cycled between all sixteen movements with the only difference being the different maximum current setting (2A for Trials 1, 4 and 3A for Trials 2, 3).

Table 3-7: The kinematics evaluation trial protocol.

Trial no	**Number of sets**	**Movement sequence**	**Max motor current**
1	4	1-16	2 A
2	4	1-16	3 A
3	1	1-16	3 A
4	4	1-16	2 A

3.4.1.3 *Data analysis*

There was no option for synchronisation of the triggering between the two acquisition systems, as a result the synchronisation of the signals had to be performed post-hoc. To align the two signals several approaches for automatic data synchronisation and sensor fusion were considered. Such methods included the approach suggested by (Madgwick et al., 2011) and (Rhudy, 2014). Nevertheless, manual synchronisation was deemed as the most effective for the specific application. As such, for a given dataset from the Xsens the measurements were converted into angular displacement and then plotted against the data acquired from the robot.

Examination of the plots allowed the identification of the point in time where movement was initiated. By comparing, the time difference between these two points for the respective plot the delay was identified and finally that allowed the synchronisation of the signals by shifting one to match the other. The signals then were adjusted to be at the same rotational reference system. For example, the robot measures positive angular displacement clockwise while the Xsens counter-clockwise and the magnetometer provides readings of rotation according to earth's magnetic North pole. As such, the first measurement was subtracted from all the subsequent measurements to bring all measurements to 0° rotation and the Xsens measurements were multiplied by -1 to match the orientation of the robot's encoders (Figure 3-42). In addition, the rotation of the second joint of the robot was calculated as the difference in angular displacement between sensor 3 and sensor 2 (Figure 3-41).

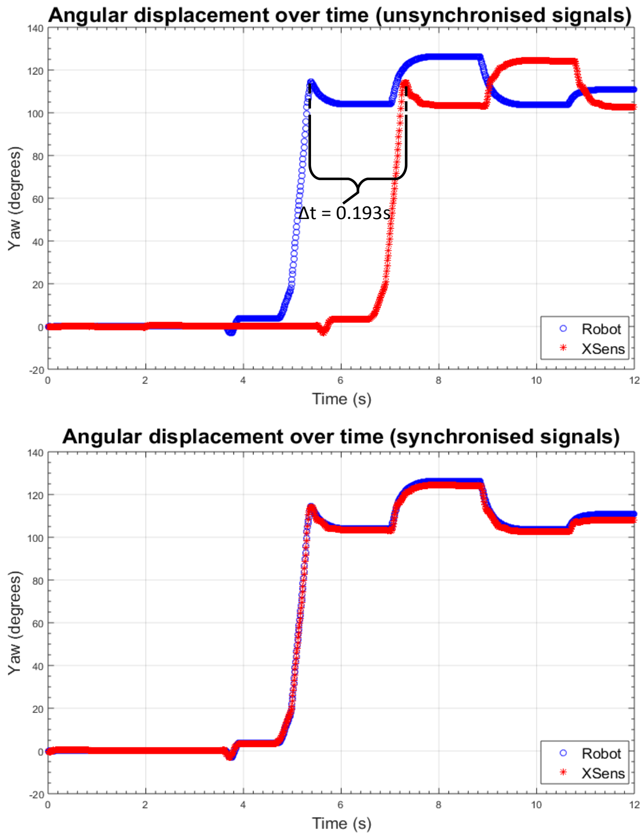


Figure 3-42: Both plots display the angular displacement of the elbow joint after the signals were analysed for two movements before and after the synchronisation of the two signals.

3.4.1.4 *Results of the kinematic analysis*

Once the signals were analysed and synchronised angular error was calculated as the difference between the angular displacement and the data acquired by the Xsens. To answer the research questions set out at the initiation of this experiment statistical analysis was performed to check whether differences existed between the data measured by the robot and the Xsens, to measure accuracy, repeatability as well as whether there was an effect of the value of maximum torque applied to the previous two.

A repeated measures analysis was performed using the linear mixed models. The targets were used as the subjects of the analysis and as repeated measures were set the trial numbers and the repetitions within the trials. The factoring variables used were i) the measurement methods i.e. the robot’s encoders (Robot/Xsens), ii) the trial number, and iii) the repetition number. The absolute value of the rotation in degrees i.e. the normalised rotation of the motors when the endpoint reached each target was used as the dependent variable. Constant variances were assumed between the different time points and the different repetitions. Furthermore, the analysis was performed separately for the shoulder and elbow joint of the robot to identify potential differences between the two links.

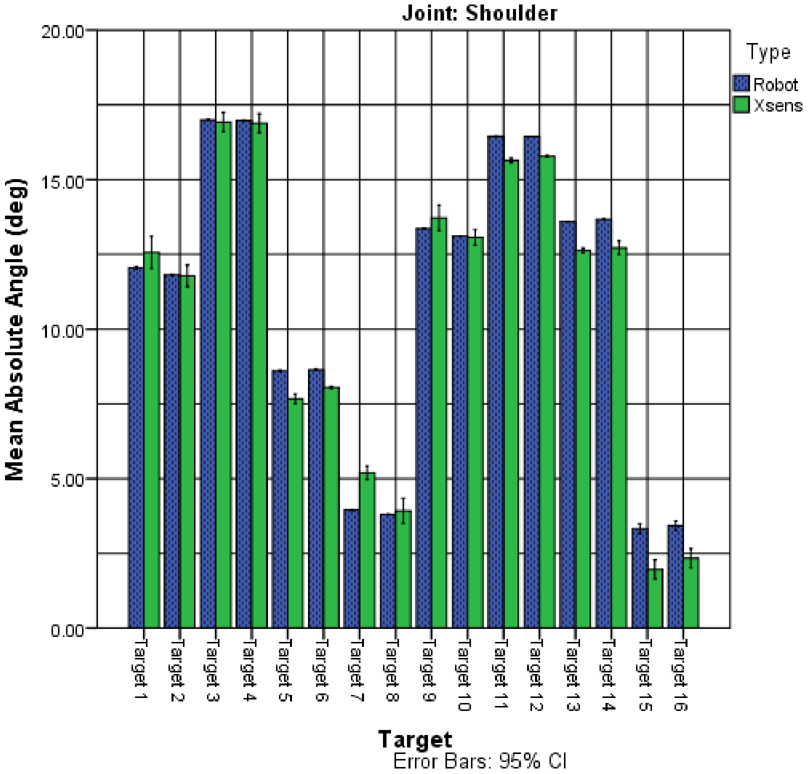


Figure 3-43: Mean absolute value of rotation for the shoulder joint as measured by the robot and the Xsens.

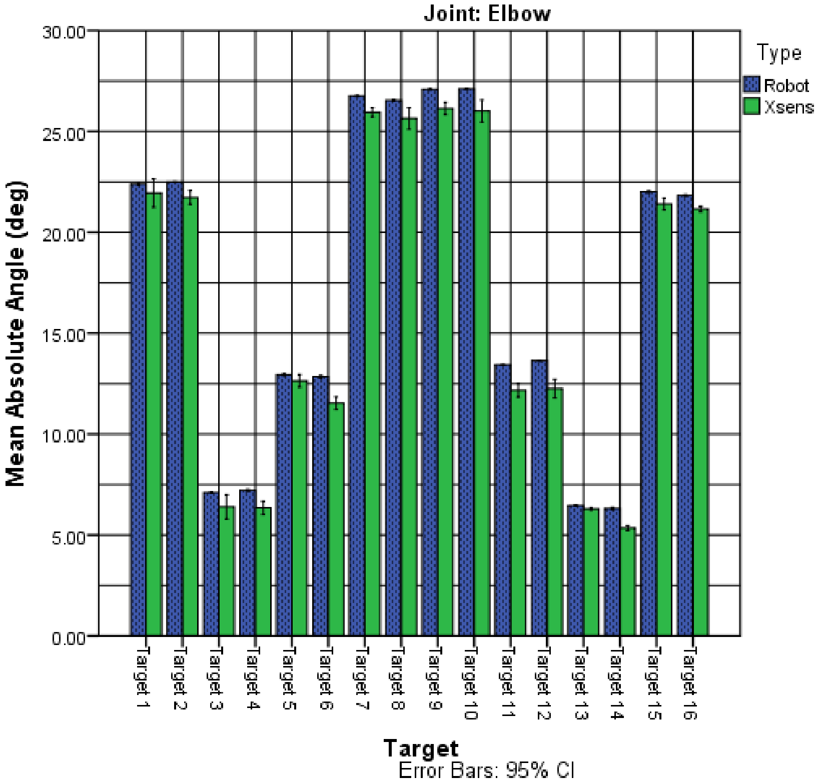


Figure 3-44: Mean absolute value of rotation for the elbow joint as measured by the robot and the Xsens.

The analysis indicated a significant difference between the two measuring methods i.e. the robot and the Xsens for both the shoulder joint F(375,1) = 43.953, p <0.01 and the elbow joint F(375,1) = 343.864, p <0.01 across all the different trials. The mean difference between the two measuring methods was 0.33^o ($p<0.05$) for the elbow joint and 0.68^o ($p<0.01$).

As the sensitivity of the Xsens for dynamic measurements is 2^o and the measured angular differences are below that threshold it is hard to draw firm conclusions as to what the cause of this difference is. A potential source for this result could be partially attributed to backlash which is defined as the difference between the thickness of a gear tooth and the distance between the corresponding teeth of the engaging gear (Oberg et al., 2012). Furthermore, another potential cause of error could be attributed to vibrations caused by the robot’s movements to the mounting frame hence introducing noise to the measurements acquired by the Xsens but not to the motors due to their different frame of reference.

When considering the effect of measurement type to the individual trials there was no significant effect identified for the shoulder F(375,6) = 0.305, p =0.934 but there was a significant effect for the elbow joint F(375,6) = 24.852, $p < 0.01$. However, when comparing the parameter estimates for the interactions between trial type and trial number all combinations provided insignificant differences ($p>0.6$) apart from trial 1 where the measurements acquired with the Xsens yielded a significant estimate of -0.78^o ($p < 0.01$). However, further inspection of the results indicated that this was not a valid effect. As shown in Figure 3-45 the differences between the measurements for each target between the different trials appear to be random. Finally, there was no significant effect of repetition between the different trials as measured by the two measuring methods for both the shoulder joint F(375,6) = 0.684, p = 0.824 and the elbow joint F(375,6) = 0.471, p = 0.969. Both findings indicated that the accuracy of the robot is not affected by the maximum current (torque) settings or by the number of repetitions it performs.

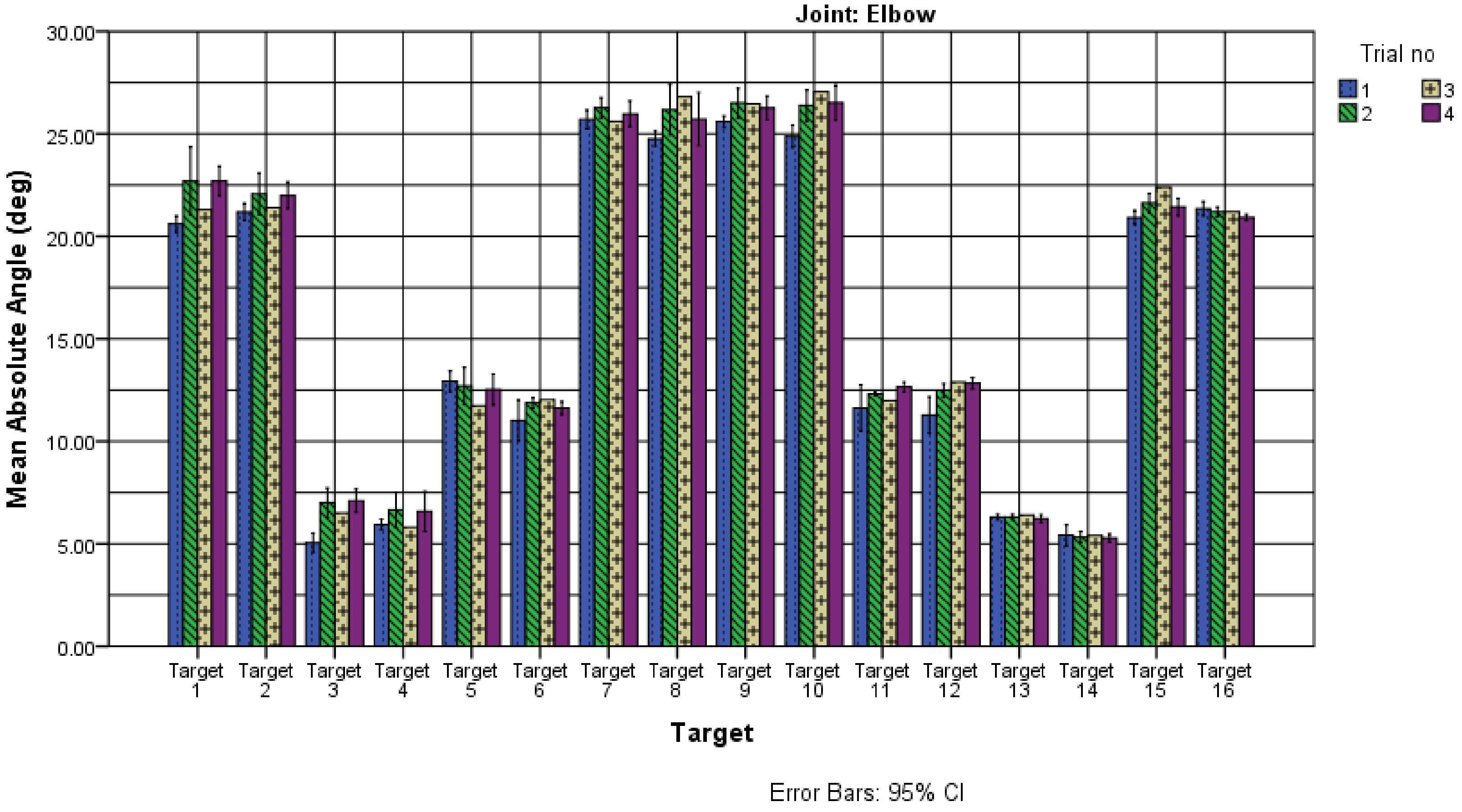


Figure 3-45: Absolute angle for the different targets as measured by the Xsens on the elbow joint of the rehabilitation robot. Positions of the elbow appear to be the same for a given target in all trials.

3.4.2 Mapping the forces generated by the rehabilitation robot

As described previously the robot cannot measure forces directly however, as mentioned in Section 3.3.1.2, by controlling the maximum permissible current (MPC) on each motor, the torque on that respective motor can be controlled. The rehabilitation robot was ultimately intended to be used by impaired adults and children as such, it was deemed crucial that the forces exerted by the robot's endpoint to be known given a certain MPC. As such an experiment was carried out measuring the forces applied by the robot's endpoint on a load cell. This experiment had a second purpose, that was to ensure that for a given value of MPC on the motors, the robot's endpoint would apply forces uniformly in all directions.

To measure the forces generated by the robot's endpoint an ATI F/T Mini 40 AT-20-1 force/torque (F/T) sensor was used (Figure 3-46) for which the measurement specifications can be found in Table 3-8. For this experiment the sensor was connected to a National Instruments CompactDAQ cDAQ-9178. To ensure that correct readings were acquired the sensor was calibrated on the z-axis. For the calibration process ten 100g (±0.01g) brass weights were used. The weights were mounted on the sensor one at a time until a maximum mass of 1kg was reached and then the weights were removed one at a time until no mass was loaded on the sensor. The process was repeated five times and the results of the measurements are displayed in Figure 3-47.

Figure 3-46: The ATI-20-1 Mini 40 force transducer.

Table 3-8: Measurement specifications for the ATI-20-1 Mini 40 F/T sensor

Sensor	**Sensing range**	**Resolution**
Fx, Fy	20 N	0.01 N
Fz	60 N	0.02 N
Tx, Ty	1 Nm	1/4000 Nm
Tz	1 Nm	1/4000 Nm

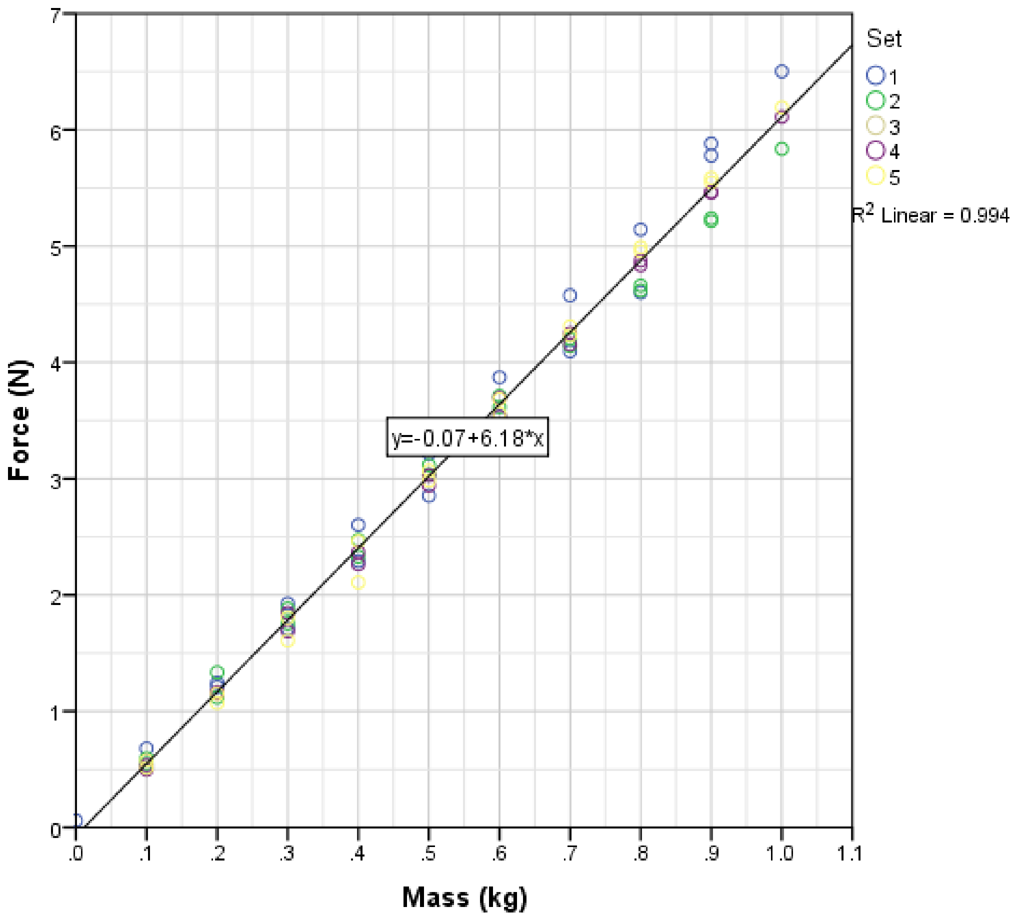


Figure 3-47: Calibration plot for the z-axis of the load cell.

In the plot of force measured (N) versus load (kg) a regression line was fitted through the least squares method (Figure 3-47). The expected value of the slope of the regression line should have been the value or close to the value of the acceleration of gravity (9.81 m/s^2) as Newton's Second Law indicates. (F=mg) Furthermore, the y-intercept of that line was expected to be zero or very close to zero. Nevertheless, the regression analysis indicated that the gradient of the regression line was 6.18 m/s^2 and the y-intercept was approximately 0 (-6x10^{-3} N). The gradient was much smaller than expected (9.81 m/s^2) and as such all subsequent measurements were adjusted by being multiplied by 1.59 (9.81 m/s^2 divided by 6.18 m/s^2).

From the results of the descriptive statistics (Table 3-9) for the calibrated forces it can be seen that the standard deviation from the mean was fluctuating between 0.1 N and 0.44 N as such the practical accuracy of the load cell was deemed to be ±0.44 N which is much higher than the theoretical error provided by the manufacturer (0.02 N).

Table 3-9: Descriptive statistics for the calibrated force measurements given a certain mass.

Calibrated Force (N)				
Mass (kg)	Mean	Std. Error of Mean	Std. Deviation	Grouped Median
.00	-.0751	.05729	.11458	-.1232
.10	.8882	.03346	.09464	.8642
.20	1.8782	.04576	.12943	1.8420
.30	2.8272	.06001	.16974	2.8302
.40	3.7560	.08508	.24065	3.7357
.50	4.8183	.06181	.17483	4.8209
.60	5.8043	.06455	.18258	5.8019
.70	6.7496	.08449	.23898	6.7050
.80	7.6875	.10976	.31044	7.7210
.90	8.7796	.13120	.37108	8.7569
1.00	9.7956	.21826	.43651	9.7817

Once the load cell was calibrated the sensor was placed on its mount with its z-axis aligned to the direction of the movement of the robot’s endpoint (Figure 3-48). This test aimed to map the forces generated by the robot’s endpoint at different positions of its workspace as well as to see the effect of the different MPC settings to forces generated by the robot.

To acquire the measurements, the robot’s endpoint was placed in the centre of its workspace. It was then programmed to move towards one of eight different directions equally distanced from each other by 45^o as shown in Figure 3-40. The load cell was placed in such a manner that the z-axis was aligned to the direction of movement and the plate of the load cell was obstructing the movement of the endpoint towards that direction. As such, when the robot attempted to move, its path was obstructed by the plate of the load cells generating forces that were in turn measured by the load sensor. For each direction two different distances from the centre of the robot's workspace were tested at 0 mm and at 80 mm. Five different measurements were taken for each position under a certain setting of MPC and in total two different MPC settings were tested of 2 and 3 Amperes, respectively.

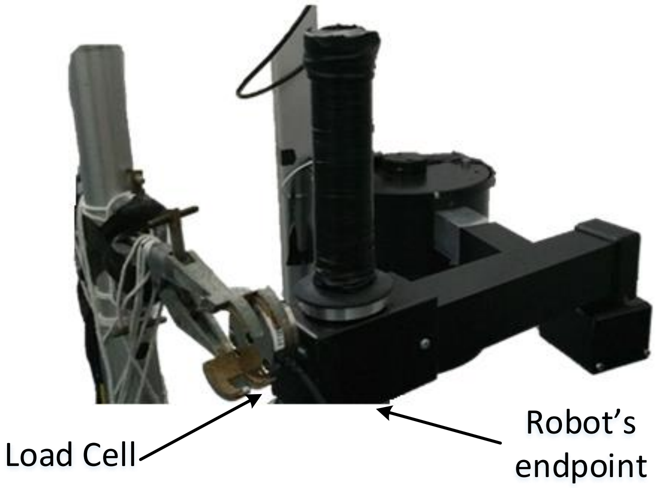


Figure 3-48: The experimental setup for force mapping.

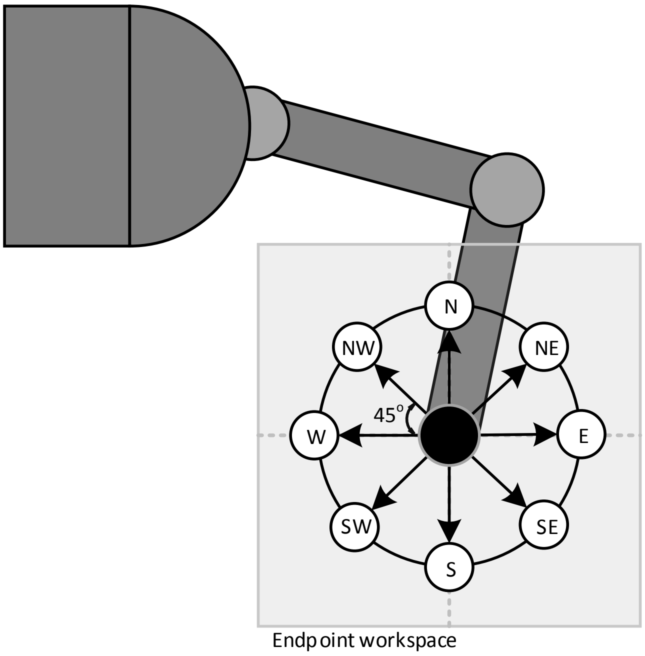


Figure 3-49: The robot's workspace and directions that were tested for the force measuring experiment.

The analysis of the results was performed individually for each value of MPC. For the statistical analysis SPSS version 22.0 was used. The model used was the equivalent of a General Linear Model by using the Linear Mixed Models options of SPSS. Force measured by the load cell was used as the dependant variable and target and distance were used as the independent. Apart from the estimates of fixed effects the estimate marginal means were calculated with Bonferroni correction for multiple comparisons. The same analysis was performed twice, one for each of the two MPC settings used in the experiment. A more extensive description of the statistical analysis method is provided in Section 4.3.5 and the findings of the statistical analysis are presented in more detail in Appendix C.

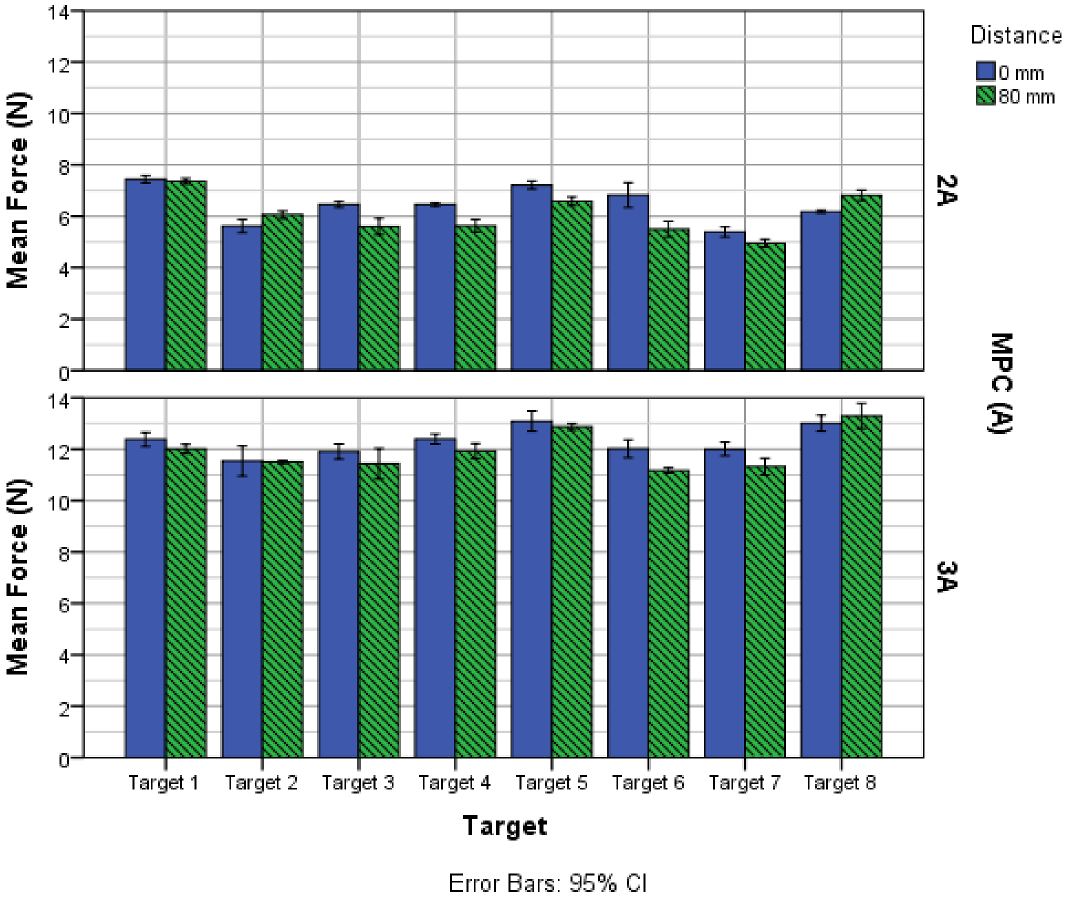


Figure 3-50: Force measurements for eight different directions at two different distances from the workspace centre (0 mm and 80 mm) and two different settings of MPC (2A and 3A).

With respect to the MPC= 2A the tests of fixed effects identified that there was a significant effect of direction on the forces exerted by the rehabilitation robot F(64,7)=146.037, $p<0.005$ and also the statistically significant interaction between target and distance F(64,7) = 43.050,

$p<0.005$ (Appendix C). The pairwise comparisons showed that the forces exerted at the different targets varied between 5.4 N – 7.5 N at 0 mm and 5-7.4 N at 80 mm depending on the direction (Figure 3-50). Regarding the forces that were exerted for MPC=3 the tests of fixed effects identified a statistically significant effect of direction to the forces exerted by the robot's endpoint $F(64,7)=54.585.p <0.005$ and also a statistically significant interaction between target and distance $F(64,7)=7.939$, $p<0.005$ (Appendix C). The pairwise comparisons showed that forces exerted at MPC=3 varied between 11.5-13.1 N at 0 mm and 11.2-13.3 N at 80 mm (Figure 3-50).

Interestingly the maximum range of measurements was very wide for both settings of MPC. More specifically the range of error in the measurements' values was ±0.50 N and ±0.65 N for MPC=2A and MPC=3A, respectively. As there range of error in the measurements by the load cell was established to be 0.88N (±0.44 N) that more error was introduced to the system most likely by the experimental setup that allowed for small misalignments between the load cell and the robots' endpoint movement. However, as this is an exploratory study to acquire an indication of the forces exerted by the robot given a certain value of MPC, higher measurement accuracy was not a requirement. Nevertheless, if more precise force measurement is required in the future then a different experimental setup will be required where the load cell is attached to the robot's endpoint and the robot's endpoint is locked into position externally.

3.5 Summary

In this chapter the system development undertaken for this project was discussed. The hardware development phase of the project involved the re-design and further development of an existing single point of attachment rehabilitation robot that was to be used as the experimental apparatus in this work. The software development involved a software developed for the systems FPGA that contained all the low level functions to implement a PID position controller. Another, aspect of the program was the real-time portion of the architecture that was deployed on a real-time computer system. This program controlled all the high level functions of the program such as the setpoint calculation, forward and inverse kinematics for the robot, angle translations, data acquisition etc.

Part of the real-time software was the HCA implementation. The different HCAs were the programs that controlled the behaviour of the system in response to the participants' movements. To provide a meaningful interface between the user and the rehabilitation robot to promote therapeutic movements, a computer game was designed which was deployed on a personal computer system. Finally, at the end of the chapter different aspects of the system were assessed mainly its accuracy and repeatability to perform movements and also an attempt was made to map the forces generated by the robot in its workspace.

4 Pilot trial to test algorithm adaptiveness parameters and the overall trial protocol

4.1 Introduction

In Section 2.7.3 an in-house implementation of the Assistance As Needed haptic control algorithm was introduced and the in Section 3.3.3.1 its implementation was discussed. AAN is a highly customisable HCA that allows control of different parameters to the user. Such parameters include the direction and amplitude of the forces produced by the robot, t_d (time between adjustment of deadband), forces applied by the robot etc.

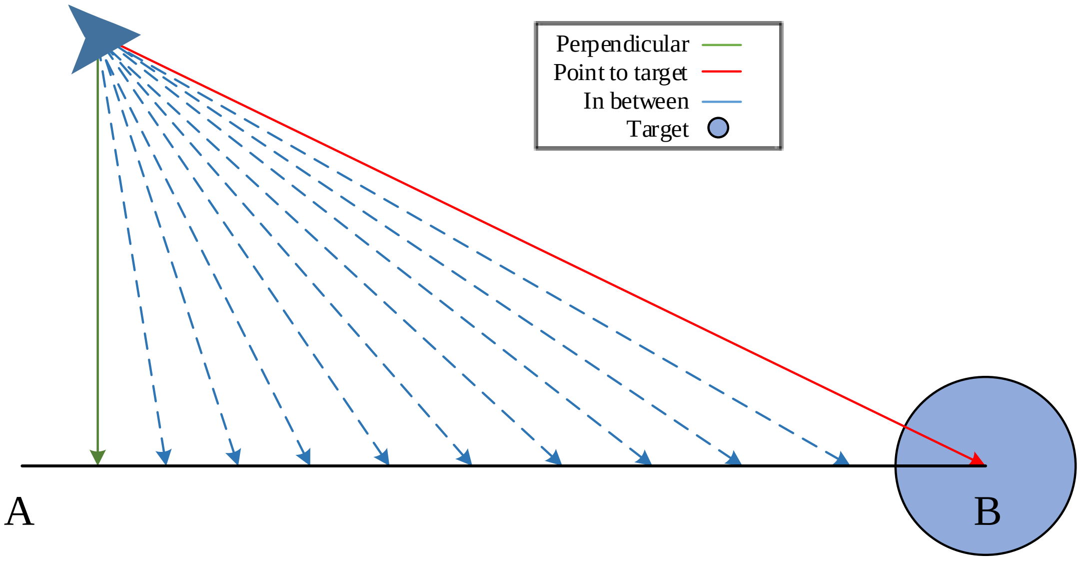


Figure 4-1: The different modes of providing forces by the AAN.

By changing the direction of the forces different behaviours of the controller can be achieved (Figure 4-1). For example, when the system is set to provide forces in the perpendicular direction towards the desired trajectory the user is assisted to reduce tracking error but not to reach the target. On the other hand, when forces are directed towards the target of the movement the user is assisted to reach the target but without reducing accordingly the tracking error. Finally, by placing the forces between the target and the perpendicular direction then the forces are assisting to reduce tracking error while assisting the user to reach the target. The system can be adjusted to move closer to one direction or the other in order to bias behaviour of the algorithm to apply forces towards one trajectory more than the other.

Another feature that can be customised on AAN is the duration of time before performance is assessed and deadbands are adjusted accordingly. This feature is important as it allows for the system to adapt to participants' performance that may vary throughout the training session for reasons such as fatigue, spasticity etc. and allow to complete their training.

4.2 Pilot trial

As described in the previous section Assistance As Needed evaluates performance as the average movement error over certain period of time (t_d) however, by studying the literature it was unclear whether the duration of t_d would be a significant factor that would affect the effectiveness of AAN in the motor learning of healthy adults. It appears that other studies have chosen parameters of their controllers based on experience and trial and error (Krebs et al., 2003; Vergaro et al., 2010). To investigate if there is an optimal period of time within which the system should adapt to the user's movement a human trial was designed with able-bodied participants. This trial had also a second purpose, which was to serve as a pilot trial to test different parameters of the system as well as the trial protocol in order to make necessary adjustments before the human investigatory trial of this project.

4.2.1 Research questions of the pilot trial

The trial that was undertaken set out to answer three main research questions:

1) Do different time intervals (t_d) where an HCA adapts to user's performance (rates of adaptiveness) affect the motor learning process and its retention in healthy adults?

2) Can bilateral transfer of skills be measured by the system? Do different rates of adaptiveness of the Assistance As Needed haptic control algorithm affect it?
3) Does the rate of adaptiveness of the algorithm affect the emotional state condition of the participant?

Although Question no 2 is not directly related to robotic rehabilitation it can actually help in the understanding of the internal processes of the brain and how they are affected by robotic therapy. To the authors knowledge there has not been an attempt to study the effects of robot training and different HCAs on the bilateral transfer of learning as suggested where training has been only received one arm as suggest by the Bilateral Transfer Therapy (BTT) as described in Section 2.4.3 (i.e. not bimanual/mirror therapy).

Furthermore, as this trial doubled as a pilot of a larger trial studying the effectiveness of different HCAs on the motor learning of healthy adults two more questions arose which are as follows:

4) Is the trial protocol sufficiently measuring motor learning?
5) How much exercise can healthy adults receive before they reach a plateau in their improvement?

4.2.2 Pilot trial protocol

Ten participants were included in this study all of which were volunteers that responded to an advertisement placed within the University campus. Inclusion criteria were non-ambidextrous (Edinburgh Handedness Inventory score $\neq 0$) able-bodied adults aged between 18 and 65 years with no history of neurological impairment. The participants were randomly assigned to one of two groups. Both groups received identical amount of exercise while interacting with the rehabilitation robot implementing AAN. All settings of AAN were the same for both groups with the only difference being that the adaptation of the algorithm occurred at different intervals t_{d1} = 30 seconds and t_{d2} = 60 seconds. From previous experimentation it was found that for a healthy individual it took on average 1.7 s to perform a reaching movement therefore 29s to complete one set of sixteen movements. Therefore the time intervals after which the HCA adapts for each group were selected to correspond to approximately one set of movements and two sets of movements for the 30s and 60s group respectively.

Pre-trial, participants were asked to complete the Edinburgh Handedness Inventory (EHI) a measurement scale in the form of a questionnaire that assesses the dominance of an individual's arm (Oldfield, 1971). The scale ranges from -10 to 10 with all values indicating dominance of the left arm, all the positive indicating dominance of the right arm and a value of 0 indicating ambidexterity. Participants received all exercise in one session that lasted approximately 2 hours. Once it was assured that participants met all the inclusion criteria they all signed an informed consent form in accordance to the ethics regulations of the Manchester Metropolitan University. For this trial ethical approval was received from the Ethics Committee of the Manchester Metropolitan University.

4.2.3 Trial task

The participants were sat in front of the rehabilitation robot holding its handle. By controlling the position of the endpoint of the rehabilitating robot they controlled a cursor in the game's workspace displayed on a computer screen which was placed in front of them. In the game environment 9 targets were displayed all of which had the same colour. Eight of the targets were placed along a circle with a 45^{o} degree distance between them and one target was placed in the centre of the circle.

A target would change colour to indicate that it was active (ready to be reached) and a straight line would connect that currently active target with the one that was previously activated. Once a target was reached it would change colour to indicate it was deactivated and another target would change colour to indicate that it was active. At any given time only one target would appear as active. Movements would always start from the centre towards an active target in the perimeter of the circle. Once that target was achieved then the centre target would be activated in order to initiate the target to centre movement. The participants were informed that the task was to follow the line that appeared on the screen from the current position of the cursor towards the active target as quickly and as accurately as they could (Figure 4-2).

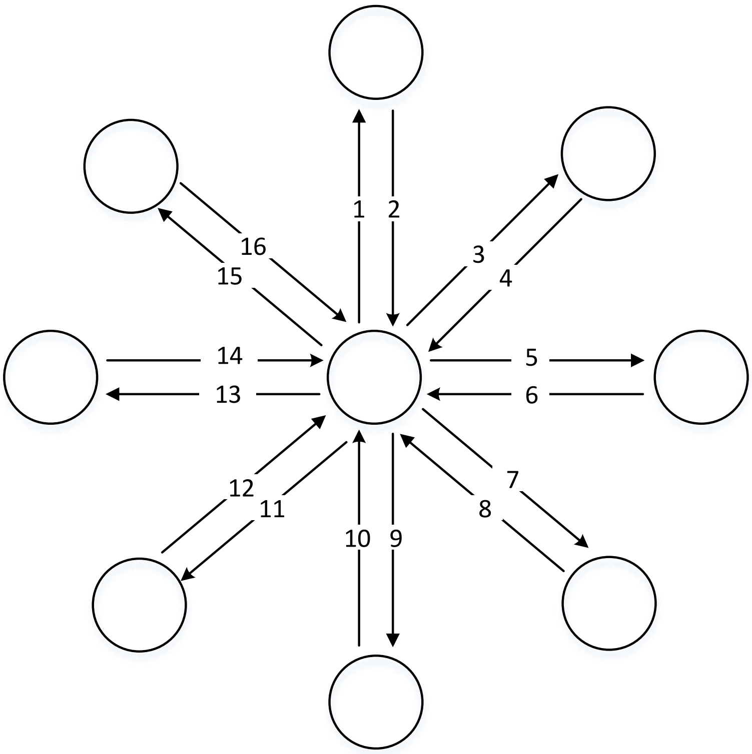


Figure 4-2: The reaching task. Each movement was assigned to a number to distinguish between them.

The actual workspace of the robot was 160 mm wide and 160 mm long and it was translated into an 800-pixel by 800-pixel workspace on the computer screen. As such there was a fixed translation ratio of 1mm to 5 pixels. Eight targets were placed in a circular orientation with a radius of 70 mm and each of the circle shaped targets had a radius of 5mm. As such the minimum length of movement between the targets was 60 mm (Minimum path length =

Centre to target length – Target 1 size – Target 2 size or Minimum path length = 70mm – 5mm – 5mm). Figure 4-3 shows a dimension diagram of the actual workspace.

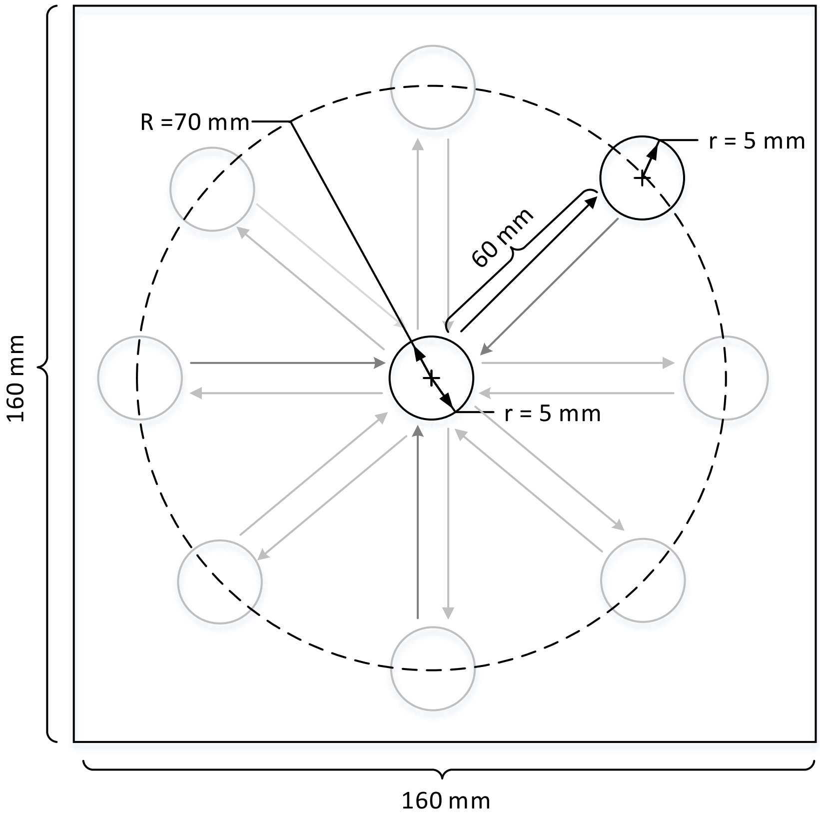


Figure 4-3: Trial workspace dimension diagram.

4.2.4 Session protocol

The participants were sat in front of a computer screen at a distance of approximately 0.5 meters, while having the robot's handle in the middle of their body (Figure 4-4). The seat was adjusted in height and position (forward and backward) in order to achieve a 90° angle of the elbow while holding the joystick placed in the centre of the workspace (neutral position) (Figure 4-4). In the beginning of the training session the participants undertook an adaptation (familiarisation) block where they performed a number of reaching movements from the centre towards one of the targets placed on a circle and back to the centre (Figure 4-5). In this stage the joystick was moving passively (forces turned off). They performed 5 sets of movements (1 set = 16 trials, 1 trial = 1 reaching movement) with their Dominant-Arm (DA) and 5 sets of movements with their Non-Dominant Arm (NDA) while the visual feedback was rotated by 100^o counter-clockwise (CCW) in order to introduce a new environment to the participants' movements and consequently maximise the potential for motor learning. Moreover, during the adaptation and training blocks the targets would appear in a random sequence in order to make the task less repetitive.

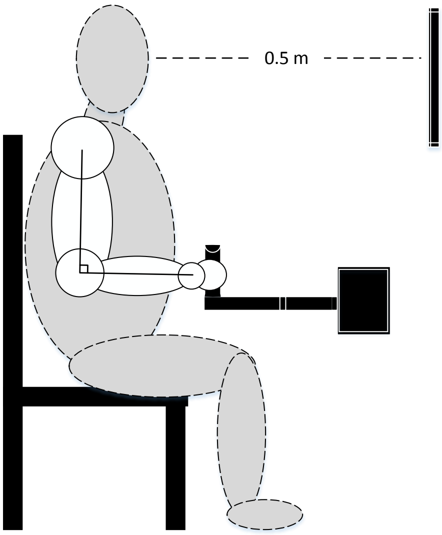


Figure 4-4: The angle of the elbow while holding the joystick at the neutral position (centre of workspace) was measured with a goniometer. In case the angle was not 90^o the participant's seat was adjusted in height and position (forward and backwards).

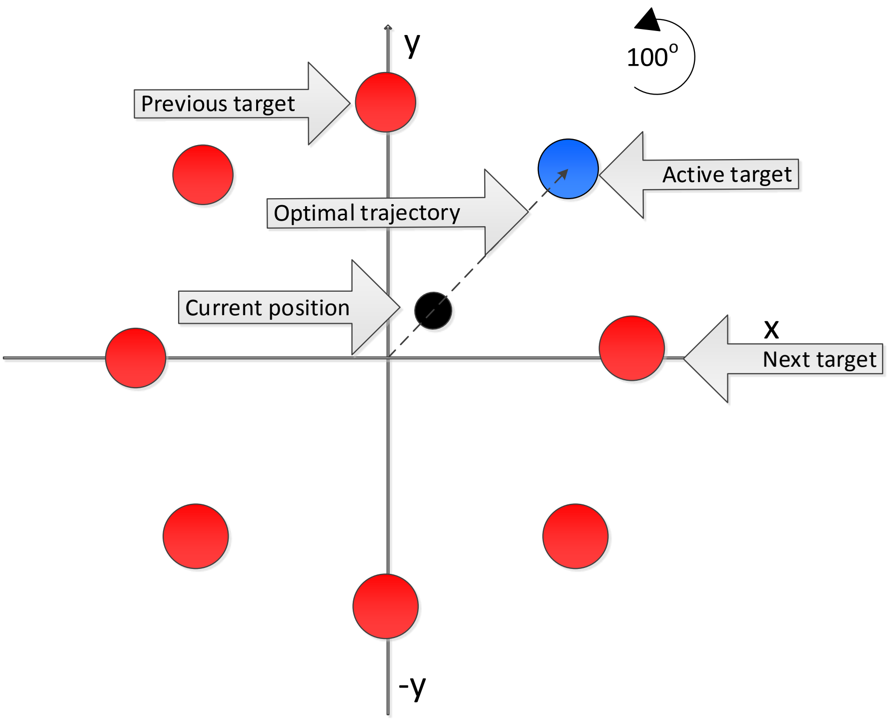


Figure 4-5: The reaching task. The user had to perform movements with rotated feedback of 100° CCW.

After the adaptation block the participants were requested to perform an assessment block for each of their arms. The assessment block was designed in order to measure and evaluate different parameters of the participants' performance in different stages of the trial. The assessment block consisted of three different tasks. In the first task of the assessment block participants had to complete a Self-Assessment Manikin (SAM) scale questionnaire for valence arousal and dominance as shown in Figure 4-6 (Bradley and Lang, 1994). For the second task participants had to perform 5 sets of reaching movements with a 100° CCW visual rotation while the robot remained passive. During the reaching movements the targets would appear in a clockwise sequence starting from the one placed on the 12 o'clock position.

Finally, the participants had to perform two sets of a circle-drawing task under the same visual rotation and without any forces applied by the robot. To perform the circle drawing task the participants were moving the joystick in order to track a circle-shaped path in the clockwise direction (Figure 4-7). The circular path was displayed and the targets would activate consequently to indicate the order they should be reached in.

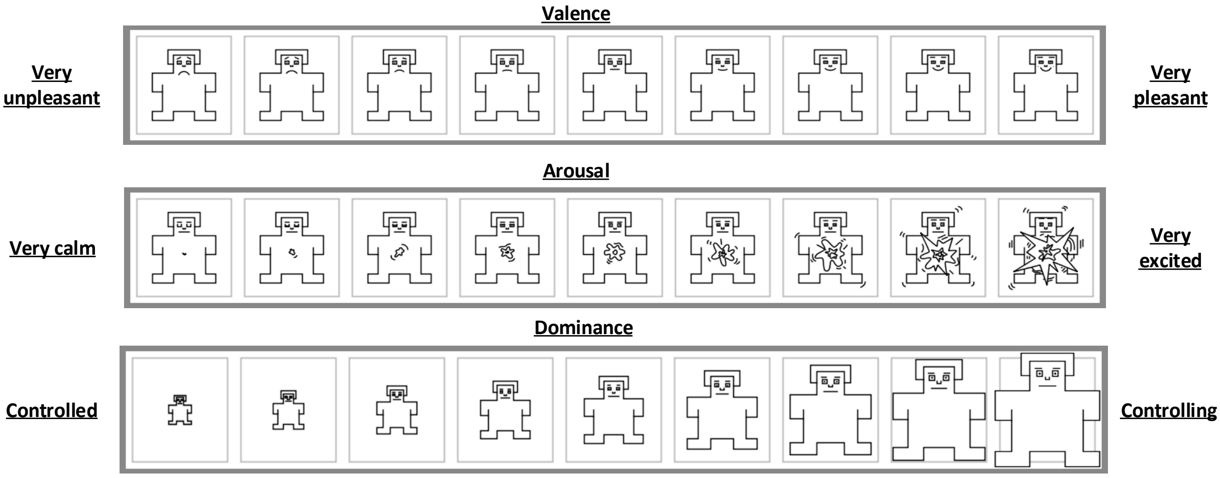


Figure 4-6: The Self-Manikin Assessment questionnaire for Valence, Arousal and Dominance. Adapted from: (Bradley and Lang, 1994)

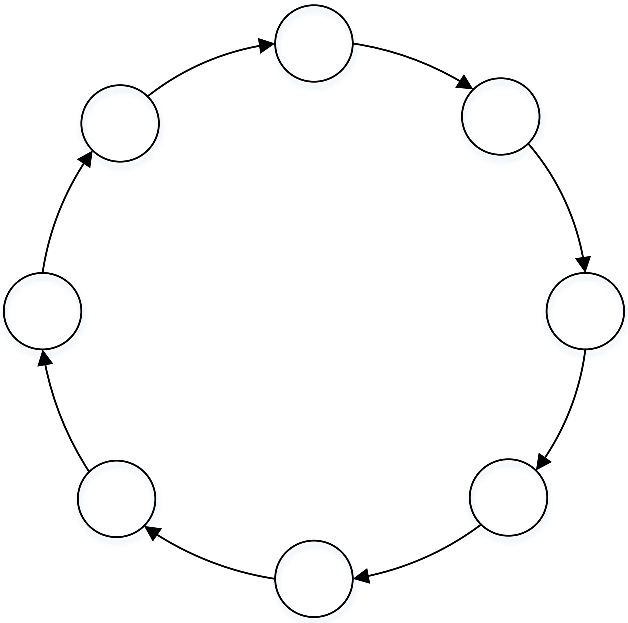


Figure 4-7: As part of the assessment blocks participant had to perform a circle-drawing task.

Once the last assessment was complete four identical blocks of training followed namely training block 1, 2, 3 and 4 with intermittent assessment blocks between them. During the training blocks the participants performed 20 sets of 16 centre-out and back movements towards 8 targets while using their NDA. Similar to the adaptation block the targets were placed on a circular orientation 45^0 from each other however, in the training blocks the robot applied forces to the subject's hand.

Following the completion of the last assessment after training block 4 the participants undertook another assessment but this time on their DA. The assessment on the DA was followed by a de-adaptation block where the participants performed 10 sets of reaching movements, similar to the other blocks using their NDA with the robot not applying any forces to the hand and the manipulation (i.e. rotation) of visual feedback turned off. That was done in order to assess the rate of washout. Finally, the participants undertook one assessment block for each arm starting with the NDA and following with the DA where rotation was set to 100^o exactly as in the previous assessment blocks in order to assess retention of the previously learned task. After each assessment block the participants were asked to rest for 1 minute or longer if that was necessary. An overview of the trial protocol is presented in Figure 4-8 and Figure 4-9.

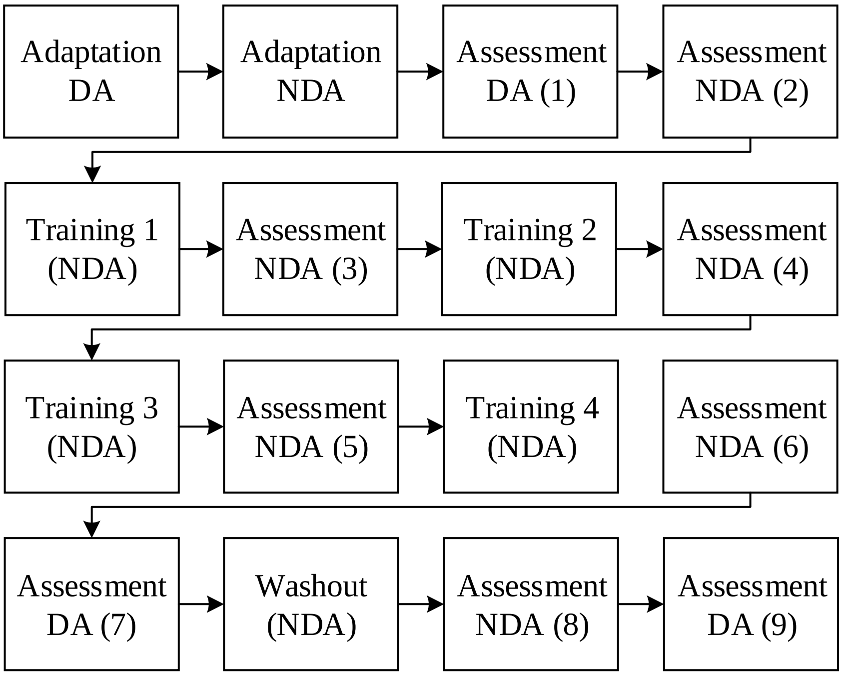


Figure 4-8: The protocol for the pilot trial.

Block name	Description	Duration (estimated)
Adaptation	5 sets– Forces are turned off (dominant arm) 5 sets - Forces are turned off (non- dominant arm)	2 min
Training block 1,2,3,4	20 sets – Forces turned on (non-dominant arm)	10.5 min
De-adaptation	10 sets - Forces turned off (non-dominant arm)	3 min
Assessment	5 sets – Reaching movements with forces turned off (visual distortion on) 2 sets of circle drawing with forces turned off (visual distortion on)	2 min
SAM	9-point Self-Assessment Manikin Scale for valence, arousal and dominance	10 seconds
Break	No practice	1 min

Figure 4-9: The different blocks of the trial protocol in detail (1 set = 16 trial/reaching movements). Visual distortion = visual rotation 100^o CCW.

4.2.5 Evaluation of performance

During the assessment blocks the system was recording kinematic data (Cartesian coordinates (X-Y)) of the position of the robot, time elapsed between movements and the perpendicular distance away from the desired trajectory of the robot's endpoint. In addition, for each of the measurements information was recorded as to which target was active at that specific moment during which set of movement in order to be able to distinguish between specific movements and the stage of the assessment block that they occurred at. All data were recorded with a frequency of 100 Hz.

The kinematic measures that were selected for further analysis were movement error (error to reach target), movement duration (time between beginning and end of a movement), mean velocity, normalised jerk as a measure of movement smoothness and finally initial error that is the direction that the movement had the first 100 ms from when it started. Furthermore, with the SAM questionnaire collected data on the emotional state of the participants during the different stages of the trial.

4.2.6 Results of the pilot trial

During the different assessment blocks performance was assessed in both arms at different stages of the trial. However, only the NDA received training with AAN. This approach was undertaken in order to measure whether the algorithm had an effect in bilateral transfer of the skill. The analysis of the results of the trial was undertaken on three stages in order to answer research questions one to three respectively. As such, the first stage was the analysis of the kinematic data collected for the NDA, the second was the analysis of the DA and finally the last question was the analysis of the results collected by the SAM questionnaire.

The statistical analysis was performed with IBM SPSS™ statistics version 22.0. For the analysis of the trial a mixed design was selected with a within-subjects factor (assessment) and a between-subjects factor (HCA group). As such a two way repeated measures ANOVA using general linear models of variance was selected as the most suitable statistical model for the current trial design as it has been extensively used in (Casadio et al., 2009; Elizabeth B Brokaw et al., 2011).

Post-hoc tests were performed with Bonferroni correction for multiple measures. The results of the analysis are reported as a factor of three parameters. The F value (F-ratio) denotes how random the variation within a group is; with a value of 1 (or close to 1) confirming the null hypothesis i.e. the variation is random. The p value indicates the significance level between the difference of the measurement means. A value of $p \leq 0.05$ rejects the null hypothesis hence confirming that the differences are significant. Finally partial η^2 is a measure of effect size in other words a measure of the treatment effect.(Salkind, 2007). According to the guidelines provided by (Cohen, 1977) for interpreting the effect sizes an effect size 0.20-0.5 is considered small while an effect size 0.50-0.8 is considered moderate and an effect size ≥ 0.80 is considered large.

4.2.6.1 *Analysis of the non-dominant arm*

Performance on the NDA was evaluated in 6 assessments throughout the trial. Once pre-training (Adaptation NDA), one after each training block (Training 1-4) and one after the washout phase (Washout NDA) as shown in Figure 4-8. It was hypothesized that performance would be at its lowest during the assessment after the adaptation block and then it would improve in the assessments following training blocks 1-4 where it would eventually reach a plateau. Finally, a deterioration in performance was expected during the washout phase. Improved performance would be reflected by lower error, duration and normalised jerk and increased mean velocity.

It was also hypothesised that movement error and duration were correlated, as for the same level of skill (level of motor learning achieved) quicker movements would be expected to be prone to more (endpoint) error and vice-versa as indicated by Fitts' law (Fitts, 1954). Although Fitts' law predicts a linear relationship between movement duration and the difficulty of a task, the relationship between mean error and mean duration for a given assessment was expected to be quadratic forming a parabola where for a given level of performance achieved there would be an optimal point with the lowest possible error and duration above which movements would become more accurate but slower or faster but less accurate.

To investigate this hypothesis, mean error across all sets was calculated for each participant across each of the assessments. Mean values were selected instead of the individual measurements in an attempt to reduce variability of the data as reaching movements in humans vary greatly (Gordon et al., 1994). Then a scatter plot was generated with duration on Y-axis and error on the X-axis. The points were coloured according to the assessment they were collected in.

Regression analysis was performed to estimate the relationship between error and movement duration in each of the assessments. The best fit to the data was a cubic relationship (Figure 4-10) between the two variables as indicated by the high values of the coefficient of determination (R^2) for the adaption, training one and training two assessment blocks ($0.780 \leq R^2 \leq 0.932$). In assessment blocks following training blocks 3, 4 and the adaptation the values of R^2 were significantly lower namely, 0.388, 0.336 and 0.499. This an interesting finding as it appears that the participants have changed their movement behaviour towards a more random pattern. This could be attributed to the long training protocol that potentially caused the participants to experience fatigue or loss of interest in the task which subsequently resulted in loss of concentration.

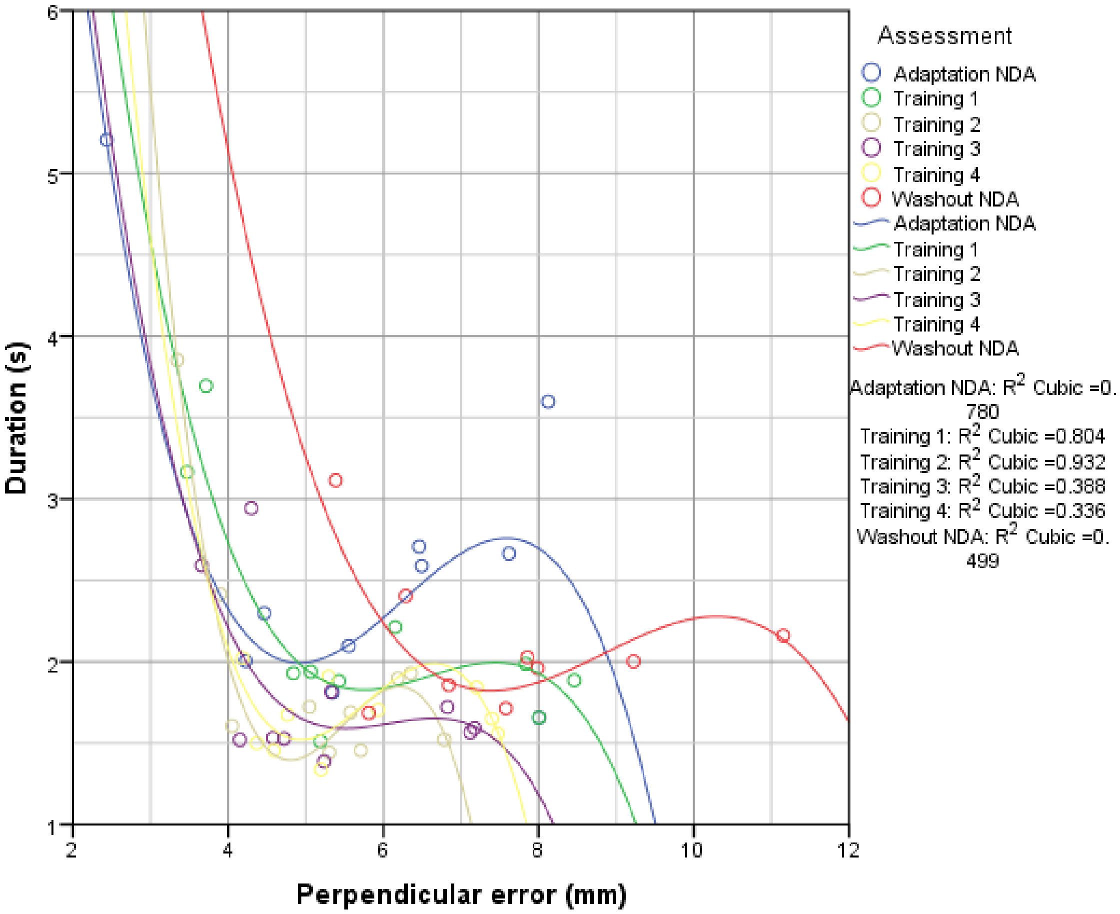


Figure 4-10: Relationship of mean Duration and mean Perpendicular Error across assessment blocks. The value of R^2 demonstrates how good a curve fits to a dataset. Its values vary from 0 to 1 with 1 being an absolute fit to the data and the 0 a horizontal line crossing the Y axis at the mean value of the dataset.

4.2.6.1.1 Kinematic analysis of the non-dominant arm

As mentioned in the beginning of this sub-section to quantify motor learning different measures were selected namely error, duration, mean velocity and normalised jerk. Improvements in performing the task, hence motor learning, would result in reduced duration, error and normalised jerk and increased mean velocity. When considering movement error and duration (Figure 4-11) both T1 and T2 groups improved during the exercise part of the trial by performing quicker and more accurate movements.

While both groups improved in a similar fashion in terms of duration two different patterns emerged when error was considered. The group that received AAN with rate of adaptiveness T1= 30s improved error throughout training blocks 1 and 2 until the assessment after training block no 3 where error increased slightly and after training block 4 where error reached almost pre-training levels. However, those increases in error coincided with respective decreases in duration. At the assessment after the washout phase for both conditions error increased to above pre-training levels but duration only increased for T1= 30s and not for T2 = 60s.

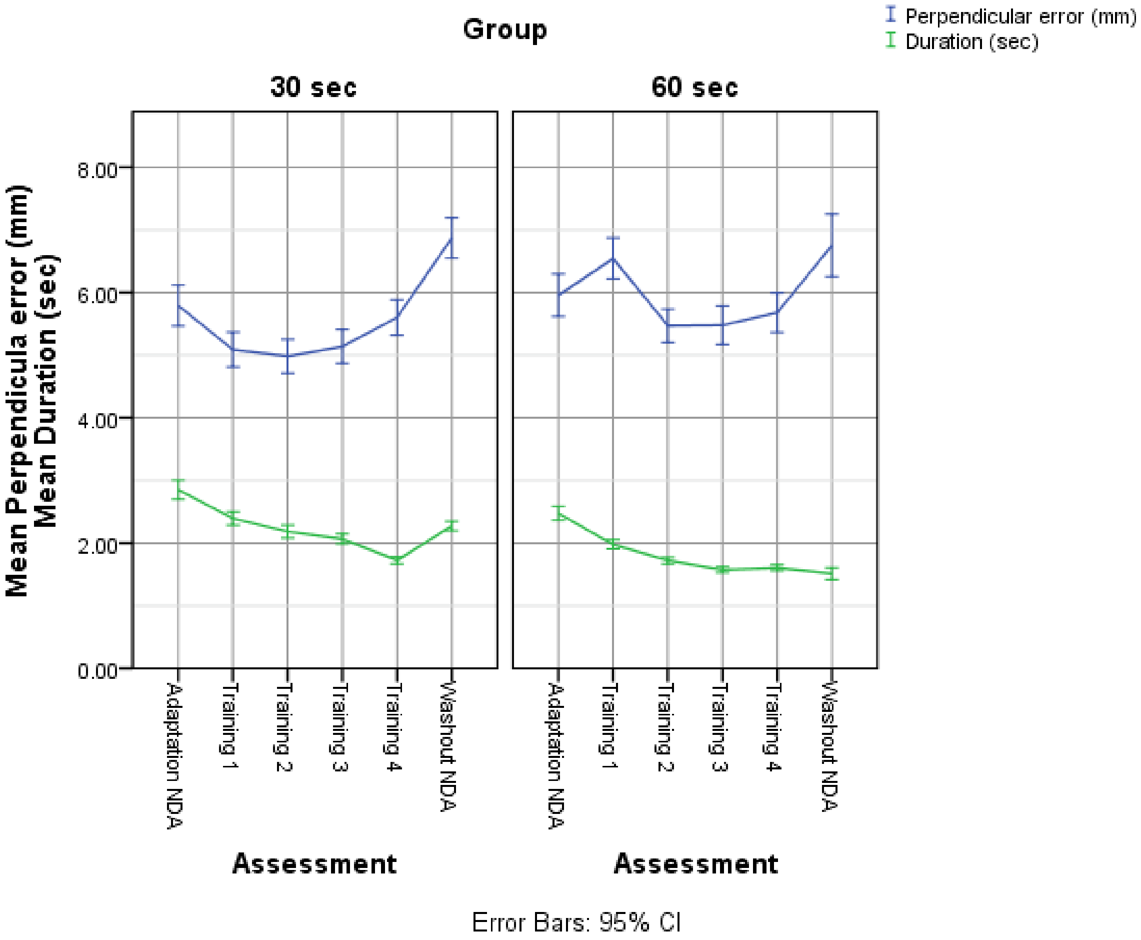


Figure 4-11: Mean error and mean duration across all the assessment blocks of the NDA for the two conditions.

A mixed ANOVA was performed on the dataset for movement duration, error, mean velocity and normalised jerk. The between-subjects factor was the intervention groups they were assigned (T1 =3s, T2 = 60s) and the within subjects factor was the different assessment blocks for the NDA. A more detailed overview of the analysis is presented in Appendix A.

When considering movement duration (Figure 4-11) there was no statistically significant interaction between the intervention groups and the assessment blocks on movement duration (p =0.263). This means that there was no statistically significant effect of the intervention type to the two groups, however, there was a statistically significant difference in movement duration for the different assessment blocks, F(5, 25) = 10.980, $p < 0.0005$, partial $\eta^2 = 0.687$. This indicates that motor learning occurred and there was retention in terms of duration. Finally, there was no statistically significant effect of duration between the groups ($p = 0.401$). This last finding verifies that both groups were not different from each other in terms of their movement duration.

When considering movement error (Figure 4-11) in the analysis, findings were similar. Again there was no significant interaction between group and assessment blocks in terms of movement error ($p = 0.844$). Nevertheless, there was significant effect of the assessment blocks on movement error F(5, 30) = 0.6.697, $p<0.005$, partial η2 = 0.527. Finally, both groups behaved similarly as there was no effect of intervention group on movement error, ($p = 0.129$).

Mean velocity (Figure 4-12) appears to have improved for both groups in a similar manner as there was no statistically significant interaction between group and assessment ($p = 0.545$). However, there was a significant effect of the assessment blocks on movement error F(5, 30) = 390.458, p <0 .0005, partial $\eta^2 = 0.609$, where velocity increased throughout the training blocks. After the washout phase it appears that velocity decreased but never reached the pre-training levels. Finally, both groups behaved similarly in terms of their mean velocity as there was no effect of intervention group to the velocity of the movements F(1, 6) = 4.322, $p = 0.344$, partial $\eta^2 = 0.149$.

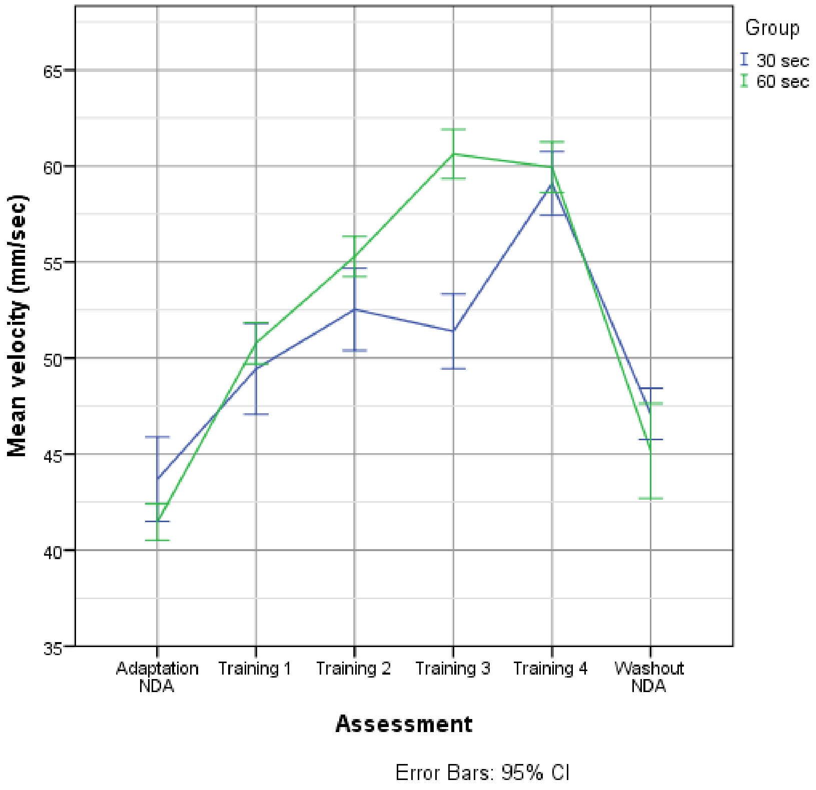


Figure 4-12: Mean velocity for each assessment block of the pilot trial for both groups.

Participants’ movements became smoother (Figure 4-13) throughout the trial for both groups and were kept at the same levels after the washout block but this effect of training was not found to be significant for normalised jerk (p = 0.108). In addition, there was no effect of intervention type on the performance after the different blocks, (p = 0.401) and there was no effect of intervention groups on normalised jerk in general (p = 0.419) in that perspective in both groups movement smoothness was similar.

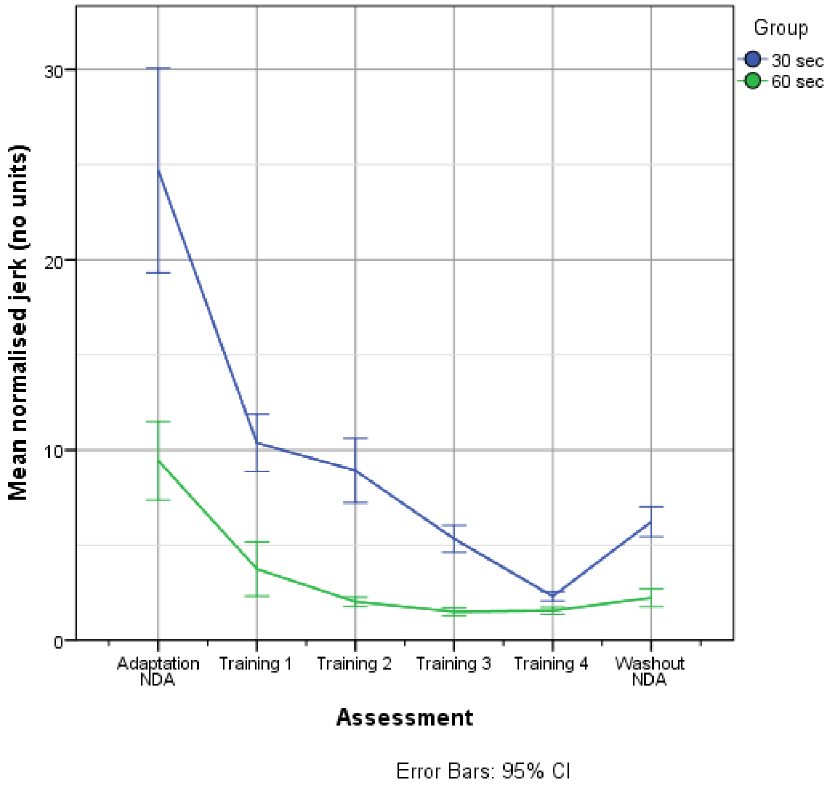


Figure 4-13: Normalised jerk for each of the assessment of the pilot trial for both groups.

4.2.6.1.2 Kinematic analysis of the dominant arm

Notwithstanding the NDA did not receive any exercise outside the adaptation stage it did show improvement before the washout phase in the error and duration of its movements (Figure 4-14) as well as the mean velocity (Figure 4-15) and normalised jerk (Figure 4-16). However, after the washout phase error was increased to even greater levels than the ones pre-training. An interesting remark was that although, for group T1 = 30s both duration and jerk increased, for group T2 = 60s both remained the same. Even more interestingly the velocity of movement dropped for group T1 pre-washout and increased post washout while group T2 increased its movement velocity throughout the trial. In either of these measures there was no significant effect of intervention.

More specifically there was no significant interaction between group and assessment, for movement duration ($p = 0.508$), movement error ($p = 0.459$), mean velocity ($p = 0.471$) and normalised jerk ($p = 0.480$). Conversely, there was a statistically significant interaction between group and assessment for movement duration F(2, 8) = 10.306, $p < 0.05$, partial $\eta^2 = 0.720$), but not for movement error (p = 0.681), mean velocity (p = 0.226) and normalised jerk (p = 0.200).

This is an interesting finding indicating that even though there was an effect of bilateral transfer of learning for movement duration, this effect was not found for movement accuracy, mean velocity and movement smoothness. Lastly, both groups were similar in terms of performance as assessed by the different measures as there was no difference between group and duration (p = 0.137), error (p = 0.466), mean velocity (p = 0.151) and normalised jerk (p = 0.480).

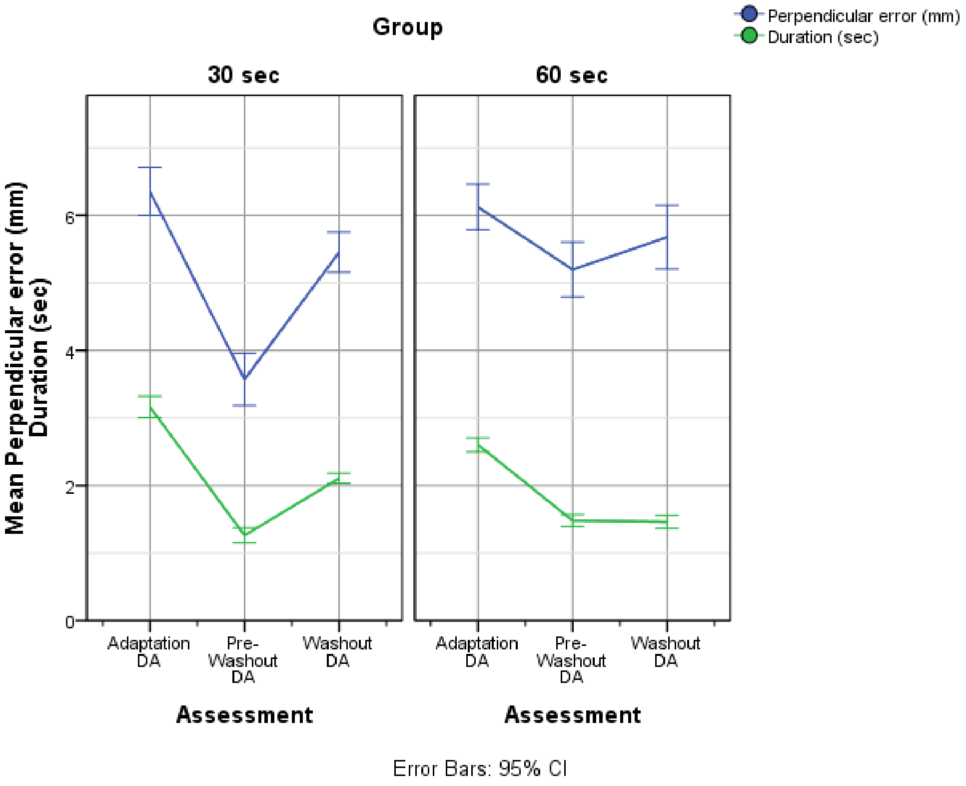


Figure 4-14: Mean error and mean duration across all the assessment blocks of the NDA for the two groups while using their DA.

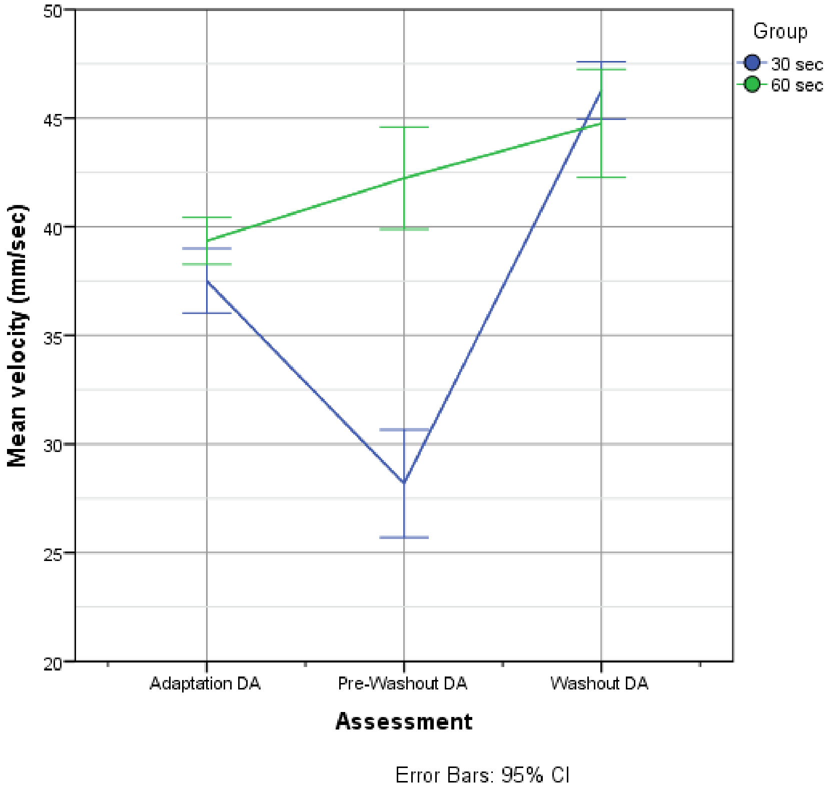


Figure 4-15: Mean velocity for each assessment block of the pilot trial for both groups using their DA.

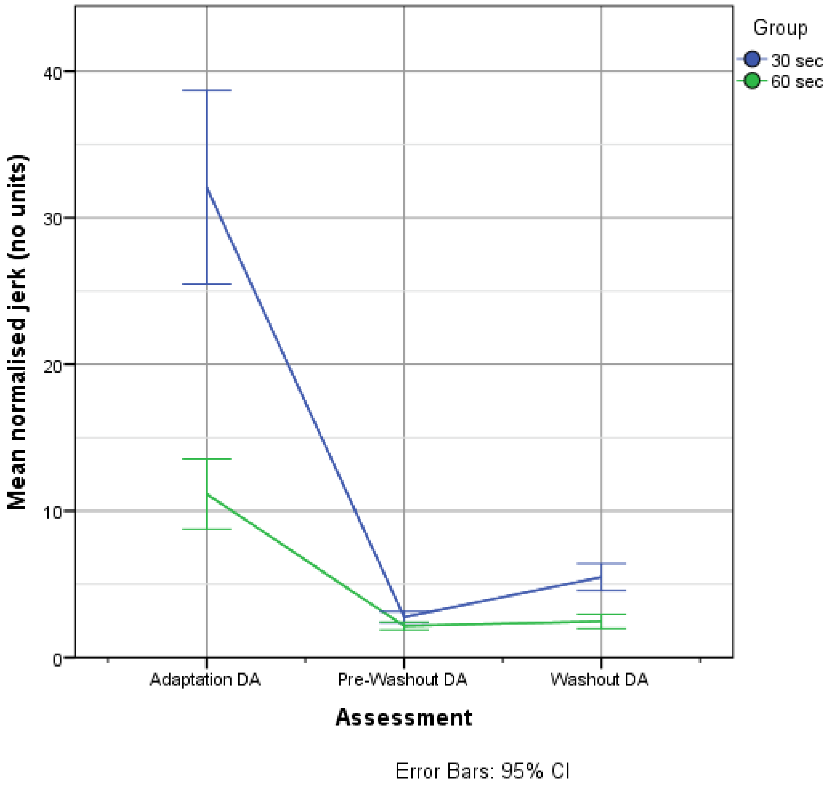


Figure 4-16: Normalised jerk for each of the assessment of the pilot trial for both groups using their DA.

4.2.6.2 *Analysis of the Self-Assessment Manikin questionnaire*

With regard to the Valence, Arousal and Dominance measures the responses of participants demonstrated such a high variance between individuals that no useful results could be obtained. The analysis revealed that there was no statistically significant interaction between group and assessment for Valence ($p = 0.249$), Arousal ($p = 0.999$) and Dominance ($p = 0.974$). Likewise, there was no effect of assessment on Valence ($p = 0.882$), Arousal ($p = 0.991$) and Dominance ($p = 0.974$). Lastly, there was no effect of intervention type on Dominance ($p = 1.000$). Nonetheless, there was a statistically significant effect of intervention with regards to Valence ($F(1,70) = 66.025$, $p < 0.01$ and Arousal ($F(1, 70) = 8.222$, $p < 0.001$) indicating that groups were inherently different on how they experienced dominance throughout the trial.

More specifically, the 60s group experienced higher valence and arousal than the 30s group. The three plots below represent the mean answers of the participants on the SAM questionnaire at the different assessment blocks for Valence (Figure 4-17), Arousal (Figure 4-18) and Dominance (Figure 4-19)

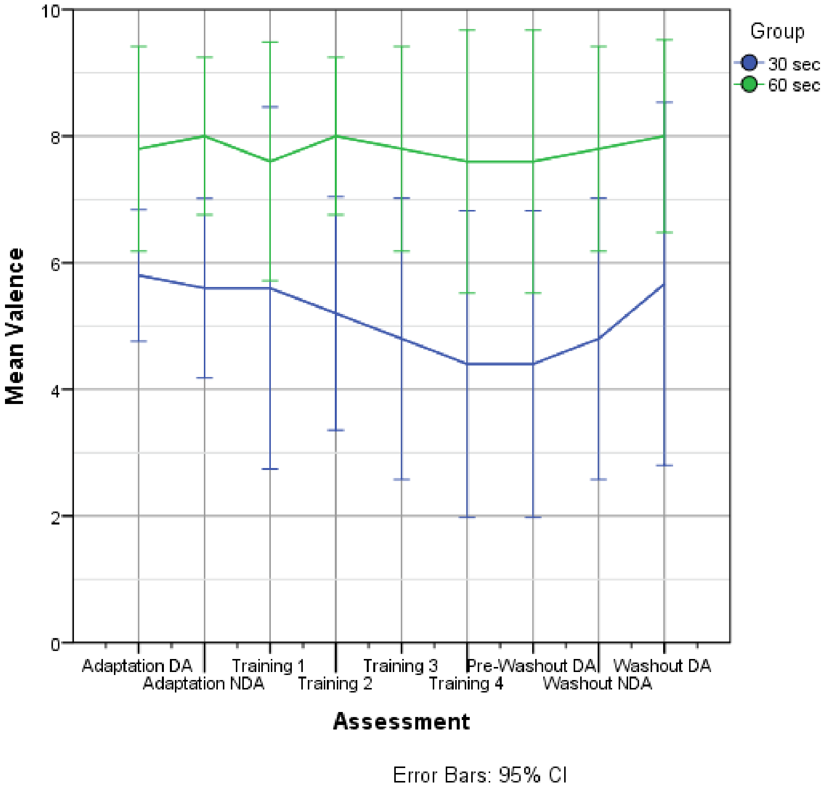


Figure 4-17: Mean score for Valence at the different assessment blocks for both groups.

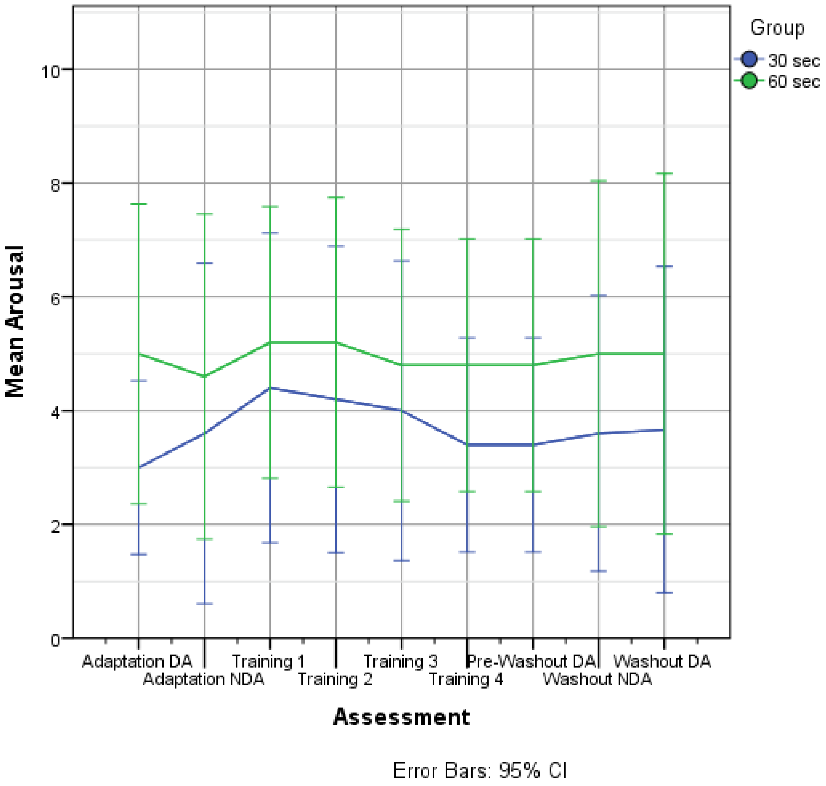


Figure 4-18: Mean score for Arousal at the different assessment blocks for both groups.

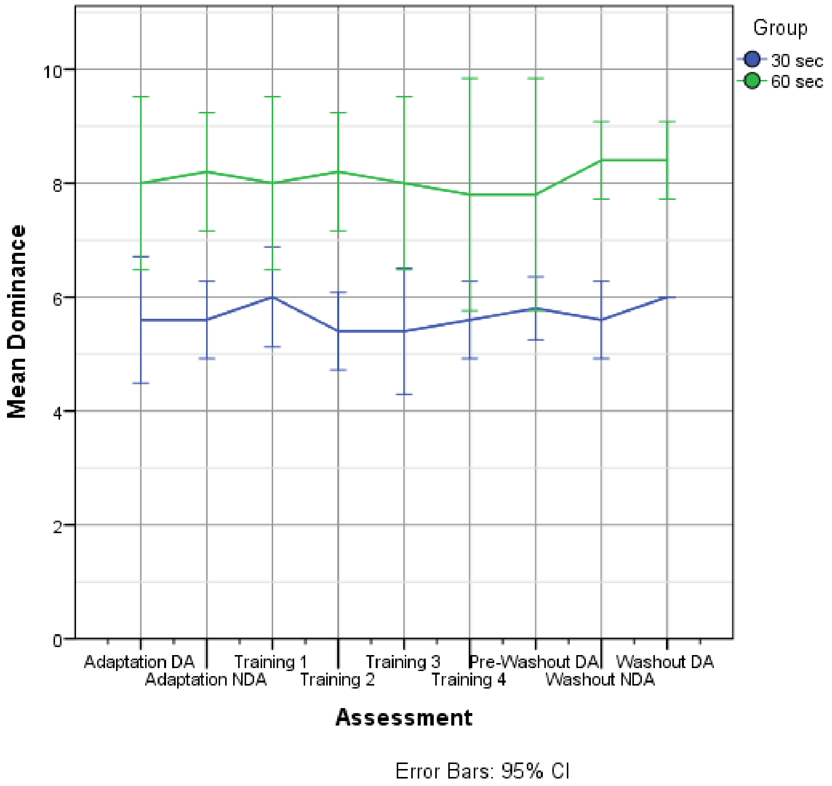


Figure 4-19: Mean score for Dominance at the different assessment blocks for both groups.

4.2.7 Discussion

With respect to the first question of this study as to whether the different rates of adaptation affected motor learning of healthy adults it appears that the two grouping conditions did not have a significant effect. This has been a consistent finding across all the different kinematic variables for both arms as well as across the different measures of the SAM assessment. Despite the small population size the results indicated that there was no effect of the rate of adaptation of the algorithm on the motor learning or bilateral transfer of that learning on able-bodied algorithms.

The data analysis provided evidence indicating that intervention blocks had a clear effect on the performance of the participants. Regarding the NDA there was a significant improvement in movement error, duration and normalised jerk after the first training block and that improvement continued throughout the different training blocks but at a slower rate. Furthermore, after the washout block performance in all deteriorated but did not return to the levels pre-training. This means that the washout block effectively washed-out the learned task but not completely which leads to the conclusion that there was measurable retention of the learned task. Another interesting finding was, that although normalised jerk followed the same trend (improvement post training, worsened after washout but never rose to the levels of the adaptation stage) however, the statistical analysis could not identify a statistically significant effect of the intervention to normalised jerk.

The analysis of the assessments performed on the DA showed that there was a significant change between the different assessment blocks in terms of movement error, duration and mean velocity. Normalised jerk improved as well but results were not statistically significant. As the DA did not receive any exercise, improvement in its performance could be attributed to bilateral transfer. However, although DA did not receive training they performed 5 sets of movements on each assessment block which could potentially be significantly enough exercise to induce learning. Nonetheless, the fact that after the washout block there was a deterioration on the performance on the NDA indicates that the results were probably a cause of bilateral transfer.

With respect to the impact of the intervention to the emotional state of the participants there was no significant effect of intervention type or training stage across both groups. However, some complained to the researcher about experiencing mental fatigue caused by the repetitive nature of the exercise.

As mentioned in the introduction of this section the trial served as a pilot test trial in order to verify the experimental protocol and also as a means to identify weaknesses and aspects that may need change. The trial successfully measured motor learning as it occurred in different stages of the trial and for both arms. However, although there was a significant change from the baseline assessment during the training assessments the values of the different kinematic data during the pre-training sessions could have been affected by the long adaptation blocks that preceded them within which learning may have already occurred. As such, by reducing the size of the adaptation blocks a more obvious effect of the intervention may be observed.

Furthermore, in most measures the participants reached or approached a plateau after training block number three. In training block 4 movement duration and mean velocity improved significantly, but error worsened indicating that there was a shift towards quicker movements but with less attention to keeping the error low. This may be due to fatigue and loss of concentration caused by the prolonged duration of the protocol that in most cases lasted for more than two hours. This was a clear indication that the protocol needed to be shortened for the investigatory trial as the fourth block of training seemed to have a negative effect on one of the kinematic measures.

When considering the suitability of the task for the purpose of the trial a methodological error was identified. As previously mentioned the task involved reaching movements from one target to another. Nevertheless, in the way the system was setup when one target was reached another would was activated instantly. The implication of that was that the movements were not discrete and had the form of a continuous movement from one target to another. Likewise, as the target was considered as being successfully reached in the instance the cursor reached its area, there was no way of determining whether that success in reaching the target accidental or intentional thus affecting the analysis of the movements.

4.2.8 Considerations on the design of the pilot trial protocol

As the main aim of this trial was to identify and quantify how motor learning in able bodied adults was affected by the different setting of the adaptiveness of the AAN throughout a course of a training exercise. For this a very common trial design was selected, that has been extensively used in the literature (Bajaj et al., 2005; Finley et al., 2009; Shirzad and Van der Loos, 2012).

Over the years, there have been many variations of this protocol presented in the literature yet, the main characteristics remain the same. According to this design the participants perform reaching movements from a starting point towards targets placed on a circular configuration around the starting point. As this protocol was designed for able bodied participants, they have to be presented with a new task in order for learning to occur. To achieve this a visual perturbation is implemented on the environment in the form of visual rotation of the visual feedback with respect to the coordinate frame of the actual movement (Figure 4-20).

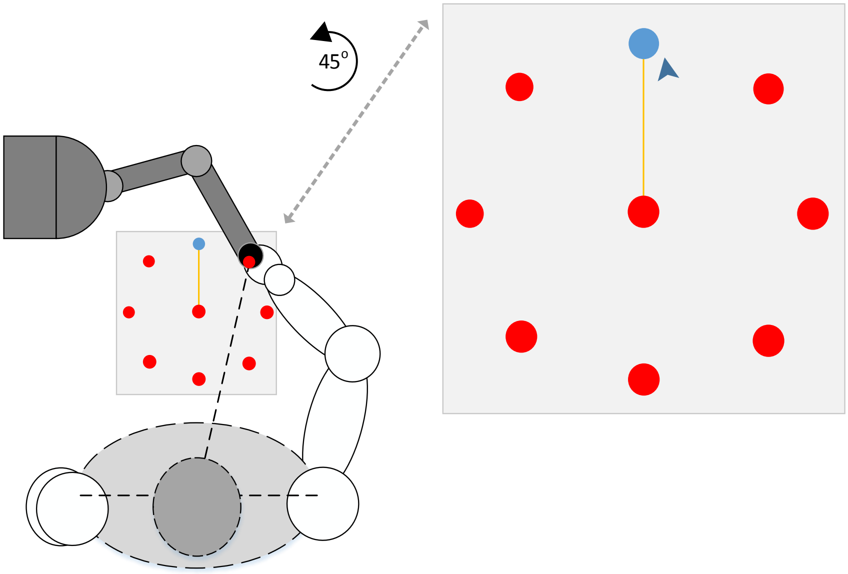


Figure 4-20: An example of a rotation of the visual feedback of 45° counter-clockwise. On the left is the actual workspace of the robot and on the right a representation of what would be displayed on the computer screen

In the studies where a visual rotation was introduced to the participants' movements (Krakauer et al., 2005; Shirzad and Van der Loos, 2012; Patton et al., 2013) a value of 30° was commonly used as the angle of rotation. Nevertheless, the same studies did not specify why this value of visual rotation was chosen. As such, it appears that it has been selected more for historical reasons rather than scientific. A main consideration for the design of the study was to maximise the difficulty of the task in order to allow for greater potential of motor learning to occur. It was hypothesised that the greater the amount of rotation the more difficult the task would be.

To test this hypothesis, a trial was performed with a single able-bodied participant. The participant performed the same protocol for five rotations of the visual feedback 0^o, 30^o, 60^o, 80^o and 100^o respectively. The task involved the participant performing 5 sets of 16 reaching movements towards 8 targets in a circular configuration and back to the centre of the circle using the rehabilitation robot in passive mode (no forces). The path length was set to be 60 mm. The participant used their non-dominant arm in order to maximise the potential for motor learning to occur.

Two measures were analysed namely the perpendicular error and the movement duration. The hypothesis was that error and duration would be low for easier to learn visual rotations and high for more difficult. A limitation to the design of this trial was that the design was cross-over as the same participant was exposed to all the different conditions therefore it was unavoidable for some learning to occur between the iterations of the exercise. To compensate for this the user was introduced first to the smaller visual rotations and incrementally to larger visual rotations. As such, if for example motor learning occurred throughout the trial the conditions with larger visual rotations would benefit from improved levels of these measures as the participant would have received more exercise before.

The analysis of the results indicated that in general performance deteriorated when the participant was introduced to a greater value of visual rotation. Figure 4-21 clearly demonstrates this trend. Interestingly, for the condition of visual rotation of 30^o there was an improvement in performance as measured by the movement error and movement duration measures. An explanation for this would be that this is due to the similarity of this condition to the control condition of no rotations. Because of this similarity the participant was able to adapt quickly to the new environment and further improve. This further supports the initial hypothesis that greater values of visual rotation would be more challenging to the participant as they provide greater deviation from the normal conditions where movement would occur hence an environment that is more novel to the participant.

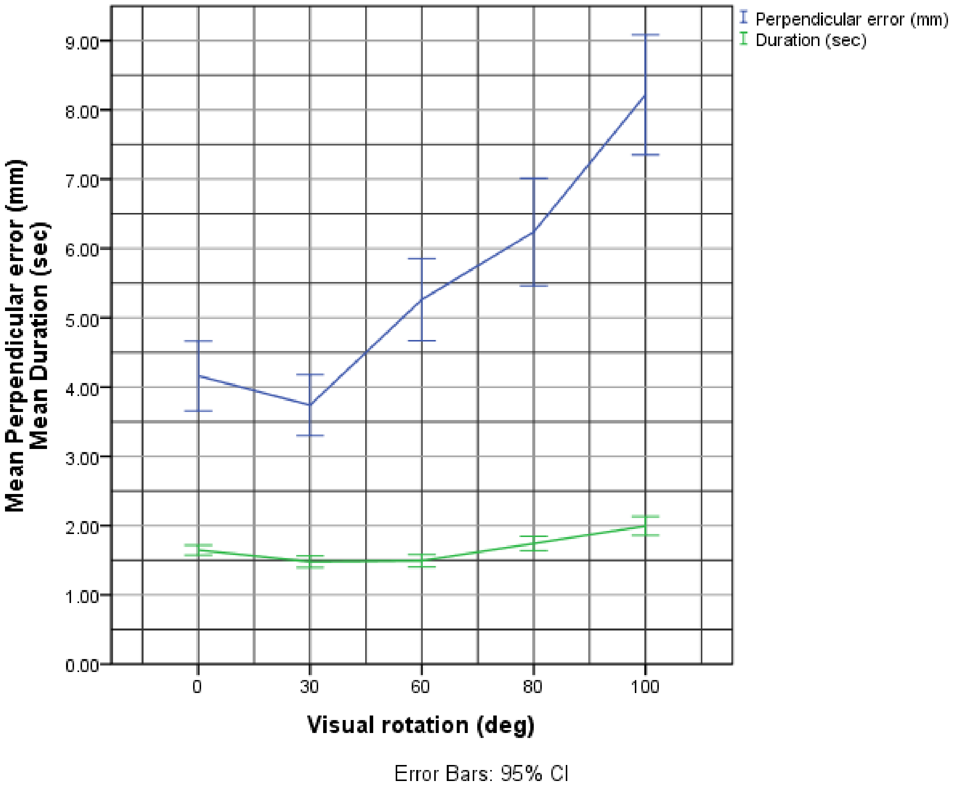


Figure 4-21: Mean Perpendicular error and mean Duration follow a similar pattern across the different conditions of visual rotation. There is a clear trend that the larger visual rotation is the worse the participant's performance gets.

Informed by the results of the trial with a single participant a visual rotation of 100^o was selected to be used in further experiments in order to introduce the participants in a novel environment. Furthermore, in order to provide an extra level of difficulty to the participants they were asked to exercise using their non-dominant arm which would allow for potentially more motor learning to occur.

4.3 Design of the trial for the investigation of the effectiveness of the developed HCAs on the motor learning of healthy adults

The primary objective of the investigatory trial was to evaluate the effectiveness of the three haptic control algorithms (HCAs), that were developed for this project (EAA, EAP and AAN), on the motor learning of able-bodied adults. Details on the different HCAs can be found in Section 2.7. The design of the investigatory trial was informed by the findings of the pilot study described in Section 4.2 and adjusted accordingly. Only one trial was undertaken with participants being assigned to one of four different intervention groups (one for each algorithm and a Control group) however, four different analyses of the results were performed which will be presented in the following four chapters.

The methodology of the analysis of the results remained the same for each of the analyses/models with the only difference being the groups that were under investigation. As such in chapter 6-8 each of the developed algorithms namely AAN, EAA and EAP is compared against the Control group while in chapter 9 all groups are compared against each other. This chapter serves as an introduction to the protocol that was used in the investigatory trial and the methodology of the analysis of its results.

4.3.1 Trial protocol

Forty subjects participated in the study, all of which responded to advertisements placed within the University campus. As it has been shown that findings of studies on the motor learning of able-bodied adults can transfer to the impaired (Iosa et al., 2016) the inclusion criteria were the same as in the pilot trial, able-bodied non-ambidextrous adults (18-65 years) with no history of neurological impairments. Participants were pseudo-randomly assigned into four equally sized intervention groups. Three groups received training with the robot implementing one of the developed HCAs while the fourth group performed passive movements (no forces by the robot) throughout the trial. The participants were blinded with regards to which group they were assigned to. It must be noted that the magnitude of the forces exerted by the rehabilitation robot were selected in consultation with experienced physiotherapists to be suitable for able-bodied adults.

Before undertaking the trial, all participants were asked to complete the extended Edinburgh Handedness Inventory (EHI) to assess the dominance of their arms. Once it was ensured the participants met all the inclusion criteria they had to provide signed consent in accordance with the Ethics regulations of Manchester Metropolitan University. An overview of the trial population and group allocation can be found in Tables 4-1 to 4-4.

Table 4-1: Population characteristics for the AAN group.

Participant	Gender	Age	EHI score	Dominant arm
18	Male	27	R_2	Right
19	Male	29	R_10	Right
20	Female	31	R_4	Right
21	Male	30	R_5	Right
22	Female	33	R_8	Right
43	Female	29	L_1	Left
44	Female	37	R_2	Right
45	Female	29	R_10	Right
46	Male	38	R_1	Right
47	Female	55	R_3	Right

Table 4-2: Population characteristics for the EAA group.

Participant	Gender	Age	EHI score	Dominant arm
13	Male	27	L_4	Left
14	Male	21	R_2	Right
15	Male	22	R_6	Right
16	Female	32	L_3	Left
17	Female	35	R_10	Right
38	Female	40	R_1	Right
39	Male	24	R_10	Right
40	Male	26	R_2	Right
41	Female	46	R_1	Right
42	Male	32	R_7	Right

Table 4-3: Population characteristics for the EAP group.

Participant	Gender	Age	EHI score	Dominant arm
28	Female	25	R_10	Right
29	Female	38	R_5	Right
30	Male	38	R_3	Right
31	Male	21	R_7	Right
32	Female	25	R_6	Right
48	Male	34	R_6	Right
49	Female	25	R_3	Right
50	Male	27	L_2	Left
51	Female	29	R_7	Right
52	Female	30	R_6	Right

Table 4-4: Population characteristics for the Control group.

Participant	Gender	Age	EHI score	DA
23	Female	37	R_10	Right
24	Male	26	R_10	Right
25	Female	26	L_3	Left
26	Male	26	R_8	Right
27	Male	31	R_10	Right
33	Male	32	R_6	Right
34	Male	35	R_1	Right
35	Female	31	R_5	Right
36	Male	32	R_1	Right
37	Male	26	R_10	Right

4.3.2 Tasks of the trial

The task remained the same as described for the pilot trial, a description of which can be found in section 4.2.3. The users performed reaching movements from the centre out and back to eight targets placed on a circular configuration but there were some changes to the task from the pilot trial. The physical workspace of the robot was increased by 60 mm on each dimension (from 160 x 160 mm to a 220 x 220 mm). The sensitivity for reaching a target was set to 6.88 mm. As such the minimum length of movement between the target place on the centre and each of the surrounding targets was 82.45 mm (Minimum path length

= Centre to centre path length – Target 1 size – Target 2 size or Minimum path length = 96.25 mm – 6.88 mm – 6.88 mm).

Likewise, as mentioned in section 2.7 all developed HCAs had adaptive features. The frequency of adaptation (time where the system evaluates the user's performance and adjusts the HCAs settings accordingly) was set to adapt every 16 reaching movements (1 set). This selection was informed by the results of the pilot trial, i.e. the rate the HCA adapts did not influence motor learning. Furthermore, the selection of number of movements instead of time to trigger the adaptation of the algorithm was to provide one less variable to the experiment as different individuals may have performed more movements or less movements within the time specified, hence experiencing changes of the algorithm caused by the system in more or less of their movements. The selection of the number of movements was such as to match the $t_d = 30$ s group, as the average movement time was evaluated to be approximately 2 seconds, hence 16 movements x 2 seconds = 32 seconds.

4.3.3 Session protocol

The protocol design of this trial was based on the protocol of the pilot trial which is extensively presented in section 4.2.4. Certain alterations were implemented though, informed by the findings of the pilot trial (section 4.2.7). One of the findings was that the protocols duration was impeding the participant's performance mostly due to mental fatigue. As such the main concern was to reduce its duration. The first action taken to achieve this was to reduce the training time (robotic forces on) by removing one training block and the consequent assessment on the NDA that followed.

Furthermore, as the adaptation stage in the pilot trial was performed under visual rotation and due to its long duration it allowed for motor learning to occur even before the exercise took place. This issue was addressed by reducing the adaptation stage to just one set of movements by the DA with no visual rotation. With this it was ensured that the task was clear to the participants while no significant learning occurred before the actual training part of the trial. Another conclusion of the pilot trial was that reaching movements were not discrete i.e. there was no clear distinction of when a movement started and when it ended or whether the success in reaching the target was accidental or intentional. To overcome this a 300 ms delay was introduced for the duration of which the user should have stayed within the area of the target in order for the movement to be deemed as successful by the system and another target to be activated.

In the beginning of the trial all participants received an adaptation block where they performed one set (1 set = 16 movements) of reaching movements using their DA while the robot remained passive. In addition, during this block no visual rotation was introduced by the system. Following the adaptation block participants undertook one assessment block for each of their arms, starting with NDA. The assessment blocks had the same structure as in the pilot trial starting with the SAM questionnaire, then the reaching movements task followed by the circle drawing task. The only difference with the pilot trial protocol was that during the part where reaching movements were performed the number of sets was reduced from five to three.

Following the assessment blocks the participants underwent a series of three training blocks with the NDA, each one of which was followed by an assessment block on the same arm. After the assessment following training block 3, another assessment block was undertaken on the DA. Finally, the participants were introduced to a washout block where they had to perform 10 sets of the reaching task without visual rotation or forces applied by the robot. This was then followed by one assessment block for each of the arms (starting with the NDA). A major difference from the pilot trial was that all reaching movements were performed with the 300 ms delay between the movements.

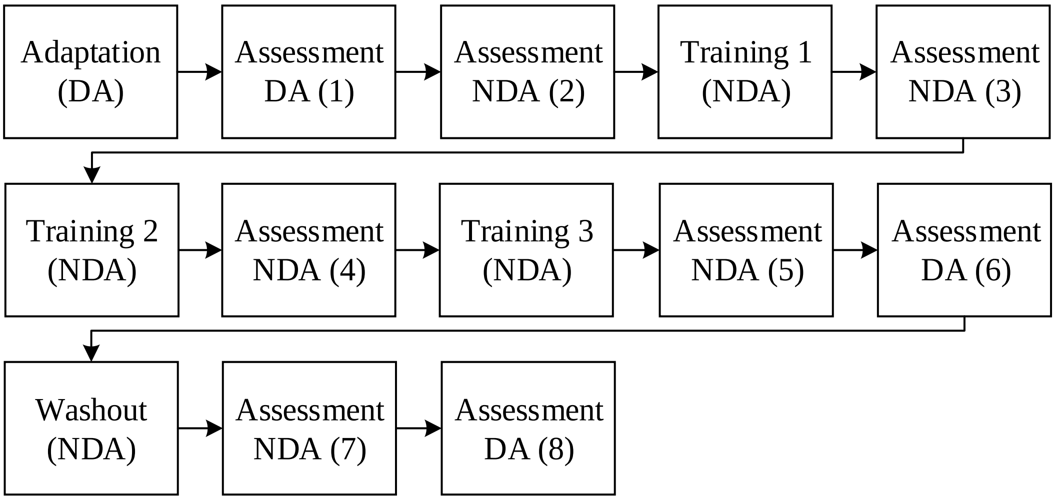


Figure 4-22: The protocol of the trial

Table 4-5: The specifics of the trial blocks. Assessments 1,6 and 8 are performed on the DA and 2,3,4,5 and 7 on the NDA.

Adaptation	1 set DA – visual rotation 100 deg.
Training block A, B, C	20 sets NDA – visual rotation 100 deg.
De-adaptation (Washout)	10 sets NDA – rotation 0 degrees
Assessment	SAM, 3 sets aiming, 2 sets circle drawing
Break	1-5 min. rest

4.3.4 Analysis of the trial results

Once the trial was completed kinematic data collected by the system were then processed following the same process as described in section 4.2.5 in order to extract the values of the measures that were later statistically analysed. The analysis of the results will be presented according to the research questions of this study. As such first the analysis of the kinematic data collected for the NDA will be presented in order to assess whether motor learning occurred and whether there was a difference between the intervention groups. Then the analysis of the DA will be presented in order to assess bilateral transfer of the motor learning.

Finally, the analysis of the data collected by the SAM assessment throughout the trial in order to get an insight to the psychological impact the two interventions had.

The main purpose of the reaching task was to evaluate the participants' performance and hence evaluate the level of motor learning that has occurred over the different stages of the trial. Five kinematic measures were analysed namely, movement error, movement duration, mean velocity, normalised jerk and initial error all measures that have been established in other studies and are commonly used in literature and are relevant to different movement parameters (de los Reyes-Guzmán et al., 2014; Nordin, S. Q. Xie, et al., 2014)

- **Perpendicular error (mm):** was measured in millimetres and was defined as the perpendicular distance from the position of the endpoint and the desired trajectory. For each movement the mean error was calculated for further analysis. Improvement in this measure would be reflected by a drop in its value.
- **Movement duration (s):** was measured in seconds and is a measure of the time that has elapsed between the movement initiation and completion. Lower values of movement duration would reflect better performance in the task.
- **Mean velocity (mm/s)**: measured in m/s is the mean velocity of each reaching movement. The higher mean velocity is the better the participants would be doing in the given task.
- **Normalised jerk (no units)**: was assessed as a measure of movement smoothness. The lower the normalised jerk the smoother the movements would be.
- **Initial error (mm)**: which is the perpendicular distance from the desired trajectory on the first 100 ms of the movement. In the initial phases of a movement where feedback is limited it is based mostly on the predictive part of motor control based on an internal model, that is commonly referred to as feedforward control (Patton, Kovic, et al., 2006; Shadmehr et al., 2010). As such, initial error is used as a measure to assess changes in

the internal model the predictive control relies on (Patton, Kovic, et al., 2006). Improvement in initial error would be reflected by smaller values of initial error.

Furthermore, the circle-drawing task was introduced to measure whether potential learning that had occurred while performing the reaching task would transfer to a different task. Circle-drawing tasks are often used in motor learning studies to measure coordination of the arm (Dipietro et al., 2007; Casellato et al., 2012; Nordin, S. Xie, et al., 2014). A common measure for this task is movement circularity, measure as the ratio of two axes of the ellipse-shaped trajectory of the participants' movement. More particularly circularity is measure as the length of the short axis of the ellipse over the long axis. Where a value of 1 would describe a perfect circle. As such the higher the value of circularity the more circular the movement. Another measure used to analyse the circle-drawing task was movement duration i.e. time to complete a circular movement. The basis of this measure is that the more skilled one becomes in drawing circles the movements will become quicker while maintaining or improving the circularity of their movements.

As such two more kinematic measures were analysed specifically to assess improvement in the circular movements task of the assessment.

Circularity (no units): A measure of how circular an ellipse is. It values range from 0 to 1 with 0 representing a line and 1 representing a perfect circle. The more circular the movement the better the coordination of the arm and as such the better the participants will be performing the task.

Circular movement duration (s): Measures the time to complete one circular movement. Improvement in this measure would be reflected by shorter duration of the movements given the same or lower levels of movement circularity.

Finally, the beginning of each assessment block the participants had to answer the SAM-questionnaire which provided a non-verbal 9-point nine scale that assesses three aspects of the psychological state of the participants namely valence, arousal and dominance. Furthermore, three assessments were undertaken using the DA of the participants. One after the adaptation block, one pre-washout and one after the washout assessment. This was done to measure whether learning would transfer from the NDA i.e. measure bilateral transfer and how it is affected by the different HCAs.

4.3.5 Statistical analysis

To analyse the data IBM SPSS Statistics version 22.0 was used. A mixed model analysis was performed using linear mixed models (LMM). LMM was selected as the preferred method of analysis as it takes into account random effects within the parameters, allow modelling of the variability, take into account dependent errors and also because they are robust against breaches of normality (Field, 2013). An example of linear mixed model which assumes random slopes and intercepts (Field, 2013) can be found in (20).-

$$Y_{ij} = \left(b_0 + u_{0j}\right) + \left(b_1 + u_{1j}\right)X_{ij} + \varepsilon_{ij} \qquad (20)$$

Where:
b_0: fixed intercept,
b_1: fixed slope,
u_0: random intercept,
u_1: random slope, ε_{ij}: residuals
j: levels of variable over which the intercept values

Covariance structures can be fitted in the random effects and repeated measures of the linear mixed models (West et al., 2015). Examples of covariance structures are the unstructured covariance which assumes random covariance, first order autoregressive covariance's which assumes that the correlation is higher the closer measurements with each other are, variance components which assumes that random effects are independent but have the same variances and diagonal which assumes independent random effects but with heterogeneous variances

(Field, 2013; West et al., 2015). To test the fit of the multilevel model chi-square likelihood tests are performed. SPSS reports the results of these tests as minus twice the log-likelihood (-2LL) and as such the lower the value the better the fit (Field, 2013).

To achieve the best fit of the model different parameters were tested. Nevertheless, the model that provided the lowest –2LL and hence the better fit is as follows:

Participants were set as subjects. As repeated measures were used the assessment number, set number and target number. As dependent variable was set the variable under investigation such as movement duration for example. As factors were set the HCA group and the Assessment number and full factorial analysis was performed for these fixed effects. Lastly, random intercepts were assumed between the participants. Covariance structure was set to diagonal for the repeated effects and the covariance model for the random effects was set to variance components.

The same model was run for each individual measure for both the assessments on the DA (3 assessments in total) and the NDA (5 assessments in total). Also, SAM measures were analysed throughout the trial and not separately for the each of the individual arm. As there was great variance within the participants' answers to the SAM questionnaire scales were normalised by subtracting the score value acquired in the first assessment (adaptation on the DA) from each individual assessment. To evaluate the results, tests of fixed effects were performed along with estimates of fixed effects. Also, to get a better estimate of pairwise comparisons the estimated marginal means were calculated all with Bonferroni adjustment for multiple measurements.

4.4 Summary

In this chapter the findings of the pilot trial were presented. The evaluation of the results was split into two main areas of focus. Firstly, the evaluation aimed to identify whether different rates of adaptiveness of an adaptive assistive algorithm (AAN) affected motor learning differently on the upper limb of able-bodied adults. In that respect the analysis of the trial findings failed to identify a significant effect. The second aim of the trial was to assess the protocol and the analysis methodology in order to inform the design of the investigatory trial of this work comparing the effectiveness of the three developed HCAs, namely assistance as needed, error augmentation adaptive and error augmentation proportional. Overall, the trial was successful in inducing and capturing changes in motor learning. Nevertheless, certain key areas were identified that needed to be modified in the protocol design of the investigatory trial with the more significant being reducing the duration of the protocol. The next chapter presents the changes that were made to the trial protocol along with the updated investigatory trial protocol.

This chapter also presented the trial protocol undertaken to study the effectiveness of the developed HCAs on promoting motor learning on the upper limb of able-bodied adults and allow a comparison to be drawn between in respect of their effectiveness. The design of the investigatory trial was based on the findings of the pilot trial. Overall, the protocol remained similar to the pilot trial with the most significant difference being a shortening in the amount of movements the participants had to perform in the practice part of the trial as well as within the assessments. One training block along with the subsequent assessment block were removed from the trial in order to shorten the duration of the trial protocol.

The kinematic measures that were selected for this study, were the same as in the pilot trial with the only exception being the addition of initial error which was introduced to the analysis of the study as a measure of improvement in the early stages of the trial. A significant difference form the pilot trial was the approach undertaken for the statistical analysis. Linear Mixed Models (LMM) analysis was used for the statistical analysis instead of the General Linear Models (GLM). This approach was selected as it takes into account random effects for the model. LMM are also more robust against breaches of normality and sphericity of the dataset, when compared to GLM.

Finally, four different models were developed; the analysis of each is presented in the subsequent chapters. The first three models (presented in Chapters 5,6,7) are comparing directly one of the groups that practice with the developed HCAs to the Control group, while the fourth a modelling that consider all four groups is presented. As such the next chapter will be presenting the statistical model where the AAN group is compared against the Control group (Chapter 5).

5 Investigating the effects of Assistance As Needed control on motor learning

5.1 Introduction

The primary objective of the investigatory trial was to evaluate the effectiveness of three HCAs, that were developed as part of this project (EAA, EAP and AAN), on the motor learning of able-bodied adults. Details on the AAN can be found in Sections 2.7.3 and 3.3.3. Although only one trial was undertaken with participants being assigned to four different intervention groups (one for each algorithm and a Control group) this chapter will present the findings of the statistical analysis of a model that only compares the findings for the AAN against the ones of the Control group. The design of the investigatory trial and the protocol undertaken for the data acquisition and analysis are presented in Section 4.3. In this chapter firstly an overview of the configuration of the AAN used in the trial is presented and then the research questions that the analysis aims to answer are presented. Finally, the main part of this chapter is focused on presenting and discussing the findings of the statistical analysis.

5.2 The Assistance As Needed algorithm

As described in Section 3.3.3 the HCA portion of the software developed was highly customisable to allow for experimentation with different settings to fine-tune the behaviour of the respective HCA under implementation. There were three main features that could be adjusted namely, a) the direction of the forces, b) the method of adaptation and c) the maximum permissible current. Among them there is an infinite number of possible combinations and thus an infinite number of possible behaviours that can be achieved. To date there are no guidelines in literature on how to adjust a haptic control algorithm to fit for purpose. As such, the required behaviour was achieved by trial and error informed by consulting experienced physiotherapists within the University.

The final settings of the AAN were set as follows (Figure 5-1):

a) The force direction was set by the line between the straight line trajectory connecting the target and the position of the endpoint and the perpendicular line connecting the endpoint and the trajectory. The direction of the forces was set 30% closer to the straight line connecting endpoint and target. To achieve this the parameters p, s were set to 50% and parameter i was set to 30% (Section 3.3.3.1).

b) Maximum Permissible Current was set to 2A

c) The method of adaptation was set to be adaptation in set zones (11 zones in total) with the width of each zone being defined by the following equation:

$$\text{width of zone } i = i*6.5\text{mm where } 1\leq i\leq 11$$

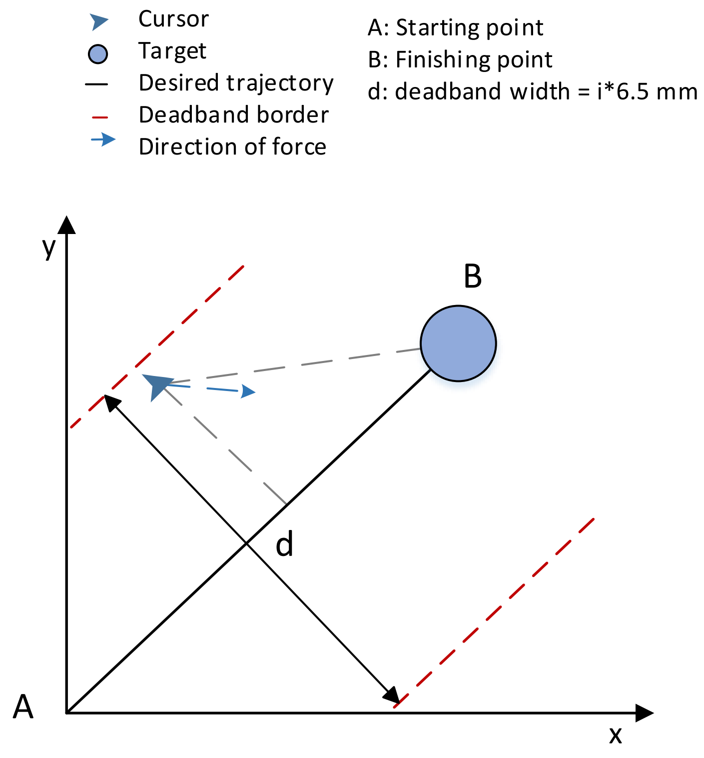


Figure 5-1: The final settings of the AAN algorithm.

5.3 Research questions

The questions that this analysis set out to answer are presented below:

1) Does the AAN affect motor learning and retention of learning on the upper limb of the able-bodied adults? If yes, what is its effect?
2) How does the effect of AAN compare to the participants' performance if the same amount of practice was received without any forces being applied by the rehabilitation robot?
3) Is bilateral transfer affected by the conditions of practice (assisted vs passive movements)?
4) Does practice with the developed HCAs have an effect on the psychological state of the participants and if so how much of that can just be attributed to the exercise?

5.4 Results of the statistical analysis

5.4.1 Analysis of the kinematic measures for the non-dominant arm

Five assessments in total were undertaken by the participants using their NDA. The first one was carried out during the adaptation stage to form a baseline assessment of performance before exercise. Three more assessments were performed one after each training block and finally the last assessment block was performed just after the washout block to evaluate retention. Similar to the pilot trial the hypothesis was the intervention (training) would lead to participants improving their performance compared to the baseline assessment which then would deteriorate after the washout protocol. Based on the findings of the pilot trial it was expected that if retention did indeed occur then the deteriorated performance would be worse when compared to the training stage but would not reach pre-intervention levels.

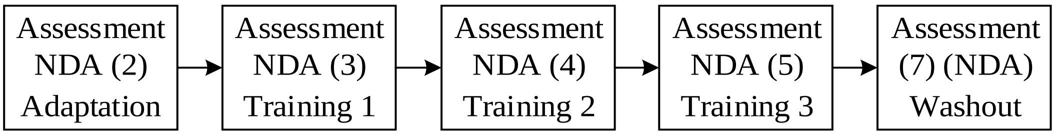


Figure 5-2: The assessments on the NDA.

5.4.1.1 *Results for the reaching task on the non-dominant arm*

With respect to the reaching task for the NDA, both groups appear to have improved in terms of their movement duration throughout the training blocks (Figure 5-3). More specifically, the tests of fixed effects showed a statistically significant effect of practice F(4,1197.087) =329.547, p<0.005 on movement duration and a statistically significant interaction between HCA group and practice F(4,1197.087) =10.659, p<0.005. From the estimated marginal means it can be seen that movement duration decreased throughout the training for both groups and while post-washout there was an increase in duration it did not reach the levels achieved in the adaptation assessment.

The estimates of fixed effects did not identify a statistically significant difference between the two groups on how movement duration changed between the adaptation assessment and training blocks 1 and 2 (p=0.095 and p=0.099, respectively). However, the same estimates indicated that the Control group improved in movement duration by 0.2s (p<0.005) more than the AAN group did when comparing the change in movement duration between the adaptation assessment and the one after training block 3. Also, post-washout, the Control group retained a greater difference, between the adaptation assessment and the post-washout assessment, than the AAN group did by an estimated 0.3s (p<0.005).

As such, both groups reduced their movement duration throughout the training blocks when compared to the baseline assessment in the adaptation stage. Both groups reduced movement duration similarly in training blocks 1 and 2 but the Control group showed a larger improvement in training block 3 when compared to the AAN group. Finally, at the washout assessment in both groups movement duration increased without returning to the baseline levels but the Control group retained more of the improved movement duration.

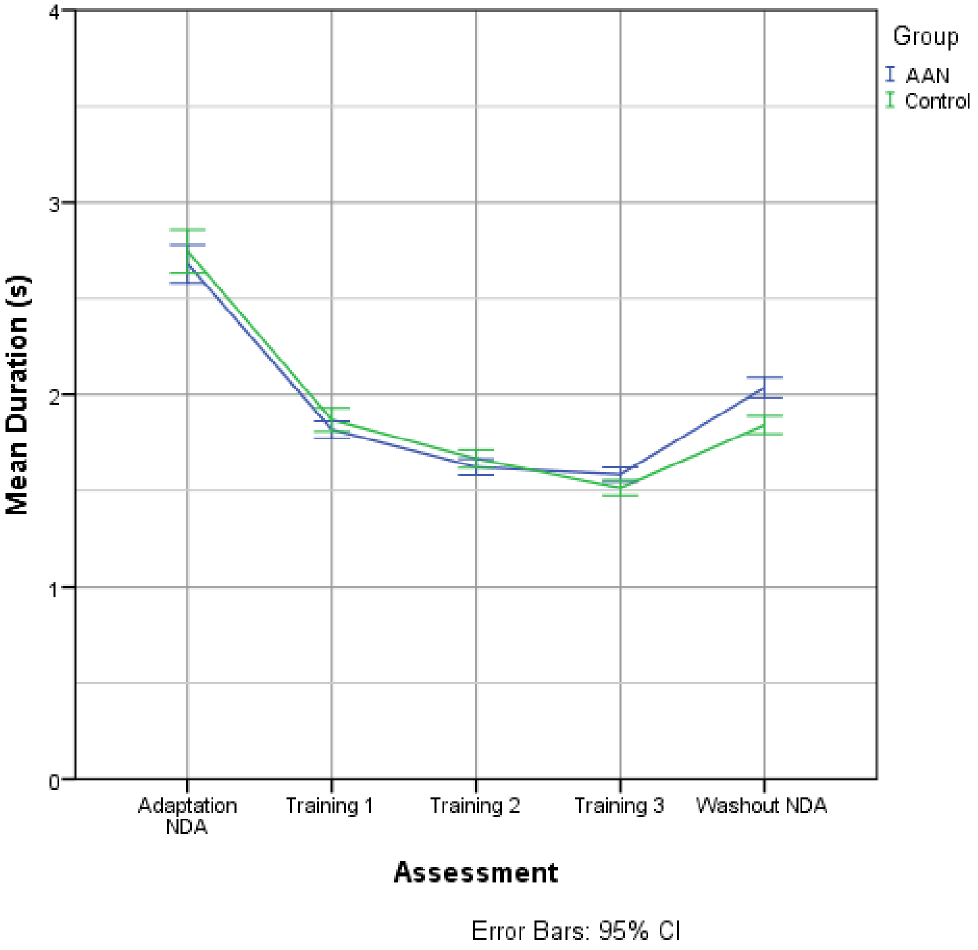


Figure 5-3: Mean duration over the different assessment blocks on the NDA for the AAN and the Control group.

Similar to movement duration there was a statistically significant effect of practice F(1042.231,4) = 281.020, $p<0.005$ on the perpendicular error of the movements (Figure 5-4) as indicated by the tests of fixed effects. Contrariwise, the same tests showed that there was no statistically significant effect of HCA group on perpendicular error F(1042.13,4) =0.852, p=0.492 indicating that both groups behaved similarly in terms of movement duration in the different assessment blocks.

The absence of an effect of HCA group on perpendicular error is further supported by the non-statistically significant estimates of fixed effects regarding the interaction between HCA group and practice (p>0.05). Therefore, only the estimates of fixed effects of practice for the entire population (AAN and control participants combined) were considered. Perpendicular error was reduced significantly after training block 1 with a mean difference of 3.4 mm (p<0.05) when compared to adaptation assessment (baseline) and continued to improve throughout the training blocks reaching a minimum in the assessment after training block 3 with a mean difference from the adaptation assessment of 3.9 mm (p<0.005). Finally, the improvement in perpendicular error was completely washed-out at the post-washout assessment as there was no significant difference between the adaptation assessment and the washout assessment (p=0.163).

From the aforementioned it can be derived that both groups behaved similarly in terms of the perpendicular error. There was a large improvement after training block 1 when compared to the adaptation assessment and perpendicular error improved further in the two assessments that followed. However, post-washout error reached the levels that were measured before any training was undertaken, indicating that any improvement in movement error was completely washed-out for both groups.

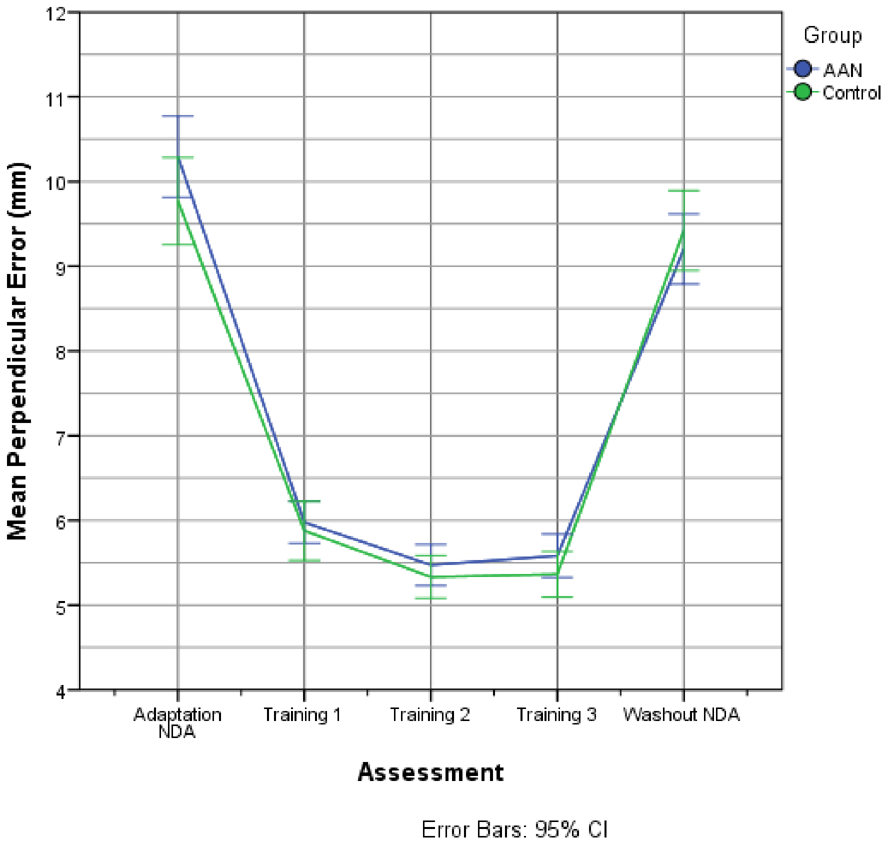


Figure 5-4: Mean perpendicular error over the different assessment blocks on the NDA for the AAN and the Control group.

When considering the mean velocity of the participants' movement (Figure 5-5) the tests of fixed effects indicated that practice had a significant effect, F(1325.366,4) =220.015, $p<0.005$ and also that there was a statistically significant interaction between HCA group and practice F(1325.366,4)=10.779, $p<0.005$. The estimates of fixed effects of practice regarding movement duration showed that both groups increased the mean velocity of their movements during the different training blocks reaching a maximum in mean velocity after training block 3. The mean difference in mean velocity between the adaptation assessment and training block 3 was 13.3 mm/s ($p<0.005$) for the AAN and 17.8 mm/s, $p<0.005$ as indicated by the estimated marginal means. Moreover, after the washout block the improvement in mean velocity was partially washed-out as mean velocity was reduced however, it did not revert back to the levels achieved in the adaptation assessment.

Likewise, the estimates of fixed effects revealed that both groups improved similarly after training blocks 1 (p=0.080) and 2 (p = 0.543) but that there was a statistically significant difference between them on how the mean velocity changed between the adaptation assessment and the one after training block 3. More specifically, the Control group improved by 4.5 mm/s (p<0.005) more than the AAN group between the two assessments. Post-washout mean velocity was washed out less for the Control group by 6.0 mm/s (p<0.005) when compared to the AAN group.

Mean velocity increased in both groups throughout the training blocks with the Control group achieving better performance than the AAN after training block 3. Also the improved movement duration was partially washed-out for both groups after the washout stage but the Control group retained more of the improved (during training) mean velocity than the AAN group did.

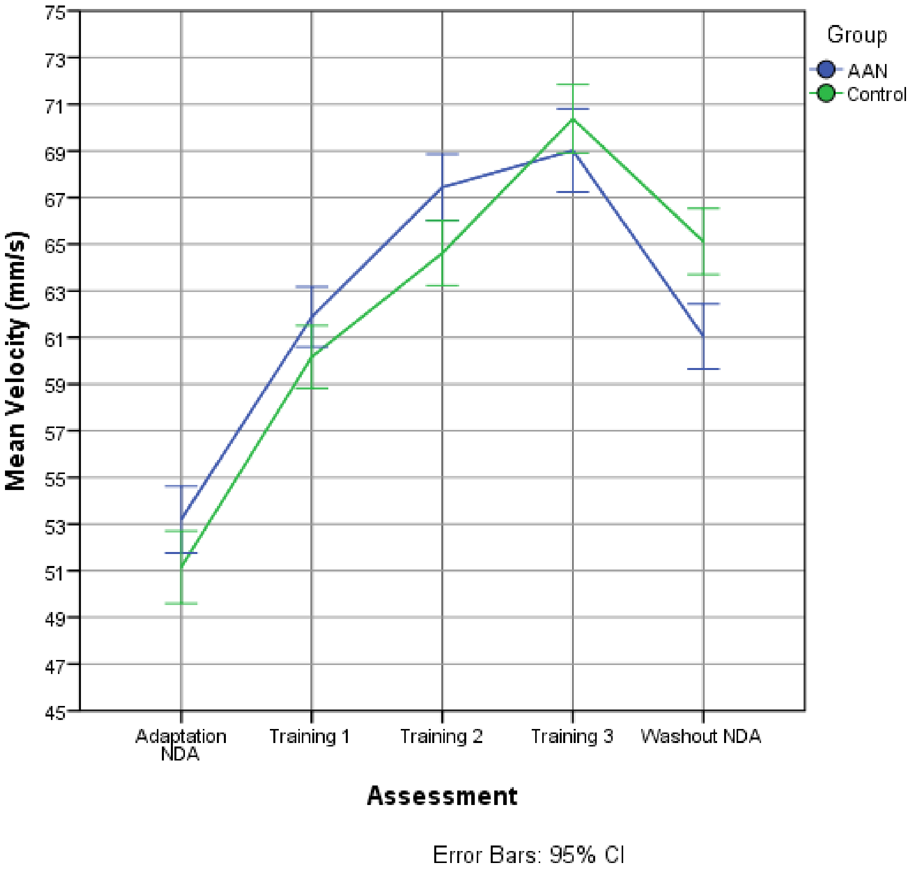


Figure 5-5: Mean velocity over the different assessment blocks on the NDA for the AAN and the Control group.

With respect to normalised jerk (Figure 5-6), the tests of fixed effects showed that there was a statistically significant effect of practice F(579.057,4) =0.209, $p<0.005$ as well as that there was a statistically significant interaction between HCA group and practice F(579.057,4) =7.961, $p<0.005$. From the estimated marginal means for the two groups, it can be derived that both groups started with very high normalised jerk that was rapidly decreased after the first block of training. Between the training blocks small changes occurred with the lowest normalised jerk being achieved after training block 3 with a mean difference from the adaptation assessment of 6.4 units ($p < 0.005$) for the AAN and 8.6 units ($p< 0.005$) for the Control group.

To get an estimate of how the type of HCA affected the normalised jerk on the course of the trial the estimates of fixed effects were examined. The analysis showed that the Control group improved significantly more than the AAN group did after training block 3 by reducing normalised jerk from the adaptation assessment by 2.2 units ($p<0.05$) more than the AAN group did. Furthermore, the Control group retained more of the normalised jerk after the washout block when compared to the adaptation levels than the AAN did as the difference between the adaptation value and the post-washout value was 2.8 units ($p<0.05$) more for the Control group.

To summarise both groups reduced dramatically the normalised jerk of their movements after they received the first block of training. Normalised jerk further improved in the course of the training part of the trial. Finally, normalised jerk was partially retained for both groups after the washout block as it was increased when compared to the pre-washout assessment levels but it did not approach the pre-training levels as measured by the adaptation assessment. Finally, the Control group performed better than the AAN group in terms of the normalised jerk as it improved more during the training stage and retained more of its improved normalised jerk post-washout.

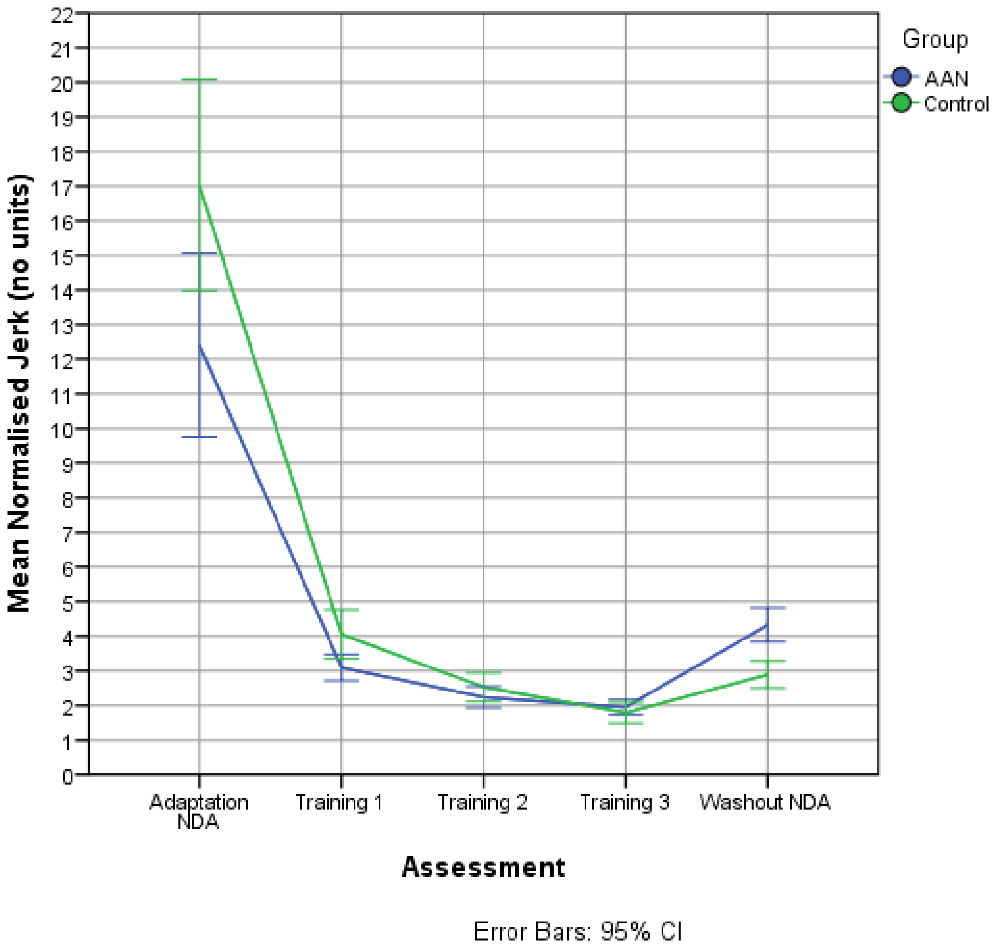


Figure 5-6: Normalised jerk over the different assessment blocks on the NDA for the AAN and the Control group.

When considering initial error (Figure 5-7) the tests of fixed effects showed a statistically significant effect of practice F(4,1539.747) = 5.720, $p < 0.005$ but also that there was no significant interaction between practice and HCA Group F(4,1539.747) = 5.720, $p = 0.931$. As such, it is logical to assume that both groups behaved in the same manner in the course of the trial with regards to initial error. To get some insight on what that behaviour was the estimates of fixed effects were examined with the assessment as the only factor.

The results showed that there was no statistically significant difference in initial error between the adaptation and the assessments after training block 1 and the washout block ($p>0.2$). Nevertheless, the estimates showed a statistically significant difference in the initial error after training block 2 when compared to the adaptation, where initial error was reduced by 0.3 mm ($p<0.005$). Also, a marginally non-significant difference was found in initial error between the adaptation and training block 3 with a difference of 0.2 mm (p=0.055). To conclude, there was no statistically significant effect of practice on the initial error except from a small reduction after training block 2. Also both groups behaved similarly as there were no significant differences on initial error between the two groups.

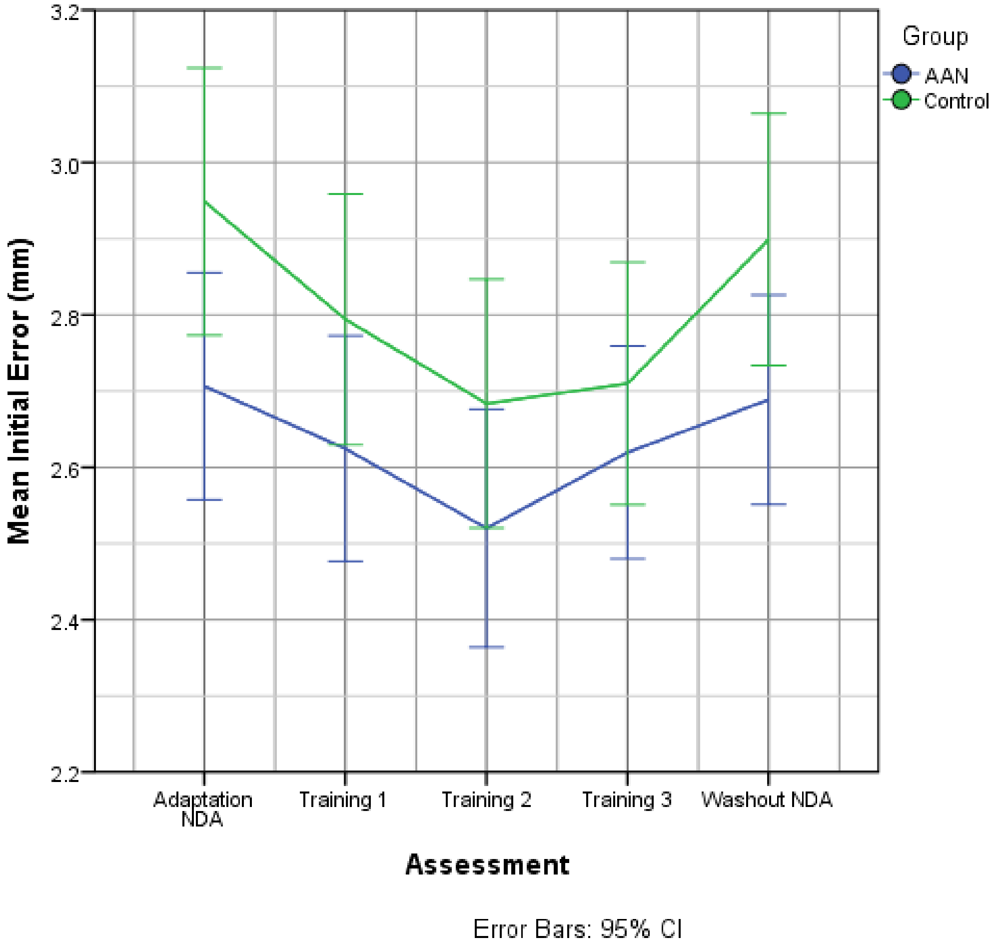


Figure 5-7: Initial error over the different assessment blocks on the NDA for the AAN and the Control group

5.4.1.2 *Results of the circle-drawing task for the non-dominant arm*

During the circle drawing task, both groups behaved in a similar manner in terms of how circular their movements were (Figure 5-8) as the test of fixed effects did not show a statistically significant interaction between practice and HCA group F(4,47.499) =0.606, p = 0.660. However, the test of fixed effects showed a statistically significant effect of practice on movement circularity F(4,47.99) = 3.526, $p < 0.05$. Nevertheless, the analysis of the estimates of fixed effects revealed that there was no statistically significant difference between the adaptation assessment and the other assessment blocks (p>0.05) with the only difference being a statistically significant increase by 0.04 units (p<0.01) in movement circularity after training block 3.This change in movement circularity could be attributed to learning that occurred in the course of the trial however as this finding is isolated (there is no evidence of learning in the previous training blocks) and very small it is highly probable this was a false positive result of the statistical analysis.

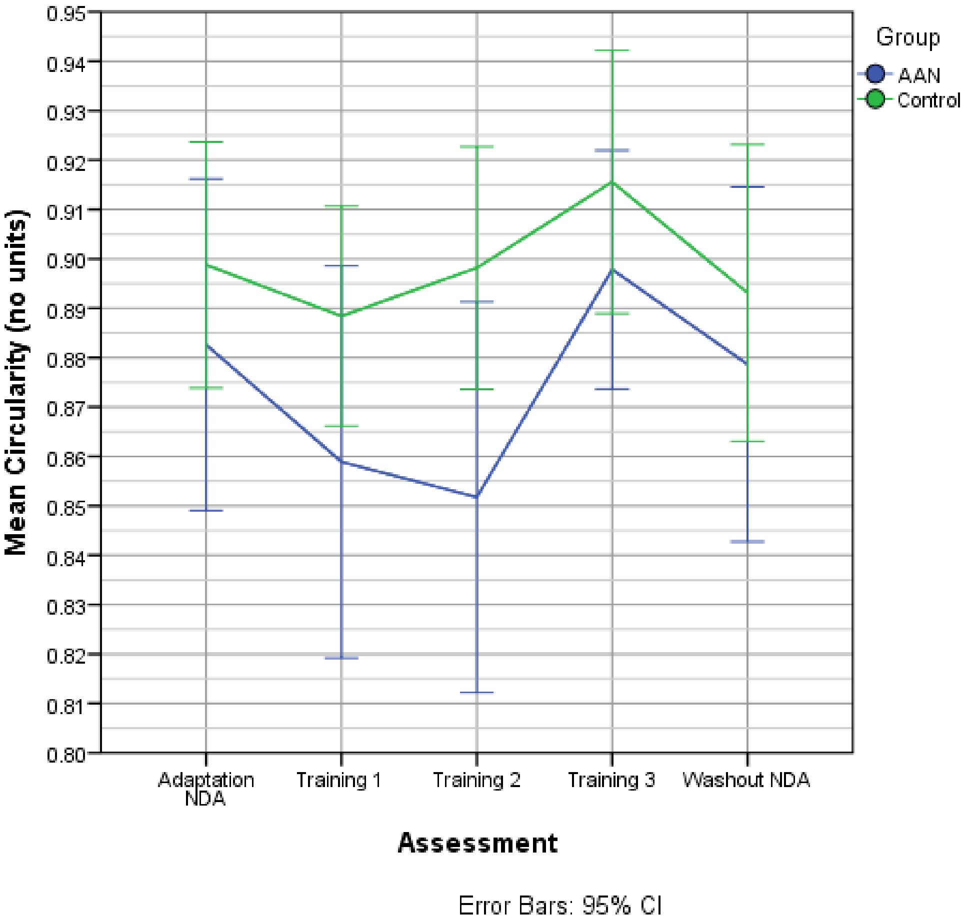


Figure 5-8: Movement circularity over the different assessment blocks on the NDA for the AAN and the Control group.

Nonetheless, both groups behaved similarly regarding the duration of the circular movements (Figure 5-9) as the tests of fixed effects did not find a statistically significant interaction between practice and HCA group, F(4,33.927) =1.845, p=0.143. However, the same tests showed that there was a significant effect of practice on the duration of the movements F(4,33.927) =5.239, p<0.005. The estimated marginal means indicated that duration reached a statistically significant difference from the adaptation block in training block 2 with a mean difference of 2.4s ($p<0.05$). When comparing the different training blocks and also the washout block there was no statistically significant difference between them ($p>0.05$) indicating that movement duration remained at the same levels for the rest of the trial.

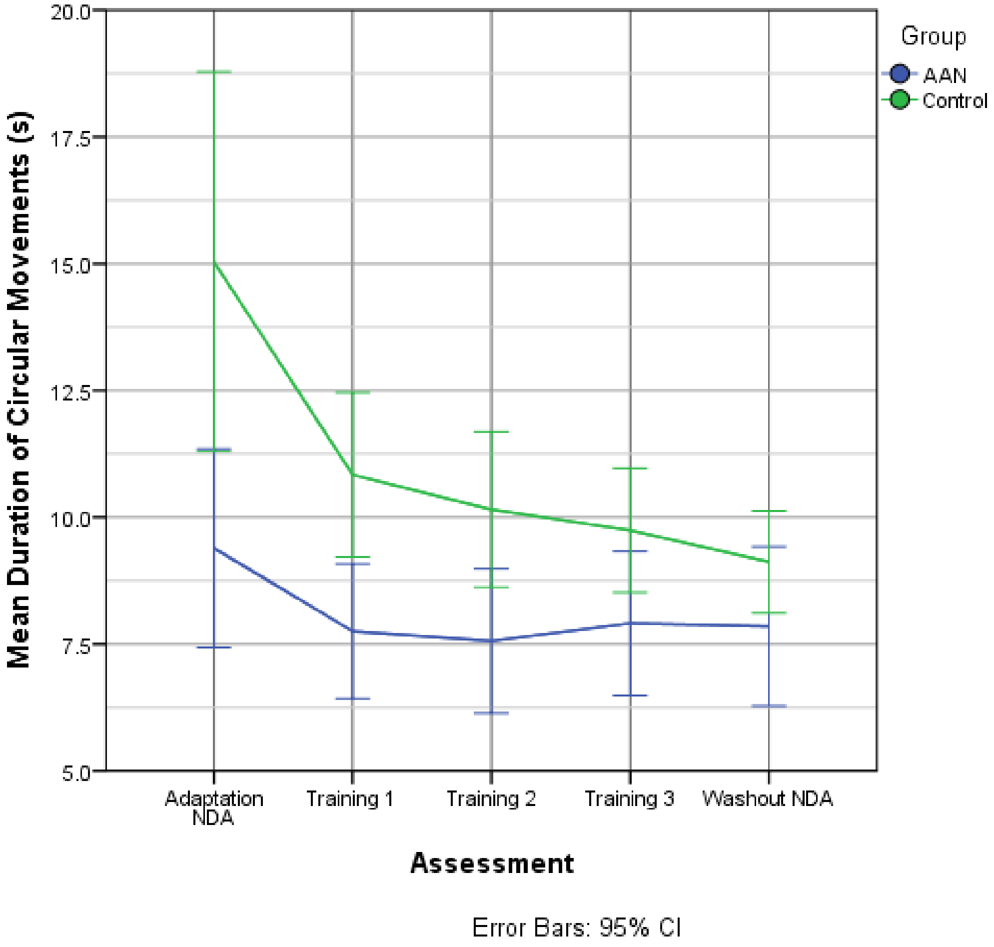


Figure 5-9: Duration of the circular movements over the different assessment blocks on the NDA for the AAN and the Control group.

Table 5-1: Summary of the findings on the analysis of the effectiveness of the trial on the AAN and Control group for the NDA.

Measure	**Learning pre-washout**	**Retention post-washout**	**Improved more pre-washout**	**Retained more post-washout**
Duration	Yes	Yes	Control	Control
Perpendicular error	Yes	No	No difference	No difference
Mean velocity	Yes	Yes	Control	Control
Normalised jerk	Yes	Yes	Control	Control
Initial error	Yes (small)	No	No difference	No difference
Circularity	Yes (small)	No	N/A	N/A
Circular movement duration	Yes	Yes	No difference	No difference

5.4.2 Analysis of the kinematic measures for the dominant arm

As in the pilot trial the DA did not receive any exercise during the session apart from the movements performed on the three assessment blocks one in the pre-training phase in order to serve as a baseline, one after the last training block (training block 3) to evaluate whether improvement occurred and hence bilateral transfer of learning, and one after the washout block in order to assess retention of the learning.

5.4.2.1 *Results for the reaching task on the dominant arm*

With regards to movement duration of the DA (Figure 5-10), the tests of fixed effects showed that there was a statistically significant effect of practice F(2,487.545) =487.545, $p<0.005$ and also that there was a statistically significant interaction between HCA group and practice F(2.487.545)=16.5572, $p<0.005$. By looking at the pairwise comparisons of the estimated marginal means there was a significant improvement in movement duration at the pre-washout assessment for both groups. More specifically the AAN group reduced the movement duration by a total of 1.5s ($p<0.05$) in the pre-washout assessment and the Control group by 2s ($p<0.05$). With regard to the post-washout assessment movement duration remained unchanged for the Control group (2s) as there was no statistically significant difference in duration pre and post-washout ($p=0.375$) indicating an absolute retention of the improvement. On the other hand, the AAN group increased their movement duration, when compared to the pre-washout levels, by an average of 0.1s ($p<0.05$). This last finding indicates that there was indeed a small amount of change/improvement in movement duration washed-out for the AAN group.

From the estimates of fixed effects, it can be seen that the Control group reduced movement duration by 0.5s ($p<0.005$) more than the AAN did between the adaptation and the pre-washout assessments. Post-washout the Control group appears to have retained more of the improved movement duration as it showed a larger difference of 0.6s ($p<0.005$) from the adaptation levels than the AAN did. This is consistent with the findings of the estimates of marginal means discussed in the previous paragraph indicating that the AAN group lost some of the improved movement duration to washout. To summarise both groups improved in movement duration after at the pre-washout assessment indicating that bilateral transfer did occur for both groups which was retained partially by the AAN group and totally by the Control group.

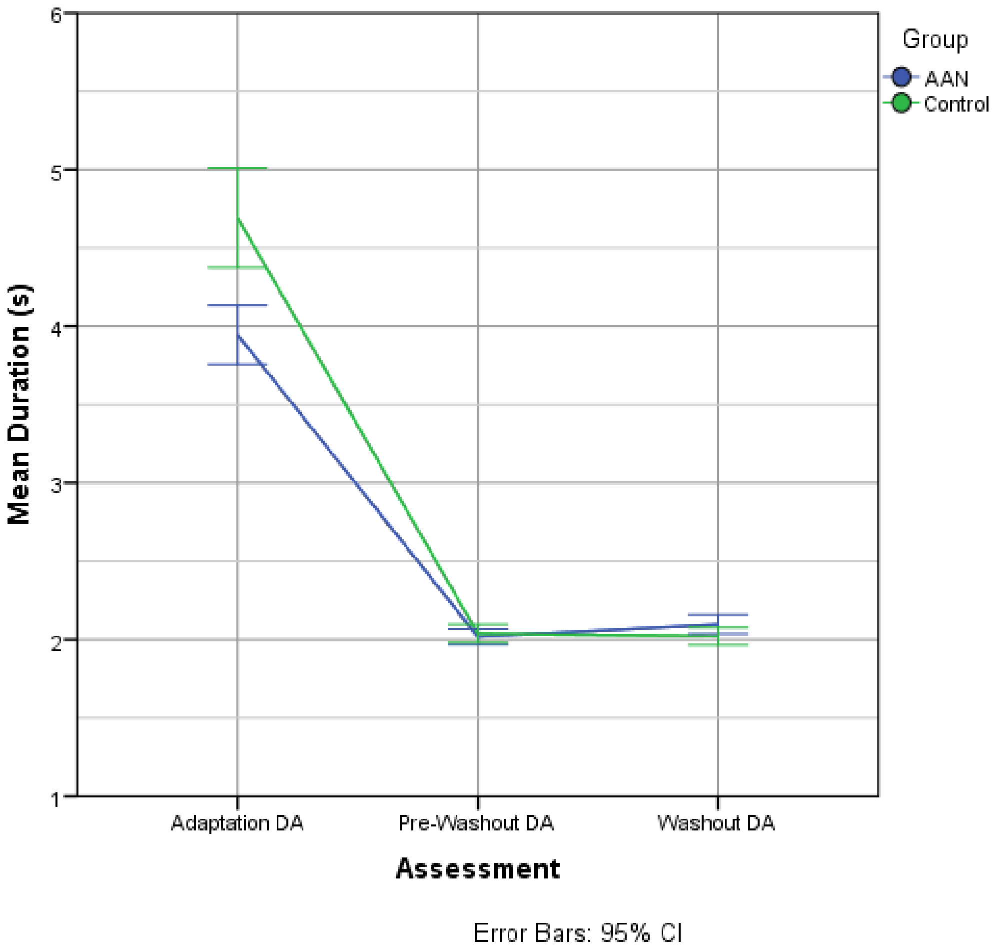


Figure 5-10: Mean duration over the different assessment blocks on the DA for the AAN and the Control group.

When considering the perpendicular error (Figure 5-11), the tests of fixed effects showed that there was a statistically significant effect of practice F(2,1192.133) =179.631, $p < 0.005$ and also that there was a statistically significant interaction between HCA group and practice F(2,1192.133) =10.543, $p<0.005$. The estimates of marginal means for the pairwise comparisons showed that the AAN group reduced error by an average of 4.3 mm ($p<0.005$) at the pre-washout assessment while the Control group reduced error by 3.2 mm ($p< 0.005$) at the same assessment. Furthermore, both groups seem to have retained the improved perpendicular error post-washout as there was not statistically significant difference pre-and post-washout for the AAN ($p=1.00$) and the Control group increased its mean error by an average of 0.6 mm ($p< 0.05$).

The estimates of fixed effects indicated that there was a difference on how the perpendicular error had changed for the two groups in the different assessment blocks. The AAN group reduced perpendicular error by 1.1 mm ($p<0.005$) more than the Control group did at the pre-washout assessment when compared to the baseline. Also, post-washout the mean difference of perpendicular error from the baseline was 1.9 mm greater for the AAN when compared to the Control group. This latter finding further supports the results of the estimates of fixed effects that showed that AAN retained completely the improved perpendicular error after the washout block while despite being very little (0.6 mm) there was some washout of the perpendicular error for the Control group.

To summarise both groups improved at the pre-washout assessment indicating that bilateral transfer did indeed occur. The AAN group showed greater improvement than the Control group when comparing the adaptation assessment with the pre-washout. Also, the AAN group seemed to be unaffected by the washout block while the Control group reduced its accuracy on the same block.

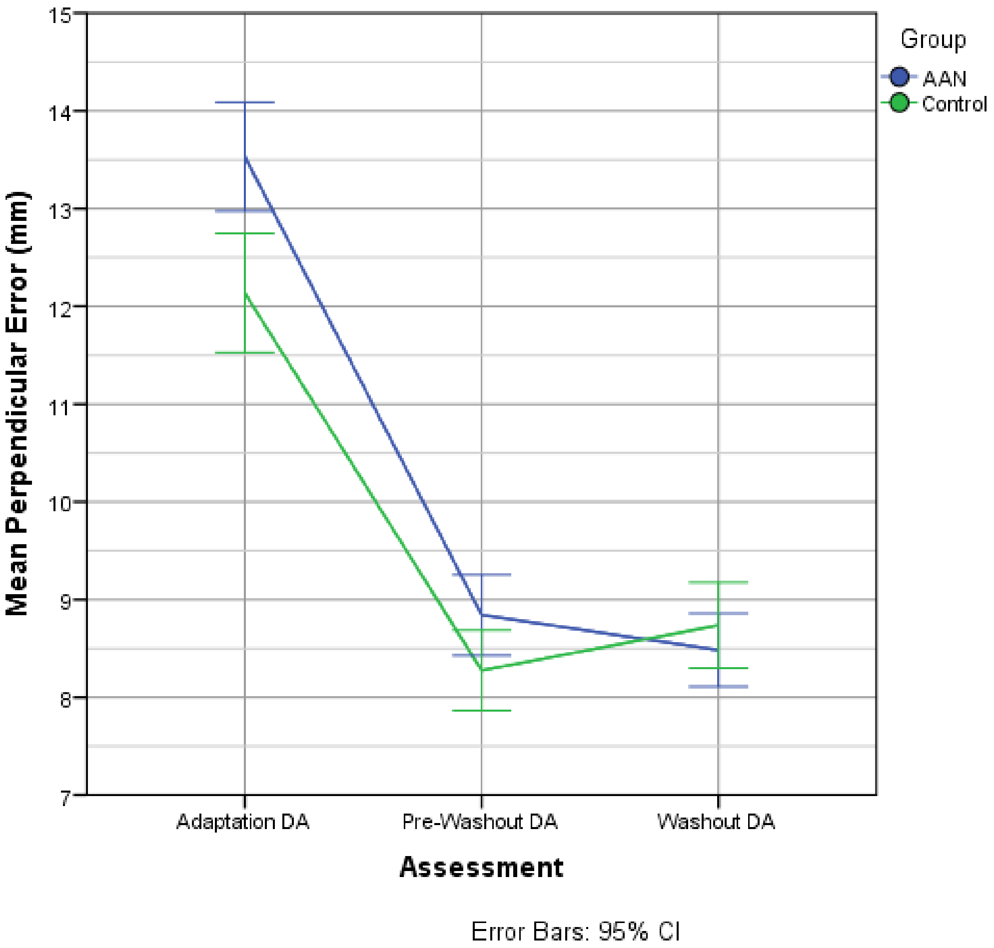


Figure 5-11: Mean perpendicular error over the different assessment blocks on the DA for the AAN and the Control group.

Similarly, the tests of fixed effects showed that there was a statistically significant effect of practice F(2,1491.542) =588.526, p<0.005 on the mean velocity of the DA and also that there was a statistically significant interaction between HCA group and practice F(2,1491.542) = 9.532, p<0.005. From the pairwise comparisons of the estimated marginal means it can be seen that both groups increased significantly the mean velocity of their movements in the pre-washout assessment with a mean increase of 14.4 mm/s (p<0.005) for the AAN group and 16.9 mm/s for the Control group (Figure 5-12). Post-washout the mean velocity remained unchanged for both the AAN group (p=1.000) and the Control group (p=1.000) indicating that the improvement in mean velocity was fully retained after the washout block.

The estimates of fixed effects showed that there was a statistically significant difference on how mean velocity changed for the two HCA groups. More specifically the Control group showed a greater difference between the adaptation and pre-washout assessments than the AAN group did, by an estimate of 2.5 mm/s. Furthermore, the estimates of fixed effects revealed that there was a significant difference in mean velocity between the two groups post-washout with the Control group retaining 4.6mm/sec more of the mean velocity when compared to the AAN group in the post-washout assessment.

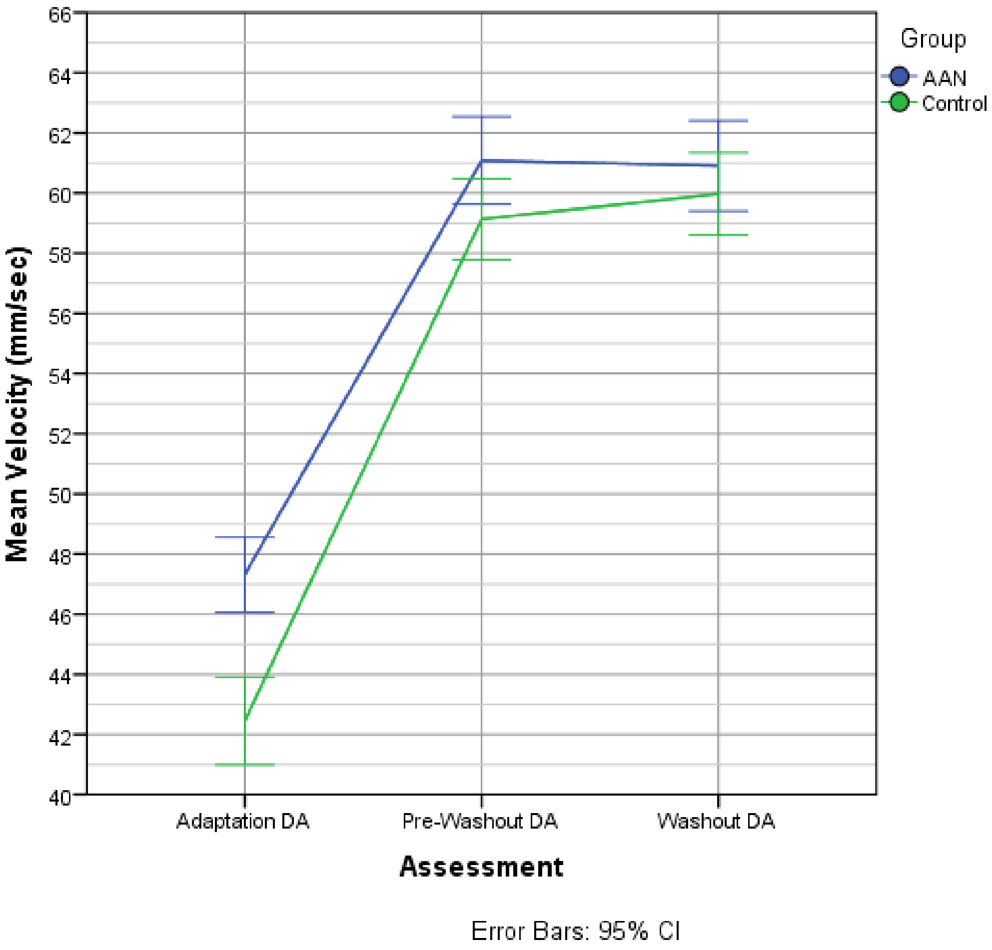


Figure 5-12: Mean velocity over the different assessment blocks on the DA for the AAN and the Control group.

Regarding the normalised jerk of the DA (Figure 5-13) the tests of fixed effects showed a statistically significant effect of practice as well as a statistically significant interaction between HCA group and practice F(2,115.855) =20.820, p<0.005. For both groups movements became smoother on the pre-washout assessment block as normalised jerk decreased by 13.7 units (p<0.005) for the AAN group and 27.6 units (p<0.005) for the Control group as indicated by the estimates of marginal means. Also, post-washout normalised jerk increased for both groups by 0.5 units (p<0.05). However, this increase was very small indicating that smoothness was retained after the washout block.

The estimates of fixed effects showed that the Control group improved by 13.4 units (p< 0.005) more than the AAN group did in the pre-washout assessment. However, this is probably due to the fact that the AAN group demonstrated significantly less normalised jerk in the adaptation assessment, as the Control group had 13.6 units (p<0.005) normalised jerk than the AAN group as shown by the estimated marginal means. However, it appears that both groups reached the same levels pre-washout as there was no difference in normalised jerk between the groups (p = 0.854). Also, post-washout both groups behaved similarly in terms of normalised jerk as there was no difference between the groups (p=0.0452).

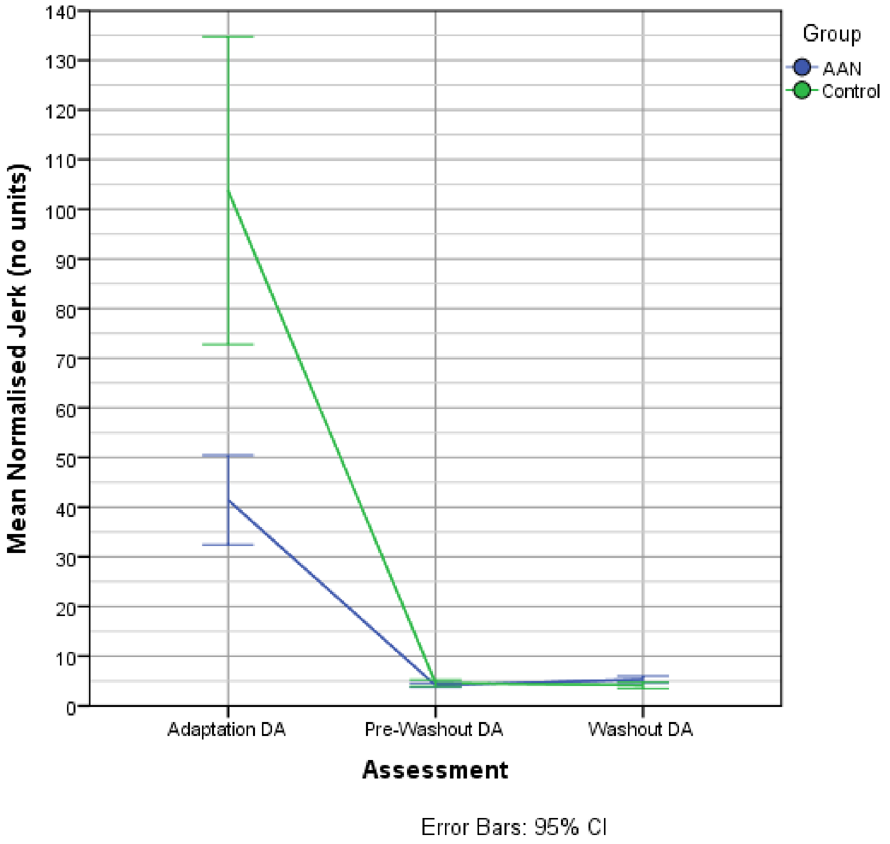


Figure 5-13: Normalised jerk over the different assessment blocks on the DA for the AAN and the Control group.

The tests of fixed effect showed that there was a statistically significant effect of practice on initial error F(2, 1655.068) =7.928, p<0.005 (Figure 5-14). Nevertheless, the same tests failed to identify a statistically significant interaction between HCA group and practice F(2, 1655.068) =0.364, p=0.695. The estimates of fixed effects showed that initial error decreased for both groups by 0.29 mm (p<0.05) per washout. The same estimates showed that the difference from the adaptation assessment was 0.25 mm less than the adaptation assessment (p<0.05). Nevertheless, the estimated marginal means showed that initial error was not affected by the washout block as there was no statistically significant difference from its value pre and post-washout (p=0.645).

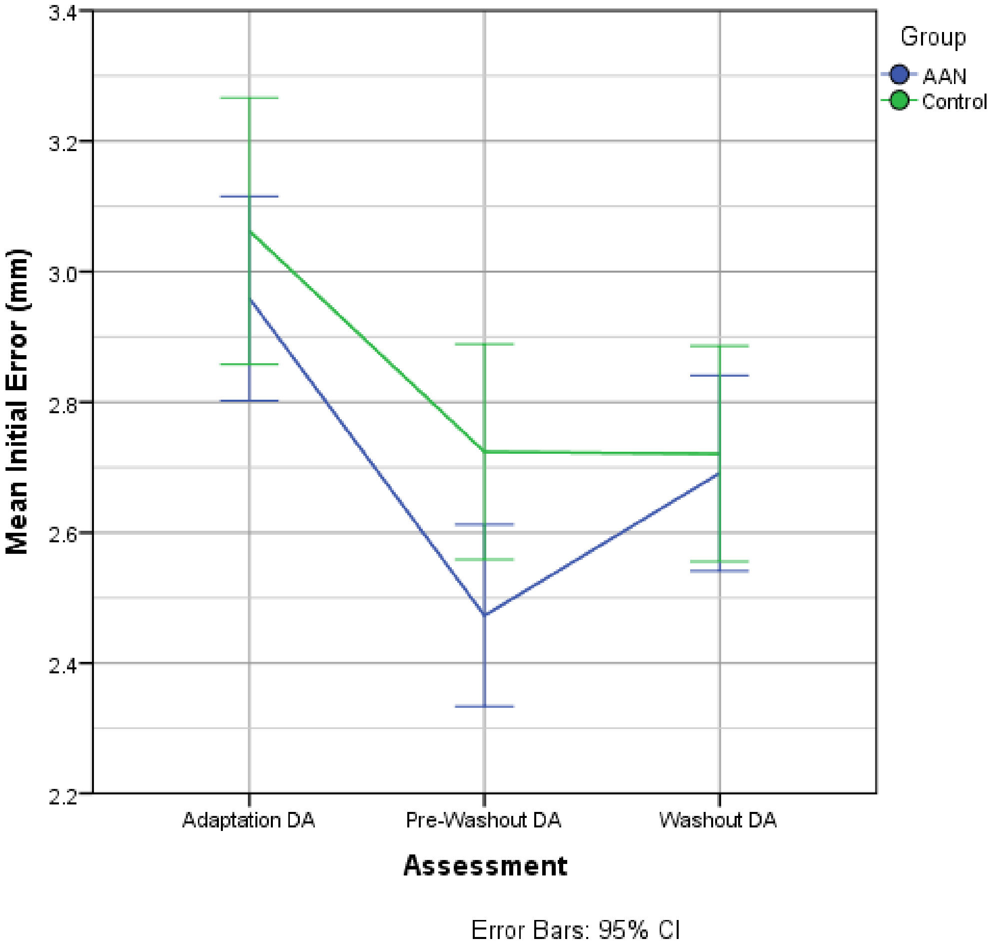


Figure 5-14: Initial error over the different assessment blocks on the DA for the AAN and the Control group.

5.4.2.2 *Results of the circle-drawing task for the dominant arm*

The results of the tests of fixed effects for movement circularity (Figure 5-15) during circle-drawing task of the DA indicated that there was no significant effect of practice F(2,69.348) =0.387, p=0.680. on movement circularity. Also, there was no significant interaction between HCA group and practice on movement circularity F(2,69.348) =0.472, p<0.626.

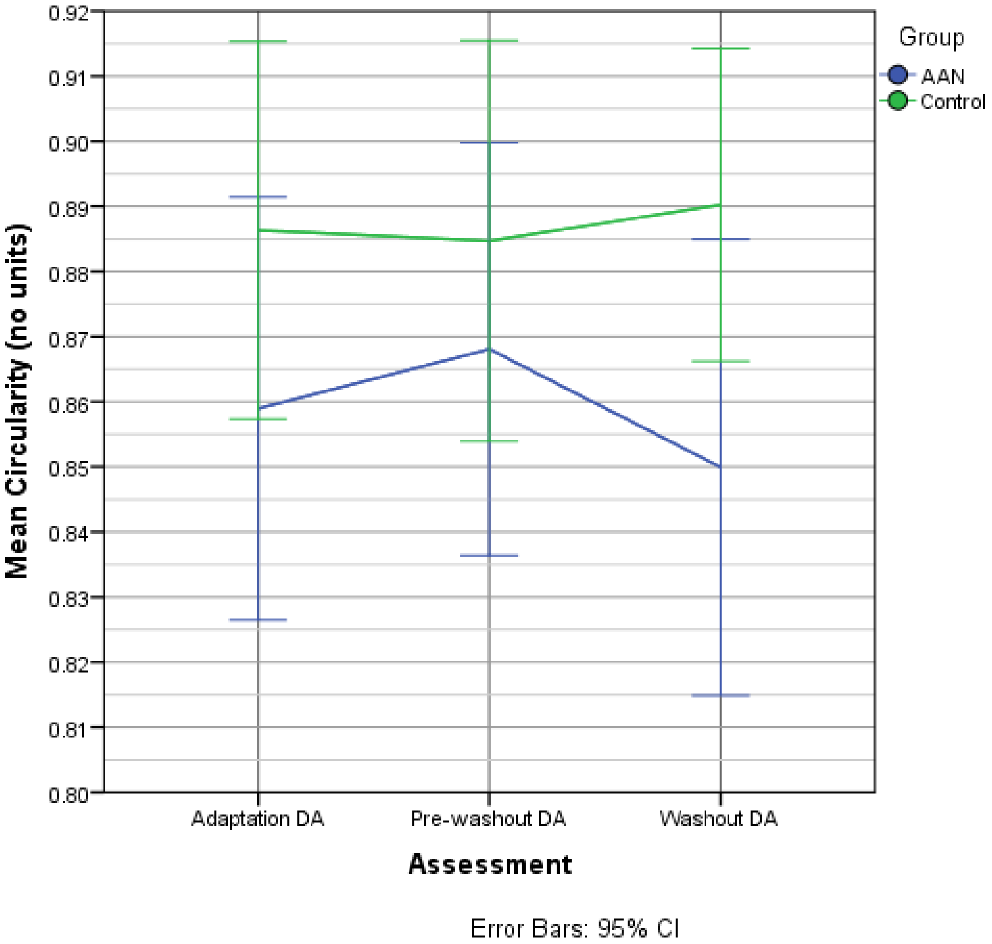


Figure 5-15: Movement circularity over the different assessment blocks on the DA for the AAN and the Control group.

With respect to the duration of the circular movements of the DA (Figure 5-16) the tests of fixed effects showed that there was a statistically significant effect of practice F(2,40.126) =17.852m p<0.005 but also showed there was no statistically significant interaction between HCA group and practice F(2,40.126) =0.590 p<0.005, indicating that both groups behaved similarly throughout the trial. The estimates of fixed effects indicated that movement duration was reduced at the pre-washout assessment when compared to the adaptation assessment by an estimated 8.8s (p<0.005) and that it was reduced even further post-washout as the estimate of the circular movement duration was 9.3s (p<0.005).

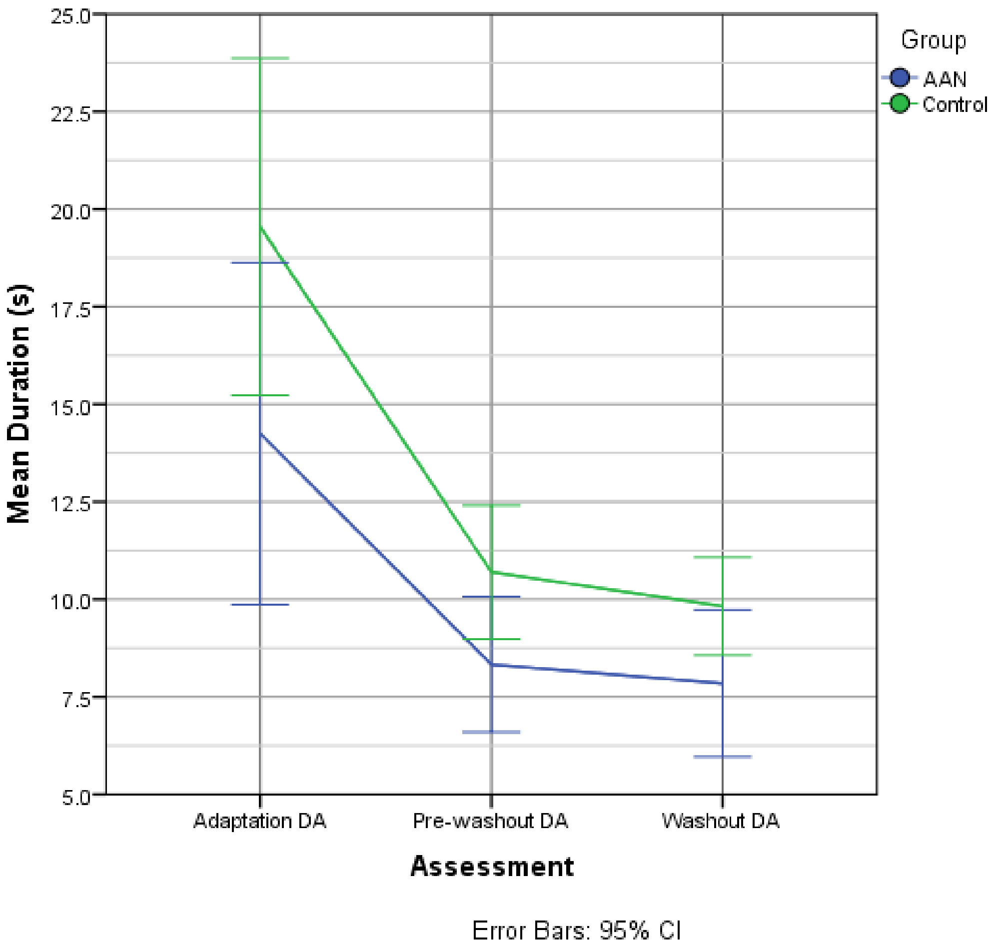


Figure 5-16: Movement duration over the different assessment blocks on the DA for the AAN and the Control group.

Table 5-2: Summary of the findings on the analysis of the effectiveness of the trial on the AAN and Control group for the DA.

Measure	**Learning pre-washout**	**Retention post-washout**	**Improved more pre-washout**	**Retained more post-washout**
Duration	Yes	Yes	Control	Control
Perpendicular error	Yes	Yes	AAN	AAN
Mean velocity	Yes	Yes	Control	Control
Normalised jerk	Yes	Yes	Control	No difference
Initial error	Yes (negligible)	No	No difference	No difference
Circularity	No	No	N/A	N/A
Circular movement duration	Yes	Yes	No difference	No difference

5.4.3 Analysis of the Self-Assessment Manikin questionnaire

Considering the potential psychological effects of the trial at the different stages the participants were asked to complete the SAM questionnaire, where valence, arousal, and dominance were assessed in a scale from one (not at all) to nine (very much so). The tests of fixed effects results indicated that there was no statistically significant effect of practice on valence F(6,62.254) = 1.012, p = 0.426, nor was there a statistically significant interaction between HCA group and practice F(6,62.254) = 1.921, p = 0.091, as shown in Figure 5-17.

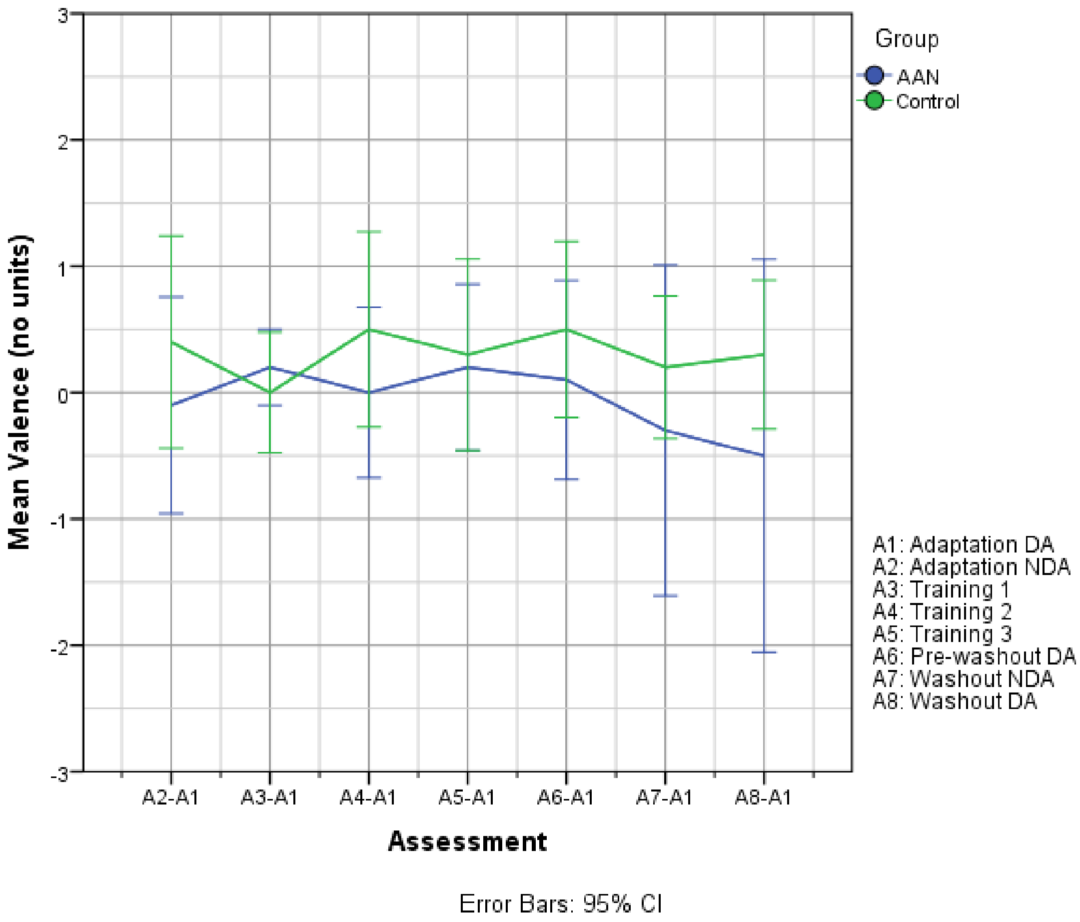


Figure 5-17:Mean change in Valence from the first assessment block (baseline).

The tests of fixed effects showed that there was a statistically significant effect of training on the arousal of the participants F(6,55.658) = 2.723, p <0.05, (Figure 5-18) and a statistically significant interaction between HCA group and practice F(6,55.658) = 2.499, p<0.05. The participants' arousal dropped in the course of the trial for both groups but it reached a mean difference of less than 1 unit (p<0.05). The estimates of fixed effects identified a statistically significant difference between the two groups when comparing the change in arousal the adaptation assessment of the NDA and the post-washout assessment on the NDA where the AAN group showed a higher arousal by an estimated 1 unit (p<0.05). However, as no other difference between the groups was identified this difference can be attributed a random occurrence rather an effect of HCA group.

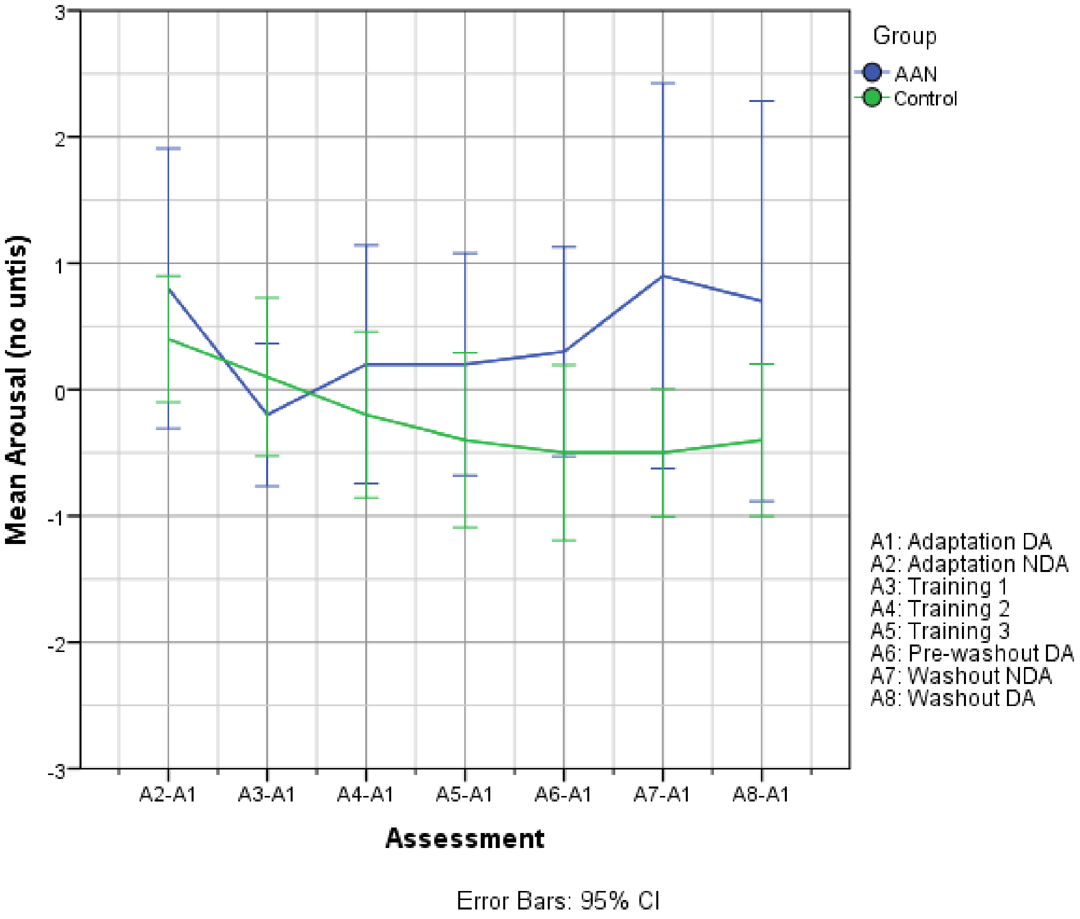


Figure 5-18: Mean change in Arousal from the first assessment block (baseline).

The tests of fixed effects showed a statistically significant effect of practice F(6,57.181) =5.871, $p<0.005$ on the participant's dominance (Figure 5-19) but failed to identify a statistically significant interaction between HCA group and practice F(6,57.181) =1.593, p=1.66. The participants appear to have been feeling more in control in the pre-washout part of the trial. More specifically, dominance increased by an estimate of 0.6 units ($p<0.05$) in the adaptation assessment of the NDA and at the training stages the increase fluctuated between 0.8 and 0.9 units ($p<0.05$). In the post-washout assessment, the participants felt less in control (reduced dominance) as there was no statistically significant difference between the assessment following the adaptation on the NDA block and the post-washout assessment on the NDA (p=0.153). Finally, dominance increased in the final assessment (post-washout on the DA) by 0.9 units ($p<0.05$) when compared to the adaptation on the NDA assessment.

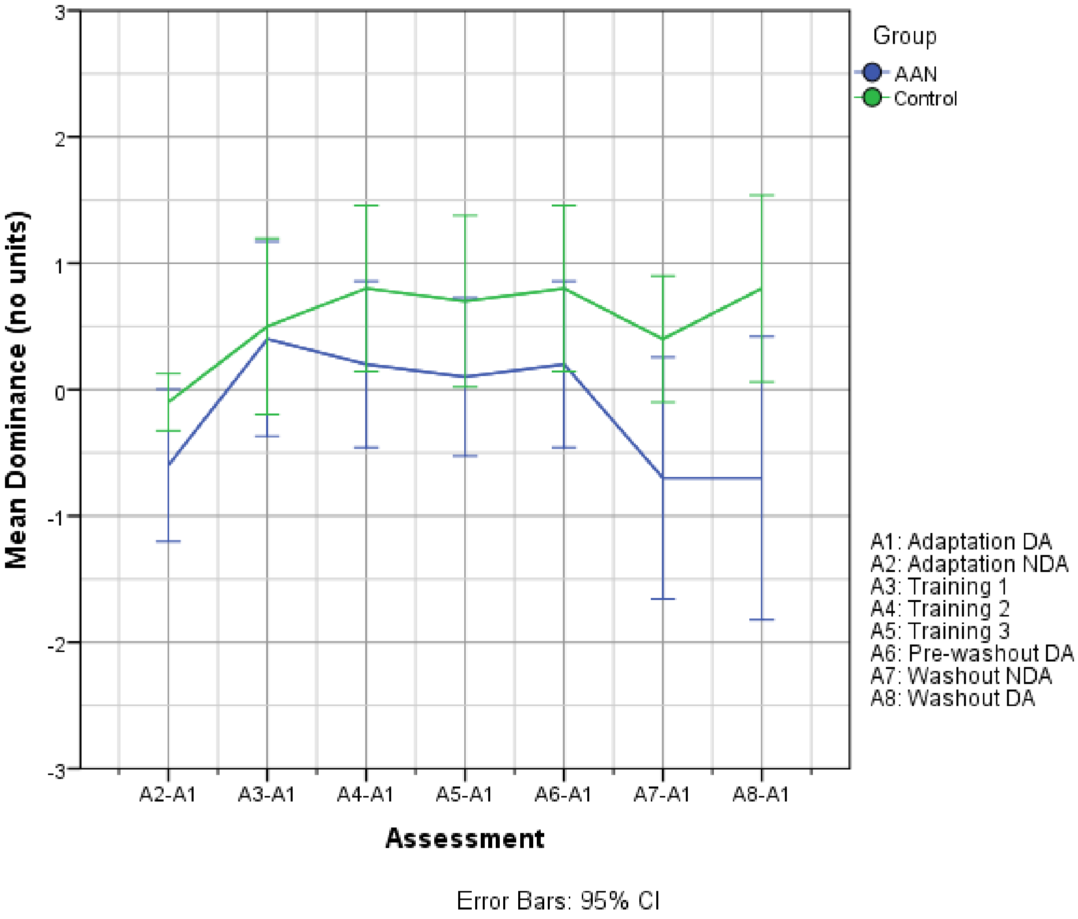


Figure 5-19: Mean difference in Dominance from the first assessment block (baseline).

Table 5-3: Summary of the findings on the analysis of the effectiveness of the trial on the AAN and Control group for the SAM questionnaire

Measure	**Effect of practice**	**Difference between the groups?**
Valence	No	No
Arousal	Yes (↓)	Yes
Dominance	Yes (↑)	No

5.5 Discussion

The kinematic analysis of the reaching movements using the NDA indicated an interesting pattern for both groups. The values of all measures improved (e.g. reduced error/movement duration, increased mean velocity) throughout the different training blocks with the only exception being initial error which appears to be unaffected by the trial. This gradual improvement in all measures across the different training blocks indicated that motor learning occurred throughout the training part of the trial. Nevertheless, it must be noted that the most dramatic change in all measures that showed improvement, occurred after the first training block while in the subsequent training blocks changes were subtler. The latter finding indicated that most of the learning occurred in the first training block while in the subsequent training blocks the fine tuning took place. When comparing the effect of the groups had on motor learning, the Control group appears to have performed better than the AAN group. More specifically, the Control group improved more in the reaching movement duration, mean velocity and normalised jerk from the baseline assessment, while on the other measures no difference was identified between the two groups.

Likewise, after the washout block most kinematic measures deteriorated slightly or remained at the same levels as pre-washout. Nevertheless, none of the measures returned to pre-training levels indicating retention of the learned task a direct result of the exercise the participants received with the only exception being the perpendicular error which reverted back to the adaptation levels. The Control group retained a greater difference from the adaptation assessment in its movements’ duration, mean velocity and normalised jerk, than the AAN group did. In all other measures, namely perpendicular error and initial error both groups behaved similarly.

When considering the circle-drawing task movements showed high circularity from the beginning of the session before any practice was undertaken and did not change in terms of circularity throughout the trial. This can be partly explained by the fact that the participants were healthy and hence they did not experience abnormal muscle synergies, something that would affect circular movements. Furthermore, the circle-drawing task requires symmetrical movements around the centre of the workspace and as such it is likely that the participants choose to ignore the visual feedback and perform the movement based solely on proprioception. If this is indeed the case, then the visual rotation would have no impact in in making the task performed more challenging.

This is further supported by the finding that although movement duration was reduced after training block 1 for both groups it remained at the same levels throughout the rest of the assessment blocks and more importantly the washout phase. The latter provides a clear indication that the de-adaptation phase (washout) did not have any effect on the circularity of the movements in the circle drawing task and subsequently the visual rotation did not affect the way the participants performed the circular movements.

From the findings of the kinematic analysis of the participants NDA movements it can be derived that although both groups learned how to perform the reaching task under the visual rotation, unassisted movements were equal or better at inducing motor learning than the AAN algorithm did as indicated by the more improved kinematic measures of the Control group. The outcome of the analysis falls in line with other studies (Kahn et al., 2006; Kadivar, Sung, et al., 2011) that have shown that given the same amount of training assistive and unassisted movements have comparable effects on motor learning as demonstrated by the improvement in kinematic parameters, with unassisted movements having a small added benefit in improving certain kinematic parameters such as movement smoothness (Kahn et al., 2006).

By analysing the kinematic measures collected during the assessments on the participant's DA that did not receive any training but only performed three assessment blocks (pre-training, post-training, post-washout), the level of bilateral transfer of motor learning could be evaluated. Regarding the measures collected on the reaching task a clear pattern formed across all the kinematic measures assessed with the only exception being initial error which remained at the same levels throughout the trial. There was a significant improvement on the post-training assessment that was retained after the washout block. The AAN group showed a greater improvement and retention of the movement accuracy while the Control group resulted in more improved duration, velocity and smoothness. When comparing retention between the two groups, the AAN showed a greater difference in the perpendicular error between the adaptation and washout assessments while the Control group retained more of its mean velocity. Both groups performed similarly in all the other measures.

Additionally, when comparing the participants' performance on the circle-drawing task across the different assessment blocks there was no difference throughout the trial in terms of movement circularity. However, there was an improvement after the training block in movement duration that, as with the NDA, was retained after the washout block. This may be due to the same reasons that caused a similar behaviour in the NDA during this particular task i.e. the performance of this particular task was not affected by the visual rotation.

From the analysis of the findings it can be derived that passive movements had a better impact on inducing bilateral transfer from the NDA to the DA as reflected by most kinematic measures while the AAN had a comparable effect. The findings of the analysis indicate that increased effort results in increased bilateral transfer. This is further supported by the findings of the study by (Park et al., 2012) which showed that an adaptive assistive algorithm that would provide assistance as needed had a greater effect on bilateral transfer from its non-adaptive equivalent. The implications of the findings of this study for the impaired population are great as they further support the existing evidence that bilateral transfer can occur between the healthy and impaired arms and as such by practising movements with the healthy arm can transfer learning to the impaired.

Another aspect of the assessment was a psychological test in the form of a questionnaire assessing participant’s valence, arousal and dominance throughout the assessment blocks. The results showed that the participants did not change their valence levels throughout the trial for both groups, as such the trial and training did not affect how happy the participants were. On the other hand, the statistical analysis indicated that both groups became less aroused in the course of the trial. This could be attributed to mental fatigue due to the repetitive nature of the trial task. Nevertheless, the mean difference in arousal that was observed was very small never exceeding 1 unit.

The participants’ dominance increased in the training part of the trial for both groups indicating that the more the participants practised the more in control they felt. Interestingly in the first of the post-washout assessments (washout NDA) both groups reported a drop in their dominance which in the subsequent assessment returned to the elevated pre-washout levels. This drop in dominance could be an effect of the washout block which may have disrupted the participants’ confidence that was built up in the training blocks. This explanation also falls in line with the increased dominance in the second post-washout assessment where the participants after experiencing a more “familiar” environment for their movements in the washout assessment on the NDA felt again in control.

5.6 Summary

Some key findings of the analysis can be found below:

- Both interventions (group training conditions) led to a) improvement in the participants’ movements of the NDA in all parameters pre-washout and b) retention of improvements post-washout except for perpendicular error, initial error and circularity.
- AAN was less effective on improving and retaining movement duration, mean velocity.
- Reaching tasks and bilateral transfer led to similar patterns of improvement except for perpendicular error where AAN was more effective in improving and retaining the improvements in this measure.
- Bilateral transfer appears unaffected by washout.
- There was no effect of practice type on the changes of the psychological state of the participants.

6 Investigating the effects of Error Augmentation Adaptive control on motor learning

6.1 Introduction

The main aim of this chapter is to investigate the effect on motor learning of the EAA utilising the data acquired in the investigatory trial of this project (Chapter 4.3). To do so the group that practised with EAA in the investigatory trial is compared against a Control group that undertook the same amount of practice but without any forces being applied to the participants' arm from the rehabilitation robot. The findings of the analysis are meant to serve as preliminary evaluation that will inform a later trial with the participation of the impaired which is a common and recommended practice amongst relevant studies (Dobkin, 2009). This chapter firstly presents the reader with the configuration of the EAA that was used in the trial followed by the research question the analysis set out to answer. Finally, the findings of the analysis are presented and discussed in the context of the research questions.

6.2 The Error Augmentation Adaptive Algorithm

In Section 3.3.3 the software implementation of the EAA was presented. By adjusting parameters within the system the desired behaviour was achieved. There are three possible areas of adjustment within the software namely, a) the direction of the forces, b) the method of adaptation and c) the maximum permissible current. The selection of these settings was informed by trial and error as well as by consulting experienced physiotherapists. It must be noted that the settings were adjusted to be suitable for able-bodied users and in the case the system is used by the impaired they should be adjusted accordingly.

The final settings of the EAA were set as follows:

a) The direction of the forces was set in the perpendicular direction away from the desired trajectory.

b) Maximum Permissible Current was set to 2A to achieve a maximum permissible force of approximately 5N.

c) The method adaptation was set to be adaptation in infinite zones as set by Equation (19) where $\alpha W = 1.63$ mm and $\beta = -1$. The minimum allowable width was set to be 3.3 mm and the maximum allowable width of was set at 228 mm.

An example of the configuration of the EAA is provided in Figure 6-1.

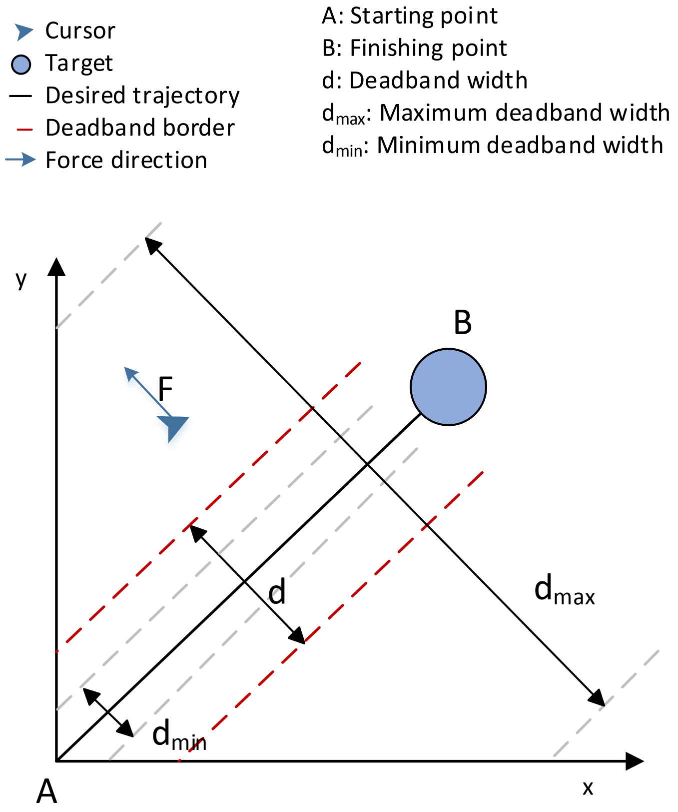


Figure 6-1: The EAA as it was implemented for the trial on able bodied participants.

6.3 Research questions

The questions that this analysis set out to answer are presented below:

1) Does the EAA affect motor learning and retention of learning on the upper limb of the able-bodied adults? If yes, what is its effect?
2) How does the effect of EAA compare to the participants' performance if the same amount of practice was received without any forces being applied by the rehabilitation robot?
3) Is bilateral transfer affected by the conditions of practice (EAA vs passive movements)?
4) Does practice with the EAA have an effect on the psychological state of the participants and if so how much of that can just be attributed to the exercise?

6.4 Results of the statistical analysis

6.4.1 Analysis of the kinematic measures for the non-dominant arm

In total five assessment blocks were performed using the NDA. One assessment was undertaken before any exercise was received (baseline assessment), followed by three assessment blocks, one after each training block, and finally an assessment block that followed the washout block. According to the results of the previous trials, it was expected that performance in terms of kinematic measures would improve throughout the trial after the baseline assessment, until the washout block after which performance was expected to deteriorate but not to return pre-exercise levels. More detailed description about the measures used and analysis performed can be found in Section 4.3.

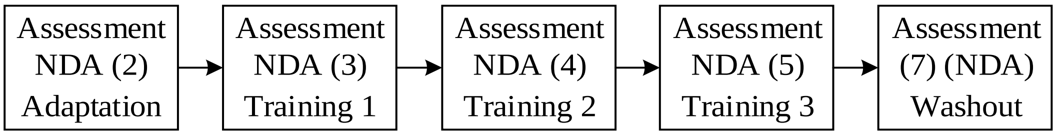


Figure 6-2: The assessments on the NDA.

6.4.1.1 ***Results for the reaching task on the non-dominant arm***

When considering the movement duration (Figure 6-3) of the NDA in reaching movements of the NDA the tests of fixed effects showed that there was a statistically significant effect of practice in the duration of movements, F(4,1157.583) = 38.753, $p < 0.005$. Also the tests of fixed effects showed a significant interaction between HCA group and practice F(4,1157.583) =12.288, $p<0.005$. However, the estimates of fixed effects for the interaction between the two groups showed that only in the washout assessment there was a statistically significant difference between the two groups where the Control group achieved a greater difference of 0.2 mm ($p<0.005$) between the adaptation and the washout assessment. This is an indication of the Control group retained more the improved duration post-washout than the EAA group did.

With regard to the effects of practice in movement duration both groups behaved similarly in the training stage of the trial. The estimates of fixed effects showed that the maximum improvement occurred after training block 3 where the movements lasted for an estimated 1.13s ($p<0.005$) less when compared to the adaptation assessment. Post-washout the duration was increased when compared the pre-washout levels with an estimated difference of 0.1s ($p<0.05$) for the EAA group and 0.3s ($p<0.05$) for the Control group indicating that the control retained more of the improved duration of its movements post-washout.

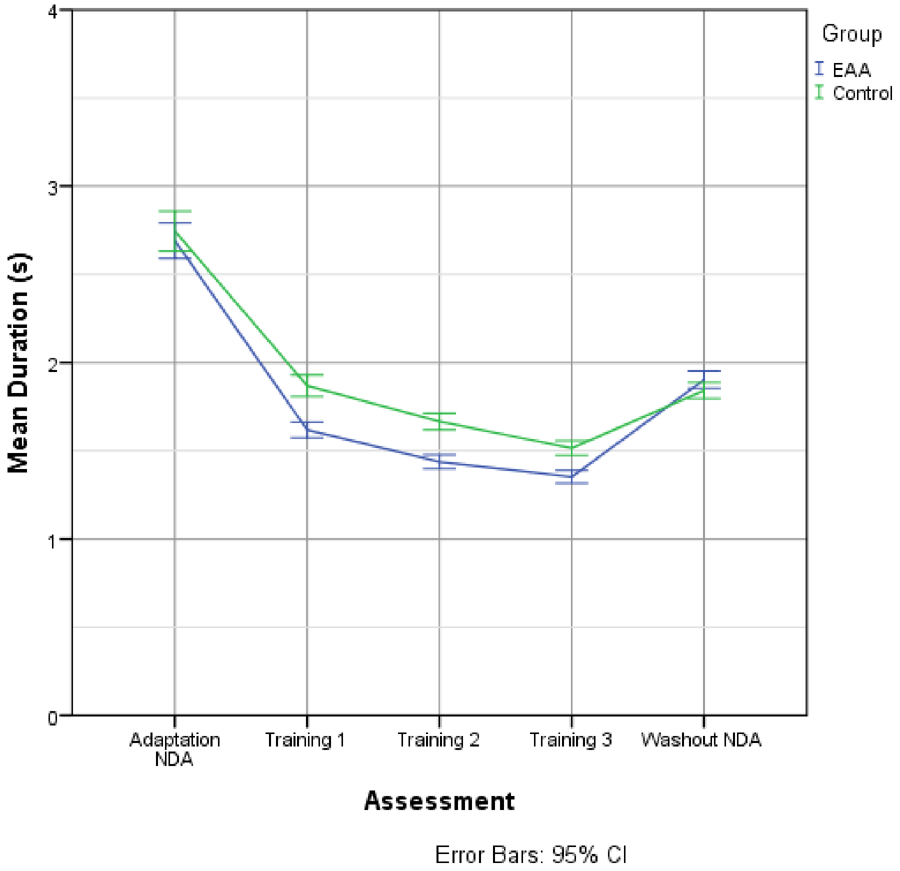


Figure 6-3: Mean duration over the different assessment blocks on the NDA for the EAA and the Control group.

There was a statistically significant effect of practice on movement error (Figure 6-4) as indicated by the tests of fixed effects F(4,1075.187) = 288.935, p<0.005. Moreover, perpendicular error in the participants' movements changed in the same manner for both groups as there was no statistically significant interaction between HCA group and practice F(4,1075.187) =0.580, p=0.677. By consulting the estimates of fixed effects, it can be derived that perpendicular error was reduced throughout the training blocks reaching a maximum difference of 3.9 mm (p<0.005) from the adaptation levels after training block 3.

At the washout assessment perpendicular error increased to levels similar to the adaptation assessment. This is indicated by the estimates of fixed effects that failed to identify a statistically significant difference (p=0.178) between the adaptation and post-washout assessment in terms of the perpendicular error. To summarise both groups behaved similarly throughout the trial with respect to the perpendicular error of their movements. Perpendicular error reduced throughout the training blocks of the trial indicating that learning did indeed occur. However, after the washout block error increased and reached values comparable to those achieved before any training had been undertaken indicating a complete washout.

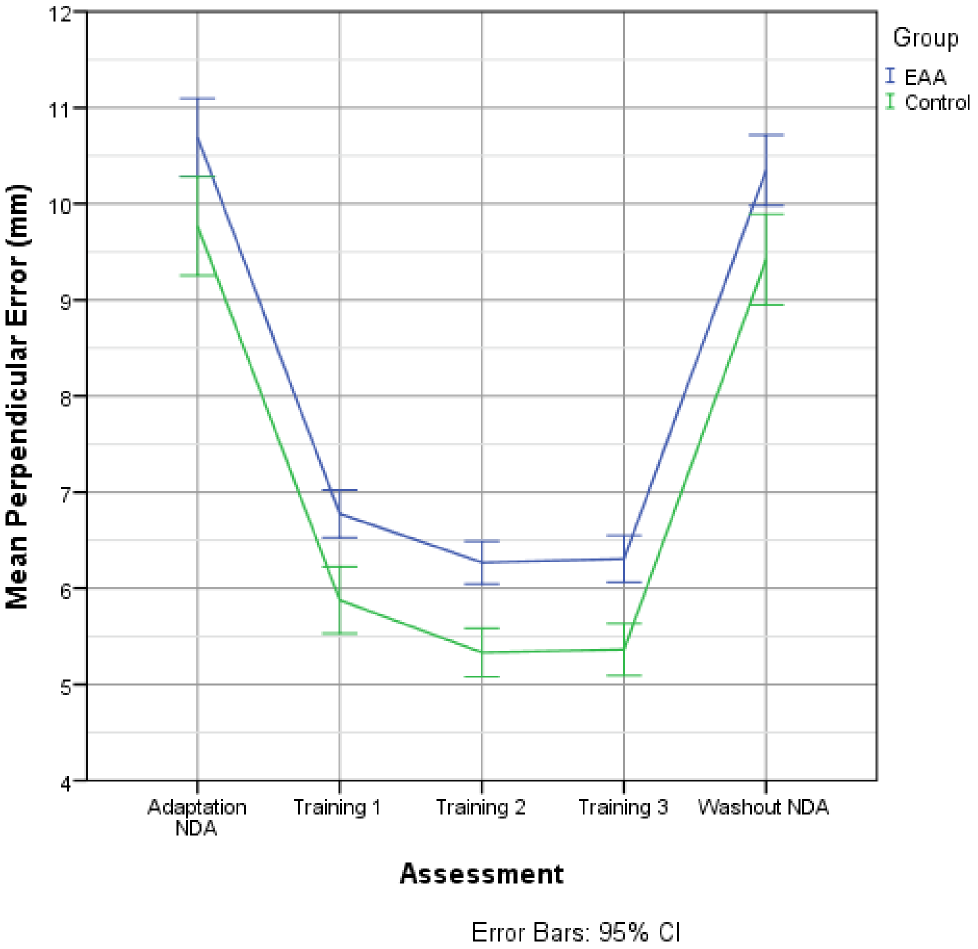


Figure 6-4: Mean perpendicular error over the different assessment blocks on the NDA for the EAA and the Control group.

There was a significant effect of practice on the mean velocity F(4,1511.340)=298.312, p<0.005 of the reaching movement as indicated by the tests of fixed effects (Figure 6-5). Furthermore, the same tests showed a statistically significant interaction between HCA group and practice F(4,1511,340)=22.6, p<0.005. More specifically, both groups increased the mean velocity of their movements throughout the training part of the trial with the EAA group increasing its mean velocity by 26.9 mm/s (p<0.005) after training block 3 when compared to the adaptation assessment. The Control group also increased the mean velocity of the reaching movements by an estimate of 18.4 mm/s also after training block 3.

From the estimates of fixed effects, it can be seen that the EAA showed a greater change in mean velocity, when compared to the adaptation levels, than the Control group did throughout the trial reaching a maximum difference of 8.5 mm/s after training block 3. ($p<0.005$). Post-washout both groups reduced their mean velocity when compared to the pre-washout levels with a mean difference in mean velocity pre and post washout of 16.0 mm/s ($p<0.005$) for the EAA and 5.0 mm/s ($p<0.005$) for the Control group. As such, although the EAA improved more in terms of the mean velocity in the training blocks of the trial, the Control group retained more of the improved mean velocity post-washout.

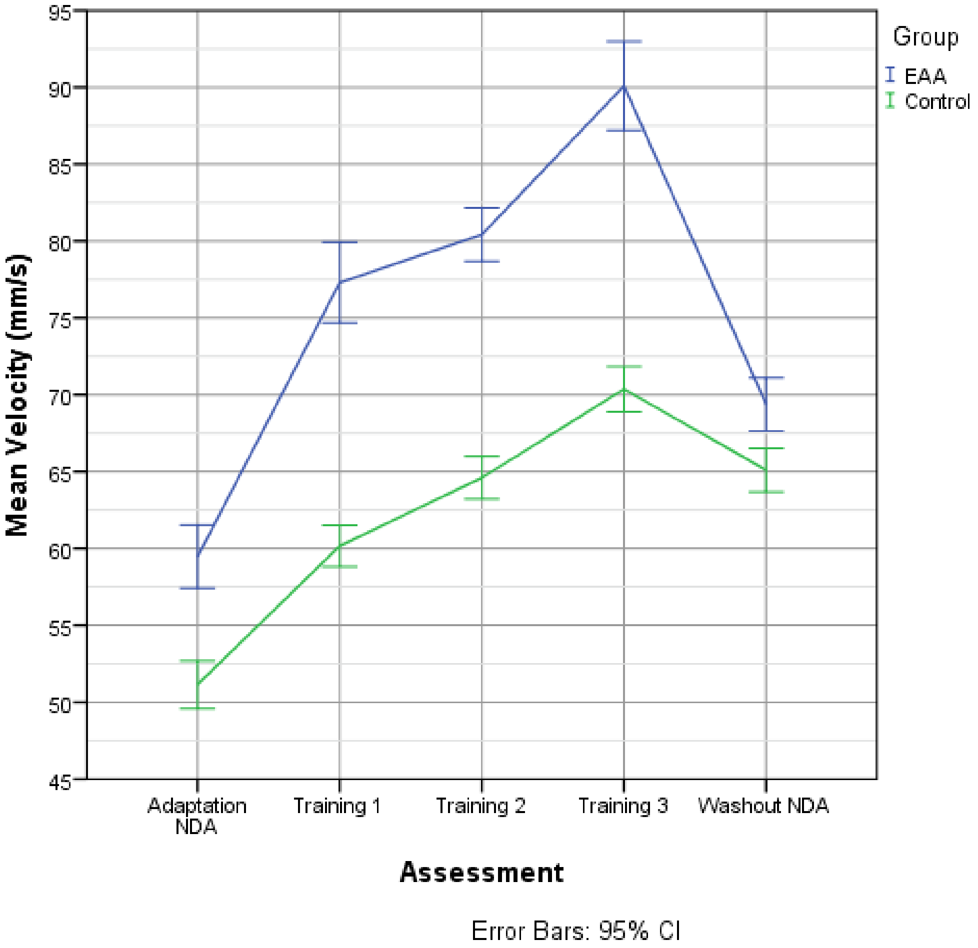


Figure 6-5: Mean velocity over the different assessment blocks on the NDA for the EAA and the Control group.

The tests of fixed effects showed that there was a statistically significant effect of practice on the normalised jerk (Figure 6-6) of the reaching movements F(4.492.668)=129.541, $p<0.005$ and also that there was a statistically significant interaction between HCA group and practice F(4,432.668)=11.331, p<0.005. Both groups started with high normalised jerk at the adaptation stage that was substantially reduced after training block 1 (by 5.72 units, p<0.005 for the EAA and by 7.160 units for the Control group). The EAA group reached a plateau after training block 2 as the estimates of fixed effects did not show a significant difference between training blocks 2 and 3 (p=1.000) but the Control group improved throughout the training stage of the trial (p<0.005). The estimates of fixed effects showed that the Control group reduced normalised jerk by 2.6 units (p<0.05) more than the EAA group did during the training part of the trial. As such, the Control group demonstrated smoother movements than the EAA did, at training block 3 when compared to the adaptation assessment.

Nevertheless, this bigger improvement may be due to the Control group demonstrating much higher normalised jerk (2.5 units, p<0.05) in their movements during the adaptation assessment than the EAA group did. This is further supported by the estimated marginal means that failed to identify any difference between the two groups in the assessments after training blocks 2-3 (p>0.1). Nevertheless, it must be noted the same estimates showed a marginally statistically insignificant difference between the groups at the assessment after training block 3 where the estimate for normalised jerk for the Control group was a 2.5 units lower (p=0.052) than the same estimate for the EAA group which suggest although both groups reached the same levels of improvement eventually the Control group improved faster than the EAA group.

Post-washout both groups performed less smooth movements when compared to the pre-washout assessment as they increased their normalised jerk by an average of 1.5 units (p<0.005) for the EAA group and 0.9 units (p<0.005) for the Control group between the pre- and post-washout assessments. As such, it appears that the Control group retained more of the improved smoothness post-washout than the EAA did. Nonetheless, both groups demonstrated comparably improved smoothness when compared to the adaptation assessment.

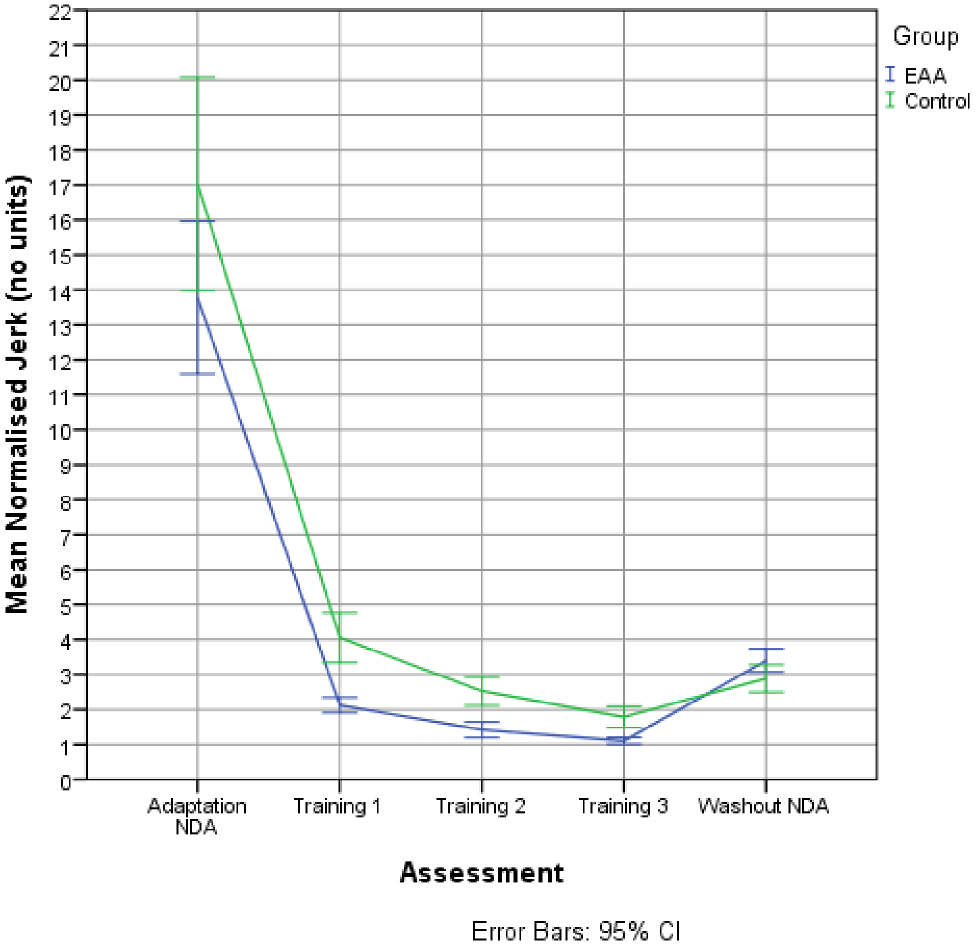


Figure 6-6: Normalised jerk over the different assessment blocks on the NDA for the EAA and the Control group.

The tests of fixed effects showed that there was a marginally non statistically significant effect of practice on initial error F(4,1729.949) =2.354, p=0.052 and also that there was no statistically significant interaction between HCA group and practice F(4,1729.949) =0.547, p=0.701 (Figure 6-7). The estimates of fixed effects showed a similar pattern with initial error having no significant difference at any block of the trial (p>0.05) with the only exception being a statistically significant difference between the adaptation assessment and the assessment after training block 2 where initial error was increased by 0.29 mm (p<0.05. Nevertheless, this is probably a false significant result as the estimated marginal means failed to identify the same effect (p>0.05). As such, it appears that initial error of the reaching movements of both groups was not affected by practice or by the HCA group the participants were assigned to.

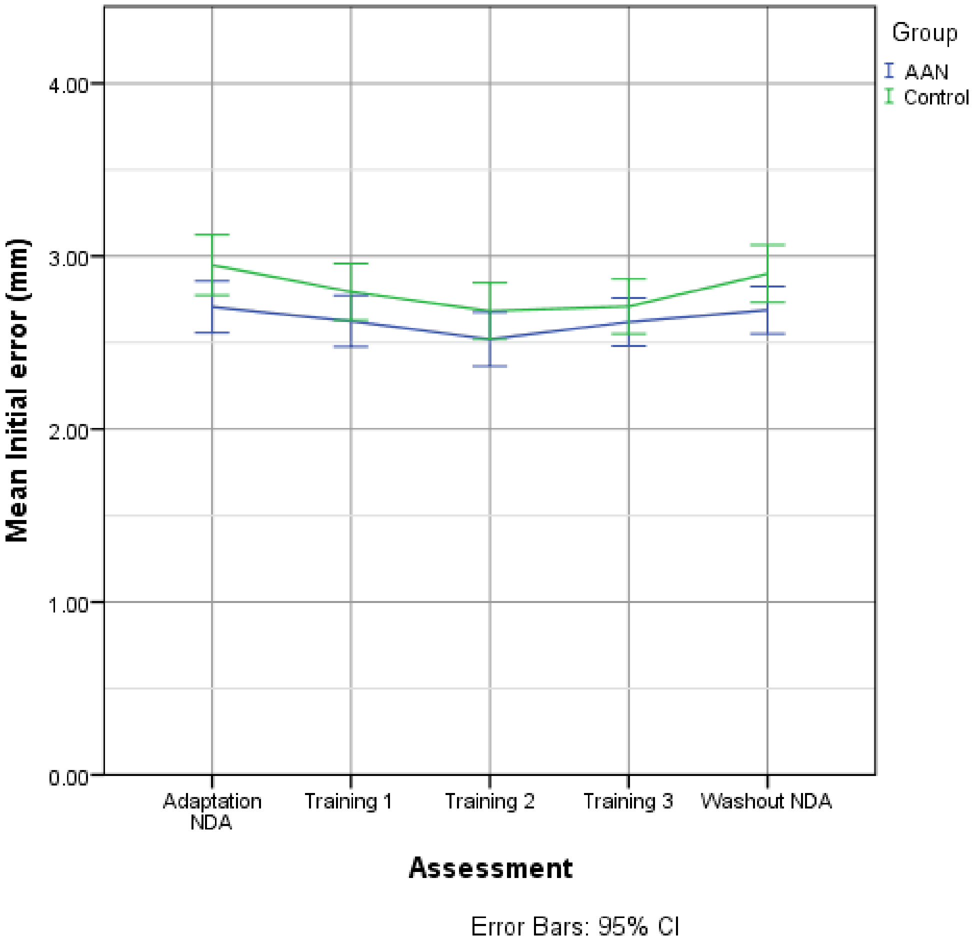


Figure 6-7: Initial error over the different assessment blocks on the NDA for the EAA and the Control group.

6.4.1.2 ***Results of the circle-drawing task for the non-dominant arm***

The tests of fixed effects showed that there was no statistically significant effect of practice F(4,46.643) =2.124, p = 0.093 on the circularity of the participants' movements and that there was no statistically significant interaction between HCA group and practice F(4,46.643) =0.164, p=0.956. As such, the circularity of the movements was unchanged throughout the trial and both groups performed similarly circular movements (Figure 6-8).

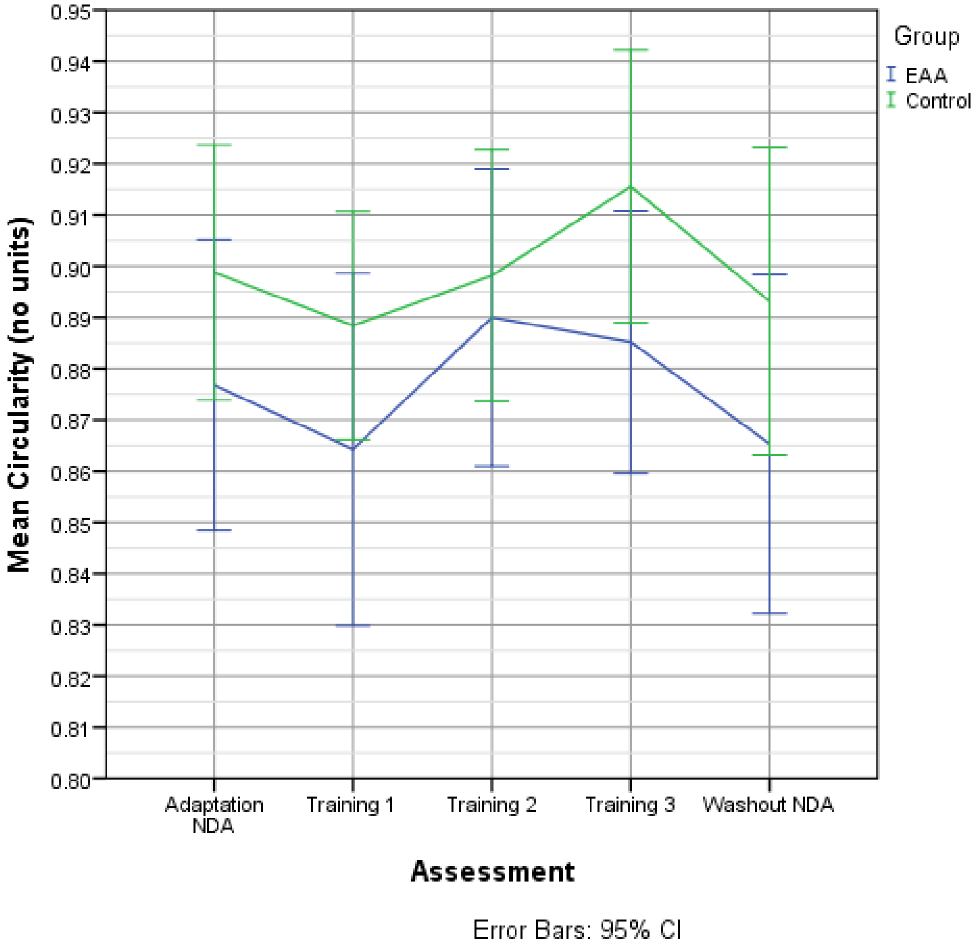


Figure 6-8: Movement circularity over the different assessment blocks on the NDA for the EAA and the Control group.

There was a statistically significant effect of practice F(4,43.719) = 9.049, $p<0.005$ on the duration of participants' circular movements (Figure 6-9) as indicated by the test of fixed effects. The same tests failed to identify a statistically significant interaction between HCA group and practice indicating that both groups behaved in a similar manner in relation to the duration of the circular movements. The estimates of fixed effects showed that movements became increasingly shortened in duration throughout the different assessment blocks of the trial (including the washout) reaching a maximum difference, when compared to the adaptation levels, of 4.2 s ($p<0.005$) at the washout assessment. This is an indication that the duration of the circular movements by the washout was unaffected by the washout block.

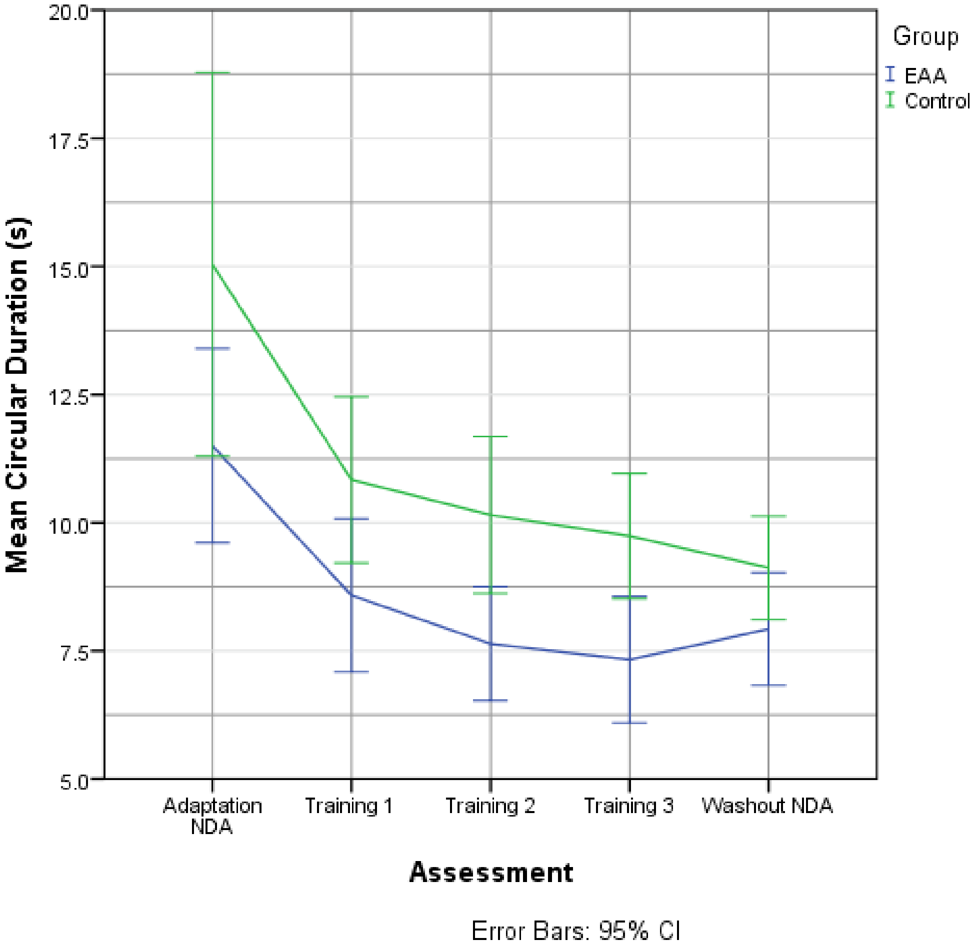


Figure 6-9: Movement duration for the circle drawing task over the different assessment blocks on the NDA for the EAA and the Control group.

Table 6-1:Summary of the findings on the analysis of the effectiveness of the trial on the EAA and Control group for the NDA.

Measure	**Learning pre-washout**	**Retention post-washout**	**Improved more pre-washout**	**Retained more post-washout**
Duration	Yes	Yes	No difference	Control
Perpendicular error	Yes	No	No difference	No difference
Mean velocity	Yes	Yes	EAA	Control
Normalised jerk	Yes	Yes	Control	Control
Initial error	No	No	No difference	No difference
Circularity	No	No	No difference	No difference
Circular movement duration	Yes	Yes	No difference	No difference

6.4.2 Analysis of the kinematic measures for the dominant arm

The DA did not receive exercise during the training of the washout blocks. However, three assessment blocks were undertaken using the DA, one at the beginning of the session, one before the washout block and finally one at the end of the trial. It was hypothesized that if interhemispheric transfer did indeed occur then performance would be improved between in the pre-training assessment and the pre-washout assessment. Furthermore, if retention did occur there would be a deterioration of the different measures when compared to the pre-washout assessment levels but would still remain improved with regards to the adaptation levels.

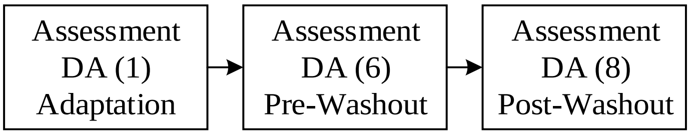


Figure 6-10: The assessments on the DA.

6.4.2.1 ***Results for the reaching task on the dominant arm***

Movement duration (Figure 6-11) of the DA has changed significantly for both groups in the course of the trial and also this change was different between the two groups as the tests of fixed effects showed a statistically significant effect of practice in movement duration F(2,775.828), p<0.005 and a significant interaction between HCA group and assessment F(2,775.818)=14.256, p<0.005. The estimates of fixed effects showed that both groups reduced duration of the movements in the pre-washout assessment (p<0.005) however the Control group reduced it by 0.45s (p<0.005) more than the EAA did. Post-washout, duration increased slightly when compared to the pre-washout assessment (0.08s for the EAA group and 0.04s for the Control group, p<0.05) indicating that movement duration achieved at the pre-washout level was almost completely retained.

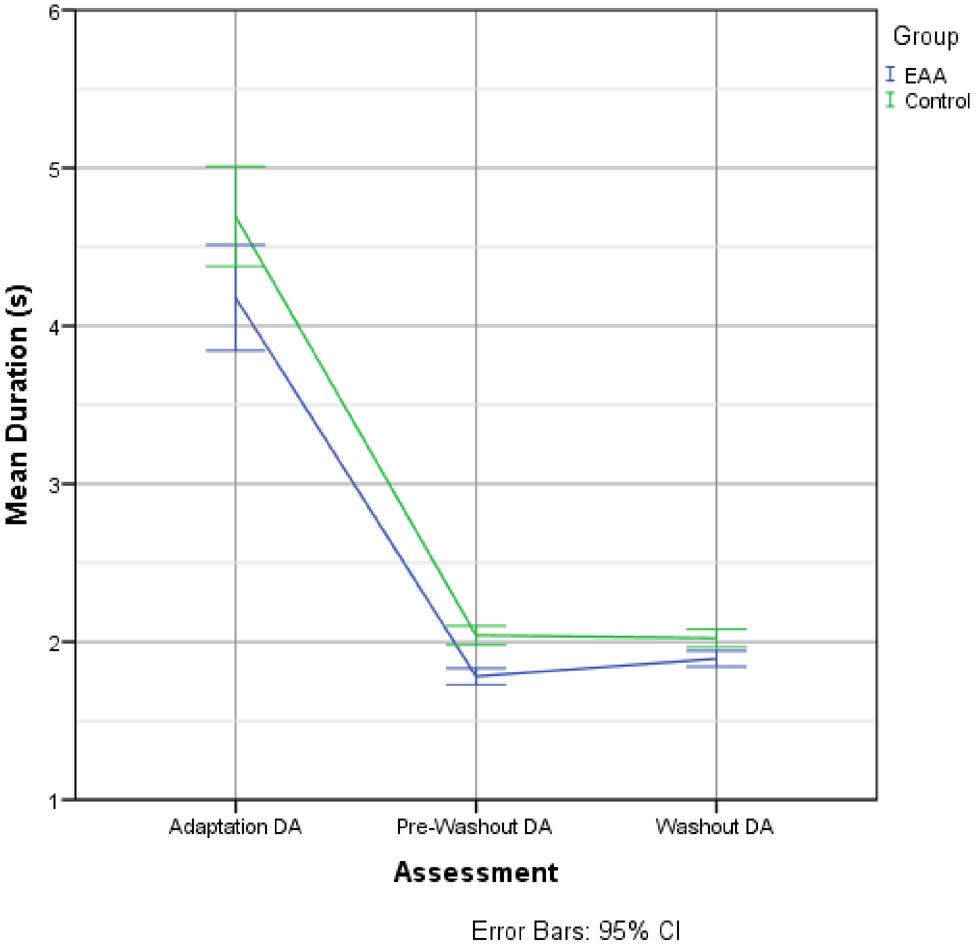


Figure 6-11: Mean duration over the different assessment blocks on the DA for the EAA and the Control group.

The tests of fixed effects showed a statistically significant effect of practice on the perpendicular error of the reaching movements F(2,1152.053) =121.181, $p<0.005$ and also that there was a statistically significant interaction between HCA group and practice F(2,1152.053) =5.983, $p<0.005$. Both groups reduced the perpendicular error (Figure 6-12) of their movements reaching a mean difference from adaptation of 3 mm for the Control group and 3.5mm for the EAA group. However, the estimates of fixed effects did not show a statistically significant difference (p=0.598) on how the error changed for the two groups between the adaptation and the pre-washout assessment.

Post-washout perpendicular error remained at the same levels as it did pre-washout for the Control group as the estimate marginal means showed a non-significant difference (p=0.231) indicating complete retention of that improved error. Interestingly, the EAA group reduced the perpendicular error even further at the post-washout assessment by an estimate of 0.7 mm (p<0.05).

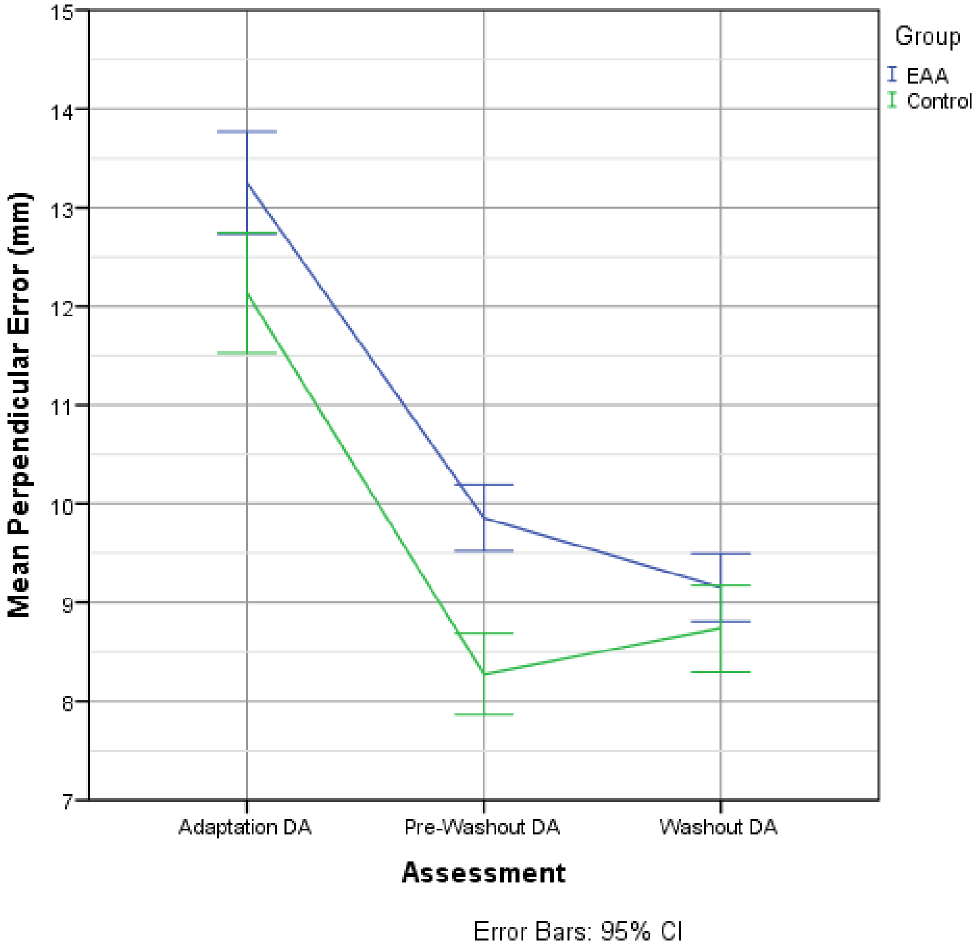


Figure 6-12: Mean perpendicular error over the different assessment blocks on the DA for the EAA and the Control group.

With respect to the mean velocity of the participants' reaching movements (Figure 6-13), the tests of fixed effects showed that there was a statistically significant effect of practice F(2,1319.598)=553.582, p<0.05 and that there was a significant interaction between HCA group and practice F(2,1319.598)=13.117, p<0.05.

When compared to the adaptation assessment mean velocity for both groups increased at the pre-washout assessment (mean difference, 21.0 mm/s, p<0.005 for the EAA group and 16.4 mm/s for the Control group). Nevertheless, the estimates of fixed effects showed that the EAA group improved more than the Control group did by 5.0 mm/s (p<0.005) when comparing the difference in mean velocity between the pre-washout and the adaptation assessments. Post-washout, mean velocity was reduced for the EAA group when compared to the pre-washout block by an estimated 16.0 mm/s, p<0.005, while it remained the same for the Control group as there was no statistically significant difference between the pre and post-washout assessments (p=0.533).

To summarise, although both groups increased the mean velocity of their movements in the pre-washout assessment, the EAA showed a greater improvement. When it comes to the washout assessment, the Control group fully retained the mean velocity of the movements demonstrated at the pre-washout assessment while the EAA group only partially retained that improved velocity as the mean velocity of their movements was reduced but it remained significantly improved when compared to the adaptation assessment.

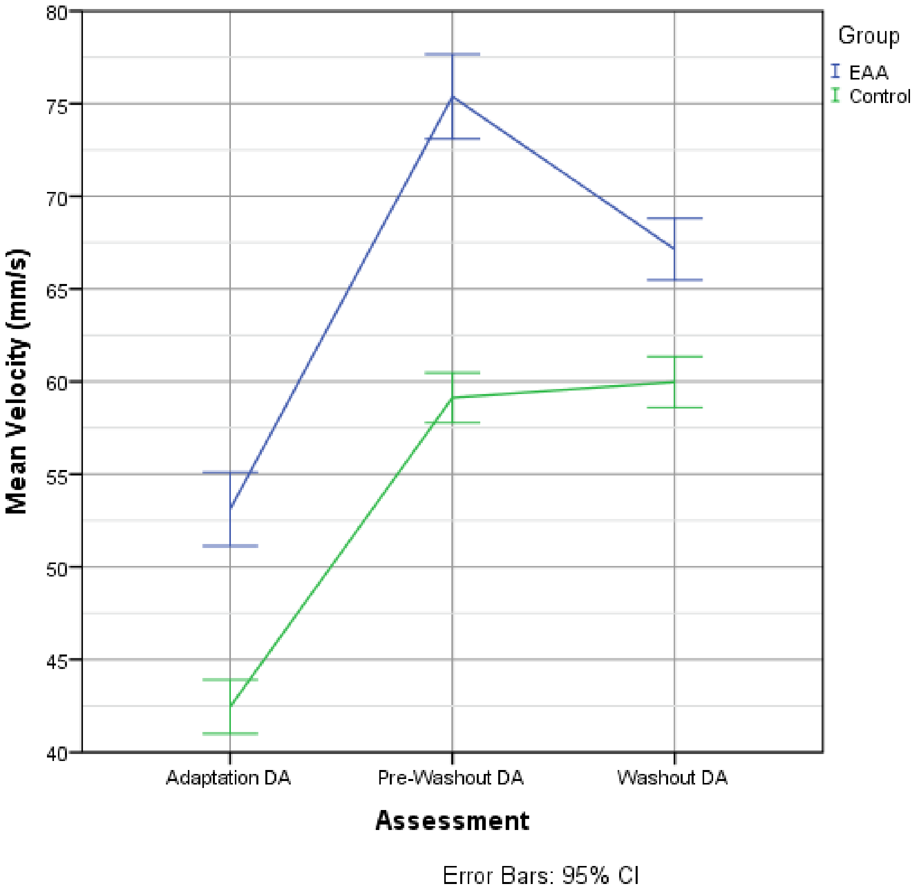


Figure 6-13: Mean velocity over the different assessment blocks on the DA for the EAA and the Control group.

The tests of fixed effects for normalised jerk (Figure 6-14) showed that there was a statistically significant effect of practice F(2,352.911) =13.471, p<0.005 and also that there was a significant effect of HCA group and practice F(2,352.911) =13.053, p<0.005. Both groups reduced normalised jerk during the washout block with a mean difference from the adaptation assessment of 14.7 units (p<0.005) for the EAA and 25.2 units (p<0.005) for the Control group. As indicated by the estimates of fixed effects the Control group improved by 10.5 (p<0.005) units more than the EAA group did when comparing the pre-washout assessment with the adaptation assessment.

Post-washout normalised jerk remained the same for the Control group as there was no statistically significant difference in the normalised jerk of the participants' movements pre- and post-washout. On the other hand, the EAA group increased the mean velocity of its movements by a mere 0.4 units (p<0.05) post-washout. As such, it is safe to conclude that both groups retained fully the improved smoothness even after the washout block.

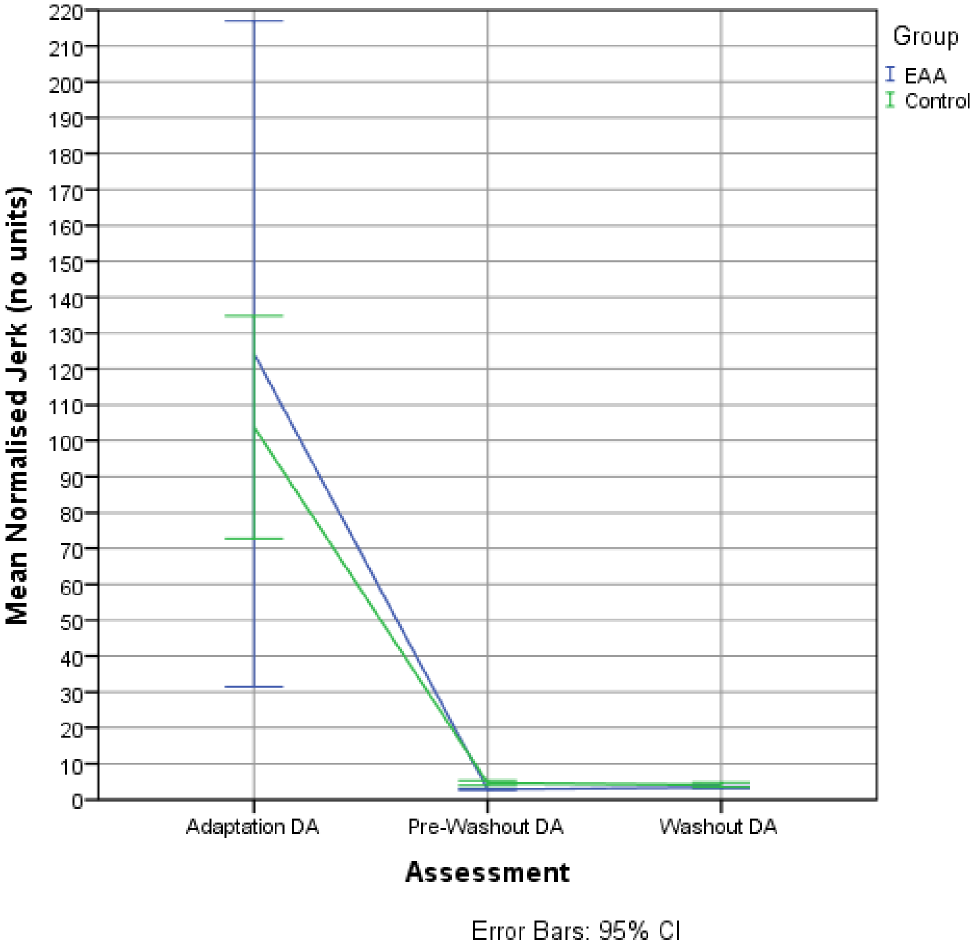


Figure 6-14: Normalised jerk over the different assessment blocks on the DA for the EAA and the Control group.

Regarding initial movement error (Figure 6-15), the tests of fixed effects indicated a statistically significant effect of practice F(1657.903) =11.643, p<0.005 but failed to identify a significant interaction between HCA group and practice F(1657.903) =11.643, p<0.005. The estimates of fixed effects showed that there was a statistically significant difference in initial error between the adaptation assessment and the pre-washout assessment where initial error was reduced by 0.31 mm (p<0.05) in the adaptation assessment. It appears that this improvement was fully retained post-washout as there was no statistically significant difference in initial error between the pre- and post-washout assessments (p=1.00).

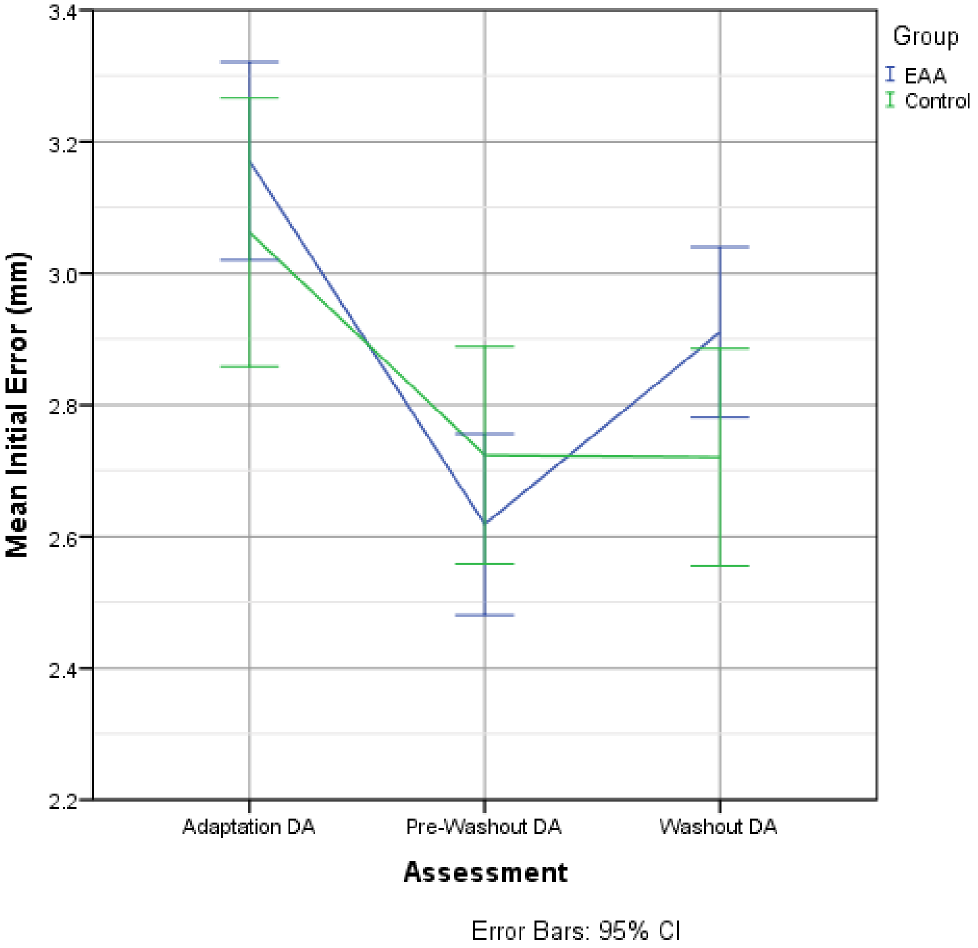


Figure 6-15: Initial error over the different assessment blocks on the DA for the EAA and the Control group.

6.4.2.2 ***Results of the circle-drawing task for the dominant arm***

The LMM analysis of the duration of circular movements used for the previous measures, failed to converge and hence to provide a reliable result. Different attempts were made to change the settings of the estimation including changing the increasing the number of maximum iterations to run the model, the number of maximum step halving and also changing the estimation method from restricted maximum Likelihood (REML) to Maximum Likelihood as well as the covariance type. However, none of these attempts resulted in convergence of the model. Therefore, an alternative approach was undertaken that was to remove the random effects from the model. The analysis of the movement circularity of the DA remained the same as in all other measures (excluding duration of circular movements for the DA).

The analysis of movement circularity (Figure 6-16) on the circle drawing task showed that circularity remained unchanged for both groups as the tests of fixed effects failed to identify a significant effect of practice F(2,50.512) =2.640, p=0.081.

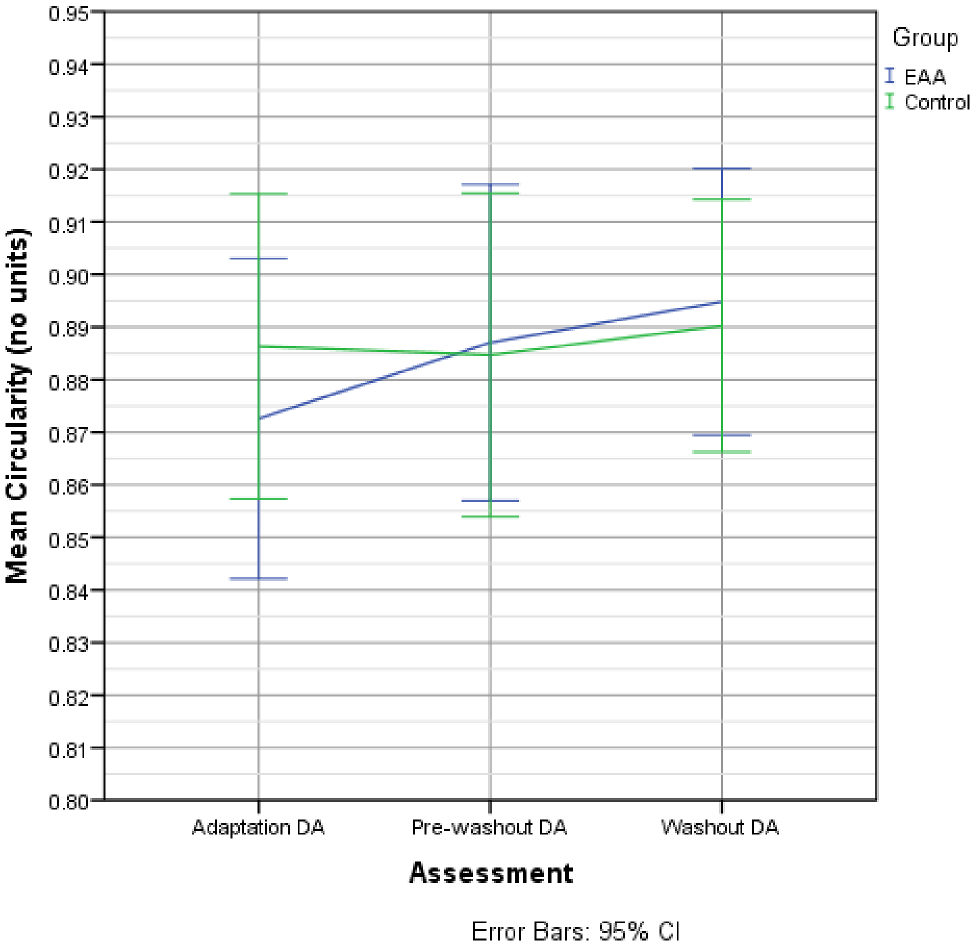


Figure 6-16: Movement circularity over the different assessment blocks on the DA for the EAA and the Control group.

Conversely, the duration of the circular movements (Figure 6-17) was affected by the different assessment blocks as the tests of fixed effects indicated a statistically significant effect of practice F(2,54.092) = 20.528, p < 0.005. In addition, the two groups behaved differently between the different assessment block as the same tests indicated a non-statistically significant interaction between HCA Group and practice F(2,54.092) = 0.434, p =0.65.

Duration was reduced in the course of the trial as the mean difference between the baseline assessment and the pre-washout assessment was 8.8s (p<0.005), indicating that bilateral transfer of the circular movements did indeed occur. On the other hand, there was no statistically significant difference pre- and post-washout in the circular movement duration (p=1.00) indicating that the washout block did not have an effect on the participants' performance in the circular task.

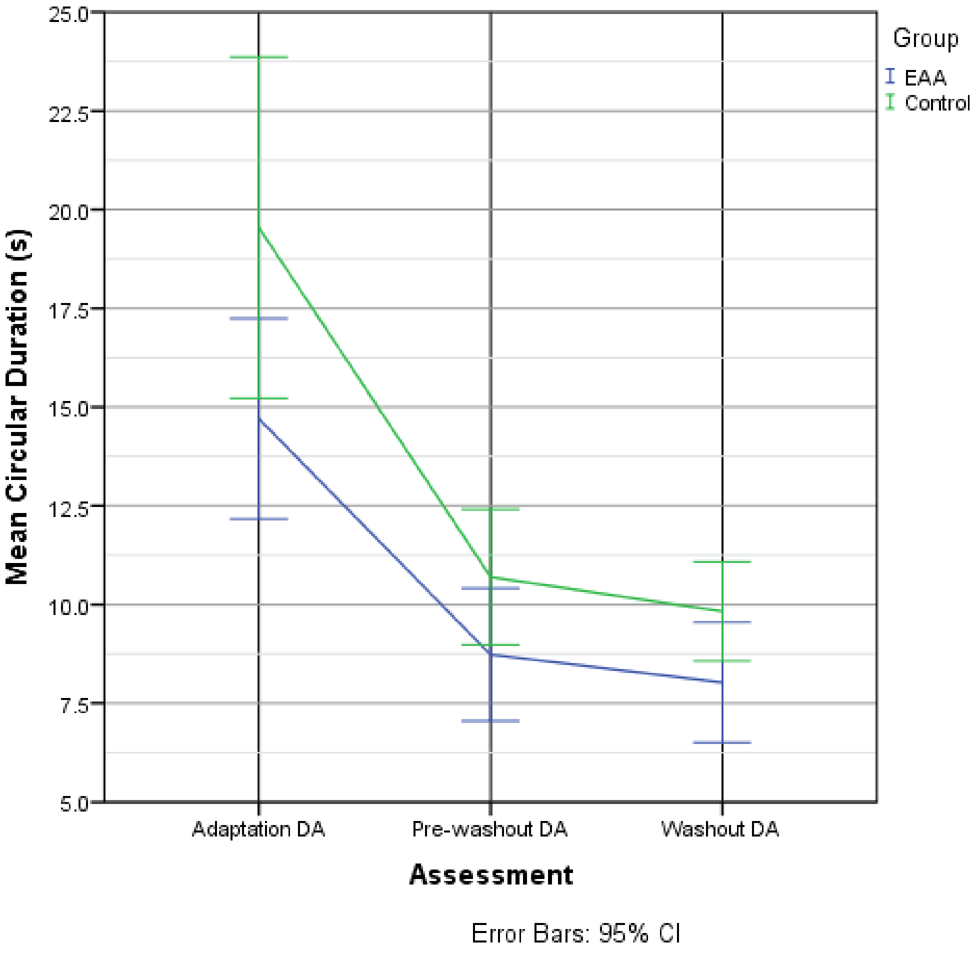


Figure 6-17: Circular movement duration over the different assessment blocks on the DA for the EAA and the Control group.

Table 6-2:Summary of the findings on the analysis of the effectiveness of the trial on the EAA and Control group for the DA.

Measure	**Learning pre-washout**	**Retention post-washout**	**Improved more pre-washout**	**Retained more post-washout**
Duration	Yes	Yes	Control	Control
Perpendicular error	Yes	Yes	No difference	EAA (↓)
Mean velocity	Yes	Yes	EAA	Control
Normalised jerk	Yes	Yes	Control	Control
Initial error	Yes	Yes	No difference	No difference
Circularity	No	N/A	No difference	No difference
Circular movement duration	Yes	Yes	No difference	No difference

6.4.3 Analysis of the Self-Assessment Manikin questionnaire

The SAM questionnaire was administered to the participants during the different assessment blocks in an attempt to measure potential changes in the emotional state of the participants throughout the trial in terms of their valence, arousal and dominance.

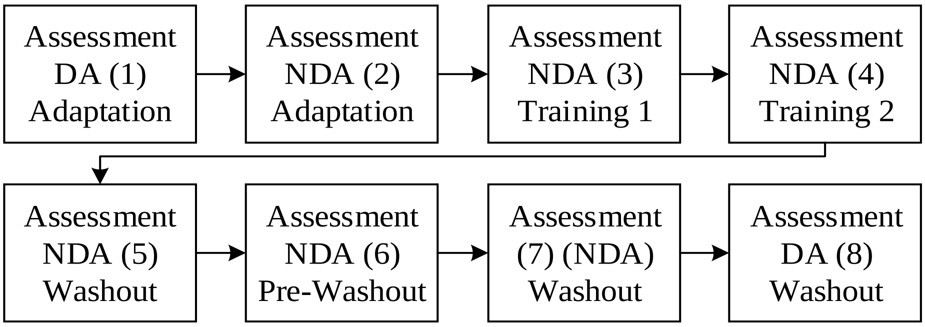


Figure 6-18: The different assessment blocks where the SAM questionnaire was administered.

The tests of fixed effects with regards to valence (Figure 6-19) indicated that there was a statistically significant effect of practice $F(6, 56.213) = 3.173$, $p < 0.05$ but that there was no statistically significant interaction between HCA group and practice F(6, 56.213) = 1.221, p=0.310. Nevertheless, the estimates of fixed effects showed only a statistically significant difference on how valence changed between the adaptation assessment on the DA and the adaptation assessment on the NDA where valence was reduced by an estimate mean of 0.4 units (p<0.05) on the adaptation assessment on the NDA. Due the small difference between the two assessments and the lack of any other difference between the assessment blocks, the change that was measured can be attributed to a random occurrence rather than an actual effect of practice.

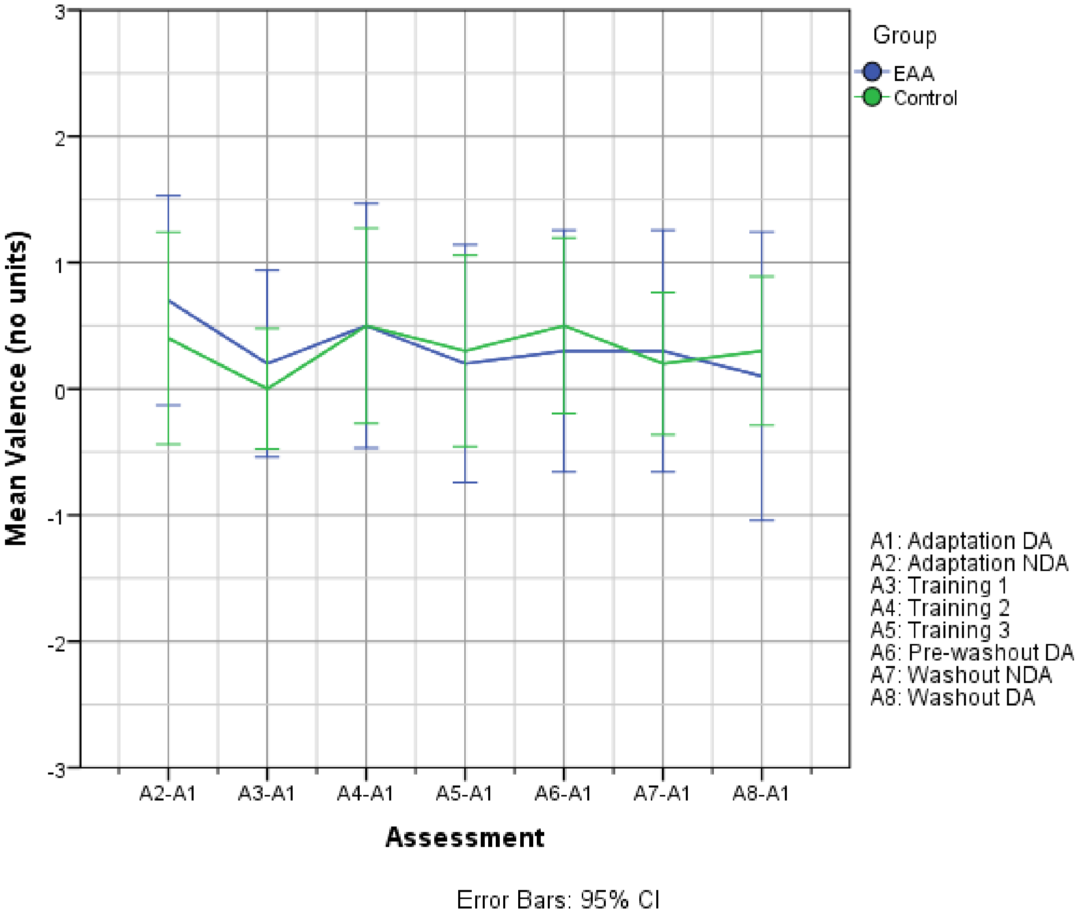


Figure 6-19: Valence over the different assessment blocks on the DA for the EAA and the Control group.

According to the tests of fixed effects there was a statistically significant effect of practice on the participants’ arousal F(6,45.522) = 8.013, p <0.005 and that there was no statistically significant interaction between HCA group and practice F(6,45.522) =0.852, p=0.537 (Figure 6-20). The estimates of fixed effects showed a statistically significant difference in the participants’ arousal which decreased throughout the trial, reaching a maximum difference of 0.9 units ($p<0.05$) at the washout assessment of the NDA. According to the results of this model it appears that participants became more relaxed in the course of the trial irrespective of the task that they were asked to perform.

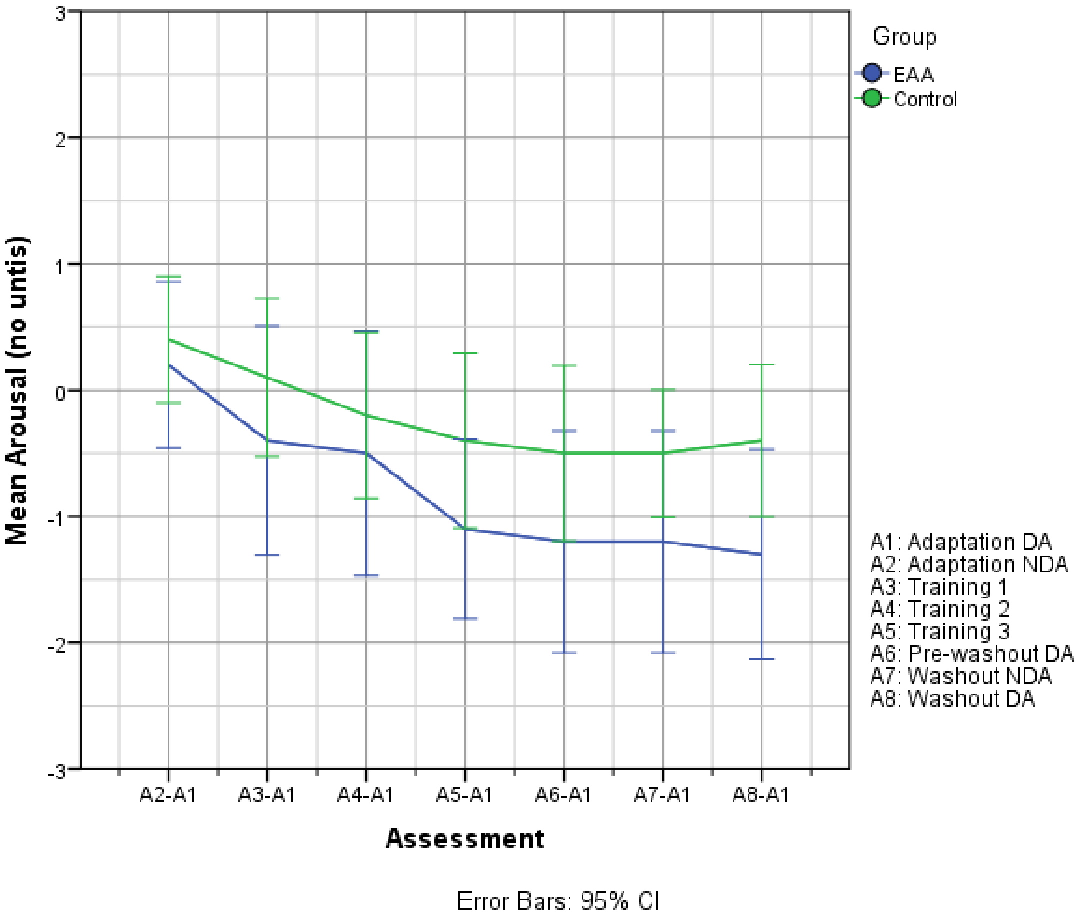


Figure 6-20: Arousal over the different assessment blocks on the DA for the EAA and the Control group.

The tests of fixed effects indicated that there was a statistically significant effect of practice $F(6,53.442) = 4.394$, $p<0.05$ on the participants’ dominance (Figure 6-21) but no significant interaction between HCA group and the practice $F(6,53.442) = 1.447$, $p=0.214$. According to the estimates of fixed effects the participants became more empowered (dominant) in the course of the trial reaching a statistically significant difference from the adaptation assessment of 0.9 units ($p<0.005$) at the assessment after training block 2 which remained at similar levels (fluctuated between 0.8 and 0.9) for the rest of the trial with the only exception being a marginally insignificant difference in the post-washout assessment of the NDA where the difference dropped by 0.5 units (p=0.053). As such, the participants felt more empowered at the course of the trial when compared to the initial stages of the trials.

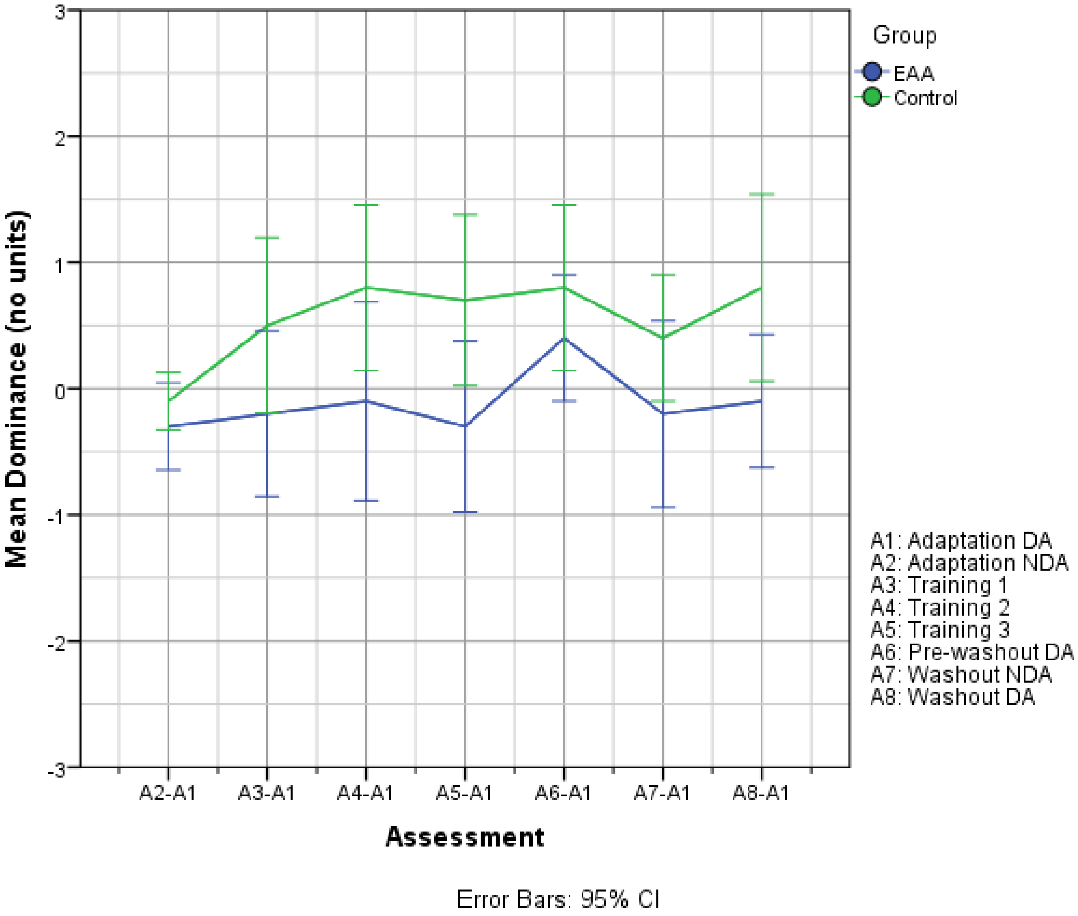


Figure 6-21: Dominance over the different assessment blocks on the DA for the EAA and the Control group.

Table 6-3: Summary of the findings on the analysis of the effectiveness of the trial on the EAA and the Control group for the SAM questionnaire.

Measure	**Effect of practice**	**Difference between the groups?**
Valence	No	No
Arousal	Yes (↓)	No
Dominance	Yes (↑)	No

6.5 Discussion

The analysis of the kinematic measures collected during the reaching task drew a clear pattern. Performance, as reflected by the values of the different kinematic measures improved throughout the training phase of the trial indicating that motor learning did indeed occur on the NDA during the course of the trial. The only exception to this pattern was initial error which remained unaffected throughout the trial. Interestingly, the analysis showed that the Control group improved more than the EAA group in the smoothness of its movements while EAA group demonstrated a greater improvement in the mean velocity of its movements. Furthermore, there was no difference between the two groups on how movement duration, perpendicular error and initial error had changed throughout the trial.

The latter supports the findings of a recent study by (Majeed et al., 2015) which compared the effect of an error augmentation algorithm based on machine learning to movements under no robotic forces in the rehabilitation of the upper limb of stroke patients. This study although it successfully measured improvement in both groups as reflected by several kinematic measures such us perpendicular error and movement duration it failed to identify differences between the two conditions. Interestingly, the same study found no difference between the two conditions on the velocity of the movements and their smoothness which is in contrast to the findings presented in this report that indicated an increased benefit of EAA on the mean velocity and of movements under no force by the rehabilitation robot to movement smoothness.

A possible interpretation of this finding could be that two different strategies were undertaken by the two groups both equally effective in completing the task accurately and quickly. According to this interpretation the EAA group improved the velocity of its sub-movements in the expense of smoothness and vice versa. In the case that the aforementioned interpretation holds ground then it can be assumed that this was an actual effect of the HCA assigned to each group (EAA, no forces).

Another interpretation of the abovementioned findings of the trial could be that both groups behaved similarly in improving the different measures to the same levels close to the possible limits of performance (plateau) in these measures that could be achieved for this task. As such, the group that demonstrated the worse initial performance would show greater improvement (change) in these measures while reaching similar levels of performance at the training stage as the other group. This interpretation described quite accurately the findings for normalised jerk where the Control group demonstrated significantly higher normalised jerk than the EAA did in the adaptation stage, which was reduced to similar levels to the EAA in the training stage of the trial. However, the results for mean velocity contradict this interpretation as the group that improved the most (EAA), was the one with that demonstrated better performance (higher mean velocity) in the beginning of the trial.

Regarding the circle-drawing task using performed using NDA, the circularity of the movements for both groups was unaffected by practice as it remained the same throughout the trial. Nevertheless, the duration of the circular movements was reduced for both groups in the course of the training part of the trial. The latter can be explained if it is assumed that learning within this task did indeed occur solely reflected by the decrease in movement duration. Interestingly, movement duration continued improving even after the washout block. This is indication that learning in the circle drawing task, did occur due to the participants practising the circle-drawing movements rather than as an effect of the training part of the trial.

After the washout block most measures deteriorated but did not reach the pre-training levels. This was a clear evidence of retention. Post-washout, the Control group retained more of the improved duration, mean velocity and normalised jerk when compared to the adaptation assessment than the EAA group did. This can be attributed to an effect of the group the participants were assigned to. However, an alternative interpretation could be once more that both groups achieved similar levels on each measure in the post-washout assessment but as the Control group demonstrated worse performance than the EAA group in the adaptation stage, the difference between that baseline assessment and the washout assessment would favour the Control group as it will be greater. As such, in this case the difference captured by these measures wouldn’t be an effect of the algorithm (or the absence of) that is measured but an inherent heterogeneity between the two groups before any training was received. The latter explanation is the most likely to be accurate as it is further supported by the absence of a statistically significant difference between the two groups in the estimated marginal means of movement duration, mean velocity and normalised jerk in the washout assessment, while the same estimates show worse values for the Control group in the adaptation assessment.

With respect to the reaching task on the DA all measures improved in the pre-washout assessment for both groups indicating that bilateral transfer of the learning did occur. The Control group improved more in the mean duration of its movements as well as in the smoothness of its movements than the EAA group did. On the other hand, the EAA improved more in the mean velocity of its movements. Finally, there was no difference between the two groups on how the perpendicular error and the initial error had changed between the adaptation and pre-washout assessment. The higher improvement in movement duration for the Control group could be possibly attributed to the higher initial movement duration that the Control group demonstrated in the adaptation assessment. This is further supported by the finding that both groups reduced their movement duration in similar values as the estimates of marginal means did not identify a difference in the value of movement duration (p=0.189) in the pre-washout assessment.

The abovementioned interpretation however is contradicted by the findings of the analysis regarding the mean velocity of the movements and the normalised jerk where the group that improved the most (EAA in mean velocity, control in normalised jerk) was the group that demonstrated better performance in the adaptation assessment. These findings could be interpreted by the different strategies approach described earlier in this section. Nevertheless, it is a very interesting finding that improvement of the DA mirrored the improvement that occurred on the NDA, with the EAA group improving more the mean velocity for both the DA and NDA and the Control group improving more the normalised jerk of its movements for both arms. Such a feature can be exploited in the upper limb rehabilitation of those with severe neurological impairments that cannot complete movements with the impaired limb as it opens the possibility of benefiting from practising with challenge-based algorithms using their unimpaired limb.

With respect to the circle drawing task for the DA there was no difference between the HCA groups. Movement circularity remained unchanged for both groups throughout the trial. Nevertheless, the duration of the circular movements was reduced in the pre-washout assessment indicating that transfer of learning to this task did occur. One the other hand, because there was a lack of a measured effect post-washout, the pre-washout improvement can be also attributed to potential learning that occurred within the assessment block on the DA.

Finally, it appears that neither of the algorithms or the intervention in total had a significant effect on the participants' valence. Nonetheless, participants' arousal was reduced in the course of the trial while their dominance increased. Although a small change was measured in the two measures it is indicating a clear pattern that as participants felt more comfortable in performing the task, they became more relaxed and felt more empowered. This is further supported by a small drop that was measured in the participants' dominance in the first assessment post-washout which in turn was restored in the subsequent assessment. An explanation for this finding can be that the participants felt less capable of performing the reaching task under the visual rotation post-washout, also by the change in kinematic measures. During the post-washout assessment on the NDA some learning occurred and hence their confidence was restored in the subsequent assessment. No difference was measured between the groups in either of the SAM questionnaire measures indicating that both groups were equally affected by the trial.

Interestingly, the findings of the analysis were opposite to the findings of the study by (Shirzad and Van der Loos, 2012) where healthy participants increased their valence and arousal while experiencing reduced dominance in the course of the trial while performing movements under a combination of visual and haptic error augmentation. As the aforementioned study had a very small population (N=10) and followed a crossover protocol where the participants were subjected to five different conditions within the same trial it is difficult to draw any firm conclusions. Nevertheless, the difference of the findings of this study and the study by (Shirzad and Van der Loos, 2012) could be potentially interpreted as an effect of the visual error augmentation and as such further investigation is recommended.

6.6 Summary

Some key findings of the analysis can be found below:

- Both interventions (group training conditions) led to a) improvement in the participants' movements of the NDA in all parameters except for initial error and movement circularity pre-washout and b) retention of improvements post-washout except for perpendicular error, initial error and circularity.
- EAA was more effective on improving mean velocity.
- EAA was less effective in improving movement smoothness.
- Reaching tasks and bilateral transfer led to similar patterns of improvement.
- Bilateral transfer appears unaffected by washout.
- There was no effect of practice type on the changes of the psychological state of the participants.

7 Investigating the effect of Error Augmented Proportional control on motor learning

7.1 Introduction

The main aim of this chapter is to present the findings of the statistical analysis comparing the EAP and Control groups from the trial described in Section 4.3. While the algorithm's effect on motor learning is evaluated with able-bodied participants the findings of the analysis are transferable to the impaired population (Krakauer, 2006). Firstly, an overview of the configuration of the EAP used in the trial followed by the research questions that this analysis was trying to answer. Finally, the results of the analysis are presented and discussed at the end of the chapter.

7.2 The Error Augmented Proportional algorithm

In Section 2.7.2 the conceptual design of the EAP HCA was introduced while in Section 3.3.3 the software implementation was presented. EAP as well the other developed HCAs is highly customisable offering an infinite number of configurations. EAP adjusts the magnitude of the maximum permissible forces that are exerted by the robot's endpoint on to the user's hand proportionally to the distance away from the desired trajectory. As such the further, the endpoint is, the greater the magnitude of the maximum permissible forces will be. The direction of the forces is always away from the desired trajectory. To achieve this behaviour, the workspace is divided into eleven zones of adjustable width which are placed on each side of the desired trajectory (Figure 7-1). Also within each zone the maximum permissible force applied to the participants' arm can be adjusted as a factor of the maximum permissible current. The settings selected for this algorithm were adjusted to be appropriate for able-bodied participants and need to be adjusted accordingly if they are to be used by impaired.

The settings selected for the EAP are as follows:

a) The direction of the forces was set in the perpendicular direction away from the desired trajectory

b) The robot's outer wall of each zone was placed in distances equal to n*1.6 mm where n the zone number on each side of the desired trajectory

c) The MPC on each zone was set to be (n-1)0.3A, where n is the zone number on each side of the desired trajectory. As such, the values of MPC would range from 0A for zone 1 to 3A for zone 11.

An example for the first four zone is provided in Figure 7-1.

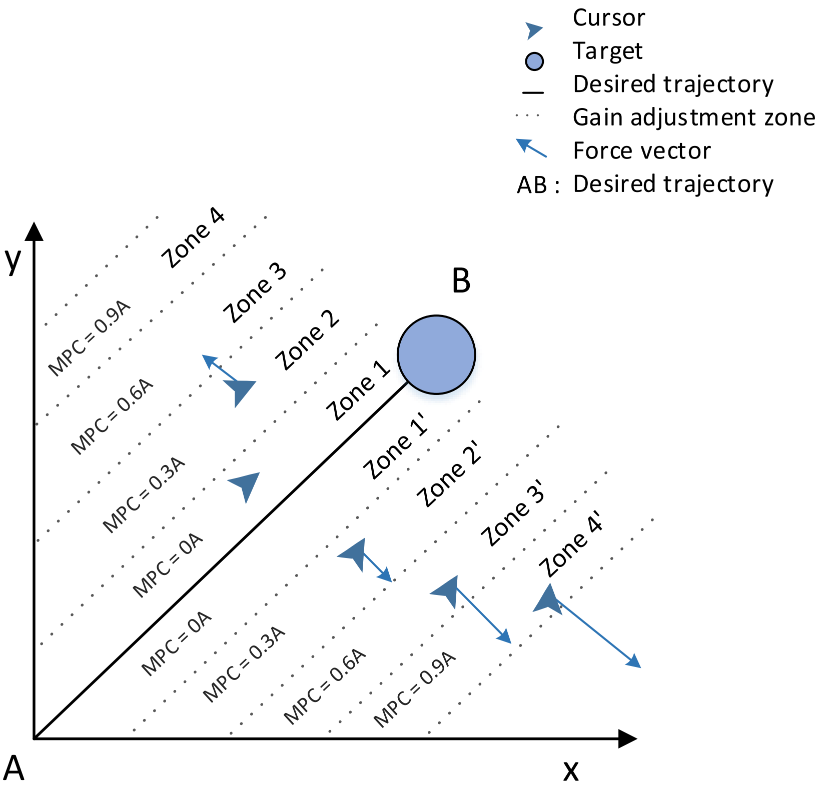


Figure 7-1: Example of the EAP for the first four zones.

7.3 Research questions

The questions that this analysis sets out to answer are presented below:

1) Does the EAP affect motor learning and retention of learning on the upper limb of the able-bodied adults? If yes, what is its effect?
2) How does the effect of EAP compare to the participants’ performance if the same amount of practice was received without any forces being applied by the rehabilitation robot?
3) Is bilateral transfer affected by the conditions of practice (EAP vs passive movements)?
4) Does practice with the EAP have an effect on the psychological state of the participants and if so how much of that can just be attributed to the exercise?

7.4 Results of the statistical analysis

To test the effect of EAP on motor learning a trial was conducted with able-bodied participants. The trial protocol and the analysis methodology are both described extensively in Section 4.3.

7.4.1 Analysis of the kinematic measures for the non-dominant arm

Five in total assessments were performed with the participants using their NDA. The first assessment was carried out after the adaptation stage before any training took place. The subsequent three assessments were undertaken after each of the training blocks and the final assessment was carried out after the washout phase in order to assess retention. Performance was evaluated from the values of the kinematic measures collected throughout the trial. In the course of the trial as the participants practised more it was expected that performance, as reflected by the values of the kinematic measures, would improve when compared to the baseline (adaptation) assessment. Also, if retention did indeed occur then this would be reflected by better performance when compared to the baseline assessment and comparable levels of the kinematic measures to the pre-washout assessments.

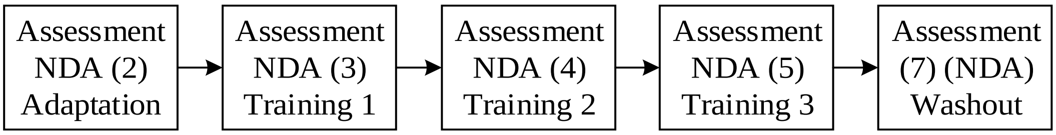


Figure 7-2: The assessments on the NDA.

7.4.1.1 *Results for the reaching task on the non-dominant arm*

The test of fixed effects indicated that there was a statistically significant effect of practice on movement duration as it was measured in the different assessment blocks F(4,1265.586) = 395.687, $p < 0.005$. Additionally, the same tests identified a statistically significant interaction between HCA group and practice F(4,1265.586) = 8.330, $p<0.005$.

More specifically, movement duration (Figure 7-3) dropped throughout the training blocks when compared to the baseline assessment (the assessment after the adaptation block). After training block 3, the duration of the participants' movements was reduced by 1.3s ($p < 0.01$) for the EAP group and 1.1s for the Control group. After the washout block the participants' movements became slower, when compared to levels achieved at the training stage of the trial, but remained improved when compared to the adaptation block by 0.9s ($p < 0.005$) for the EAP group and by 0.8s ($p<0.005$) for the Control group.

When comparing the two groups, the EAP improved the duration of its movements by 0.18s ($p<0.05$) more than the Control group did when looking at the difference between the assessment after training block 3 and the adaptation assessment. On, the other hand the EAP group increased its movement duration post-washout by 0.03s ($p<0.005$) more than the Control group did. Conversely, for both groups movement duration improved throughout the training part of the trial with both groups reaching similar levels of movement duration after training block 3. However, it must be noted that the EAP group started with a higher movement duration which might be the cause of the greater improvement when compared to the Control group. Furthermore, post-washout both groups reduced their movement duration to levels similar to the ones achieved in training block 1, indicating that partial washout did occur but not complete washout. The Control group demonstrated more retention of movement duration but only for a negligible amount of 0.03s ($p<0.05$).

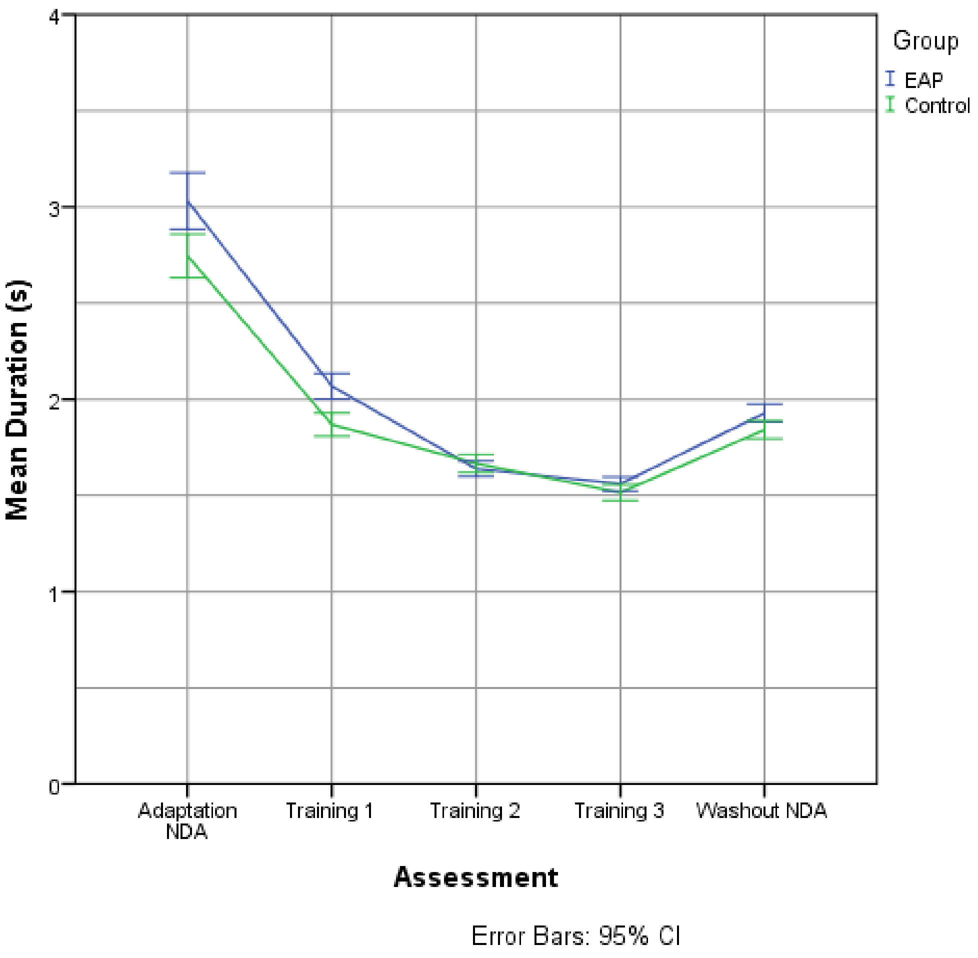


Figure 7-3: Mean duration over the different assessment blocks on the NDA for the EAP and the Control group.

Similarly, there was a statistically significant effect of practice group on movement error F(4,1088.906) =334.469, $p<0.005$ as indicated by the tests of fixed effects. On the contrary, the same tests failed to identify a significant interaction between HCA group and practice F(4,1088.906) =1.721, p=0.143 indicating that the there was no significant difference between the two groups on how the perpendicular error of the movements has changed throughout the trial.

From the estimates of fixed effects, it can be seen that movements became more accurate as perpendicular error was reduced in the different assessment blocks following the training stage of the trial, reaching a maximum difference with the baseline assessment of 3.8 mm ($p < 0.005$) after training block 3 (Figure 7-4). Post-washout movement error increased to the levels of the adaptation assessment (no statistically difference between the washout assessment and the adaptation assessment, $p=0.536$) indicating that improvement in movement error was completely washed out.

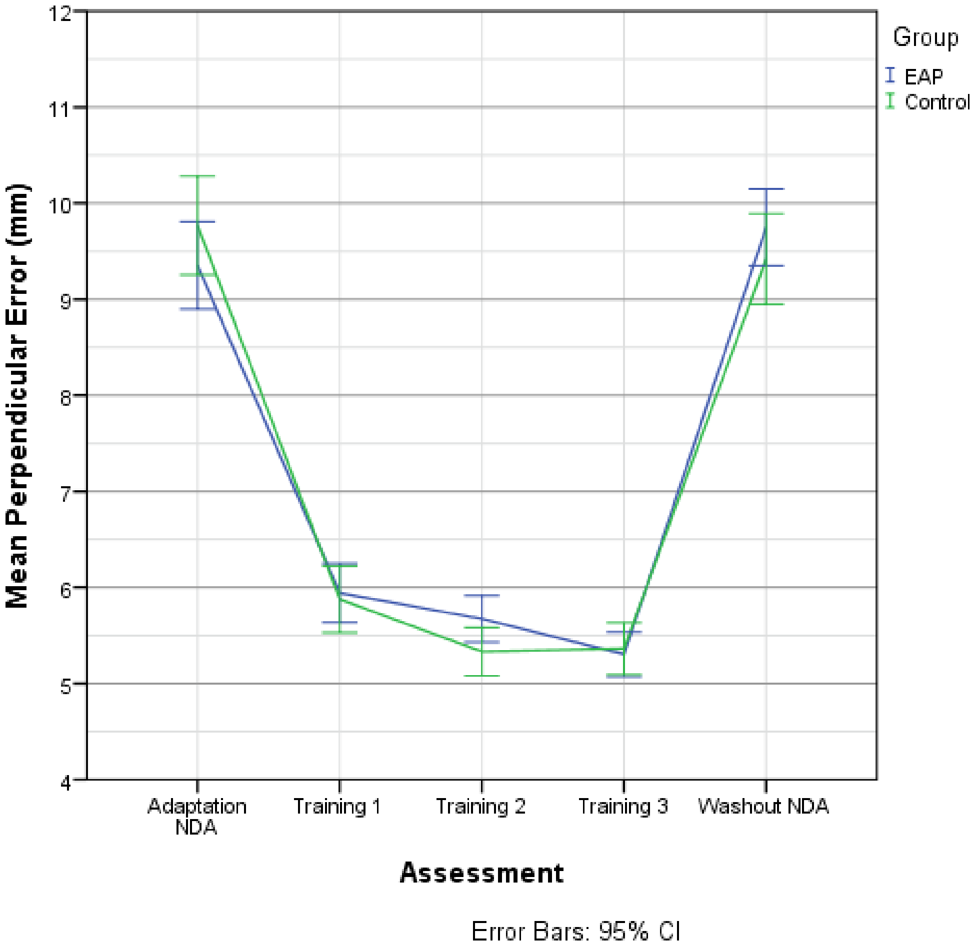


Figure 7-4: Mean perpendicular error over the different assessment blocks on the NDA for the EAP and the Control group.

With respect to the mean velocity (Figure 7-5) the test of fixed effects showed a statistically significant effect of practice F(4,1392.531) =402.921, $p<0.005$ along with a statistically significant interaction between HCA group and practice F(4,1392.531) =15.436, $p<0.005$.

When compared to the baseline assessment the mean velocity increased in the training part of the trial with the EAP group reaching a maximum mean difference from the baseline assessment of 18.0 mm/s ($p<0.005$) after training block 2 while the Control group reached the same difference after training block 3 ($p<0.005$). After training block 3 the EAP group did not improve further as there was no statistically significant difference ($p=0.216$) in movement duration between the assessment after training blocks 2 and 3. Post-washout movement velocity was partially washed-out as it was reduced for both groups by an average of 5.0 mm/s ($p<0.005$) from training block 3 however it remained significantly improved when compared to the training block 1 for both groups.

As such, both groups increased the mean velocity throughout the training stage of the trial with the EAP group reaching its peak mean velocity one training block faster than the Control group (training block 2 for EAP and training block 3 for the Control group). When it comes to washout, both groups reduced the mean velocity of their movements when compared to the pre-washout assessments indicating that mean velocity was partially washed for both groups and that the washout was the same for both groups.

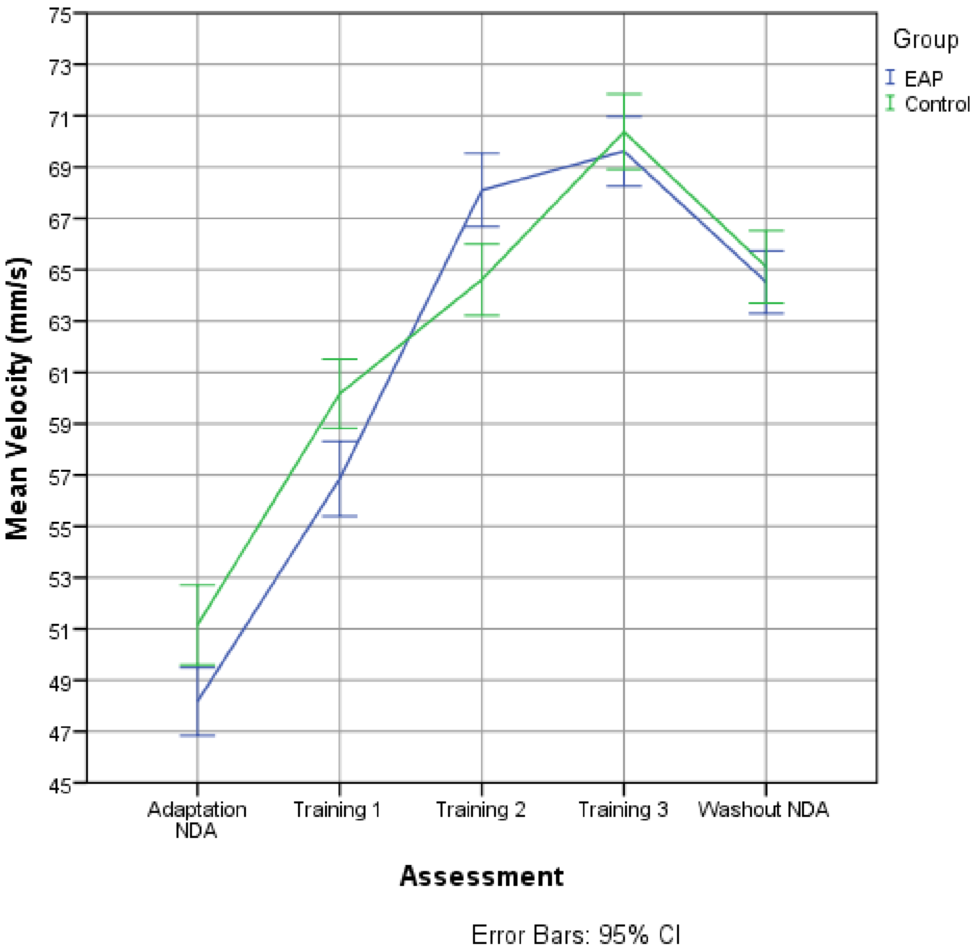


Figure 7-5: Mean velocity over the different assessment blocks on the NDA for the EAP and the Control group.

In relation to movement smoothness as measured by the normalised jerk (Figure 7-6) the tests of fixed effects showed that there was a statistically significant effect of practice F(4,522.801) =161.235, p<0.005 as well as a statistically significant interaction between HCA group and practice F(4,522.801) =3.803, p<0.05.

The interaction between HCA groups and practice identified by the tests of fixed reflects is not evident in the estimates of fixed effects as it appears that there is no significant difference between the two groups on how normalised jerk changed in the different assessments (p>0.05). As such, only the estimates of fixed effects for both groups as one population will be taken into account. Consequently, the estimates of fixed effects showed that the participants' movements became smoother as normalised jerk was reduced in the assessment following the training part of the trial with a maximum difference from the adaptation being reached in the assessment following training block 3 where normalised jerk was reduced by 10 units, p<.005. Post-washout normalised jerk was increased when compared to the pre-washout assessment by 1 unit (p<0.005) indicating that a partial washout did indeed occur to movement smoothness. Nevertheless, the participants retained most of the improved smoothness after the washout block, as the mean difference from the adaptation assessment was approximately 9 units (p<0.005).

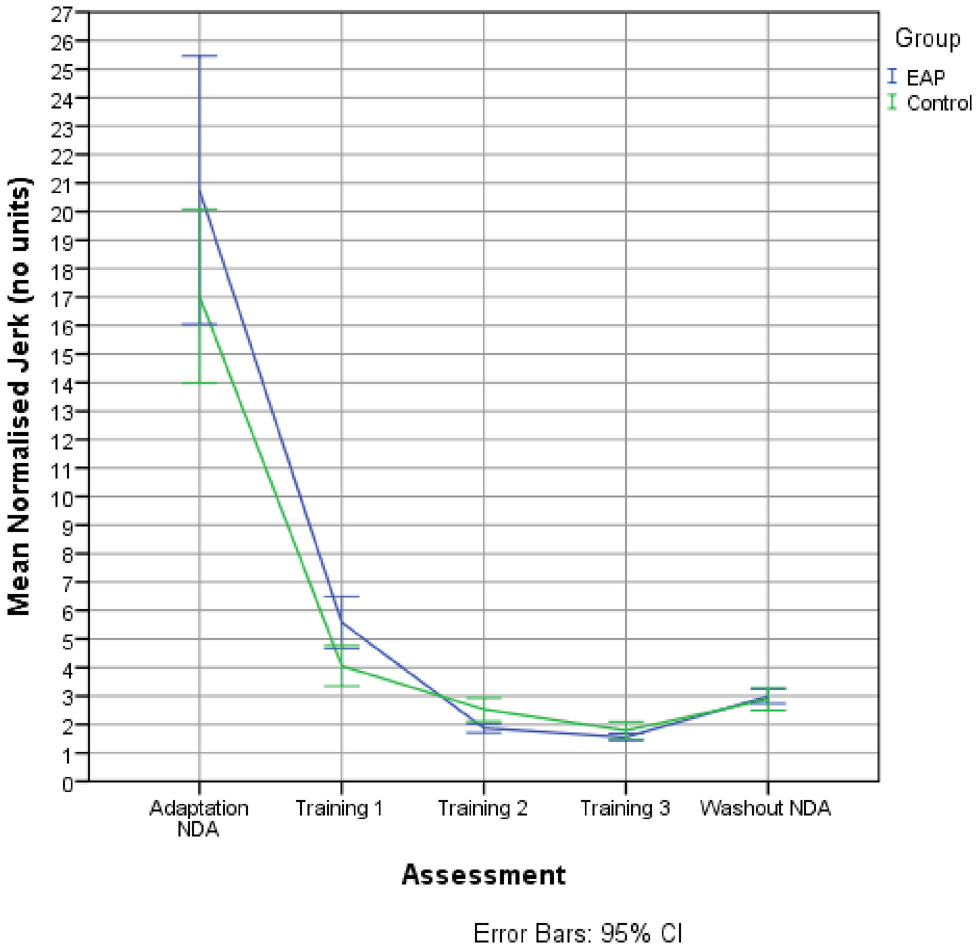


Figure 7-6: Normalised jerk over the different assessment blocks on the NDA for the EAP and the Control group.

The estimates of fixed effects showed that there was a statistically significant effect of practice on the initial error of the movements F(4,1808.927) =3.337. p<0.05 (Figure 7-7). On the contrary, the same tests did not identify a statistically significant interaction between HCA group and practice F(4,1808.927) =0.256, p=0.901. However, the test of fixed effects only showed a significant difference in the initial error of the participants' movements between the adaptation assessment and the assessment after training block 2, where initial error was reduced by an estimated 0.25mm (p<0.05). However, due to the lack of significant difference between the adaptation assessment and the other assessments (except for the one following training block 3) it can be concluded that there was no real effect of practice on initial error.

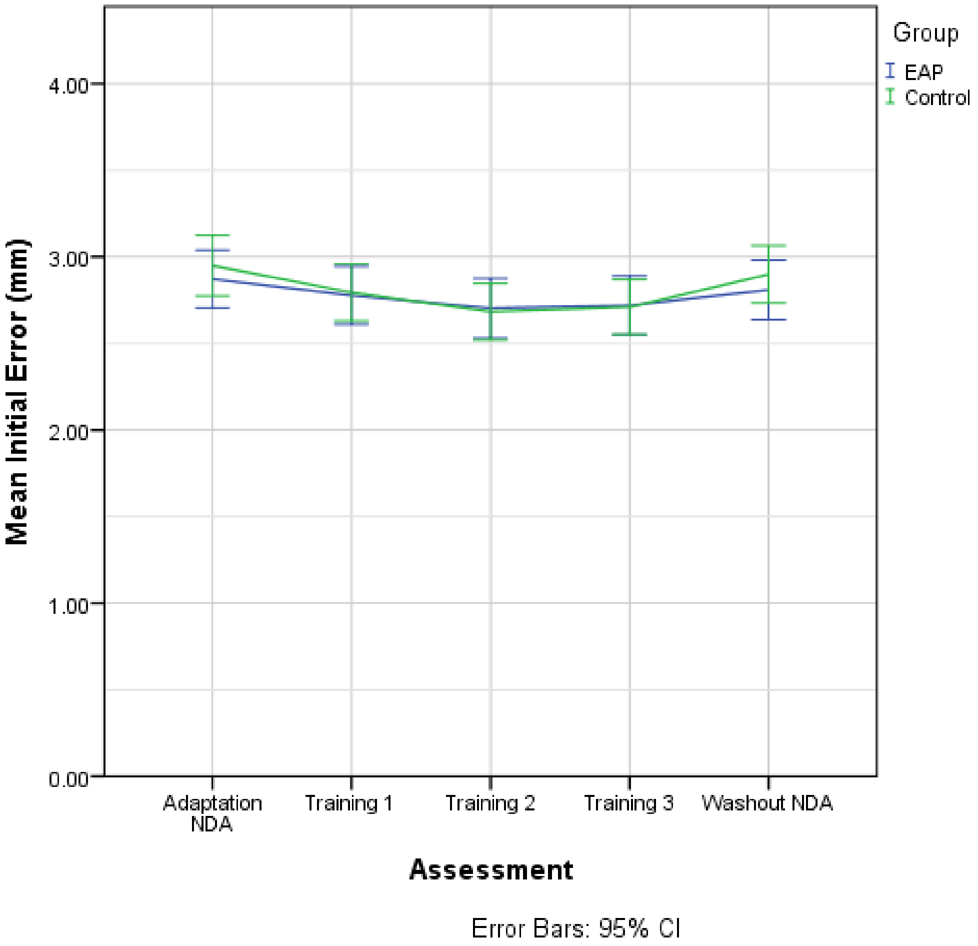


Figure 7-7: Initial error over the different assessment blocks on the NDA for the EAP and the Control group.

7.4.1.2 *Results of the circle-drawing task for the non-dominant arm*

Regarding the circle-drawing task (Figure 7-8) the tests of fixed effects showed that there was a statistically significant effect of practice F(4,34.778) =2.768, p<0.05 but no statistically significant interaction between HCA group and practice F(4,34.778) =1.756, p=0.160. Nevertheless, the estimates of fixed effects did not identify a significant difference in movement circularity between the adaptation assessment and the other assessments (p>0.05). Consequently, it is logical to conclude that movement circularity was unaffected by practice pre- and post-washout.

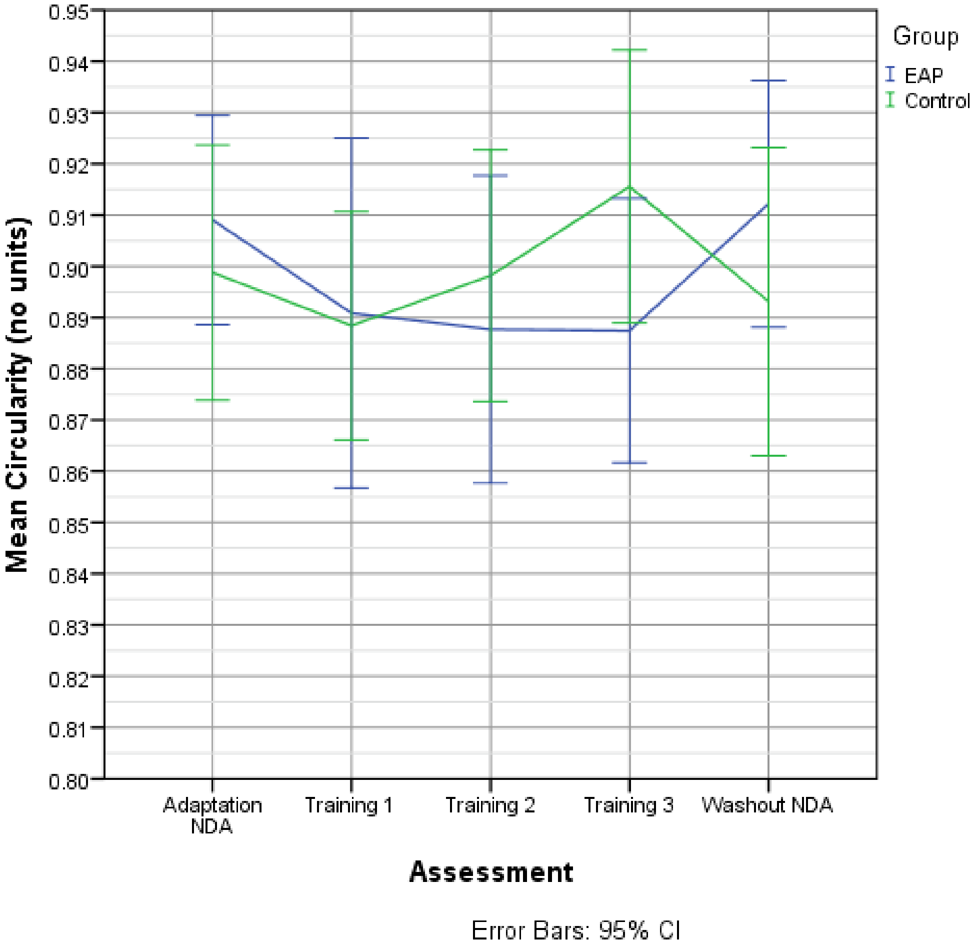


Figure 7-8: Movement circularity over the different assessment blocks on the NDA for the EAP and the Control group.

The duration of movements in the circular task (Figure 7-9) was significantly affected by practice F(4,35.629) =11.954, $p<0.05$ as indicated by the tests of fixed effects. In contrast, there was no statistically significant interaction between HCA group and practice as indicated by the same tests F(4,35.629) =0.380, $p=0.822$. The estimates of fixed effects, showed that the duration of the circular movements was reduced throughout the training part of the trial reaching a maximum difference from the adaptation assessment of 4s ($p<0.005$) after training block 3. Post-washout movements continued to shorten in duration as in the washout assessment duration was improved by 4.3s ($p<0.005$) indicating that the washout block did not affect the duration of the circular movements.

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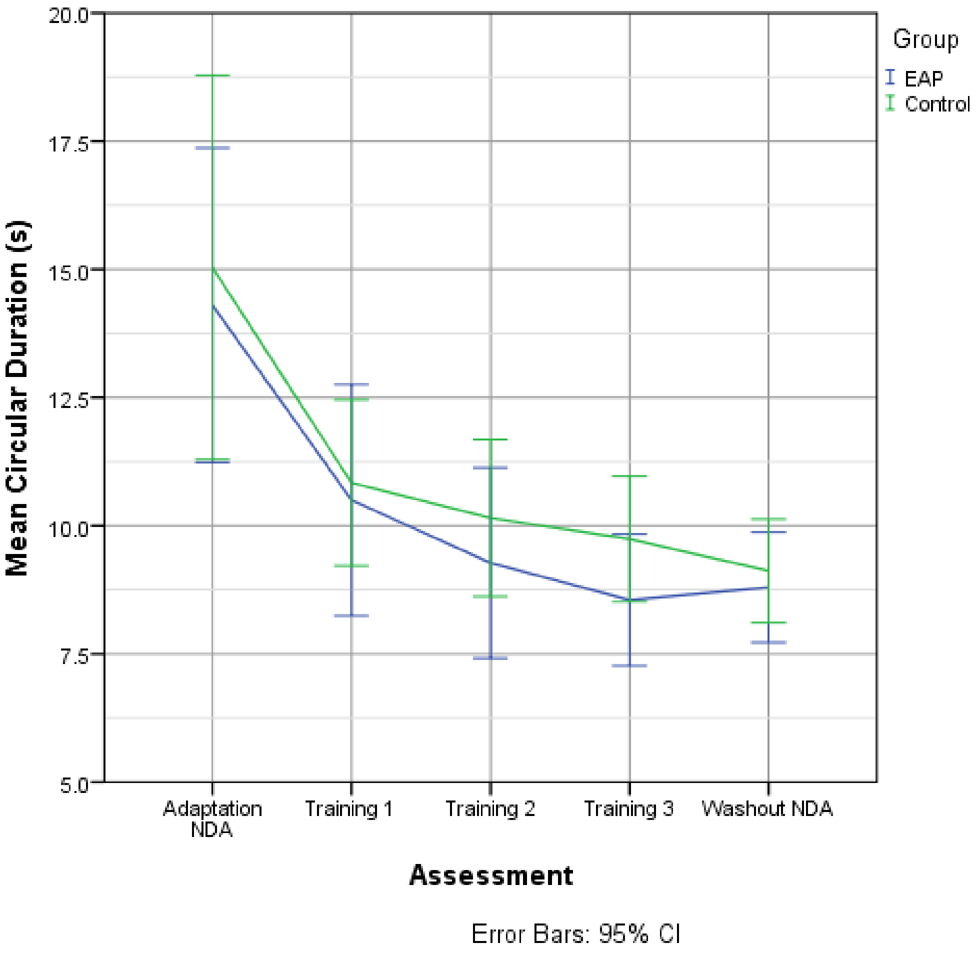


Figure 7-9: Movement duration for the circle-drawing task over the different assessment blocks on the NDA for the EAP and the Control group.

Table 7-1:Summary of the findings on the analysis of the effectiveness of the trial on the EAP and Control group for the NDA.

Measure	**Learning pre-washout**	**Retention post-washout**	**Improved more pre-washout**	**Retained more post-washout**
Duration	Yes	Yes	EAP	Control
Perpendicular error	Yes	No	No difference	No difference
Mean velocity	Yes	Yes	EAP (same levels but achieved them faster)	No difference
Normalised jerk	Yes	Yes	No difference	No difference
Initial error	No	N/A	No difference	No difference
Circularity	No	N/A	No difference	No difference
Circular movement duration	Yes	Yes (↓)	No difference	No difference

7.4.2 Analysis of the kinematic measures for the dominant arm

Assessments on the DA were performed in order to evaluate the effect of the different interventions on the bilateral transfer of motor learning and subsequently motor skills. Apart from the assessment blocks, no training was received by the DA during the course of the trial. In total three assessment blocks were undertaken using their DA, one pre-training, one at the end of the training blocks and one after the washout phase.

The hypothesis of this experiment was that if bilateral transfer did indeed occur the kinematic measures post-training would show improvement when compared to the pre-training levels. Furthermore, it was expected that if the values of the kinematic measures would remain improved at the post-washout assessment when compared to the pre-training levels, this would suggest retention of the acquired skills.

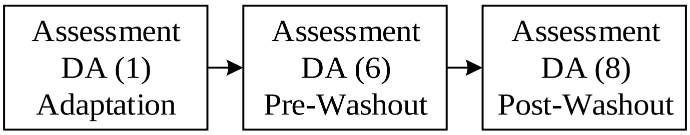


Figure 7-10: The assessments on the DA.

7.4.2.1 ***Results for the reaching task on the dominant arm***

Regarding the movement duration of the DA (Figure 7-11), the tests of fixed effects showed a statistically significant effect of practice F(2,704.132) =425.886, $p<0.005$ and a statistically significant interaction between HCA group and practice F(2,704.132) =3.734, $p<0.05$. The estimated marginal mean showed that both groups reduced the duration of the movements in the pre-washout assessment when compared to the adaptation assessment. More specifically, the EAP group reduced the duration of its movements by an average of 2.4s ($p<0.005$) while the Control group reduced movement duration by 2s ($p<0.005$).

The estimates of fixed effects showed that there was indeed a statistically significant difference between the two groups on how movement duration has changed between the adaptation and pre-washout assessment with the EAP group improving by a 0.4s ($p<0.05$) more than the Control group did. Post-washout both groups retained the improved movement duration they demonstrated in the pre-washout block, as the estimates of fixed effects showed that there was no statistically significant difference in movement duration between the pre- and post-washout assessment ($p=1.000$ for the EAP, $p=0.977$ for the Control group)

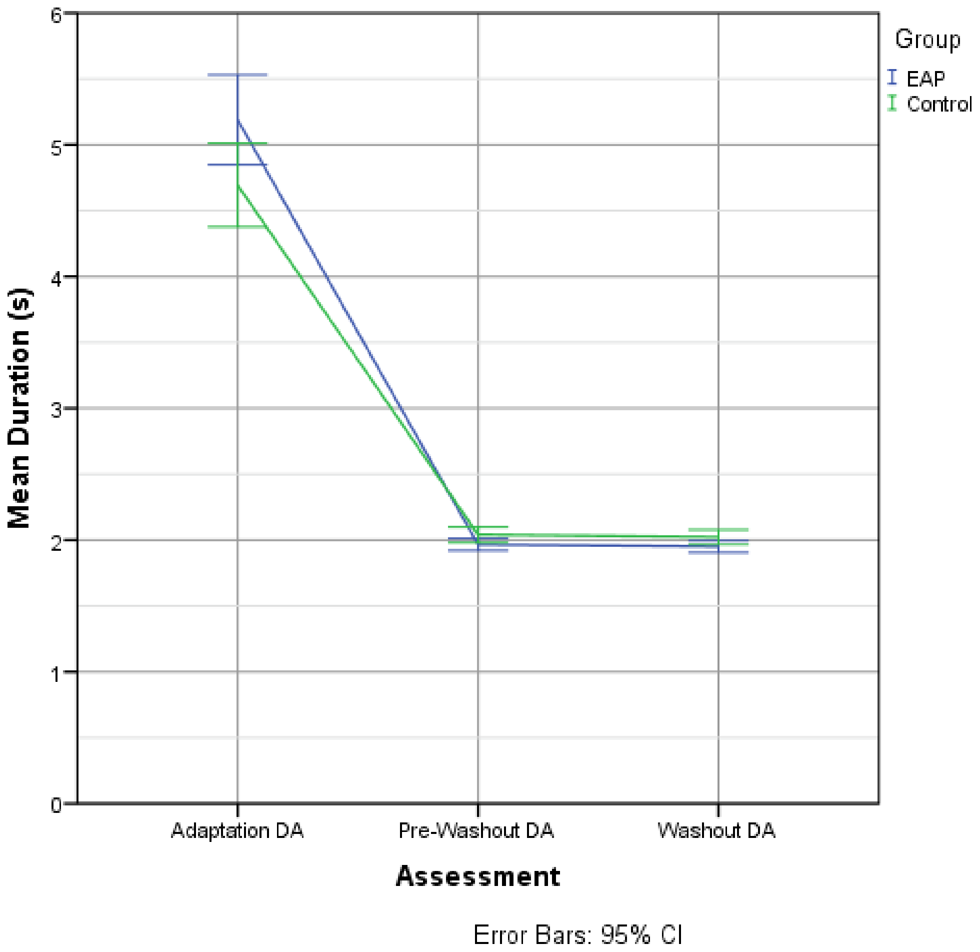


Figure 7-11: Mean duration over the different assessment blocks on the DA for the EAP and the Control group.

The tests of fixed effects revealed that there was a statistically significant effect of practice on the perpendicular error of the movements F(2,1183.64) =119.305, p<0.005, but that there was no statistically significant interaction between HCA group and practice F(2,1183.64) =1.526, p=0.218. From the estimates of fixed effects, it can be seen that perpendicular error was reduced for both groups (Figure 7-12) by an estimate of 3.2 mm (p<0.005) in the pre-washout assessment. Post-washout, the estimates of fixed effects showed a difference from the adaptation assessment of 2.7 mm (p<0.05), which indicates that perpendicular error, increased post-washout. However, this finding must be considered with caution as the estimated marginal means failed to identify a statistically significant difference in perpendicular error between the pre- and post-washout assessments (p=0.540).

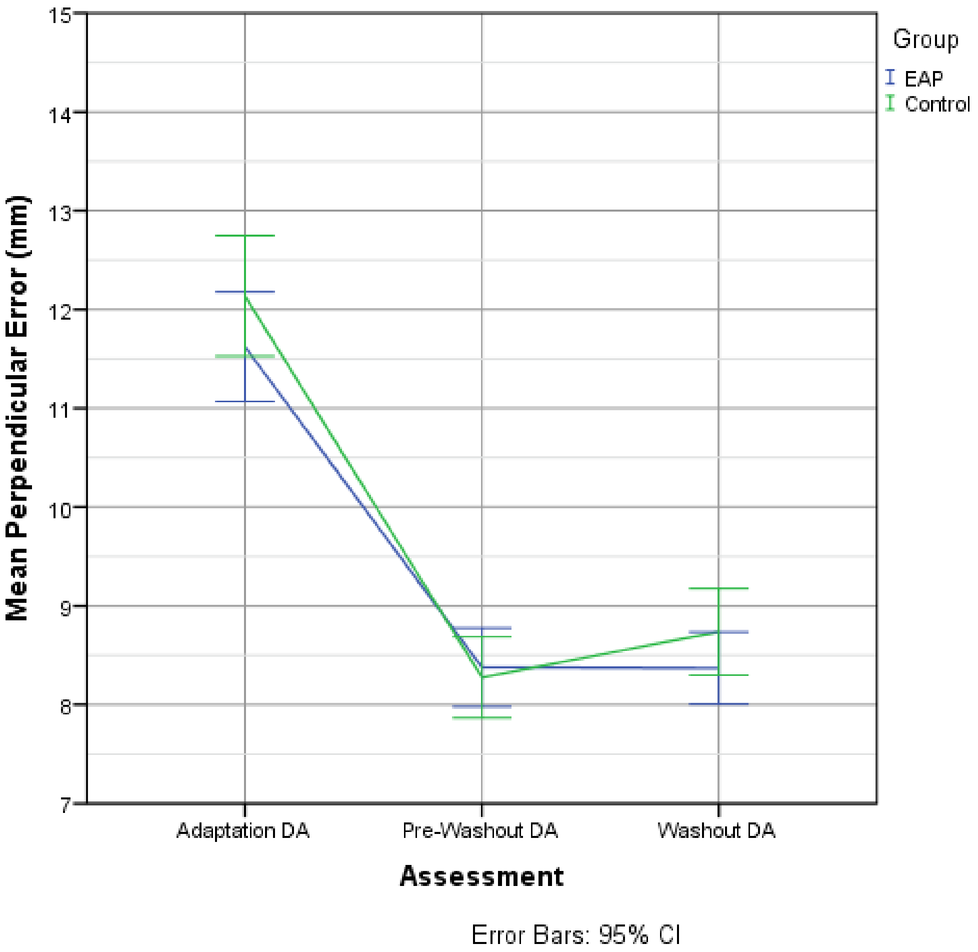


Figure 7-12: Mean perpendicular error over the different assessment blocks on the DA for the EAP and the Control group.

Similarly, the mean velocity of the movements (Figure 7-13) was significantly affected by practice F(2,1516.893) =1033.428, p<0.005 as the tests of fixed effects indicated. Furthermore, the same tests showed that there was a statistically significant interaction between HCA group and practice F(2,1516.893) =8.960, p<0.005.

The estimated marginal means showed that both groups increased the mean velocity of their movements in the pre-washout assessment with a mean difference from the adaptation assessment of 21.0 mm/s (p<0.005) for the EAP group and 17.0 mm/s for the Control group. Furthermore, the estimates of fixed effects also verified that the EAP increased its mean velocity by 4 mm/s (p<0.005) more than the Control group did between the adaptation and the pre-washout assessment. The estimated marginal means of the fitted models showed that there was no statistically significant difference in mean velocity between the two groups pre-and post-washout (p=1.000 for the EAP and p=0.354). However, the estimates of fixed effects showed a small increase post-washout in mean velocity for both groups with the EAP group increasing its mean velocity by 3.0 mm/s than the Control group did. It is difficult to distinguish whether this is a valid effect of the intervention. Nevertheless, the findings of the analysis showed that the mean velocity of the movements of both groups was unaffected by the washout block.

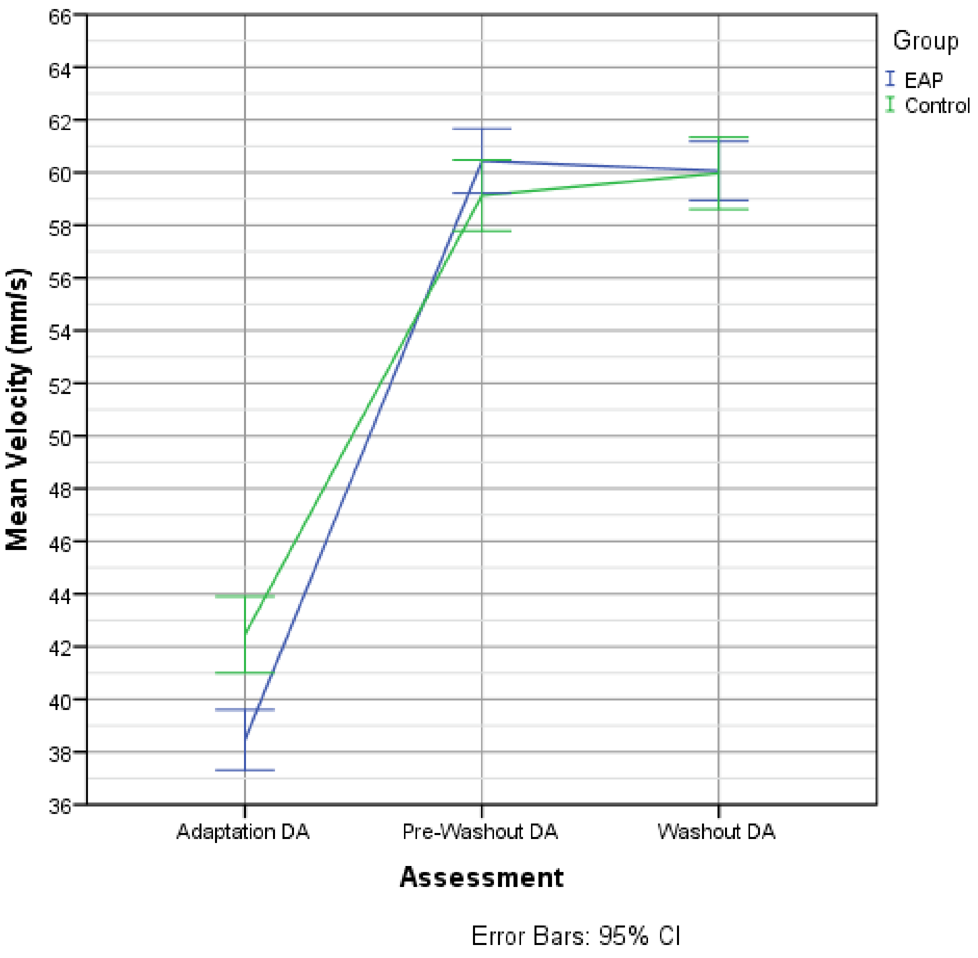


Figure 7-13: Mean velocity over the different assessment blocks on the DA for the EAP and the Control group.

Normalised jerk (Figure 7-14) was affected by practice as indicated by the tests of fixed effects F(2,228.987) =89.209, p<0.005. The same tests did not identify a significant interaction between HCA group and practice F(2,228.987) =0.873, p=0.419. The latter finding indicates that both groups behaved similarly regarding the smoothness of their movement as measured by the normalised jerk measure throughout the trial. As such, the estimates of fixed effects showed that movement became smoother after the training stage of the trail, as normalised jerk was significantly reduced from the adaptation assessment in the pre-washout assessment by an estimated of 25.2 units (p<0.005). The improved smoothness was fully retained post-washout as there was no statistically significant difference in the normalised jerk between the pre- and post-washout assessments (p=1.000) as the estimates of marginal means indicated.

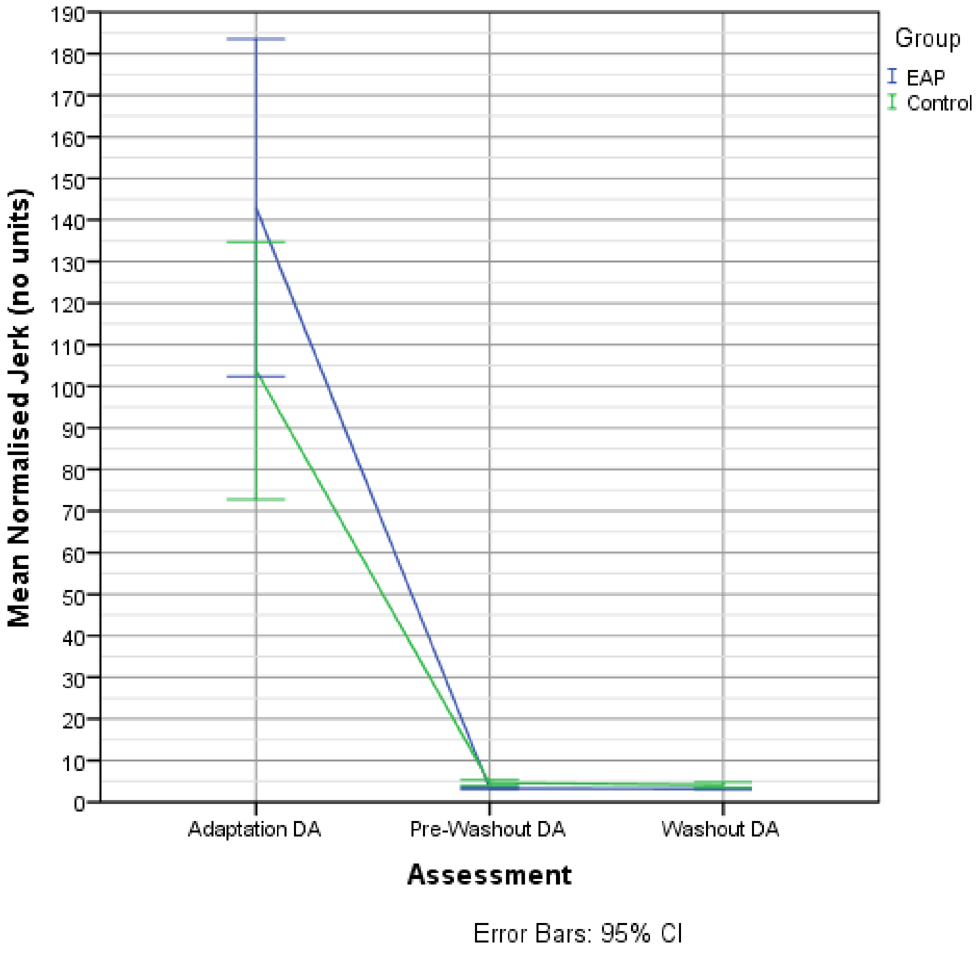


Figure 7-14: Normalised jerk over the different assessment blocks on the DA for the EAP and the Control group.

Initial error of the DA (Figure 7-15) was unaffected by practice and by the HCA group the participants were assigned to, as the estimates of fixed effects did not identify a significant effect of practice F(2,1662.252) =1.963, p=0.141 or a significant interaction between HCA group and practice F(2,1662.252) =1.706, p=0.182.

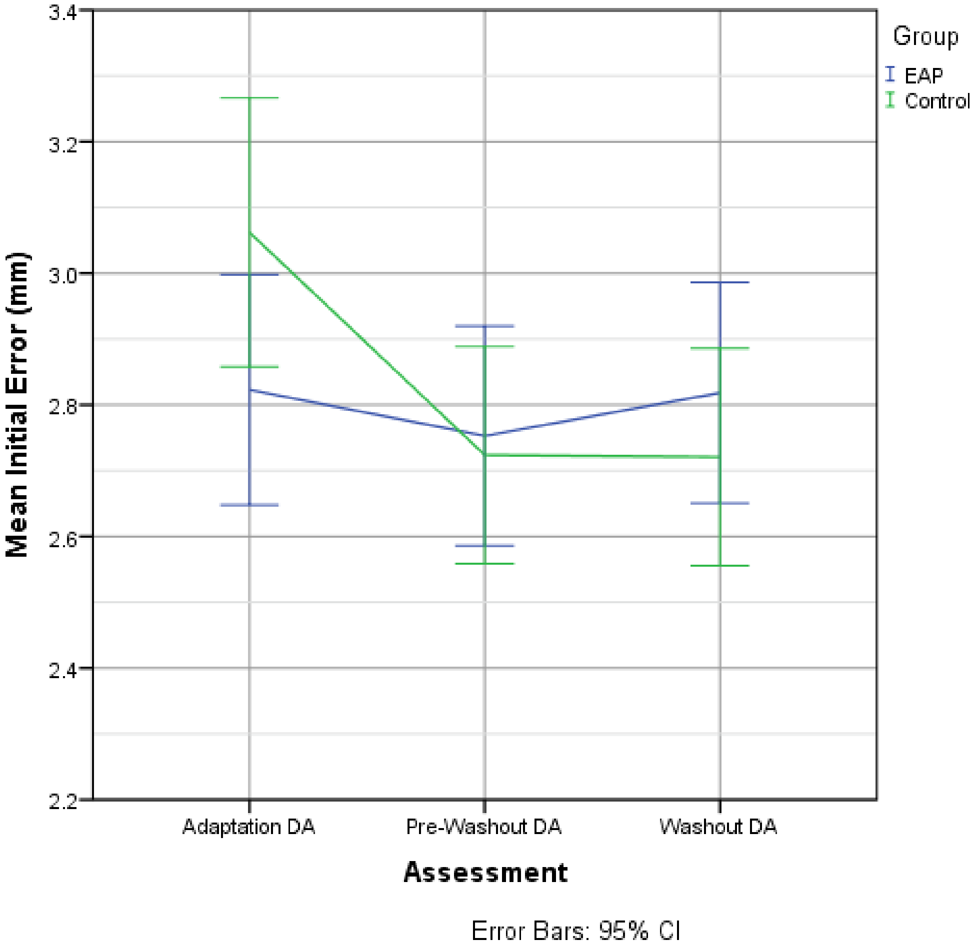


Figure 7-15: Initial error over the different assessment blocks on the DA for the EAP and the Control group.

7.4.2.2 ***Results of the circle-drawing task for the dominant arm***

The test of fixed effects failed to identify a statistically significant effect of practice on movement circularity (p=0.321) or a statistically significant interaction between HCA group and practice (p=0.987). As such, movement circularity (Figure 7-16) remained unchanged throughout the trial for both groups.

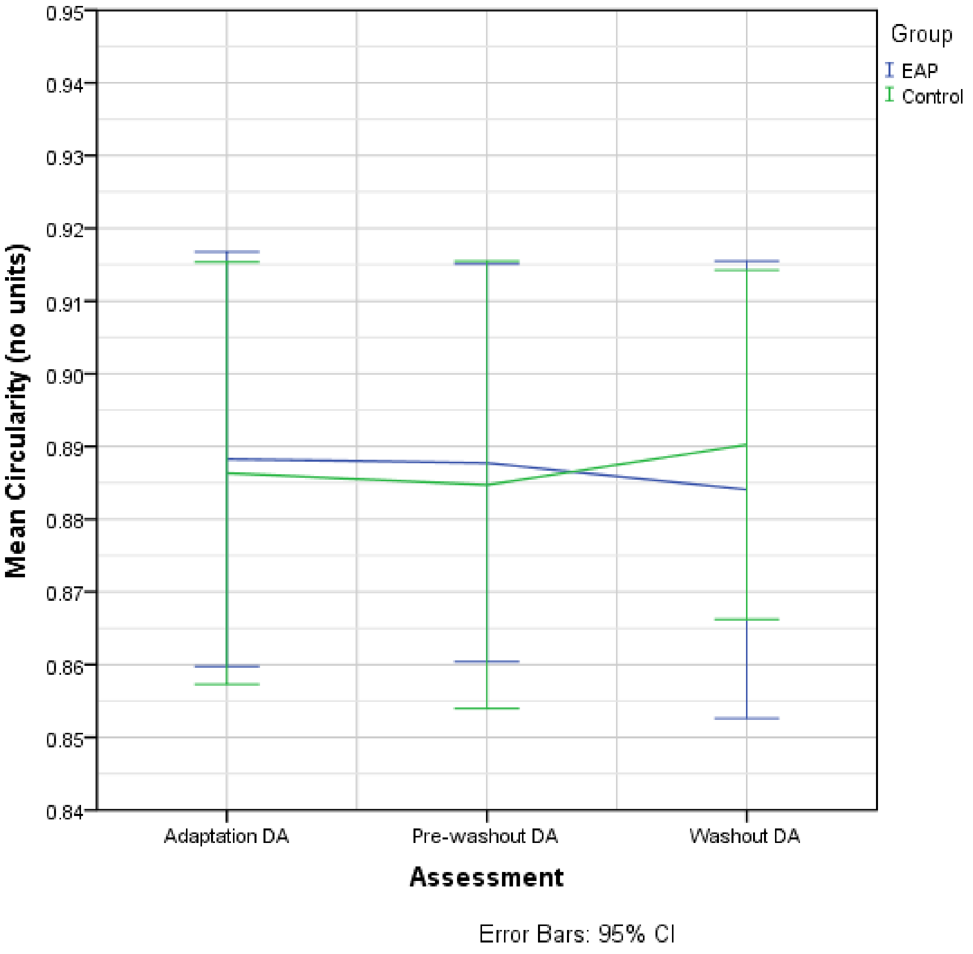


Figure 7-16: Movement circularity over the different assessment blocks on the DA for the EAP and the Control group.

In the case of duration of the circular movements the standard LMM analysis undertaken failed to converge to a solution similar to what was described in Section 6.4.2.2. As such, the same solution was employed which was to not consider any random effects in the statistical model.

The estimates of fixed effects showed that there was a statistically significant effect of practice in the duration of the circular movements F(2,47.196) =16.743, p<0.005 and also that there was no statistically significant interaction between HCA group and practice F(2,47.196) =0.005, p=0.995 (Figure 7-17). This indicates that the duration of the movement of both groups had changed similarly in the course of the trial. More specifically, the duration of the movements became shorter in the pre-washout assessment by 9.1s (p<0.005) when compared to the adaptation assessment. Interestingly, the estimates of fixed effects found an even bigger difference (9.8s, p<0.005) between the post-washout and the adaptation assessment. However, as the estimated marginal means failed to identify a statistically significant difference in the duration of the circular movement between the pre- and the post-washout assessment (p=1.000) it can be concluded that the washout block did not have an effect on the circular movement duration.

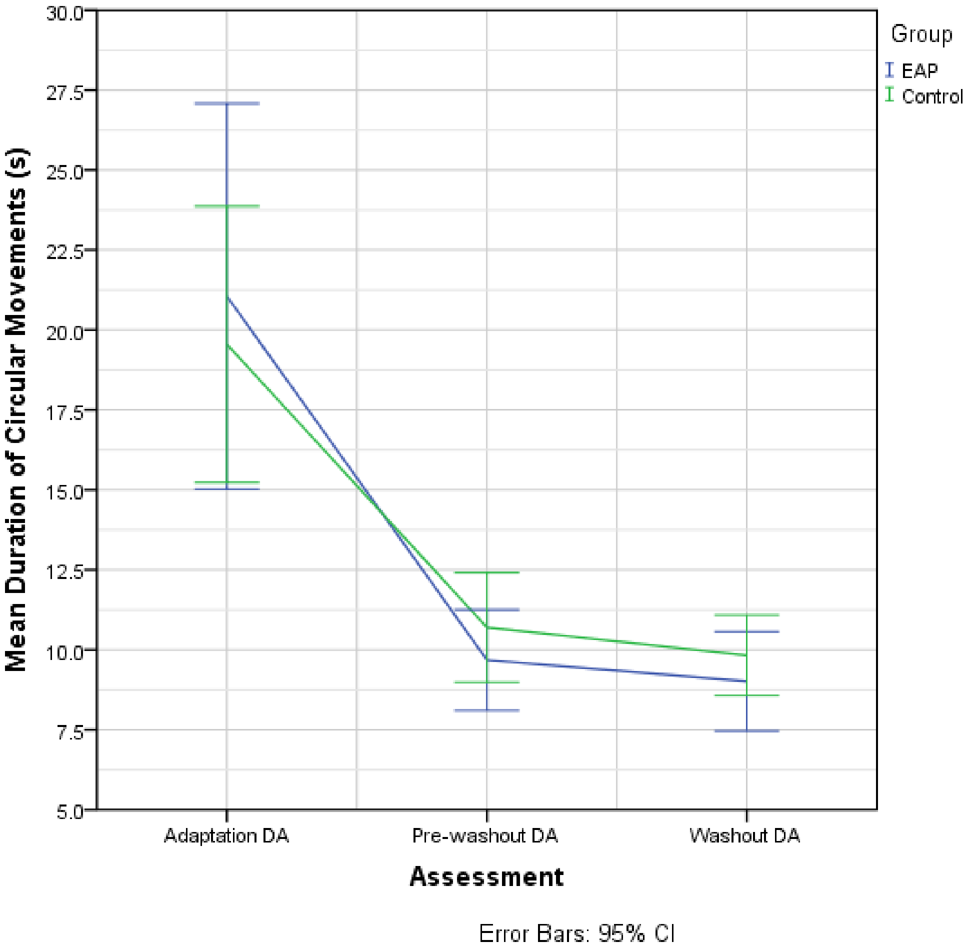


Figure 7-17: Movement duration over the different assessment blocks on the DA for the EAP and the Control group.

Table 7-2:Summary of the findings on the analysis of the effectiveness of the trial on the EAP and Control group for the DA

Measure	**Learning pre-washout**	**Retention post-washout**	**Improved more pre-washout**	**Retained more post-washout**
Duration	Yes	Yes	EAP	No difference
Perpendicular error	Yes	Yes	No difference	No difference
Mean velocity	Yes	Yes	EAP	No difference
Normalised jerk	Yes	Yes	No difference	No difference
Initial error	No	N/A	No difference	No difference
Circularity	No	N/A	No difference	No difference
Circular movement duration	Yes	Yes	No difference	No difference

7.4.3 Analysis of the Self-Assessment Manikin questionnaire

The same questionnaire was undertaken by the participants at the beginning of each assessment block in order to identify potential changes in the participants Dominance, Arousal and Valence during the course of the trial.

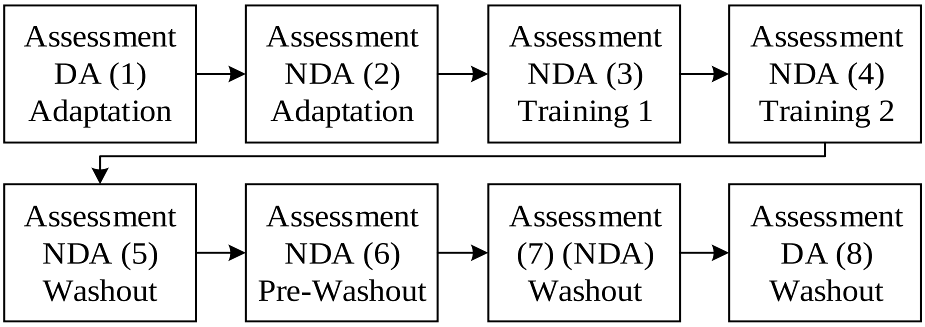


Figure 7-18: The different assessment blocks where the SAM questionnaire was administered.

According to the estimates of fixed effects there was no statistically significant effect of practice F(6,56.663) =1.144, p=0.348 on the participants' valence (Figure 7-19) as well as there was no statistically significant interaction between HCA group and practice F(6,56.663) =0.433, p=0.854. This finding indicates that the participants' valence remained unchanged throughout the trial.

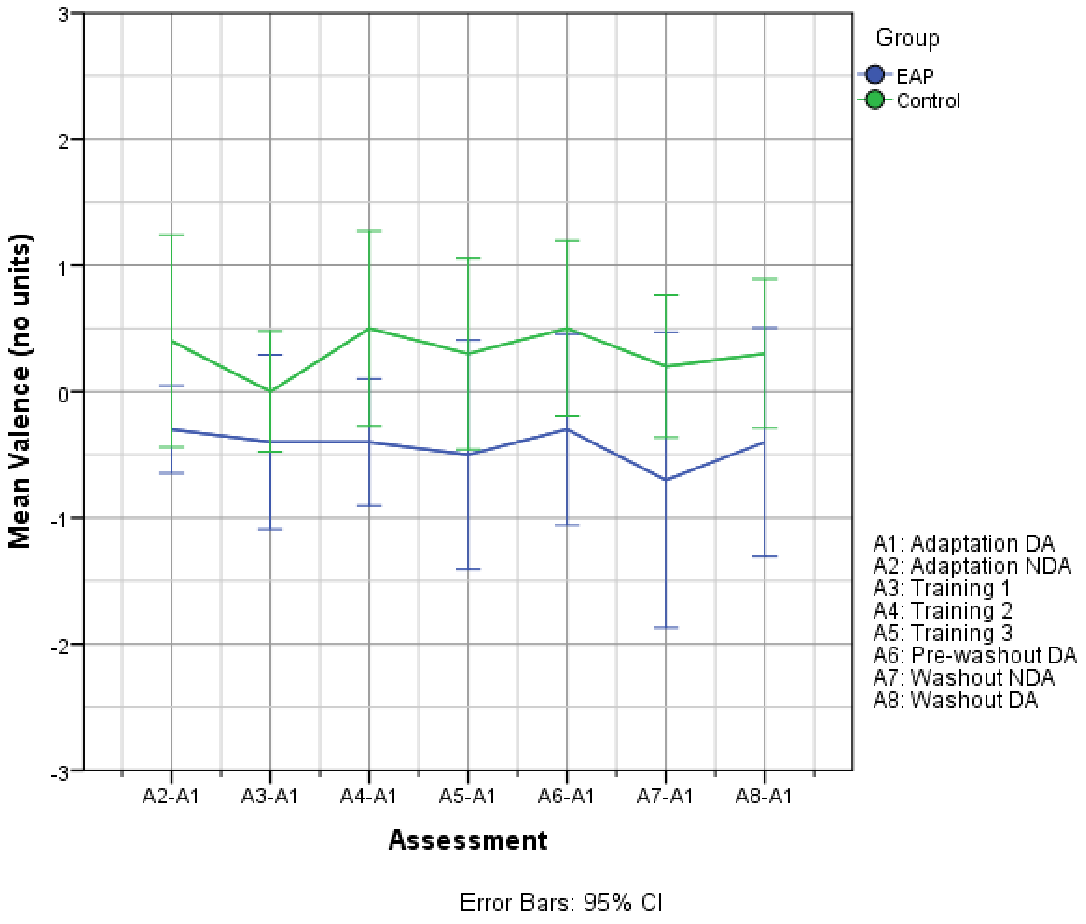


Figure 7-19: Valence over the different assessment blocks for the EAP and the Control group.

With respect to arousal (Figure 7-20), there was no statistically significant effect of practice F(6,45.530) =1.887, p=0.104 nor was there a statistically significant interaction between HCA group and practice F(6,45.530) =0.823, p=0.558. As such, according to the results of this model participants' arousal remained unaffected by the trial.

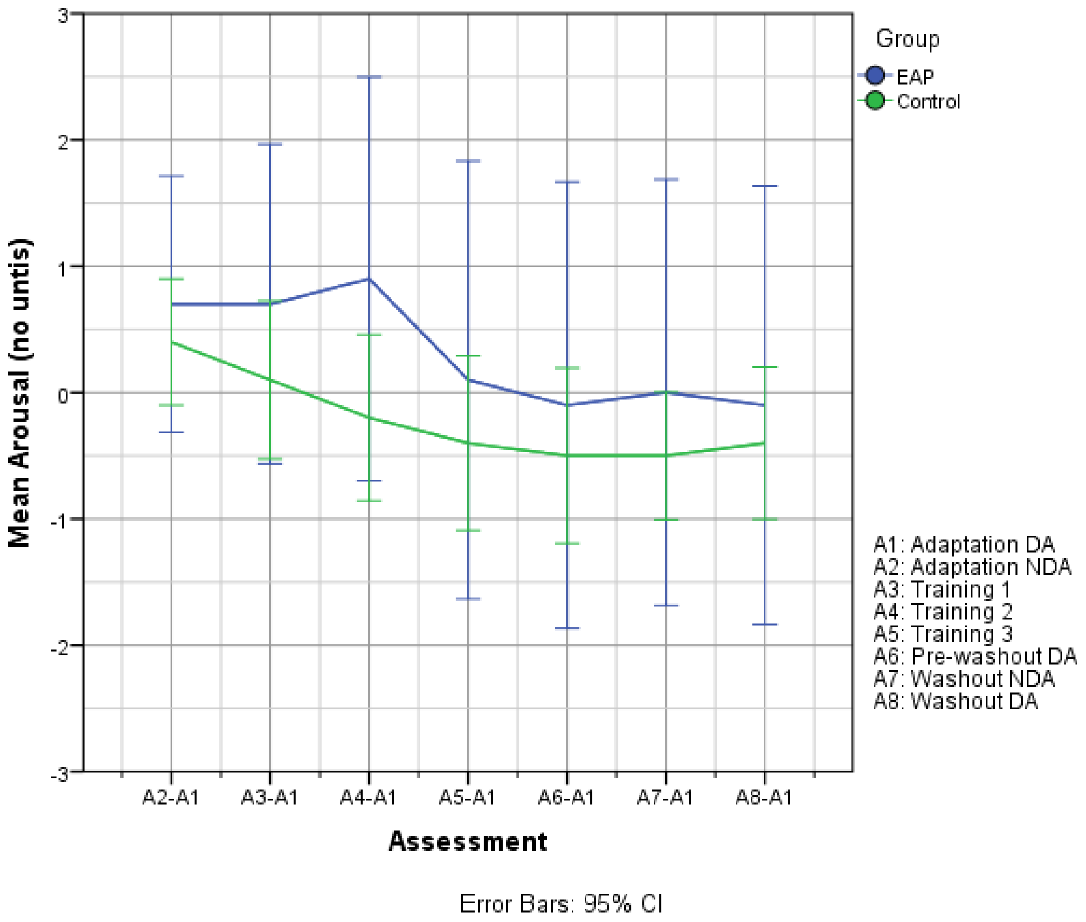


Figure 7-20: Arousal over the different assessment blocks for the EAP and the Control group.

The tests of fixed effects indicated a statistically significant effect of practice F(6,45.967) =3.516, p<0.05 on the participants' dominance (Figure 7-21) but not a statistically significant interaction between HCA group and practice F(6,45.967) =1.224, p=0.311. The estimates of fixed effects showed that participants' dominance increased in the course of the trial. More specifically, the participants felt that they were more in control (increased dominance) in the assessment blocks following the adaptation block for the DA up until the assessment after training block 3, reaching differences in arousal of 0.6-0.9 units (p<0.05). After the washout block on the NDA the dominance returned to the initial levels (p=0.129). However, at the last assessment of the trial (washout on the DA) dominance increased again to the improved levels (0.9, p<0.05) of the pre-washout assessments.

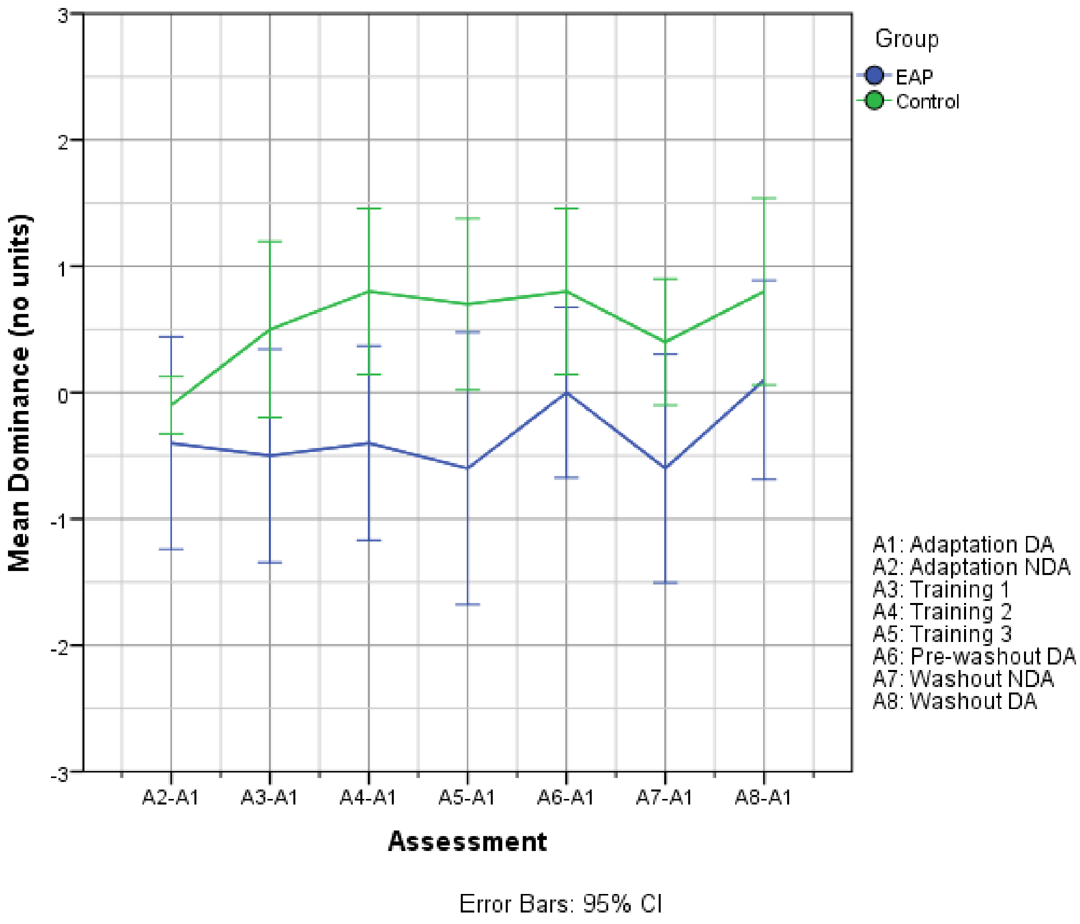


Figure 7-21: Dominance over the different assessment blocks for the EAP and the Control group.

Table 7-3: Summary of the findings on the analysis of the effectiveness of the trial on the EAP and the Control group for the SAM questionnaire

Measure	Effect of practice	Difference between the groups?
Valence	No	No
Arousal	No	Yes
Dominance	Yes (↑)	No

7.5 Discussion

The analysis of the kinematic measures collected for the NDA during the reaching task showed that motor learning did occur, for the participants of the EAP and Control groups, throughout the trial as all kinematic measures improved on the course of the training. This improvement was sustained for all measures after the washout phase of the trial, with the only exception being the perpendicular error and the initial error which both returned to the adaptation levels. It must be noted that although a statistically significant effect of practice was identified for the initial error this was discarded as a false positive effect in the analysis of the results as it appeared to be a random occurrence in just one assessment block.

When comparing the two groups namely EAP and control, they performed similarly in all measures except for the movement duration and mean velocity. EAP demonstrated a greater improvement in the duration of its movements than the Control group did. That is an interesting finding that can be attributed to the merits of the particular control algorithm. However, it must be noted that the EAP group demonstrated a higher movement duration in the adaptation assessment and the estimated marginal means did not identify a statistically significant difference at the levels achieved by both groups in movement duration as it was measured in the assessment after training block 3. This indicates that both groups reached a minimum in the duration of their movements that was possible to be achieved given the practice they received. Therefore, it is likely that the highest improvement for the EAP group in movement duration was due to the initial higher levels measured in the adaptation assessment. Nevertheless, an unexpected finding of the analysis was that post-washout there was more retention of the practice effect related to movement duration for the Control group when compared to the EAP group. The author failed to identify a similar occurrence in other studies or a possible explanation of this finding in the existing literature. As such, further investigation is recommended in order to identify whether this is a valid effect of the different HCAs and if this is indeed the case to identify a possible interpretation of this finding.

When looking at the mean velocity of the movements both groups achieved the same levels of improvement in the assessment following training block 3. The analysis however, showed that the EAP group achieved its maximum improvement in training block 2. Therefore, despite the fact that the two groups increased the mean velocity of their movements at the same levels the EAP group achieved that improvement faster. That is an indication of a potential effect of HCA indicating that the EAP group may be promoting increased movement velocity. Yet, the analysis showed that there was no difference between the two groups on how much they retained of their increased mean velocity after the washout block.

The analysis of the circle-drawing task for the NDA yielded that the intervention and the group assigned were not factors that affected the circularity of the participants' movements. However, although the participants' movement circularity remained at similar levels throughout the session the duration of the circular movements improved throughout the training part of the trial. Post-washout movement duration kept improving for both groups indicating that the washout block had no effect on the circle drawing task.

As with the EAA it appears that the EAP was more effective at improving the mean movement velocity indicating a potential benefit of EA on this specific measure. Furthermore, EAP was better at improving mean duration of the movements but not at retaining it. Given that both groups performed similarly with regard to movement error it appears that EAP was more effective at inducing motor learning than the control condition as the group that received training with this HCA completed quicker its movements while maintaining the same amount of error. Movement duration and perpendicular error are the most relevant kinematic measures to the task (participants were asked to perform the movements as quickly and as accurately as possible) and hence better descriptors for potential motor learning that occurred. A randomised control trial (RCT) study with a crossover design stroke participants by (Abdollahi et al., 2014) reported a better outcome in clinical scales such as the Fugl-Meyer Assessment (FMA) and the Wolf Motor Function Test (Section 2.3.1) when participants trained with EA instead of training without any forces or visual error augmentation provided by the system. Although only kinematic parameters were considered in the trial presented in this report the findings can be linked to clinical scales as it has been shown that kinematic measures such as perpendicular error and movement duration correlate to clinical scales such as the FMA (Bosecker et al., 2010) and WMFT (Rohafza et al., 2014).

Regarding the reaching task on the DA, all kinematic measures improved during the training stages of the trial with the only exception being initial error that remained unchanged throughout the trial for both groups. As with the NDA, EAP improved more in terms of the duration and the mean velocity of its movements than the Control group did. In both measures EAP showed worse performance in the adaptation assessment and reached same levels with the Control group in the pre-washout assessment. As such, it is less likely that this greater improvement of the EAP in movement duration and velocity was an effect of the assigned HCA (or absence of) and more likely that it was due to inherent difference between the population of the groups. This interpretation is further supported by the absence of differences between the groups on how all measures changed in the post-washout assessment. Nevertheless, both groups showed signs of bilateral transfer from the NDA to the DA throughout the trial that were not washed-out.

Movement circularity in the circle-drawing task using the DA remained unchanged throughout the trial. On the other hand, the duration of the circular movement was reduced for both groups in the pre-washout assessment and retained fully post-washout. The latter finding indicates that learning did indeed occur for the DA on the circle-drawing task however, it is impossible to distinguish whether that learning occurred due to bilateral transfer or due to motor learning that occurred within the adaptation assessments on the DA. Nevertheless, there were no differences on how the two groups behaved in the circle-drawing task as measured by the kinematic measures.

Finally, there was no difference between the two groups on the valence and arousal of the participants of either group but there was an increase in their dominance pre-washout. In the first post washout assessment (washout on the NDA) dominance returned to the adaptation levels which in turn were restored in the second washout assessment back to the increased levels post-washout. A possible explanation of this finding could be that as the participants improved throughout the trial felt more confident and hence more in control. This confidence was briefly disturbed by the washout block but as visual rotation was turned back on the participants felt again confident at performing the task and hence in control. It must be noted that no differences were identified between the groups on how either of the SAM questionnaire measures.

7.6 Summary

Some key findings of the analysis can be found below:

- Both interventions (group training conditions) led to a) improvement in the participants' movements of the NDA in all parameters except for initial error and movement circularity pre-washout and b) retention of improvements post-washout except for perpendicular error, initial error and circularity.
- EAP was more effective on improving movement duration and mean velocity.
- EAP was less effective on retaining improvements in movement duration.
- Reaching tasks and bilateral transfer led to similar patterns of improvement.
- Bilateral transfer appears unaffected by washout.
- There was no effect of practice type on the changes of the psychological state of the participants.

8 Comparison between the developed algorithms on their effect on inducing motor learning

8.1 Introduction

In Chapters 6-8, the three developed haptic control algorithms namely Assistance As Needed, Error Augmenting Adaptive and Error Augmenting Proportional were compared individually against the Control group with regards to their effect on motor learning of able-bodied adults. The participants were randomly assigned to one of four groups. The first three groups practised reaching movements while the rehabilitation robot was implementing one of the developed HCAs while the fourth group (Control group) underwent the same protocol but without receiving any forces by the robot.

Each of the previous chapters presented the results of the trial for the groups that received training with corresponding HCA in comparison to the results of the Control group. This chapter aims to compare the findings of a statistical analysis including of all four groups, in order to extract meaningful insight not only on how motor learning, retention and bilateral transfer on performing the practised task was affected by the four conditions but also how the three HCAs compare against each other in promoting motor learning. As this trial is meant to serve as an exploratory study with able-bodied participants whose results are to be applied on the impaired population (from CP/stroke), a recommended practice in the field (Dobkin, 2009), the results will be discussed with reference not only to the able-bodied population but also to those who suffer from upper limb impairments caused by stroke and CP . An overview of the four algorithms is provided in Figure 8-1.

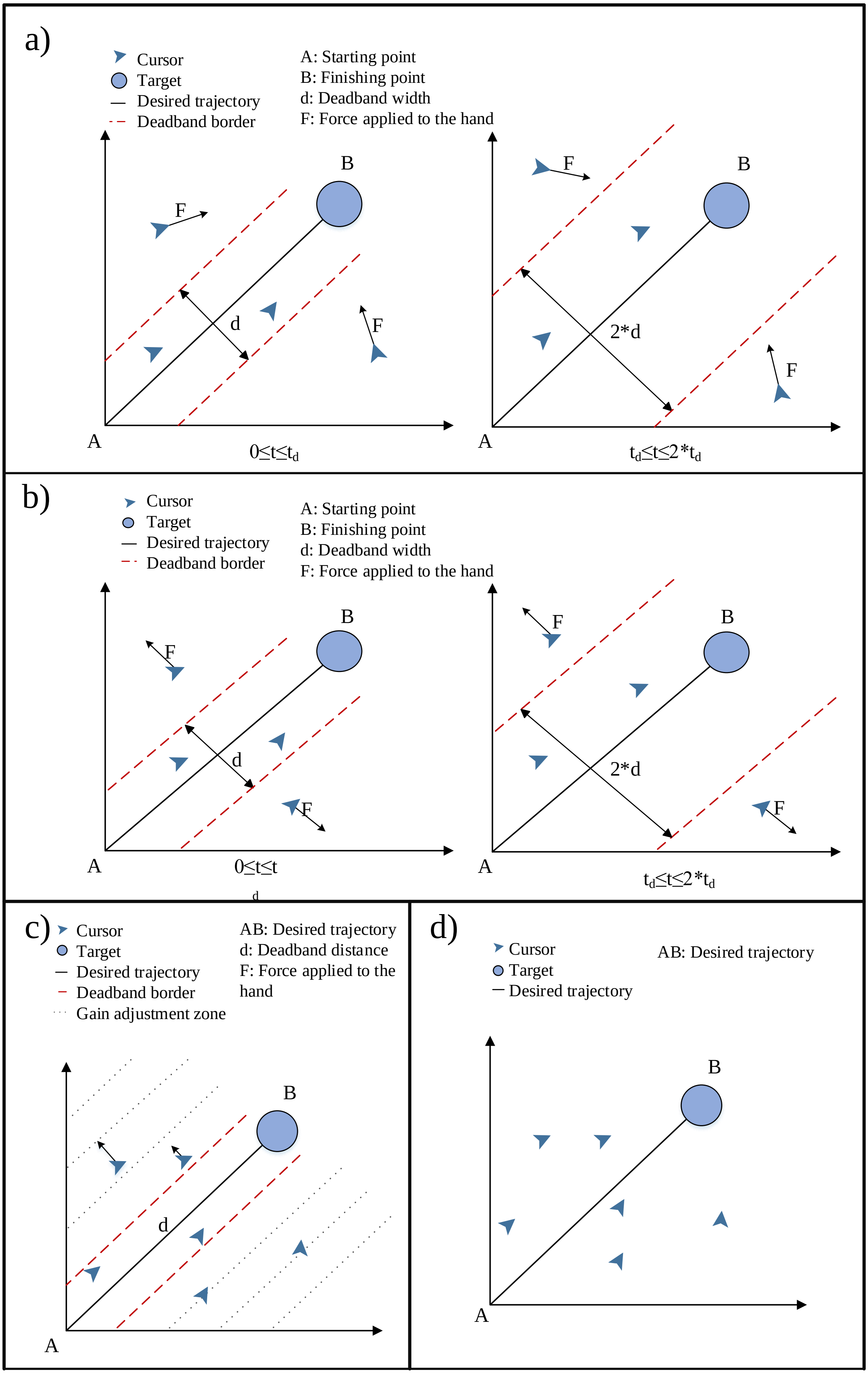


Figure 8-1: Each of the groups received training with one of four conditions. a) AAN, b) EAA, c) EAP, d) Control

8.2 Research questions

1) Is there a difference in how the different HCAs affect motor learning on the upper limb of the able-bodied adults and if so what are those differences?
2) Is bilateral transfer affected by the conditions of exercise / intervention?
3) Is there a difference between the different HCAs on how the participants' emotional state is affected?

8.3 Results of the statistical analysis

This section provides an overview of the trial and results for all four groups in order for comparisons to be made in their effect on motor learning and ultimately to identify potential differences between them. The trial protocol and the analysis methodology are presented in Section 4.3.

8.3.1 Analysis of the kinematic measures for the non-dominant arm

During the course of the trial the participants underwent five assessment blocks using their NDA (Figure 8-2), one after the adaptation block, one after each of the three training blocks and one after the washout block. The first provided a baseline measurement as no training was undertaken by the participants. The assessments following the training blocks were performed in order to assess the potential changes in the values of the kinematic measures at different stages of the trial. Finally, the post-washout assessment was introduced in order to measure at what level the changes in the kinematic measures were retained by comparing the values to compared to assessments pre-washout.

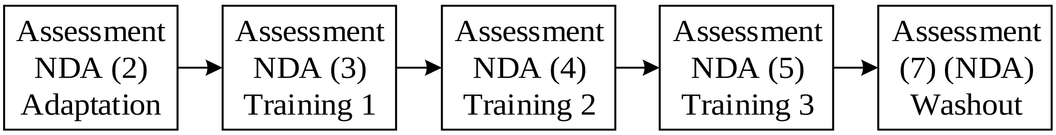


Figure 8-2: The assessments on the NDA.

8.3.1.1 *Result of the reaching task where the non-dominant arm was used*

The tests of fixed effects indicated that there was a statistically significant effect of HCA group on the duration of the movements F(4,2716.601) = 715.873, $p<0.05$ and a statistically significant interaction between HCA group and practice F(12,2716.601) =13.041, $p<0.005$ indicating that there were significant differences between the groups on how the movement duration had changed throughout practice (Figure 8-3). All groups reduced the duration of their reaching movements in the different training blocks of the trial. However, the EAA and the AAN groups reached a minimum in movement duration after training block 2 as there were no statistically significant differences between the training blocks 2 and 3 in the estimated marginal means for these two groups ($p=0.496$ for the EAA and $p=0.808$ for the AAN). The estimates of fixed effects however, showed that all groups improved similarly when comparing movement duration after training block 3 with the adaptation assessment with the only exception being the AAN group which improved by 0.23s ($p<0.005$) less than the other groups.

From the estimated marginal means it can be seen that post-washout all groups significantly increased their movement duration ($p<0.05$) indicating partial washout. Furthermore, the EAP and the Control group increased their movement duration similarly as the estimates of fixed effects did not identify a significant difference between these two groups ($p=0.108$). The EAA and the AAN groups retained less of the improved movement duration than the EAP and the Control group did. This can be seen in the estimates of fixed effects where the duration of the movements of the EAA and the ANN on the post-washout assessment were closer to the adaptation values than the other two groups by 0.24s ($p<0.005$) and 0.32s ($p<0.005$), respectively. As such, the EAP and the Control group retained more of the improved duration after the washout assessment.

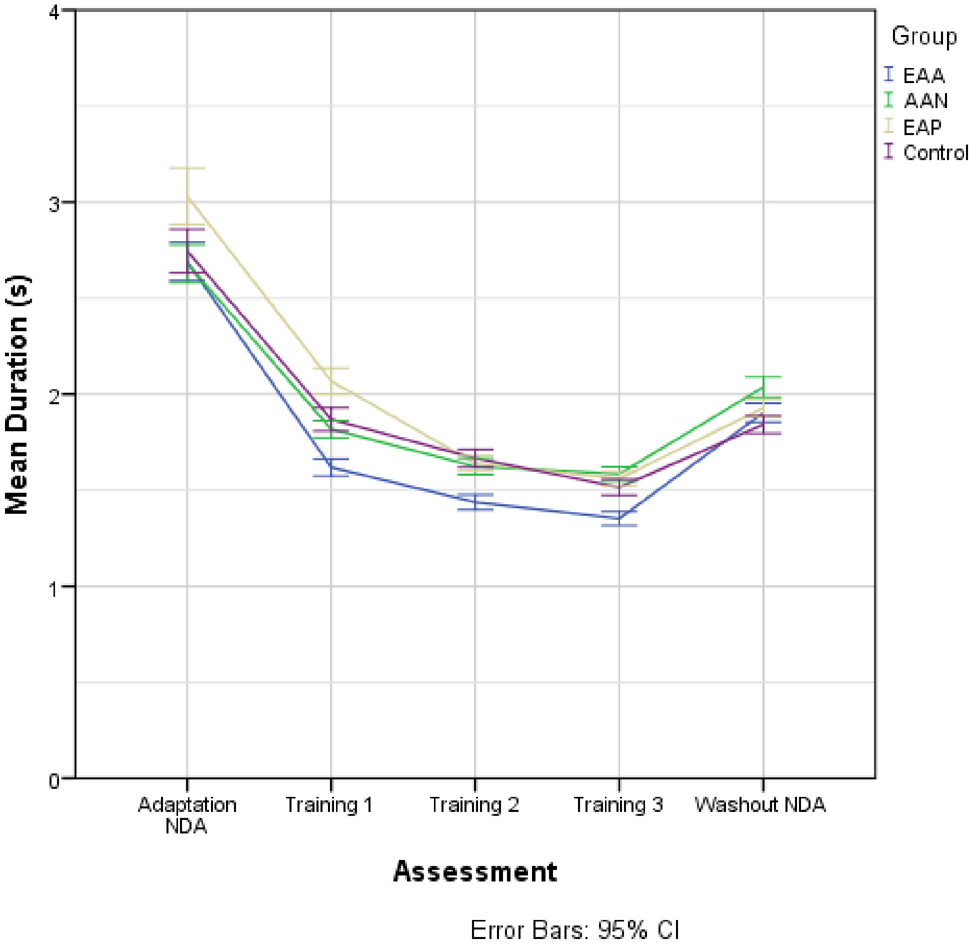


Figure 8-3: Mean duration over the different assessment blocks on the NDA for the four intervention groups.

The tests of fixed effects showed that there was a statistically significant effect of practice F(12,2308.211) =552.687, $p<0.005$ on the perpendicular error of the movements (Figure 8-4) and also that there was a statistically significant interaction between HCA group and practice F(12,2308.211) =1.877, $p<0.05$. The estimates of fixed effects showed that there was no difference on how the perpendicular error was changed in the training stage of the trial between the EAA, AAN and the Control group ($p>0.05$).

The EAP group demonstrated similar performance to the other groups on how error changed from the adaptation assessment in the assessments after training blocks 1 and 3 as there was no statistically significant difference ($p>0.05$). However, the EAP showed a statistically significant difference ($p<0.05$) on how the perpendicular error was reduced between the adaptation assessment and on the assessment after training block 2 where improvement was

0.9 mm less than the other three groups. Also the estimated marginal means showed that all groups except for the EAP reached the minimum in the perpendicular error of their movements in training block 1 as there was no statistically significant difference in perpendicular error between the assessments after trainings block 1-3 (p>0.05) for the EAA, AAN and Control group. The latter two findings if combined demonstrate a potential effect on the EAP group, which although it reached the same level of improvement at the end of the training part of the trial (after training block 3), it did so slower than the other three groups.

Post-washout all groups behaved similarly as the estimates of fixed effects failed to identify a significant difference (p>0.05) on how the perpendicular error of the different groups was changed between the post-washout and adaptation assessment. More specifically, the improvement in perpendicular error that the participants demonstrated at the training part of the trial it was completely washed-out and returned to the levels achieved at the adaptation assessment. This is supported by the estimates of fixed effects that showed no statistically significant difference between the adaptation and washout assessment (p>0.05).

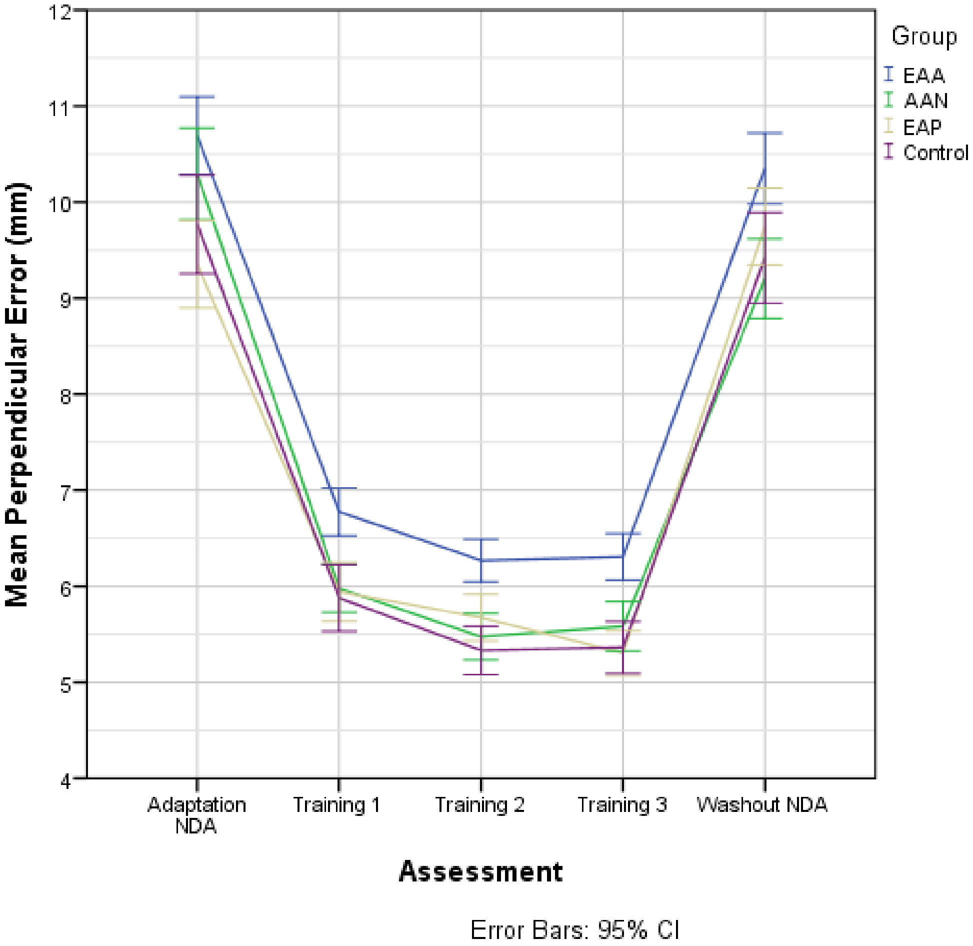


Figure 8-4: Mean perpendicular error over the different assessment blocks for the four intervention groups.

Practice had a statistically significant effect on the mean velocity of the reaching movements (Figure 8-5)as the tests of fixed effects indicated F(4,3165.041) =555.966, $p<0.005$. The same tests also identified a statistically significant interaction between HCA group and practice F(12,3165.041) =20.396, $p<0.005$. All groups reduced their mean velocity throughout the training stage of the trial.

Both the Control group and the EAP increased their mean velocity in a similar manner as the estimates of fixed effects could not identify a statistically significant difference on how the mean velocity had changed between the adaptation assessment and the assessment following training block 3, between the two groups (p=0.190). The EAA group improved more than the control and EAP groups did after training block 3 as it increased its velocity by 9.0 mm/s ($p<0.005$) more than the other two groups did after training block 3. On the other hand, the AAN group improved less than the other groups after training block 3 with an estimated difference of 5.0 mm/s ($p<0.005$), in the increase of mean velocity between the adaptation assessment and the one after training block 3, when compared to the control and EAP.

Post-washout, all groups reduced the mean velocity of their movements indicating that the improvement measured in training block 3 was partially washed out. Nevertheless, the EAP and control once more experienced a similar washout as the estimates of fixed indicated there was no statistically significant difference between the difference in mean velocity between the washout and the adaptation assessment ($p=0.069$). Conversely, on the same comparison between the adaptation and the washout assessment the estimates of fixed effects showed that there was a statistically significant difference between the AAN and the Control groups. The EAA retained less of its mean velocity than the EAP and Control group by 3 mm/s ($p<0.05$). On the other hand, the AAN group retained less of the improved velocity than the other groups did by an estimate of 6.1 mm/s $p<0.005$) when compared to the control and the EAP groups.

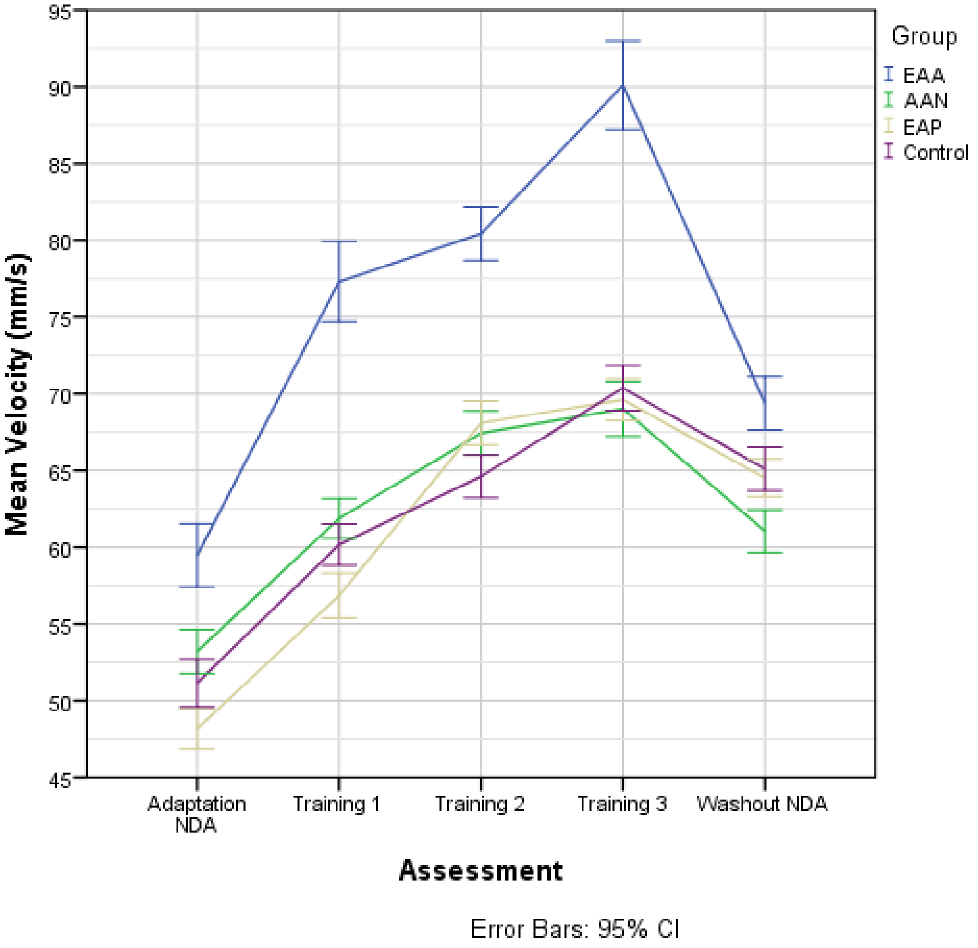


Figure 8-5: Mean velocity over the different assessment blocks on the NDA for the four intervention groups.

When considering movement smoothness (Figure 8-6) as measured by the normalised jerk measure, the estimates of fixed effects identified a statistically significant effect of practice F(4,1285.826) =223.559, $p<0.005$ as well as a statistically significant interaction between HCA group and practice F(12,1285.826) =11.617, $p<0.005$. All groups improved in terms of their movement smoothness in the training part of the trial. More specifically, the EAA and AAN groups reached a peak in the improvement of normalised jerk in training block 2 (the estimates of marginal means showed no statistically significant difference between training block 2 and 3, $p>0.05$). On the other hand, the Control group kept improving until the end of the training part of trial (estimates of marginal means showed a significant difference between training block 2 and 3, $P<0.005$).

The estimates of fixed effects indicated that the EAP and the Control group performed similarly throughout the trial as there was no statistically significant difference on how normalised jerk has changed in the different assessment blocks when compared to the adaptation assessment ($p>0.05$). However, the same estimates showed a statistically significant difference in the change of normalised jerk between the EAA and the control (and EAP) group as well as between the AAN and the Control group. More specifically, the EAA and the AAN groups improved by 3.8 units ($p<0.005$) and 3.5 units ($p<0.005$) less than the Control group did between the adaptation assessment and the assessment after training block 3. As such, the movements of the EAP and the Control group demonstrated the greatest improvement during the training stage of the trial.

When it comes to the change in normalised jerk after the washout block all groups increased the normalised jerk of their movements (movements became less smooth) indicating that washout did indeed occur. However, this washout was only partial as the movements of all groups despite being less smooth when compared to the pre-washout levels they remained significantly smoother than the ones in the adaptation block ($p<0.005$). From the estimates of fixed effects, it can be seen that there was no statistically significant difference on how normalised jerk was changed at the washout assessment when compared to the adaptation assessment, between the EAP and the Control group. The same tests found a statistically significant difference between washout and the adaptation assessment between the EAA and AAN groups and the Control group. More specifically, both the EAA and the AAN groups retained less of the normalised jerk of their movements post-washout when compared to the Control group (4.4 units ($p<0.005$) for the EAA and 4.0 units less ($p<0.05$) for the AAN).

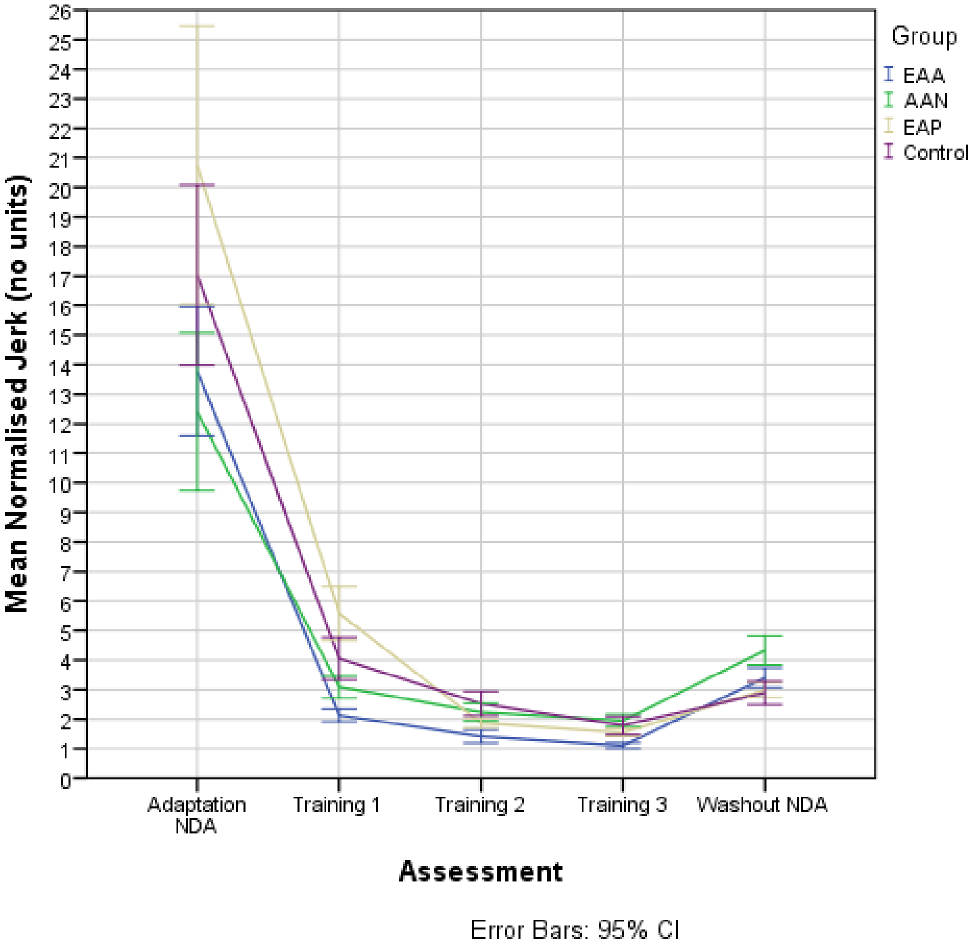


Figure 8-6: Normalised jerk over the different assessment blocks on the NDA for the four intervention groups.

The tests fixed effects indicated a significant effect of practice F(4,3181.375) =5.691, p<0.005 on initial error (Figure 8-7) but did not show a significant interaction between HCA group and practice F(12,3181.375) =0.545, p<0.886. The estimates of fixed effects found a statistically significant reduction in initial error after training block 2 (-0.24 mm, p<0.05) and training block 3 (0.25 mm, p<0.05) when compared to the initial error achieved in the adaptation assessment. This finding indicates that movements became more accurate in the initial stage in the course of the training part of the trial. Nevertheless, the estimates of fixed effects did not find a statistically significant difference in initial error between the washout assessment and the adaptation assessment (p<0.802) indicating that the improvement that occurred in training blocks 2 and 3 was completely washed out.

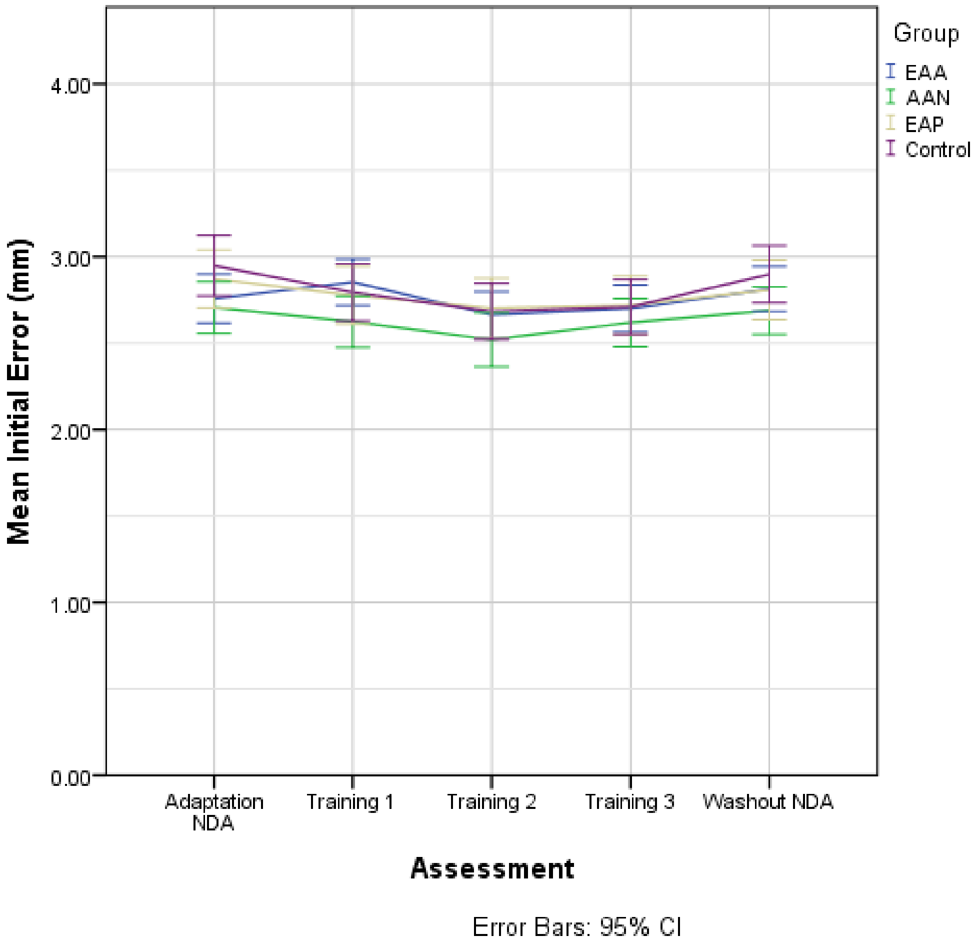


Figure 8-7: Initial error over the different assessment blocks on the NDA for the four intervention groups.

8.3.1.2 *Results of the circle-drawing task for the non-dominant arm*

In the circle-drawing task, movement circularity (Figure 8-8) appears not to be affected by practice as the tests of fixed effects did not find a statistically significant effect (p=0.470). Also the same test showed that there was no statistically significant interaction between HCA group and practice (p=0.437). Due to the aforementioned it can be concluded that no learning (or washout) in terms of circularity had occurred during the trial.

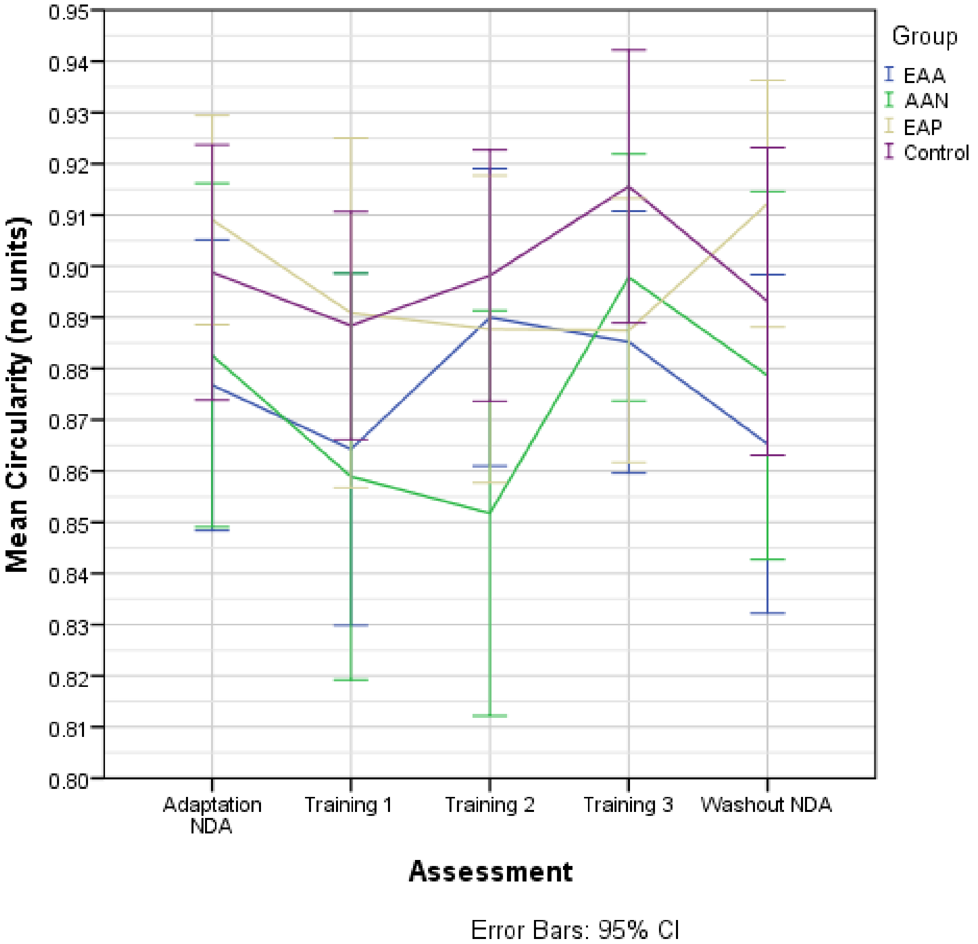


Figure 8-8: Movement circularity over the different assessment blocks on the NDA for the four intervention groups.

The tests of fixed effects showed that there was a statistically significant effect of practice F(4,66.452) =16.865, p<0.005 on the duration of the circular movements (Figure 8-9) but did not identify a significant interaction between HCA group and assessment F(12,66.452) =1.662, p=0.096. As demonstrated by the estimates of fixed effects the duration of the circular movements was reduced throughout the trial reaching a maximum difference from the adaptation assessment of 4.5s (p<0.005) at the washout assessment. This latter finding indicates that some learning did indeed occur and it was not impeded by the washout block as movement duration kept improving post-washout.

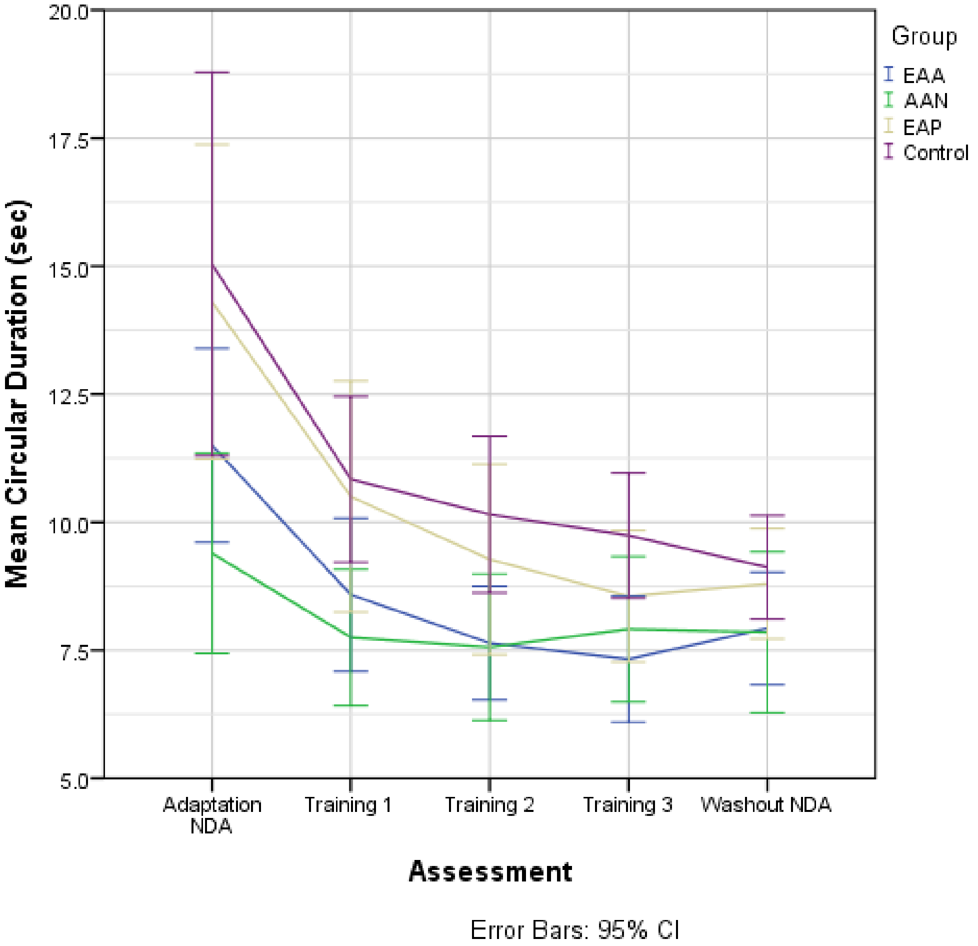


Figure 8-9: Movement duration for the circle-drawing task over the different assessment blocks on the NDA for the four intervention groups.

Table 8-1:Summary of the findings on the analysis of the effectiveness of the trial on the four different groups for the NDA.

Measure	**Learning pre-washout**	**Retention post-washout**	**Improved more pre-washout**	**Retained more post-washout**
Duration	Yes	Yes	EAA, EAP, Control (AAN, EAA reached peak performance sooner)	Control, EAP
Perpendicular error	Yes	No	No difference (EAP reached peak performance slower)	No difference
Mean velocity	Yes	Yes	EAA	Control, EAP
Normalised jerk	Yes	Yes	Control, EAP	Control, EAP
Initial error	Yes	No	No difference	No difference
Circularity	No	N/A	No difference	No difference
Circular movement duration	Yes	Yes (↑)	No difference	No difference

8.3.2 Analysis of the kinematic measures for the dominant arm

Only three assessment blocks were performed using the DA (Figure 8-10). One assessment block was undertaken in the beginning of the trial, in order to serve as a baseline assessment before any learning had occurred. One more assessment was performed at the end of the training phase of the trial to assess if learning had occurred for the DA and hence whether bilateral transfer took place. The final assessment was performed post-washout in order to assess potential retention of the learning.

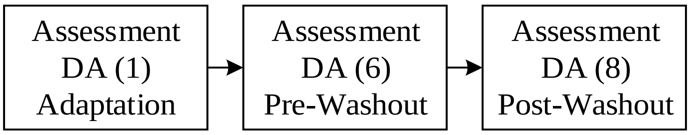


Figure 8-10: The assessment on the DA.

8.3.2.1 ***Results of the reaching task for the dominant arm***

The tests of fixed effects showed a statistically significant effect of practice F(2,1654.946) =743.691, $p < 0.005$ on the duration of the reaching movements (Figure 8-11) as well as statistically significant interaction between HCA group and practice F(6,1654.946) =16.880, $p < 0.005$. More specifically, all four groups reduced the duration of the reaching movements of their DA in the pre-washout assessment when compared to the adaptation assessment. The estimates of fixed effects showed that the EAA and AAN improved less than the Control group did when comparing the pre-washout assessment to the adaptation assessment by an estimated 0.47 s ($p<0.005$) and 0.57s ($p<0.005$), respectively. On the other hand, the EAP group was the one that improved the most in the pre-washout assessment as the duration of the reaching movements was reduced by an estimated 0.5s more than the Control group did ($p<0.005$).

Post-washout all groups retained most of the improved movement duration achieved in the pre-washout assessment. The estimates of marginal means indicated that there was no washout in movement duration for the EAA,EAP and control groups, as there was no difference between pre- and post-washout assessments (p>0.05) while the EAA experienced negligible washout in the order of 0.01 s (p<0.05). As such it can be concluded that all groups were unaffected by the washout.

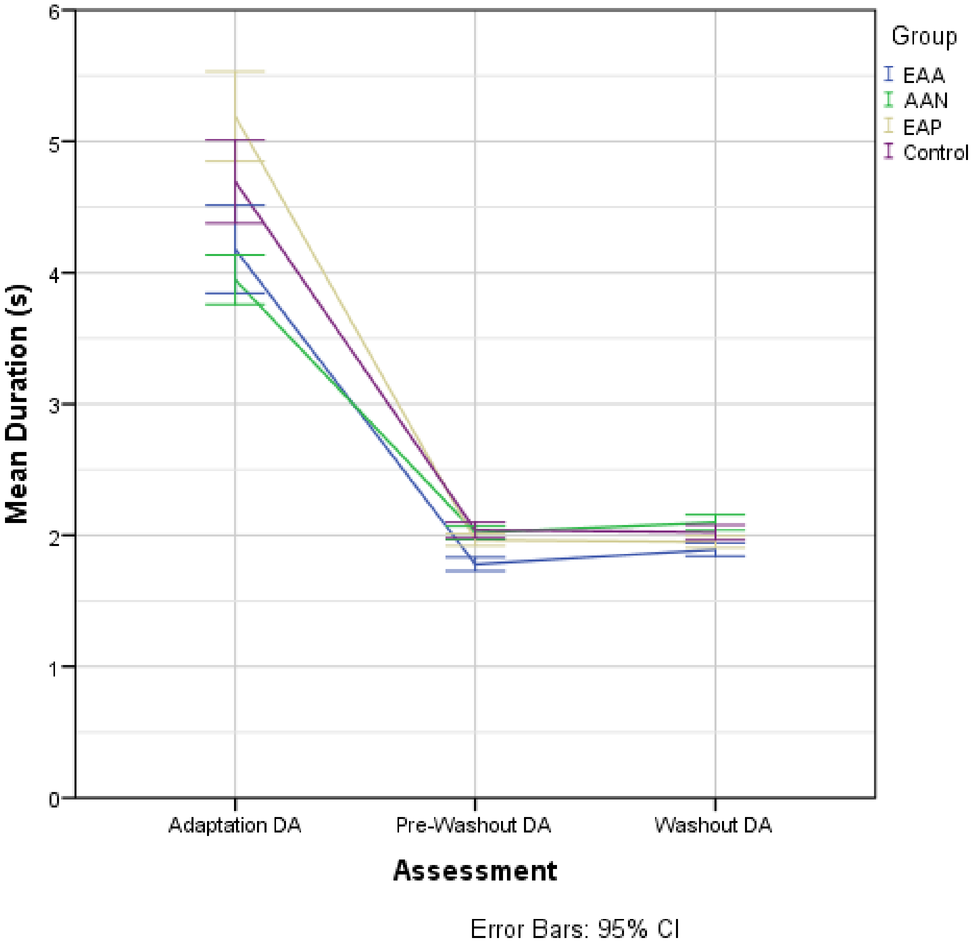


Figure 8-11: Mean duration over the different assessment blocks on the DA for the four intervention groups.

The perpendicular error (Figure 8-12) of the reaching movements was significantly affected by practice F(2,2535.887) =315.537, p<0.005 as indicated by the tests of fixed effects. The same tests also showed a statistically significant interaction between HCA group and practice F(6,2535.887) =5.856, p<0.005. All groups reduced the perpendicular error of their reaching movements at the pre-washout assessment. The estimates of fixed effects showed that the difference in the perpendicular error, achieved between the adaptation assessment and the pre-washout assessment, was not significantly different (p>0.05) for the EAA, EAP and the Control groups. Nevertheless, the same estimates showed significant difference between the Control group and the AAN, where the AAN improved by 0.1 mm (p<0.05) more than the Control group did between the adaptation and the pre-washout assessment which is a negligible difference and hence not been taken into account.

Post-washout, all groups showed some retention of the improved perpendicular error. The estimates of fixed effects did not indicate a statistically significant difference between the EAP and the Control groups on how error has changed in the post-washout assessment compared to the adaptation assessment (p>0.05). Nevertheless, from the estimated marginal means it can derived that there was no washout for the AAN, EAP and Control groups (no difference between pre and post washout, p>0.05) while there was small but negligible washout for the EAA (difference pre- and post-washout=0.6 mm, p<0.05).

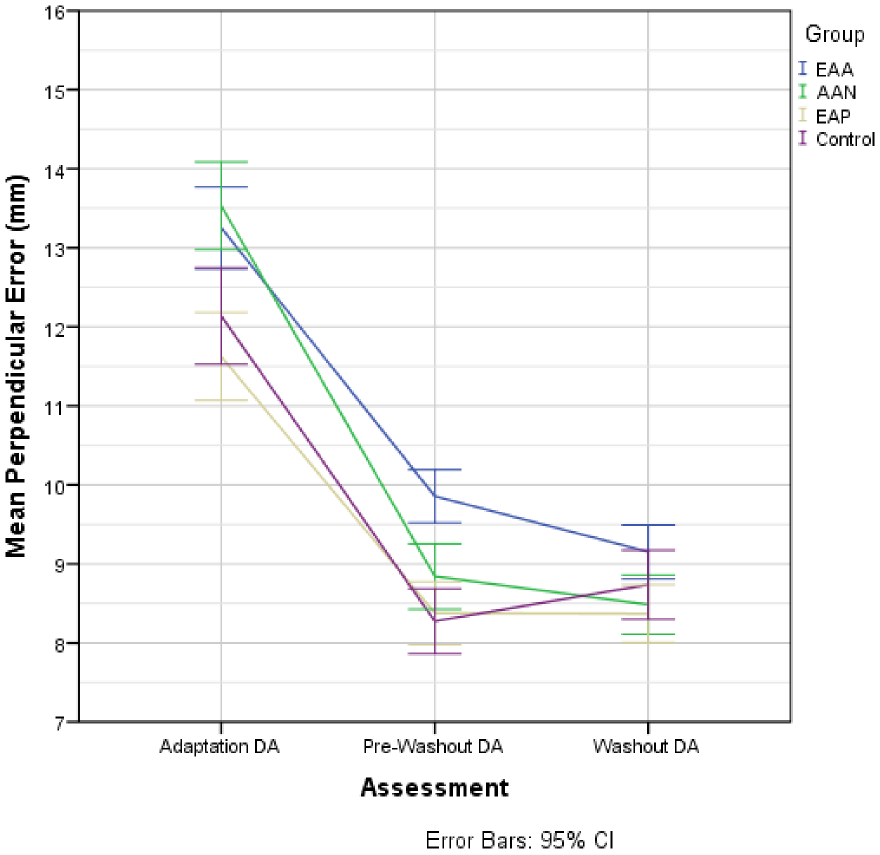


Figure 8-12: Mean perpendicular error over the different assessment blocks on the DA for the four intervention groups.

The tests of fixed effects identified a statistically significant effect of practice F(2, 3108.405) =1201.352, p <0.005 on mean velocity (Figure 8-13) and a statistically significant interaction between the HCA group and practice F(6, 3108.405) =15.375, p<0.005. Mean velocity of the reaching movements increased for all groups in the post-washout assessment. When considering the difference in mean velocity between the adaptation assessment and the pre-washout assessment the estimates of fixed effects failed to identify a statistically significant difference between the AAN and the Control group (p=0.076). Nevertheless, the same comparison identified a statistically significant difference between the Control group and the EAA and EAP groups. The EAA and the EAP groups improved more than the Control group did by an estimated 4.8 mm/s (p<0.05) for both EAA for the EAP. Also, the AAN was the group that improved the least.

Post-washout, the estimated marginal means showed that all groups retained their mean velocity fully as there was no statistically significant difference between the pre-washout assessment and the post-washout assessment (p=0.640 for the AAN, p=1.000) for the EAP, p=0.640 for the control) with the only exception being the EAA group which reduced its mean velocity by an estimated 5.7 mm/s (p<0.005) from the pre-washout assessment.

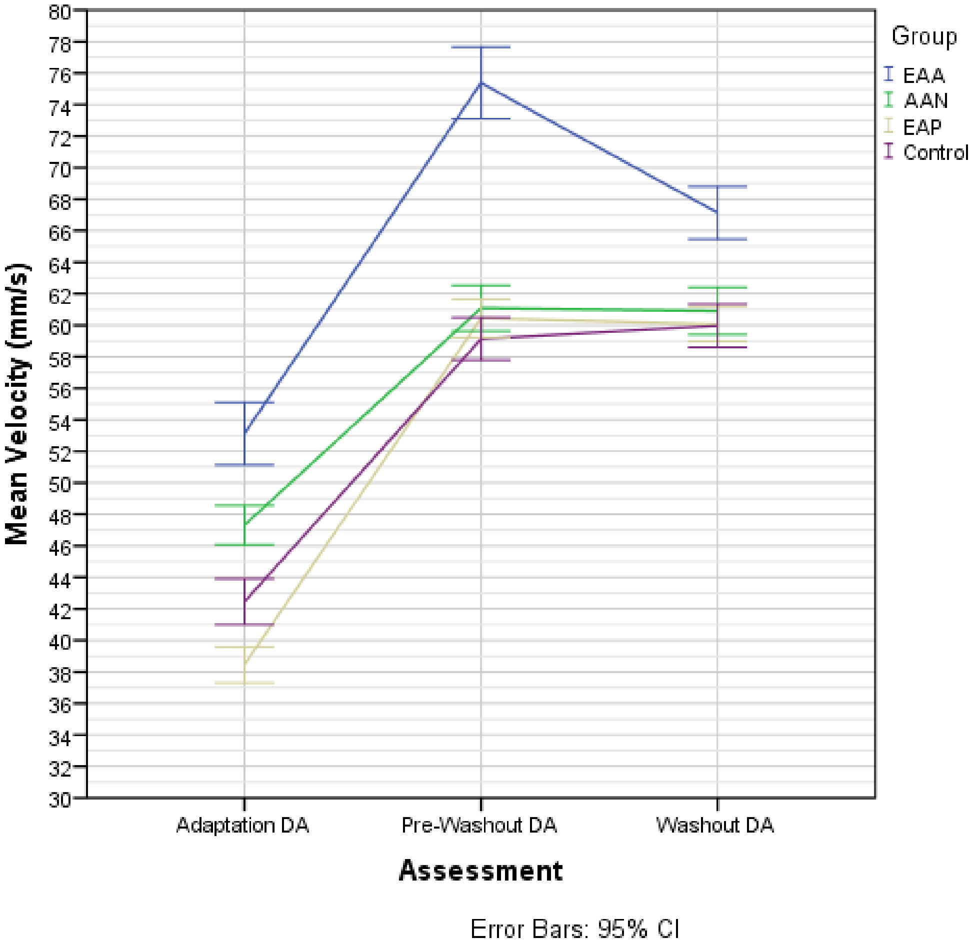


Figure 8-13: Mean velocity over the different assessment blocks on the DA for the four intervention groups.

There was a statistically significant effect of practice F(2,752.144) =141.208, p<0.005 on the normalised jerk of the participants' movements (Figure 8-14), as indicated by the tests of fixed effects. The tests of fixed effects also showed a statistically significant interaction between HCA group and practice F(6,752.144) =11.475, p <0.005. All groups reduced significantly the normalised jerk of their movements from the adaptation assessment to the pre-washout assessment. More specifically, the estimates of fixed effects showed that there was no statistically significant difference between the EAP and the Control group on how the normalised jerk has changed between the adaptation assessment and the pre-washout assessment (p=0.064).

On the other hand, the EAA and the AAN reduced the normalised jerk of their movements by significantly less in the pre-washout assessment than the Control group did. More specifically the EAA and AAN reduced the normalised jerk of their movements between the pre-washout assessment and the adaptation assessment by 12.7 units ($p<0.005$) for the EAA and 16.1 units ($p<0.005$) for the AAN, less than the Control group did. This very big difference in improvement may be influenced by the very large initial normalised jerk in the movements of the control (estimated mean =34.6 units, $p<0.05$) and EAP (estimated mean=42 units, $p<0.05$) groups when compared to the EAA (estimated mean=18.2 units, $p<0.05$) and AAN (estimated mean = 20.627 units, $p<0.05$).

Post-washout the EAA and the EAP groups fully retained the improved normalised jerk of their movements as the estimated marginal means failed to identify a statistically significant difference between the pre and post-washout assessments ($p=0.118$ for EAA and $p=0.833$ for EAP). On the other hand, both the AAN group increased its normalised jerk from the pre-washout assessment by an estimated 0.589 units ($p<0.05$) in the post-washout assessment. Moreover, the Control group further reduced the normalised jerk of its movements in the post-washout assessment by an estimated 0.662 units ($p<0.005$). These are very small differences compared to the initial drop of the normalised jerk in the pre-washout assessment. As such, it can be concluded that all groups retained the improved normalised jerk in their reaching movement with the AAN experiencing a small but statistically significant washout.

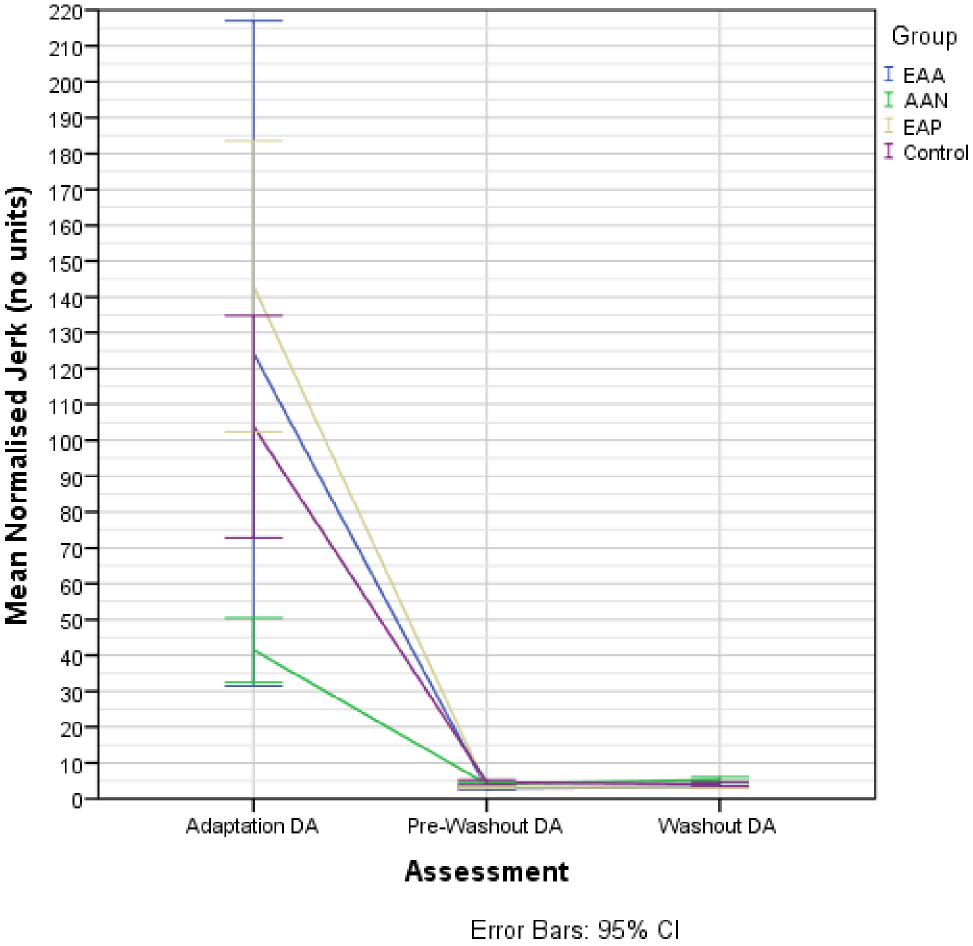


Figure 8-14: Normalised jerk over the different assessment blocks on the DA for four intervention groups.

The estimates of fixed effects showed that there was a statistically significant effect of practice F(2, 3474.130) =10.943, p<0.005 on the initial error (Figure 8-15) of the participants' movements but did not identify a significant interaction of HCA group and practice regarding the same F(6,3474.130) =1.351, p=0.231. From the estimates of fixed effects, it can be seen initial error was reduced in the movements of the participants in the pre-washout assessment by 0.29 mm (p<0.05). From the estimated marginal means it can be seen that initial error was fully retained post-washout as there was no statistically significant difference between the pre- and post-washout assessment (p=0.469).

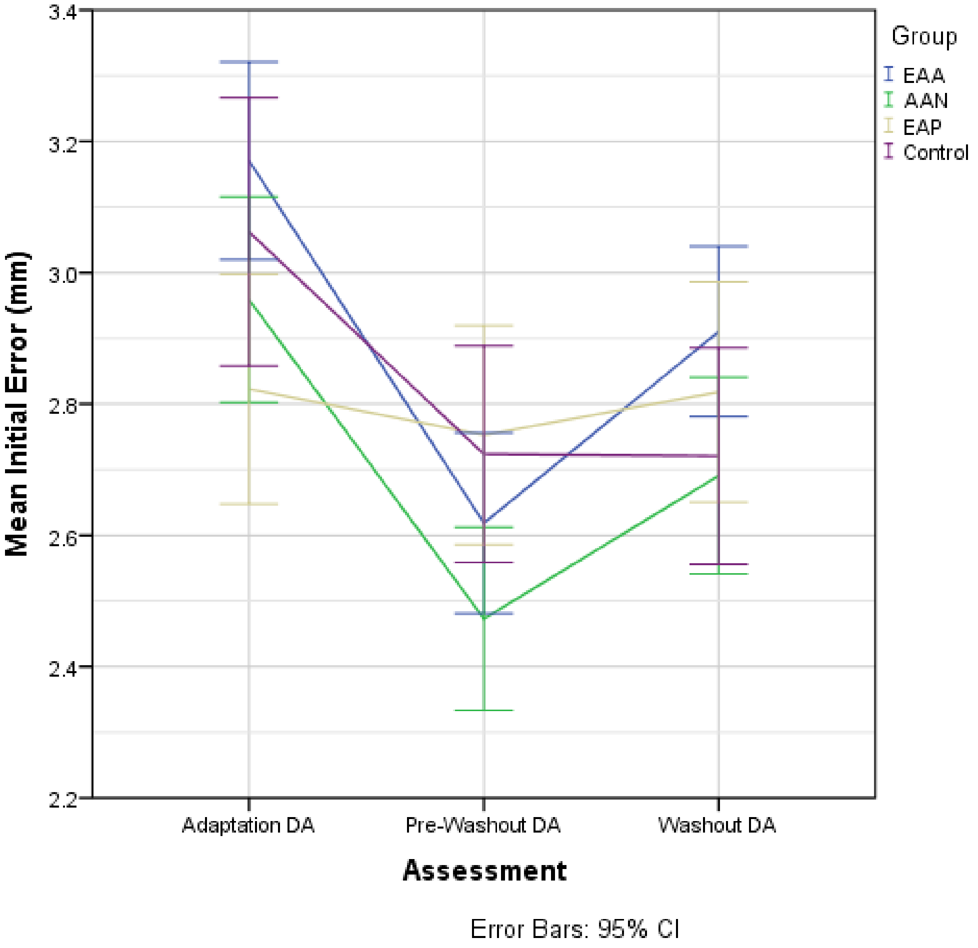


Figure 8-15: Initial error over the different assessment blocks on the DA for the four intervention groups.

8.3.2.2 *Results of the circle-drawing task for the dominant arm*

In the circle-drawing task it appears that the circularity (Figure 8-16) of the participants' movements was not affected by the training. This can be seen in the estimates of fixed effects that failed to identify a statistically significant effect of practice F(2,105.43) =0.801, p=0.064 or a statistically significant interaction between HCA group and practice F(6,105.43) =2.815, p=0.571 regarding movement circularity.

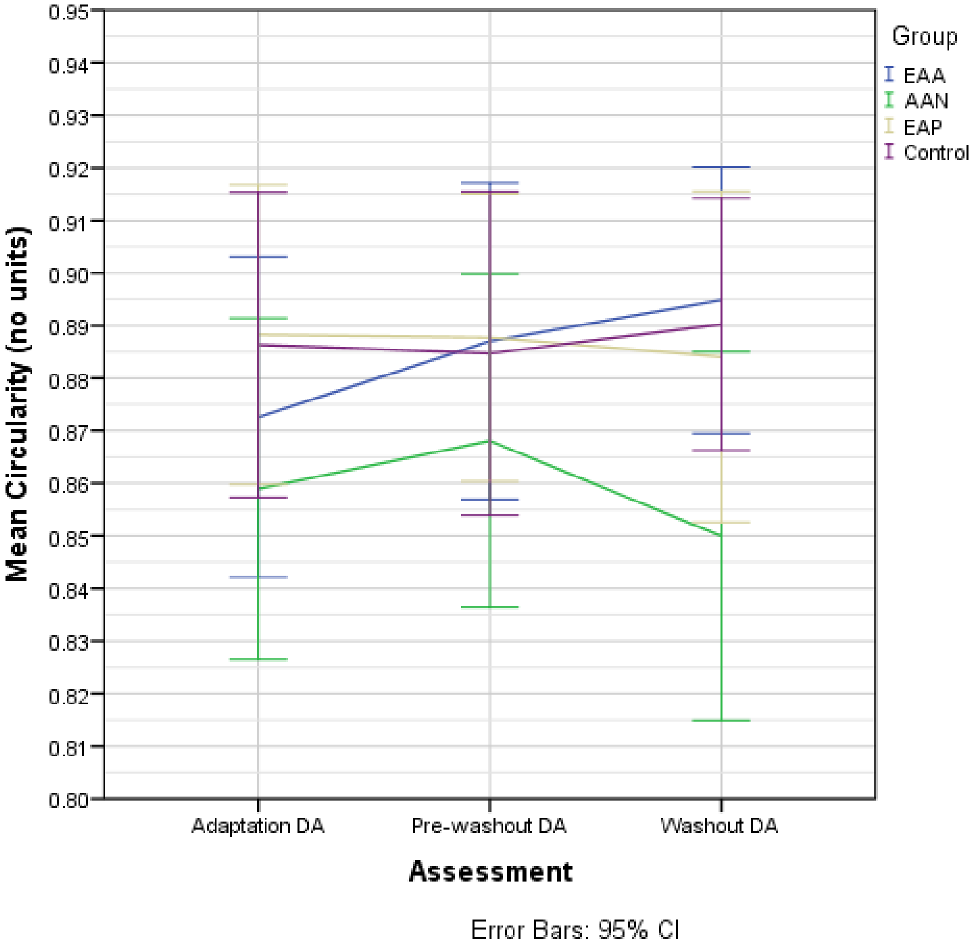


Figure 8-16: Movement circularity over the different assessment blocks on the DA for the four different groups.

The tests of fixed effects showed that there was a statistically significant effect of practice on the duration of the circular movements F(2,68.974) = 3.208, p<0.005 and also that there was no interaction between HCA group and practice F(6,68.974) =1.000, p=0.432. From the estimates of fixed effects, it can be seen that movement duration (Figure 8-17) was reduced in the pre-washout assessment by an estimated 0.91s (p<0.005). Furthermore, this improvement was completely retained post-washout as there was no statistically significant difference between the pre- and-post-washout assessment as the estimated marginal means indicated (p=0.099).

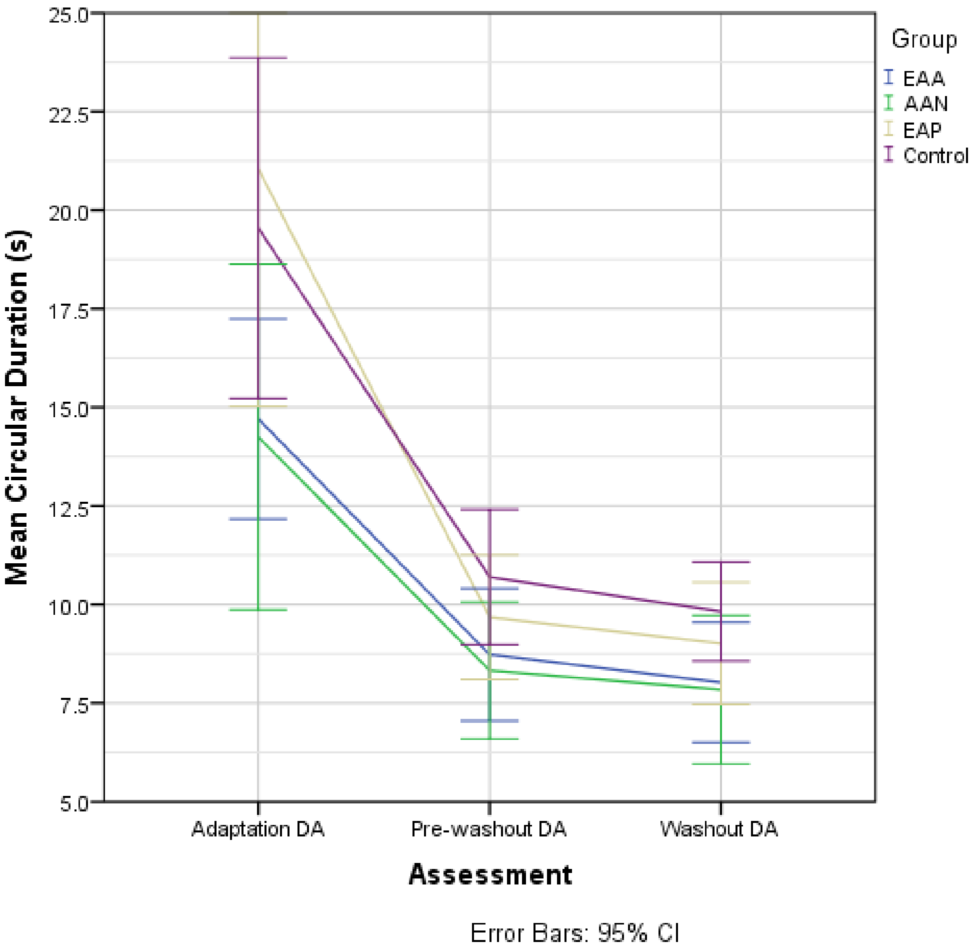


Figure 8-17: Circular movement duration over the different assessment blocks on the DA for the four intervention groups.

Table 8-2:Summary of the findings on the analysis of the effectiveness of the trial on the four different groups for the DA.

Measure	**Learning pre-washout**	**Retention post-washout**	**Improved more pre-washout**	**Retained more post-washout**
Duration	Yes	Yes	EAP	No difference
Perpendicular error	Yes	Yes	No difference	No difference
Mean velocity	Yes	Yes	EAA, EAP	ANN, EAP, Control
Normalised jerk	Yes	Yes	EAP, Control	No difference
Initial error	Yes	Yes	No difference	No difference
Circularity	No	Yes	No difference	No difference
Circular movement duration	Yes	Yes	No difference	No difference

8.3.3 Analysis of the Self-Assessment Manikin questionnaire

As a means to assess changes in the emotional state of the participants at the beginning of each assessment block they were asked to complete a 9-point SAM questionnaire for valence, arousal and dominance.

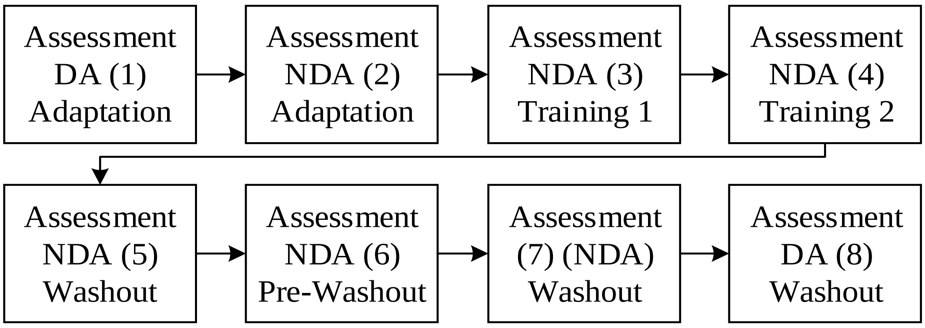


Figure 8-18: The different assessment blocks where the SAM questionnaire was administered.

The tests of fixed effects showed that there was no statistically significant effect of practice on the valence of the participants F(6,116.045) =1.778, p=0.110 and also that there was no statistically significant interaction between HCA group and practice F(18,116.045) =1.013, p=0451. This is a clear indication that the participants' valence remained unaffected throughout the trial (Figure 8-19)

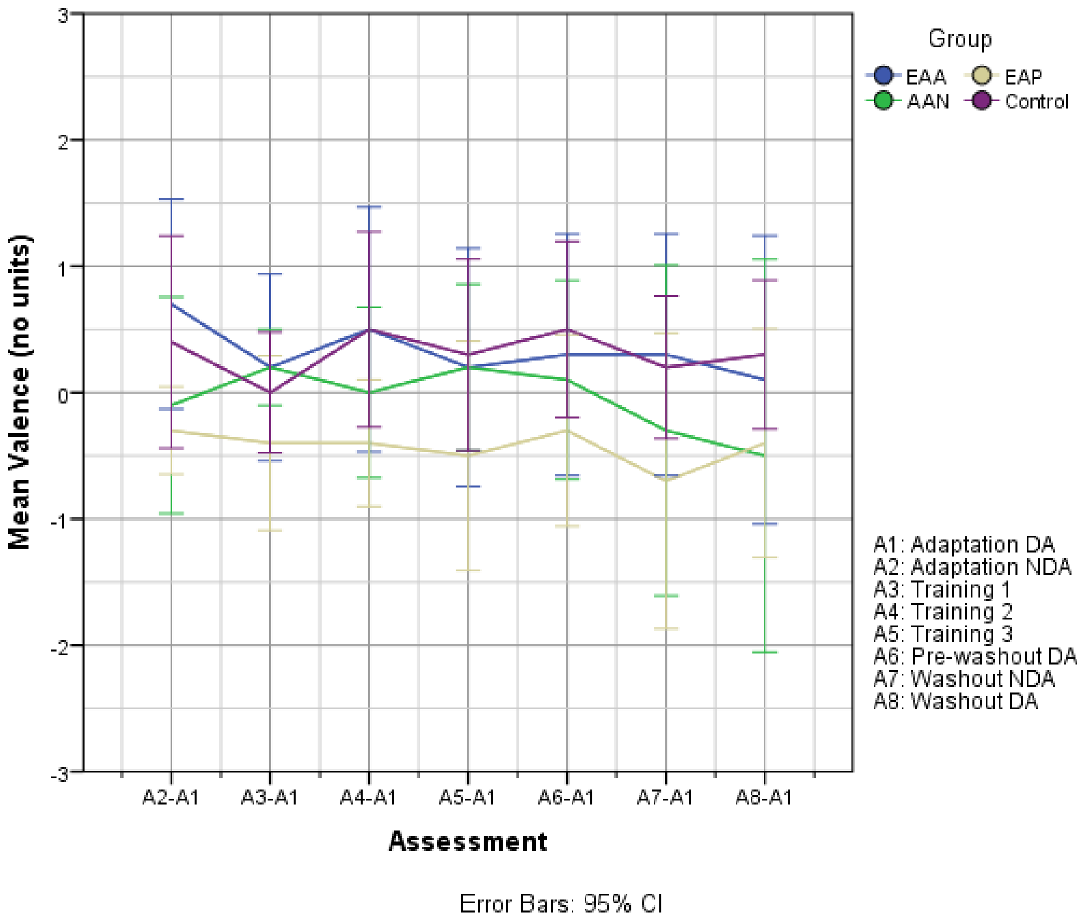


Figure 8-19: Valence over the different assessment blocks for the four intervention groups.

The tests of fixed effects showed a statistically significant effect of practice F(6,109.743) =5.640, p<0.005 on the arousal (Figure 8-20) of the participants but no statistically significant interaction between HCA group and practice F(18,109.743) =1.538, p=0.090. The estimates of fixed effects showed a statistically significant reduction in arousal in the assessments after training block 3 which fluctuated between 0.8-0.9 units (p<0.05) until the end of the trial.

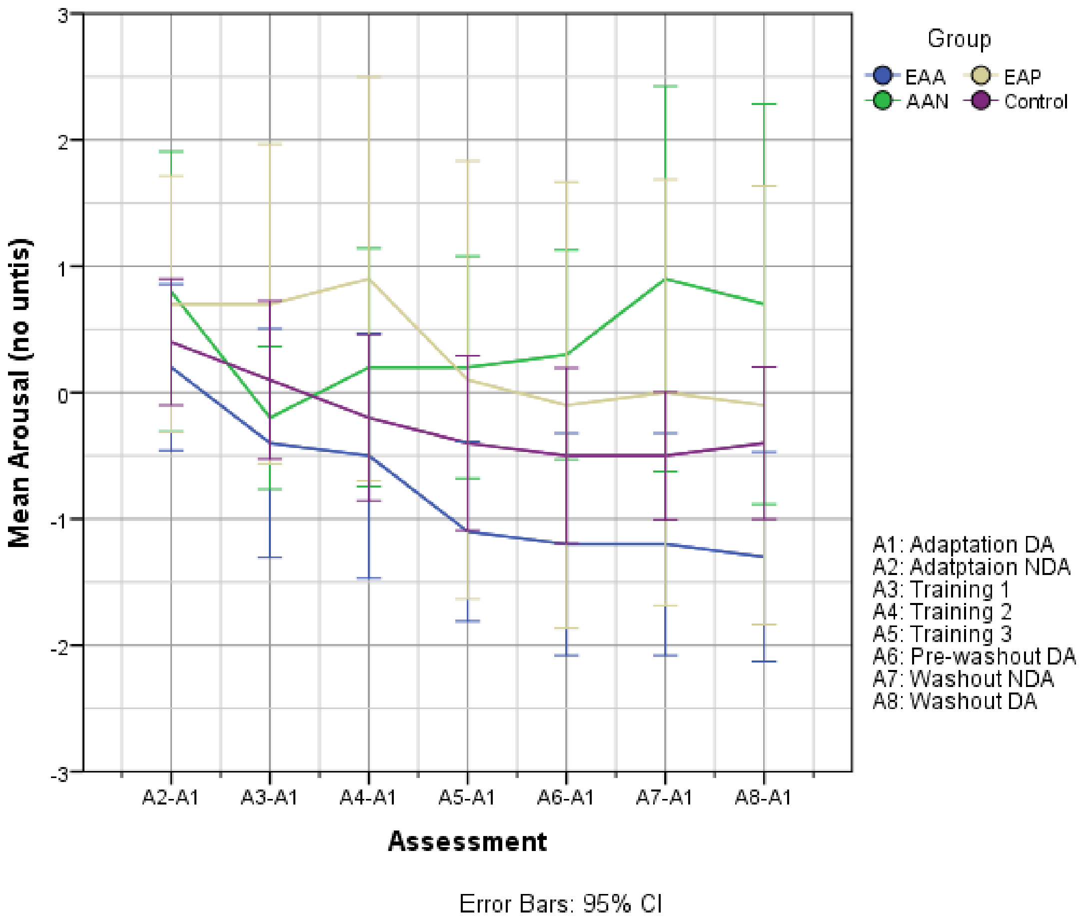


Figure 8-20: Arousal over the different assessment blocks for the four intervention groups.

The tests of fixed effects indicated that there was a statistically significant effect of practice F(6,104.020) =6.413, p<0.005 on the participants' dominance (Figure 8-21) but no statistically significant interaction between HCA group and practice F(18,104.020) =1.625, p=0.067. The estimates of fixed effects showed a statistically significant difference on how dominance changed throughout the trial. More specifically, it increased and its mean value fluctuated between 0.6-0.9 units (p<0.05) in the different assessment blocks pre-washout. Interestingly in the post-washout assessment on the NDA no statistically significant difference (p=0.129) was found with the adaptation assessment on the NDA (first assessment) indicating that the participants felt less dominant than they did in the preceding assessment blocks. Finally, the dominance increased again in the last assessment block by an estimated 0.9 units (p<0.05) when compared to the adaptation on the NDA assessment.

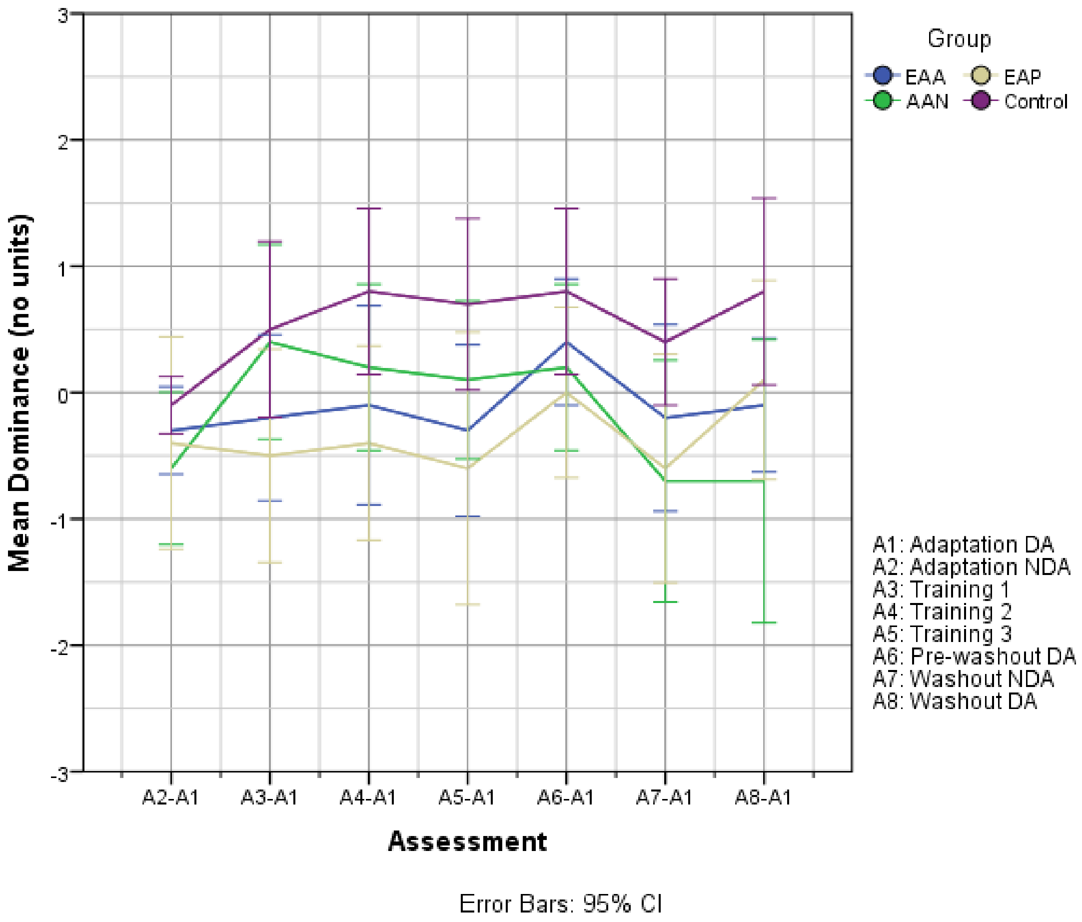


Figure 8-21: Dominance over the different assessment blocks for the four intervention groups.

Table 8-3: Summary of the findings on the analysis of the effectiveness of the trial on the four different groups.

Measure	**Effect of practice**	**Difference between the groups?**
Valence	No	No
Arousal	Yes (↓)	No
Dominance	Yes (↑)	No

8.4 Discussion

The reaching task did successfully induce motor learning on the NDA of the participants of the trial, irrespective of the group they were assigned to. All kinematic measures except for initial error improved in the course of the trial when compared to the baseline assessment and continued to improve right until the end of the training phase of the experiment. All groups improved similarly in terms of the duration of their reaching movements pre-washout with the only difference being that the AAN and EAA groups reached a peak in their performance in training block 2 while the EAP and the Control groups reached the same levels of improvement but in training block 3. Furthermore, there was no difference on how much all groups reduced the perpendicular error of their movements in the training part of the trial. However, the EAP group reached peak performance slower than the other groups did (training block 3 instead of 2).

There is preliminary evidence indicating that assistive algorithms may improve tracking errors in the short term but as participants become reliant on those forces perform worse in retention assessments where assistive forces are not present (Lee and Choi, 2010). The findings of this study seem to confirm this as the only difference between the four different groups in terms of duration and perpendicular error was that that the EAP group and the Control groups retained more of the improved movement duration post-washout. The implications of this finding is that despite the similar or superior effect on improving task performance of an assistive algorithm during the training stage of the trial challenge-based algorithms may be more effective in promoting long-lasting effects (retention of learning).

The EAA group improved the most in terms of the mean velocity of the reaching movements. This appears to be a genuine effect of the HCA as it was not the group with the worst initial mean velocity. Regarding the normalised jerk of the movement all groups showed a very significant drop in the assessment after training block 1. In the subsequent training blocks normalised jerk improved further but only marginally when compared to the initial drop. Nevertheless, the Control and EAP groups were the groups that reduced the most the normalised jerk in their movements from the levels measured in the adaptation assessment. However, both groups demonstrated higher initial normalised jerk in the adaptation assessment when compared to the EAA and the AAN group.

From the findings of the analysis presented in this chapter as well as from the analysis presented on Chapter 6 significant evidence has been identified that the EAA has an effect on promoting higher movement velocity in the reaching movements when compared to the other HCAs. To the author's knowledge this is the first time a study has identified benefits of an EA algorithm in the mean velocity of the movements. Nevertheless, EAA was not as effective in retaining the improved mean velocity as the EAP and Control retained more of their improved mean velocity. Interestingly, the analysis showed that the EAA algorithm was less effective on improving movement smoothness while the passive movements and EAP were the most effective on improving and retaining movement smoothness as indicated by the findings of the analysis.

The aforementioned findings are not in-line with the conclusions reported in the study by (Givon-Mayo and Simons, 2014) which applied error augmentation based on the velocity profile of stroke patients. More specifically, the participants were asked to follow an "optimal" bell-shaped velocity profile as accurately as possible while resistive forces were applied to enhance errors in the velocity profile. The authors reported that the Control group (no forces, N = 3) improved more the velocity of its movements while the EA group (N=4) improved more the smoothness of its movements as it managed to follow more accurately the "optimal" velocity profile.

A possible interpretation of this difference in the findings between the two studies is that the direction of forces during robot rehabilitation are affecting movement smoothness and mean velocity i.e. perpendicular forces to the movement promote high movement velocities but result in less smooth movements while parallel resistive forces promote smoother movements but don’t have as good effect on improving movement velocity. Surprisingly this cannot be extended to the assistive forces as the AAN did not have a similar effect on smoothness. Given the small sample of the study by (Givon-Mayo and Simons, 2014) it is difficult to arrive to definitive conclusions before these findings are confirmed in a trial with a bigger population. Nonetheless, it is recommended that future studies/interventions should consider different directions of forces applied by the robot when designing their HCAs.

Patton et al. in a study that investigated force fields that either enhance or reduce error in planar movements of stroke participants found that motor learning occurred only towards the directions where the forces increased errors (Patton, Stoykov, et al., 2006). However, there is very limited evidence of such clear cut findings in the relevant literature (Alexoulis-Chrysovergis et al., 2013; Israely and Carmeli, 2015) suggesting that benefits of specific HCAs may be limited to specific movement parameters or impairment levels.

The trial had no effect on the circularity of the movements in the circle-drawing task but did have an effect on the duration of the circular movements which was reduced in the course of the trial. More specifically, the duration of the movements was reduced throughout the trial even after the washout block. The aforementioned improvement indicates that the coordination of shoulder-elbow that the circle-drawing task assessments did occur as the circularity of the movements was maintained while their duration became shorter. However, it is possible that the measured improvement may have occurred as a result of practice within the assessment blocks rather than effect of the training part of the trial. Furthermore, the visual rotation appears to have had little or no effect on the circle drawing task post-washout as the duration of the movements not only was not washed-out but it improved further. This claim is further supported by the observation that the participants maintained high circularity throughout the trial and even post-washout.

In a study by (Krabben et al., 2011) where able-bodied participants were asked to perform circular movements without any visual or other perturbation with just using their arm the mean circularity of the participants' movements was found to be on average 0.66±7. In the trial presented in this work movement circularity remained always above 0.80 irrespective of the arm performing the movements. This indicated that there might be a bias towards more circular movements introduced by the geometry of the rehabilitation robot.

The reaching movements of the DA demonstrated a similar pattern. All kinematic measures improved after training except for the initial error which remained unaffected throughout the trial. Nevertheless, EAP had a better effect on improving movement duration. In addition, the EAA and EAP improved more mean velocity however the EAA was not as effective in its retention. Likewise, the EAP and control groups improved the most in movement smoothness however, this may be a true effect of the condition of practice. It appears that EA algorithms were found more effective in improving movement duration, velocity and smoothness over the AAN. While this finding does not provide conclusive evidence of the EA-type algorithms being more beneficial on bilateral transfer than AAN, it provides sufficient indication to justify further study.

The results regarding mean velocity and normalised jerk of the DA follow a similar pattern with the results of the NDA. The EAA and EAP were the groups that improved the most in terms of mean velocity pre-washout. This appears once more to be a genuine effect of the EA HCAs and are consistent with the findings of the analysis on the NDA for the EAA. Also, the Control and EAP groups improved the most in terms of normalised jerk. Nevertheless, as these two groups were the ones with the highest normalised jerk in the adaptation assessment it is unclear whether this was an effect of the HCA group the participants were assigned or whether it was due to inherent differences between the groups pre-training. In terms of retention post-washout all groups retained improvements in all measures fully with the only exception being a small washout in mean velocity for the EAA group.

Finally, there was no significant change in the participants' valence for any of the intervention groups. Conversely, the participants became more relaxed in the course of the trial as reflected by a drop in arousal. Moreover, the participants felt more empowered as dominance increased in the course of the trial. It must be noted that there were no differences between the groups on how any of the SAM questionnaire measures changed during the trial. As such, the findings from the study by (Shirzad and Van der Loos, 2012) where the participants' valence and arousal increased while their dominance was reduced in the course of the trial, were not replicated.

Furthermore, the psychological state of the participants appears not to be affected by the type of training they receive but by the training itself. The repetitive nature of the exercise appears to have affected negatively the participants' attentiveness (arousal) which was reduced in the course of the trial. On the other hand, a change in the participants' confidence was measured as reflected by the dominance measure of the SAM-questionnaire. This can be derived by the following observation; as kinematic measures improved dominance increased while in the first post-washout assessment where movement error for the participants' was completely washed-out dominance was reduced. Nevertheless, in the second post-washout assessment (DA) where movement error was retained dominance was restored to the increased pre-washout levels.

8.5 Summary

Some findings of the analysis can be found below:

- All interventions (group training conditions) led to a) improvement in the participants' movements of the NDA in all parameters except for movement circularity pre-washout and b) retention of improvements post-washout except for perpendicular error, initial error and circularity.
- EAA and AAN may be more effective in inducing faster improvement in motor learning (as reflected by the movement error and duration measures).
- EAP led to more retention of improvements in movement duration.
- Improved kinematic measure values of the NDA were retained post-washout in all measures except for perpendicular error.
- For improvement on mean velocity EAA shows the most promising results both in conventional motor learning and bilateral transfer however, EAP may be more effective in retaining improvements in this measure.
- EAA is not as effective in improving or retaining movement smoothness as the other modalities are.
- All training conditions led to bilateral transfer.
- Error augmented strategies seem more beneficial for bilateral transfer.
- The different interventions/practice conditions affected the psychological state of the participants in a similar manner.

9 Conclusions and future work

9.1 Introduction

The aim of this research project was to develop novel HCAs for upper limb rehabilitation whose design was informed by the existing literature and test their effectiveness on promoting motor learning in able-bodied adults. The findings of this project are intended to be used on further studies with the participation of adult stroke sufferers and children with CP. To reach this aim seven objectives were set in Section 2.6.2. A brief overview of the objectives identifying which chapter of the thesis they are considered and if they have been achieved is provided in Section 9.2. This chapter provides an evaluation of achievement of the set objectives. After this, the limitations of this work are presented followed by conclusions and recommendations for future work.

9.2 Evaluation of objectives

This section provides a critical review of to what extent the objectives set for this project were achieved.

Objective 1: Perform a literature review on upper limb robotic rehabilitation approaches for impairments caused by stroke and cerebral palsy to identify haptic control algorithm methodologies and trends in research.

A review of the existing literature on upper limb rehabilitation was performed in the initiation of this project and presented in Chapter 2 . As rehabilitation robotics is a multidisciplinary field of study different aspects were reviewed involving the conventional and robotic rehabilitation literature such as robotic rehabilitation devices for upper limb rehabilitation, conventional approaches for rehabilitation, robotic approaches (HCA) for upper limb rehabilitation, scales to measure effectiveness of the rehabilitation and others. This literature review informed the author’s contribution in sections 2.6 and 2.7 of the following conference paper (Weightman et al., 2014).

The review of literature identified an understudied haptic control strategy, namely error augmentation. To further investigate its effects a systematic literature review was published; (Alexoulis-Chrysovergis et al., 2013) the findings of which, updated with more recent relevant publications, are discussed in the same chapter. Subsequently, informed by the findings of the review of literature two novel haptic control algorithms were introduced both of the error augmenting type namely, Error Augmenting Adaptive and Error Augmenting Proportional. Also, a third algorithm was presented which was an in house implementation of a well-studied HCA that is Assistance As Needed.

Objective 2: Further develop an existing single point of attachment upper limb rehabilitation device.

The conceptualised HCAs were to be developed for and deployed on a single point of attachment rehabilitation robot initially developed at the University of Leeds. Certain aspects of the original device were revised to further improve the robotic rehabilitation system. The first part of Chapter 3 presents the components that were developed for the rehabilitation robot while the last section of the chapter presented the testing procedure that was undertaken to ensure its correct operation.

Objective 3: Design simulation and development environments that can be used for the development and testing of haptic control algorithms.

A simulation model was presented in Section 3.3.2.3 for the robot’s kinematics. Section 3.4.1.4 presents the trial performed to verify the developed model by deploying it on the rehabilitation robot and comparing against experimental kinematic measurements collected by a motion tracking system utilising inertial sensors namely the XSens for its accuracy.

Objective 4: Develop a computer game environment to interface the single point of attachment rehabilitation device with the end user.

In section 3.3.4 the development of a computer game environment is presented. The purpose of this environment was to provide an interface for the user to interact with the rehabilitation robot. The developed computer game met all the requirements set and presented in the design stage of the project. The game environment was appropriate for the purposes of this research project and the main engine which is based on, is robust and offers multiple options to the programmer and the therapist. Nevertheless, if it is to be deployed in multisession trials with practice protocols that are long in duration the graphics of the computer game need to be updated and diversified as in its current configuration the game can be repetitive.

Objective 5: Develop assistive and challenge based novel haptic control algorithms for upper limb rehabilitation.

In Section 3.3.3 the software implementation of the three different HCAs is presented. In the same section all the software that was developed to achieve the behaviour described by the concept phase of the design of the algorithms (see objective 1), is presented. Furthermore, all the HCAs were developed to be highly customisable to allow experimentation with different behaviours. The final fine-tuned settings for each of the developed algorithms namely AAN, EAA and EAP are presented in sections 5.2, 6.2, and 7.2, respectively.

Objective 6: Design and perform an appropriate trial to evaluate the effect of the developed haptic control algorithms in the motor learning of able-bodied adult.

To test the effect of the developed HCAs on the motor learning of able-bodied adults a trial had to be performed where different groups of participants would practice a new task while being assigned to the one of the developed HCAs. The design of the trial was informed by existing trials in literature as well as by the research questions that the trial aimed to answer.

To test the trial protocol as well as the appropriateness of the task and the measures selected, a pilot trial was performed presented in Chapter 4. In this pilot trial it was established that the protocol allowed the measurement of changes in motor learning and also identified areas that required improvement. Informed by the findings of the pilot, the investigatory trial design was adjusted accordingly and presented in Section 4.3. The trial protocol along with a description of the developed algorithms was published as a conference poster in (Weightman et al., 2015)

Objective 7: Analyse kinematic data collected in the trial in order to evaluate the effectiveness of each of the haptic control algorithms and compare them against each other.

Four different statistical models were designed to analyse the data collected from the investigatory trial. The first three are comparing the Control group against one of the developed HCAs ignoring the others, while the fourth model included all four intervention groups. This approach was undertaken to satisfy the main research questions of this study. The one to one comparisons allowed a detailed analysis aimed to identify whether practice with the developed HCAs had a different effect on motor learning than passive movements would. Once this was established, a more complicated statistical model was created in order to identify differences between all three developed HCAs. The findings of the different analyses are presented in Chapters 5-8.

9.3 Limitations of this work

Several limitations were set by the configuration of the rehabilitation robot used in this work. As mentioned previously (Section 3.2), the design strategy behind the system aimed to reduce cost in order to increase the accessibility of the system to the impaired public. The system was a single-point of attachment rehabilitation robot and as a result only the position of the hand could be controlled directly by the robot and not the corresponding position of the elbow and shoulder. As such it is unknown if the task or the developed HCAs promoted abnormal synergies to the participants' movements. Moreover, to further reduce the cost of the system, the rehabilitation robot did not have force sensing capabilities (force transducers) in its joints and this limited the types of control strategies that could be developed in this project to just two namely position control and velocity control or a hybrid controller which would be a combination of the two. As a result, force control schemes such as impedance and admittance control were not an option to implement (Sigrist et al., 2013). Additionally, the robot's workspace allowed only the control of two-dimensional movements of the hand and within a limited workspace (220 mm by 220 mm).

Other limitations were set by the trial design. The participants recruited in the studies were healthy which means that the potential of motor learning to occur was very small despite the visual perturbation introduced in the task to make it more difficult. Although it has been shown that findings of studies with able-bodied participants can be transferred to the impaired population (Krakauer, 2006) the potential difference to be measured can be very small and hence difficult to measure. Furthermore, the developed HCAs were designed to be used in the rehabilitation of impaired patients and assist on certain aspects of the impaired limbs movements certain features of those HCAs specific to the impaired population were not relevant to the able-bodied. For example, the main feature of assistive algorithms is to assist movements that the participants would not be able to perform unassisted. However, all of the participants in the trial presented in this work was capable of performing reaching movements even under the effect of a visual perturbation.

Another limitation for this work lies within the protocol design of the trial. To ensure retention of the participants the intervention was designed as a single session which is a common practice among similar studies (Patton, Stoykov, et al., 2006; Elizabeth B Brokaw et al., 2011; Shirzad and Van der Loos, 2015) . To measure retention of learning within the same session, washout was artificially introduced at the last part of the session. In that the participants practised reaching movements with the visual rotation turned off. That was done with the assumption that the predominant internal model of moving under no visual rotation would be triggered and that would result in simulating the effects of washout that would have been caused naturally; i.e. if the participants after the session went about their day performing reaching movements for the different ADLs (under no visual rotation) and came back for the washout assessment on the next day. It is impossible to know the exact number of movements under no visual rotation that would cause complete washout as this may vary between participants. This was addressed by providing as much washout practice as it was deemed practically possible.

Other studies (Kitago et al., 2013; Rotella et al., 2013) with similar protocols and amount of washout practice, reported complete washout of the adaptation however, there is the possibility of the retention measured in different measures throughout the trial to be due to the lack of sufficient washout practice. Nevertheless, this is unlikely as perpendicular error which is one of the main indicators of motor learning (Seidler et al., 2013) was completely washed out indicating that sufficient washout practice has been introduced to the participants. Likewise, there is evidence showing that successful washout of adaptation to a perturbation can occur after only 75 movements (Patton and Mussa-Ivaldi, 2004) and therefore the 160 washout movements practised in the trial described in this work should have been more than sufficient to cause complete washout.

Finally, the sample size of this exploratory study was relatively small allowing the potential for Type II errors. Nevertheless, the study identified an effect of practice and small but significant differences on the effect of the different intervention groups on motor learning. Furthermore, the population size was sufficient for a Stage II (Table 9-1) type of trial (Dobkin, 2009).

9.4 Conclusions

The main contributions of this project in the research field of rehabilitation robotics is the introduction of two novel haptic control algorithms in the limited existing literature on the effects of error augmentation and the evaluation of their effectiveness in promoting motor learning. A study by Tropea et al the authors concluded with the following “Our findings point to the need for novel neuro-rehabilitative treatments using highly-motivating environments that allow greater patient control over the movement to be performed.”. This highlights the need for more investigation of different modalities of EA and their effects on the upper limb robotic rehabilitation.

In addition, a comprehensive comparison of high methodological quality was performed that compared the two main types of haptic control strategies in upper limb rehabilitation namely assistive and challenge-based algorithms. As to the time this was written there is no consensus or sufficient evidence in the literature as to what are the effects of each type of control strategy and whether one is more effective over the other (Marchal-Crespo and Reinkensmeyer, 2009), this work contributes to the existing literature attempting to investigate this aspect by providing a clear comparison of the effect of assistive, challenge-based and no robotic forces in inducing motor learning to the upper limb the findings of which can transfer to the impaired population from conditions such as stroke and CP.

More specifically the findings of the analysis did not provide clear answer as to which algorithm/condition of training was the most effective in inducing motor learning as reflected by changes in the selected kinematic measures. The differences between the effects were more discrete and it appears that although all algorithms/training conditions have a positive effect on motor learning there were some additional benefits to certain movement parameters when training was undertaken under a certain HCA/training condition. More specifically, when compared to the other interventions EAA appears to have an effect on improving movement duration and mean velocity while the control condition and EAP appear to have a better effect on promoting movement smoothness movements and better retention on movement duration, mean velocity and normalised jerk.

A significant outcome of this study was that that all groups/practice conditions were successful in promoting motor learning on able-bodied participants as reflected by the improvement in the values of the kinematic measures in the course the training part of the trial and none of the impeded learning. All intervention groups showed a similar pattern on how the values of the kinematic measures changed throughout the trial indicating that there were no adverse effects of the intervention as all kinematic measures (except for initial error and movement circularity) showed improvement throughout the trial for all four groups/conditions. Furthermore, the analysis concluded that the satisfaction (as measured by the SAM questionnaire) remained unaffected for all training groups/practice conditions which indicates that their reaction to the type interventions/HCA was the same.

Recently there has been evidence (McCabe et al., 2015) indicating that motor recovery in stroke is mainly affected by how intense practice is rather than the type of practice. Nevertheless, the type of intervention may still play a significant role on the recovery of the patients. An example of the this can be seen in the study by (Milot et al., 2010) where participants received training with haptic guidance (assistive forces) and error augmentation both groups improved equally well. However, when the authors compared the effects of training on a subset of the participants with better initial performance; the group that received error augmentation showed greater improvement in performing the task, indicating that the participants that received assistive forces reached plateau in their improvement quicker than the EA group.

The findings of this project in combination with the abovementioned findings of other studies provide an indication of the potential of high-intensity combinatorial protocols that are adjusted to needs of individual patient. For example, for a severely impaired patient who cannot initiate or complete a reaching movement, an assistive HCA would be more appropriate. However, as the function of this patient's limb improves and reaches a plateau EA based algorithms with adaptive features can induce further improvement. This is further supported by studies comparing assistive movements to error augmentation on healthy (Lee and Choi, 2010) and stroke (Cesqui et al., 2008) participants, found that participants with worse initial performance to benefit more from assistive training while participants with better initial performance to improve more under EA training.

Another important contribution of this work is in the field of bilateral transfer. More specifically, the improvements measured in the movements of the limb that received practice translated into improvements of the limb that did not practise confirming the potential of this approach as a valid rehabilitation strategy. More interestingly, bilateral transfer seemed to be unaffected by the washout as the limb that received no training retained improvements in all measures that were achieved pre-washout. To the author's knowledge this is the first time such a finding is reported; the implications of which can be great, as BTT can be used not only to induce learning but also to promote retention of the learning achieved. There is extensive evidence of the positive outcome of robotic therapy bimanual training in literature (Van Delden et al., 2012). However, this approach requires traditionally two robotic manipulators (one for each arm) which results in such systems being expensive and thus not suitable for cost effective robotic rehabilitation solutions. On the other hand, BTT requires practice with only one arm and for that reason can be deployed in unimanual systems.

An additional novelty of this work in the field of bilateral transfer was that it directly compared the effects of movements under assistive HCAs with movements under challenge-based HCAs (more specifically EA) and movements under no robotic forces to the transfer of learning. The findings of this study can be useful to therapists that are looking to utilise BTT for upper limb rehabilitation as to which strategy would be more beneficial for improving a certain movement parameter (e.g. EAP more beneficial in improving movement duration, velocity and smoothness).

Given the promising findings of this study on the employment of BTT in the robotic rehabilitation of the upper limb it is recommended that further investigation needs to be performed exploring the effects of BTT in upper limb robotic rehabilitation of patients with stroke and/or CP.

9.5 Future work

At the conclusion of this research project several key areas were identified for future work. These areas involve mostly transferring the findings of the exploratory study into a trial with impaired participants suffering from stroke or CP and to perform the required changes to the system and the HCAs to adapt them to the target population.

9.5.1 Trials with participation of the impaired

The HCAs introduced in this work were primarily designed for the rehabilitation of the upper limb of the impaired participants. The trial presented in this work comparing the effects of the developed HCAs on the motor learning of healthy adults was designed to serve as a pilot investigation. As such future work should focus on designing a randomised control trial with an intensive multi-session protocol that compares the effectiveness of the developed algorithms on the rehabilitation of patients suffering with CP or stroke.

Dobkin et al. recommend that trials on motor rehabilitation should be performed in four phases (Dobkin, 2009) an overview of which can be found in Table 9-1. According to this classification the pilot trial presented in Chapter 4 can be considered as a Stage I type trial with the (main) trial described in Section 4.3 Chapters 5-8 can be considered as Stage II. Since potential benefits of the developed HCAs (EAA, EAP) were found and the safety of the system was established it would be recommended for a Stage III trial to be performed with the participation of participants that suffer from stroke or CP.

Table 9-1: Stages of clinical trials in motor rehabilitation as suggested by (Dobkin, 2009). Adapted from:(Iosa et al., 2016)

Stage	Studies in rehabilitation	Purpose
Stage I	Consideration of concept trials (on 6-12 patients/healthy)	To test concepts and related safety on animals or on a small group of patients
Stage II	Development of Concept Trials (>15 participants)	To standardize the new intervention and add a Control group, randomization, and masked outcomes. To establish the best dose of therapy. To assess sample size
Stage III	Demonstration of Concept Trials (on a sample with a properly computed size)	To prove effectiveness and safety of intervention
Stage IV	Proof of concept (multicenter randomized clinical trials)	To establish generalizable efficacy and safety

The protocol followed and the kinematic measures used in the trial presented in this work were deemed to be suitable to capture changes in aspects of the movement as well as motor learning (Figure 2-4) however, it is recommended that established clinical measures to also be used for the assessment of the participants' function such us the Fugl-Meyer assessment and the Gross Motor Function Measure (GMFM) scale (Sivan et al., 2011). The findings of this study indicated that the developed algorithms have great potential in promoting motor learning. Nevertheless, it must be noted that EA-based HCAs may not be suitable for severe neurological impairments where the participants cannot initiate or perform movements unassisted.

In addition, the effects of the developed HCAs on bilateral transfer need to be investigated further in the abovementioned or a separate trial with impaired participants from stroke or CP. This will allow to identify whether the positive findings on bilateral transfer of this study on the able-bodied population would transfer to those with impairments.

Moreover, in the light of the recent findings of the study by (McCabe et al., 2015) that intensity of practice is more important than the nature of practice it is recommended to explore the benefits of a combinatorial training scheme where participants instead of being assigned to a single adaptive algorithm the type of algorithm would be adapted according to the needs of the participants. An example of such a training scheme could be the following: A severely impaired participant that cannot complete a reaching movement can firstly be assigned to an assistive HCA. Once the participant is able to complete the movement a challenge-based HCA can be introduced to allow them to increase their engagement and effort two factors directly linked to be beneficial in inducing motor learning (Lee et al., 1994; Emken et al., 2007). With such an approach, it is hypothesised by the author that the potential for motor learning and improving function would lead to better outcome.

9.5.2 Amendments in the developed Haptic Control Algorithms

As the focus of future work is for the developed HCAs to be deployed in trials with impaired participants they need to be adjusted for the target population. More specifically, suitable maximum permissible current values need to be identified to adjust the forces applied by the robot to the participants' arm to requirements and capabilities of the impaired population. Identification of suitable forces can be either identified through a small pilot trial with impaired participants or through consultation with experienced rehabilitation therapists.

Another aspect that will require adjustment is the rate of adaptiveness of the system i.e. the time period/number of movements after which the system evaluates the user's performance and adapts accordingly. The benefit of a time based adaptation system takes into account that the patients may not be capable of completing the set number of movements given a setting of difficulty and the system should be able to adapt accordingly. A suggested period of adaptiveness would be an estimate of the time required by an impaired participant to complete a set of reaching movements. This could be also established by a pilot trial or with a pre-trial assessment for each individual patient.

Furthermore, to establish that the behaviour of the developed HCAs in large scale trial a pilot trial would be beneficial with the participation of the impaired to collect kinematic data during training. This will help to analyse how the algorithms adapt the participants' movements and therefore provide insight into how better adjust them to suit the rehabilitation of the impaired.

Finally, as it is likely in the proposed trial with the neurologically impaired that the system will be used under the supervision of rehabilitation therapists or researchers which are not familiar with the system the graphical user interface controlling the HCAs should be simplified in order to ensure its ease of use.

9.5.3 Modifications to the rehabilitation robot

Several improvements can be made to the rehabilitation robot. Firstly, the handle of the rehabilitation robot should be re-designed to allow for support of the arm. Such an approach has been undertaken with similar systems (Johnson, 2006) to counterbalance the weight of the arm and as such allow severely impaired patients to perform movements(Sanchez et al., 2005). As the handle of the rehabilitation robot is resembling a joystick handle, patients with severe neurological impairments may not be able to hold it or even support the weight of their arm for the duration of a practice session. As such it is recommended that the handle is rebuilt so the arm can rest on it rather than hold on to it (Figure 9-1).

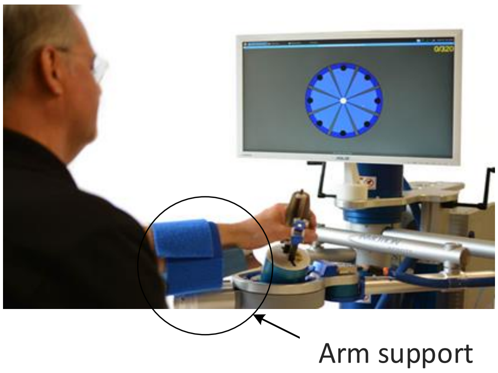


Figure 9-1: Example of hand support for an endpoint rehabilitation robot. Adapted from:(Interactive Motion Technologies, 2016)

Furthermore, the trolley where the rehabilitation robot is mounted on was designed to fit an E-ATX computer case along with all the electronic components required to control the rehabilitation robot namely the cRIO and the power source. Due to the recent developments in computing and miniaturisation technologies very powerful computers have been introduced that fit into very small form factors such as tablet computers such as the Microsoft Surface Pro® line or the systems in a stick such as Intel Compute stick® (Figure 9-2). Such computers are more than capable of running desktop grade computer games at satisfactory resolutions/frame rates. As such, the desktop unit was replaced with one of the suggested types of systems this would allow the trolley mount for the robot to be re-designed to and reduce the footprint of the system significantly. As the system was initially designed to be deployed in the home environment where there are space restrictions a redesign of the system into a smaller form factor would benefit this use-case.

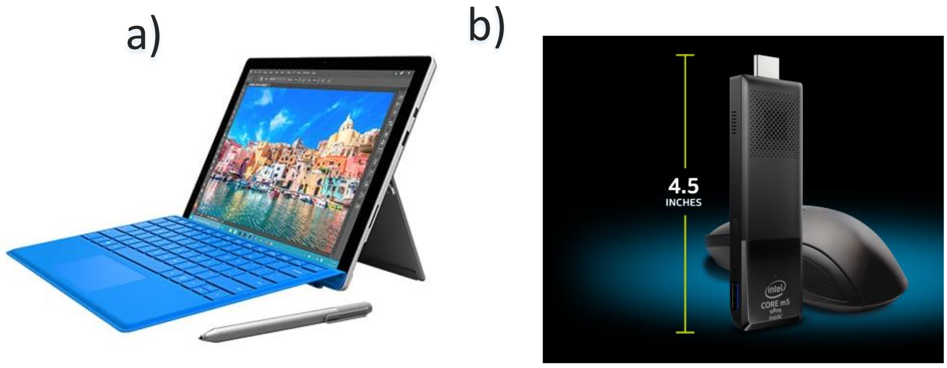


Figure 9-2: a) Examples of miniaturised computers in different form factors such as tablet computer and computer on a stick. Source a) (Microsoft Coorporation, 2016) and b) (Intel Corportation, 2016)

Furthermore, the mount for the rehabilitation robot needs to be re-designed in order to allow for height adjustability. This will allow the system to be used by patients on wheel chairs which are not height adjustable.

9.5.4 Game environment

Motivation and active engagement have been shown to have a positive correlation to the outcome of rehabilitation therapy (Colombo et al., 2007). There is evidence showing that the games used in robotic rehabilitation can increase engagement and motivation which is hindered by the repetitive nature of the practice (Rego et al., 2010). Although the game environment developed and presented in this work served its purpose for the needs for the research undertaken it requires further development to allow for more complex, interesting and diversified graphics tailored to the target population all important features that help increase engagement (Flores et al., 2008). This is expected to motivate the users and the keep them more interested in performing the required task. Furthermore, a possible direction of research is to explore the integration of augmented reality with rehabilitation therapy. Augmented reality (AR) is a method of visualisation where 3D virtual objects are overlaid on the 3D actual field of view of the user. Such methods allow the participants to practise within a more natural environment that resembles better, activities of daily living (Alamri et al., 2010; Mousavi et al., 2013).

References

Abdollahi, F., Case Lazarro, E. D., Listenberger, M., Kenyon, R. V, Kovic, M., Bogey, R. A., Hedeker, D., Jovanovic, B. D. and Patton, J. L. (2014) 'Error augmentation enhancing arm recovery in individuals with chronic stroke: a randomized crossover design.' *Neurorehabil Neural Repair*. 2013/08/10, 28(2) pp. 120–128.

Abdollahi, F., Rozario, S. V, Kenyon, R. V, Patton, J. L., Case, E., Kovic, M. and Listenberger, M. (2011) 'Arm control recovery enhanced by error augmentation.' *IEEE Int Conf Rehabil Robot*. 2012/01/26, 2011 p. 5975504.

Abdollahi, F., Rozario, S. V, Kenyon, R. V, Patton, J. L., Case, E., Kovic, M. and Listenberger, M. (2011) 'Arm control recovery enhanced by error augmentation.' *IEEE ... International Conference on Rehabilitation Robotics : [proceedings]*, 2011, January, p. 5975504.

Agrawal, N. and Mitchell, A. J. (2005) 'The national service framework for long term conditions.' *BMJ (Clinical research ed.)*, 330(7503) pp. 1280–1.

Alamri, A., Cha, J. and El Saddik, A. (2010) 'AR-REHAB: An augmented reality framework for poststroke-patient rehabilitation.' *IEEE Transactions on Instrumentation and Measurement*, 59(10) pp. 2554–2563.

Alexoulis-Chrysovergis, A. C., Weightman, A., Hodson-Tole, E., Deconinck, F. J. A., Contributions, C. and Proceedings, S. (2013) 'Error augmented robotic rehabilitation of the upper limb a review.' *In Neurotechnix 2013 - Proceedings of the International Congress on Neurotechnology, Electronics and Informatics*, pp. 167–178.

Alt Murphy, M., Resteghini, C., Feys, P. and Lamers, I. (2015) 'An overview of systematic reviews on upper extremity outcome measures after stroke.' *BMC Neurology*, 15.

Ashworth, B. (1964) 'Preliminary trial of carisoprodol in multiple sclerosis.' *The Practitioner*. ENGLAND, 192, April, pp. 540–542.

Astrom, K. J. and Hagglund, T. (2001) 'The future of PID control.' *Control Engineering Practice*, 9(11) pp. 1163–1175.

Atmel (2013) 'Atmel AT42QT1011.' Atmel Corporation.

Ausenda, C. D. (2014) 'A New Idea for Stroke Rehabilitation: Bilateral Transfer Analysis from Healthy Hand to the Paretic One with a Randomized and Controlled Trial.' *International Journal of Physical Medicine & Rehabilitation*, s3(1).

Ausenda, C. D. and Carnovali, M. (2011) 'Transfer of motor skill learning from the healthy hand to the paretic hand in stroke patients: A randomized controlled trial.' *European Journal of Physical and Rehabilitation Medicine*, 47(3) pp. 417–425.

Babaiasl, M., Mahdioun, S. H., Jaryani, P. and Yazdani, M. (2015) 'A review of technological and clinical aspects of robot-aided rehabilitation of upper-extremity after stroke.' *Disability and Rehabilitation: Assistive Technology*. Informa UK Ltd, 0(0) pp. 1–18.

Bach-y-Rita, P. (1990) 'Brain plasticity as a basis for recovery of function in humans.' *Neuropsychologia*, 28(6) pp. 547–554.

Bajaj, P., Scheidt, R. and Patton, J. (2005) 'Visual Error Augmentation for Enhancing Motor Learning and Rehabilitative Relearning.' *9th International Conference on Rehabilitation Robotics, 2005. ICORR 2005*. Ieee pp. 505–510.

Balasubramanian, S., Wei, R., Herman, R. and He, J. (2009) 'Robot-measured performance metrics in stroke rehabilitation.' *... , 2009. CME. ICME ...* pp. 330–335.

Basteris, A., Nijenhuis, S. M., Stienen, A. H., Buurke, J. H., Prange, G. B. and Amirabdollahian, F. (2014) 'Training modalities in robot-mediated upper limb rehabilitation in stroke: a framework for classification based on a systematic review.' *Journal of neuroengineering and rehabilitation*, 11(1) p. 111.

Bastian, A. A. J. (2008) 'Understanding sensorimotor adaptation and learning for rehabilitation.' *Current opinion in neurology*, 21(6) pp. 628–633.

Bax, M., Goldstein, M., Rosenbaum, P., Leviton, A., Paneth, N., Dan, B., Jacobsson, B. and Damiano, D. (2005) 'Proposed definition and classification of cerebral palsy, April 2005.' *Developmental Medicine & Child Neurology*, 47(8) pp. 571–576.

Bayón, C., Raya, R., Lara, S. L., Ramírez, Ó., J, I. S. and Rocon, E. (2016) 'Robotic Therapies for Children with Cerebral Palsy: A Systematic Review.' *Translational Biomedicine*, 7(1) pp. 1–10.

Beebe, J. a and Lang, C. E. (2009) 'Active range of motion predicts upper extremity function 3 months after stroke.' *Stroke; a journal of cerebral circulation*, 40(5) pp. 1772–9.

Blank, A. a., French, J. a., Pehlivan, A. U. and O'Malley, M. K. (2014) 'Current Trends in Robot-Assisted Upper-Limb Stroke Rehabilitation: Promoting Patient Engagement in Therapy.' *Current Physical Medicine and Rehabilitation Reports*, 2(2014) pp. 184–195.

Bolton, D. A. E., Cauraugh, J. H. and Hausenblas, H. A. (2004) 'Electromyogram-triggered neuromuscular stimulation and stroke motor recovery of arm/hand functions: a meta-analysis.'

Bosecker, C., Dipietro, L., Volpe, B. and Krebs, H. I. (2010) 'Kinematic Robot-Based Evaluation Scales and Clinical Counterparts to Measure Upper Limb Motor Performance in Patients With Chronic Stroke.' *Neurorehabilitation and Neural Repair*, 24(1) pp. 62–69.

Boyd, R. N., Morris, M. E. and Graham, H. K. (2001) 'Management of upper limb dysfunction in children with cerebral palsy: a systematic review.' *European journal of neurology : the official journal of the European Federation of Neurological Societies*, 8 Suppl 5, November, pp. 150–66.

Bradley, M. M. and Lang, P. J. (1994) 'Measuring emotion: The self-assessment manikin and the semantic differential.' *Journal of Behavior Therapy and Experimental Psychiatry*, 25(1) pp. 49–59.

Brian H. Hahn, D. T. V. (2013) *Essential Matlab for Engineers and Scientists*. Academic Press.

Brokaw, E. B., Murray, T., Nef, T. and Lum, P. S. (2011) 'Retraining of interjoint arm coordination after stroke using robot-assisted time-independent functional training.' *Journal of Rehabilitation Research and Development*. Center for Applied Biomechanics and Rehabilitation Research, National Rehabilitation Hospital, Washington, DC, United States, 48(4) pp. 299–316.

Brokaw, E. B., Murray, T., Nef, T. and Lum, P. S. (2011) 'Retraining of interjoint arm coordination after stroke using robot-assisted time-independent functional training.' *Journal of Rehabilitation Research and Development*, 48(4) pp. 299–316.

Burtner, P. a., Leinwand, R., Sullivan, K. J., Goh, H. T. and Kantak, S. S. (2014) 'Motor learning in children with hemiplegic cerebral palsy: feedback effects on skill acquisition.' *Developmental Medicine & Child Neurology*, 56(3) pp. 259–266.

Butler, C., Campbell, S. and Adams, R. (2000) 'Evidence of the effects of intrathecal baclofen for spastic and dystonic cerebral palsy.' *... Medicine & Child ...*, (3) pp. 634–645.

Butler, E. E., Ladd, A. L., Louie, S. a, Lamont, L. E., Wong, W. and Rose, J. (2010) 'Three-dimensional kinematics of the upper limb during a Reach and Grasp Cycle for children.' *Gait & posture*. Elsevier B.V., 32(1) pp. 72–7.

Caldwell, D. G., Tsagarakis, N. G., Kousidou, S., Costa, N. and Sarakoglou, I. (2007) '"Soft" Exoskeletons for Upper and Lower Body Rehabilitation - Design, Control and Testing.' *International Journal of Humanoid Robotics* pp. 549–573.

Carmichael, M. G. and Liu, D. (2012) 'A task description model for robotic rehabilitation.' *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, 2012, August, pp. 3086–9.

Casadio, M., Giannoni, P., Morasso, P. and Sanguineti, V. (2009) 'A proof of concept study for the integration of robot therapy with physiotherapy in the treatment of stroke patients.' *Clinical rehabilitation*, 23(3) pp. 217–228.

Casellato, C., Pedrocchi, A., Zorzi, G., Rizzi, G., Ferrigno, G. and Nardocci, N. (2012) 'Error-enhancing robot therapy to induce motor control improvement in childhood onset primary dystonia.' *Journal of neuroengineering and rehabilitation*. Journal of NeuroEngineering and Rehabilitation, 9(1) p. 46.

Cauraugh, J. H. and Kim, S. (2002) 'Two coupled motor recovery protocols are better than one: Electromyogram-triggered neuromuscular stimulation and bilateral movements.' *Stroke*, 33(6) pp. 1589–1594.

Celik, O. and O'Malley, M. (2010) 'Normalized movement quality measures for therapeutic robots strongly correlate with clinical motor impairment measures.' *Neural Systems and ...*, 18(4) pp. 433–444.

Cesqui, B., Aliboni, S., Mazzoleni, S., Carrozza, M. C., Posteraro, F. and Micera, S. (2008) 'On the use of divergent force fields in robot-mediated neurorehabilitation.' *In 2008 2nd IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics*. IEEE, pp. 854–861.

Chang, J.-J., Tung, W.-L., Wu, W.-L., Huang, M.-H. and Su, F.-C. (2007) 'Effects of robot-aided bilateral force-induced isokinetic arm training combined with conventional rehabilitation on arm motor function in patients with chronic stroke.' *Archives of physical medicine and rehabilitation*, 88(10) pp. 1332–8.

Chang, W. H. and Kim, Y.-H. (2013) 'Robot-Assisted Therapy in Stroke Rehabilitation.' *Journal of stroke*, 15(3) pp. 174–81.

Chemuturi, R., Amirabdollahian, F. and Dautenhahn, K. (2013) 'Adaptive training algorithm for robot-assisted upper-arm rehabilitation, applicable to individualised and therapeutic human-robot interaction.' *Journal of neuroengineering and rehabilitation*. Journal of NeuroEngineering and Rehabilitation, 10(1) p. 102.

Chen, Y.-P. and Howard, A. M. (2014) 'Effects of robotic therapy on upper-extremity function in children with cerebral palsy: A systematic review.' *Developmental neurorehabilitation*, 8423, April, pp. 1–8.

Cirstea, M. C. and Levin, M. F. (2000) 'Compensatory strategies for reaching in stroke.' *Brain : a journal of neurology*, 123 (Pt 5, May, pp. 940–53.

Claypool, K. T. and Claypool, M. (2007) 'On frame rate and player performance in first person shooter games.' *Multimedia Systems*, 13 pp. 3–17.

Cohen, J. (1977) *Statistical power analysis for the behavioral sciences*. Academic Press.

Colombo, R., Cusmano, I., Sterpi, I., Mazzone, A., Delconte, C. and Pisano, F. (2014) 'Test-Retest Reliability of Robotic Assessment Measures for the Evaluation of Upper Limb Recovery.' *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, 4320(c).

Colombo, R., Pisano, F., Mazzone, A., Delconte, C., Micera, S., Carrozza, M. C., Dario, P. and Minuco, G. (2007) 'Design strategies to improve patient motivation during robot-aided rehabilitation.' *Journal of neuroengineering and rehabilitation*, 4, January, p. 3.

Colombo, R., Pisano, F., Micera, S., Mazzone, A., Delconte, C., Carrozza, M. C., Dario, P. and Minuco, G. (2005) 'Robotic techniques for upper limb evaluation and rehabilitation of stroke patients.' *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, 13(3) pp. 311–24.

Colombo, R., Sterpi, I., Mazzone, A., Delconte, C., Minuco, G. and Pisano, F. (2010) 'Measuring Changes of Movement Dynamics During Robot-Aided Neurorehabilitation of Stroke Patients.' *Ieee Transactions on Neural Systems and Rehabilitation Engineering*, 18(1) pp. 75–85.

Colombo, R., Sterpi, I., Mazzone, A., Delconte, C. and Pisano, F. (2012) 'Taking a lesson from patients' recovery strategies to optimize training during robot-aided rehabilitation.' *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, 20(3) pp. 276–85.

Conroy, S. S., Whitall, J., Dipietro, L., Jones-Lush, L. M., Zhan, M., Finley, M. A., Wittenberg, G. F., Krebs, H. I. and Bever, C. T. (2011) 'Effect of Gravity on Robot-Assisted Motor Training After Chronic Stroke: A Randomized Trial.' *Archives of Physical Medicine and Rehabilitation*, 92(11) pp. 1754–1761.

Cooper, C. L., Phillips, L. H., Johnston, M., Whyte, M. and MacLeod, M. J. (2015) 'The role of emotion regulation on social participation following stroke.' *British Journal of Clinical Psychology*, 54(2) pp. 181–199.

Culmer, P. R., Jackson, A. E., Makower, S., Richardson, R., Cozens, J. A., Levesley, M. C. and Bhakta, B. B. (2010) 'A Control Strategy for Upper Limb Robotic Rehabilitation With a Dual Robot System.' *Ieee-Asme Transactions on Mechatronics*, 15(4) pp. 575–585.

Culmer, P. R., Jackson, A. E., Makower, S., Richardson, R., Cozens, J. A., Levesley, M. C., Bhakta, B. B. and Ieee (2009) 'Enhancing exploratory learning behaviour in people with stroke undertaking iPAM robot assisted upper limb exercises.' *In 2009 Ieee 11th International Conference on Rehabilitation Robotics, Vols 1 and 2*, pp. 892–897.

Culmer, P. R., Levesley, M. C., Mon-Williams, M. and Williams, J. H. G. (2009) 'A new tool for assessing human movement: the Kinematic Assessment Tool.' *Journal of neuroscience methods*, 184(1) pp. 184–192.

Van Delden, a. E. Q., Peper, C. E., Kwakkel, G. and Beek, P. J. (2012) 'A systematic review of bilateral upper limb training devices for poststroke rehabilitation.' *Stroke Research and Treatment*, 2012.

Dipietro, L., Krebs, H. I., Fasoli, S. E., Volpe, B. T. and Hogan, N. (2009) 'Submovement changes characterize generalization of motor recovery after stroke.' *Cortex*, 45(3) pp. 318–324.

Dipietro, L., Krebs, H. I., Fasoli, S. E., Volpe, B. T., Stein, J., Bever, C. and Hogan, N. (2007) 'Changing motor synergies in chronic stroke.' *Journal of neurophysiology*, 98(2) pp. 757–768.

Dobkin, B. H. (2004) ‘Strategies for stroke rehabilitation.’ *The Lancet. Neurology*, 3(9) pp. 528–36.

Dobkin, B. H. (2009) ‘Progressive Staging of Pilot Studies to Improve Phase III Trials for Motor Interventions.’ *Neurorehabilitation and neural repair*. NIH Public Access, 23(3) pp. 197–206.

Duret, C., Courtial, O. and Grosmaire, A. G. (2016) ‘Kinematic measures for upper limb motor assessment during robot-mediated training in patients with severe sub-acute stroke.’ *Restorative Neurology and Neuroscience*. IOS Press, 34(2) pp. 237–245.

Emken, J. L., Benitez, R., Sideris, A., Bobrow, J. E. and Reinkensmeyer, D. J. (2007) ‘Motor adaptation as a greedy optimization of error and effort.’ *Journal of neurophysiology*, 97(6) pp. 3997–4006.

Fasoli, S. E., Fragala-Pinkham, M., Hughes, R., Hogan, N., Krebs, H. I. and Stein, J. (2008) ‘Upper limb robotic therapy for children with hemiplegia.’ *American journal of physical medicine & rehabilitation / Association of Academic Physiatrists*, 87(11) pp. 929–936.

Fasoli, S. E., Ladenheim, B., Mast, J. and Krebs, H. I. (2012) ‘New horizons for robot-assisted therapy in pediatrics.’ *American journal of physical medicine & rehabilitation / Association of Academic Physiatrists*, 91(11 Suppl 3) pp. S280-9.

Field, A. (2013) *Discovering Statistics using IBM SPSS Statistics*. Sage.

Finley, M. A., Fasoli, S. E., Dipietro, L., Ohlhoff, J., MacClellan, L., Meister, C., Whitall, J., Macko, R., Bever Jr., C. T., Krebs, H. I. and Hogan, N. (2005) ‘Short-duration robotic therapy in stroke patients with severe upper-limb motor impairment.’ *Journal of Rehabilitation Research and Development*. Department of Veterans Affairs, (VA) Maryland Healthcare System, Rehabilitation Research and Development Service, Baltimore, MD, United States, 42(5) pp. 683–691.

Finley, M., Dipietro, L. and Ohlhoff, J. (2009) ‘The effect of repeated measurements using an upper extremity robot on healthy adults.’ *Journal of applied …*, 25(2) pp. 103–110.

Fitts, P. M. (1954) ‘The information capacity of the human motor system in controlling the amplitude of movement.’ *Journal of Experimental Psychology*, 47(6) pp. 381–391.

Flores, E., Tobon, G., Cavallaro, E., Cavallaro, F. I., Perry, J. C. and Keller, T. (2008) ‘Improving patient motivation in game development for motor deficit rehabilitation.’ *Proceedings of the 2008 International Conference in Advances on Computer Entertainment Technology - ACE ’08*, 7(8) p. 381.

Frascarelli, F., Masia, L. and Rosa, G. Di (2009) ‘The impact of robotic rehabilitation in children with acquired or congenital movement disorders.’ *… and rehabilitation …*, 45(1) pp. 135–141.

French, B., Thomas, L. H., Leathley, M. J., Sutton, C. J., McAdam, J., Forster, a., Langhorne, P., Price, C. I. M., Walker, a. and Watkins, C. L. (2009) ‘Repetitive Task Training for Improving Functional Ability After Stroke.’ *Stroke*, 40(4) pp. e98–e99.

Frisoli, A., Salsedo, F., Bergamasco, M., Rossi, B. and Carboncini, M. C. (2009) ‘A force-feedback exoskeleton for upper-limb rehabilitation in virtual reality.’ *Applied Bionics and Biomechanics*. PERCRO, Scuola Superiore Sant’Anna, Pisa, Italy, 6(2) pp. 115–126.

Fugl-Meyer, A., Jääskö, L., Leyman, I. and Steglind, S. (1974) ‘The post-stroke hemiplegic patient: a method for evaluation of physical performance.’ *Scandinavian journal of rehabilitation medicine*, 7(max 2) pp. 13–37.

Funkhouser, T. a. and Séquin, C. H. (1993) ‘Adaptive display algorithm for interactive frame rates during visualization of complex virtual environments.’ *Proceedings of the 20th annual conference on Computer graphics and interactive techniques - SIGGRAPH ’93* pp. 247–254.

Gajdosik, R. L. and Bohannon, R. W. (1987) ‘Clinical measurement of range of motion. Review of goniometry emphasizing reliability and validity.’ *Physical therapy*, 67(12) pp. 1867–72.

Givon-Mayo, R. and Simons, E. (2014) ‘A preliminary investigation of error enhancement of the velocity component in stroke patients’ reaching movements.’ *... Journal of Therapy …*.

Goldstein, M. (2004) ‘The treatment of cerebral palsy: What we know, what we don’t know.’ *The Journal of pediatrics*, 145(2 Suppl) pp. S42-6.

Gopura, R. (2011) ‘A brief review on upper extremity robotic exoskeleton systems.’ *... Systems (ICIIS), 2011 6th …*, 8502 pp. 346–351.

Gopura, R. A. R. C., Bandara, D. S. V., Kiguchi, K. and Mann, G. K. I. (2016) ‘Developments in hardware systems of active upper-limb exoskeleton robots: A review.’ *Robotics and Autonomous Systems*, 75 pp. 203–220.

Gopura, R. A. R. C., Kiguchi, K. and Ieee (2009) 'Mechanical Designs of Active Upper-Limb Exoskeleton Robots State-of-the-Art and Design Difficulties.' *In 2009 Ieee 11th International Conference on Rehabilitation Robotics, Vols 1 and 2*, pp. 207–216.

Gordon, A. M. (2006) 'Efficacy of Constraint-Induced Movement Therapy on Involved Upper-Extremity Use in Children With Hemiplegic Cerebral Palsy Is Not Age-Dependent.' *Pediatrics*, 117(3) pp. e363–e373.

Gordon, J., Ghilardi, M. F. and Ghez, C. (1994) 'Accuracy of planar reaching movements - I. Independence of direction and extent variability.' *Experimental Brain Research*, 99(1) pp. 97–111.

Guidali, M., Schlink, P., Duschau-Wicke, A., Riefler, R. and Ieee (2011) 'Online Learning and Adaptation of Patient Support During ADL Training.' *In 2011 Ieee International Conference on Rehabilitation Robotics*.

Hakkennes, S. and Keating, J. L. (2005) 'Constraint-induced movement therapy following stroke: a systematic review of randomised controlled trials.' *Australian Journal of Physiotherapy*. Elsevier, 51(4) pp. 221–231.

Heiss, K. A. H. and W.-D. and Hossmann, K. A. and W.-D. H. (2009) *Neuropathology and pathophysiology of stroke*. Cambridge University Press.

Hingtgen, B., McGuire, J. R., Wang, M. and Harris, G. F. (2006) 'An upper extremity kinematic model for evaluation of hemiparetic stroke.' *Journal of biomechanics*, 39(4) pp. 681–8.

Hoare, B., Imms, C., Carey, L. and Wasiak, J. (2007) 'Constraint-induced movement therapy in the treatment of the upper limb in children with hemiplegic cerebral palsy: A Cochrane systematic review.' *Clinical Rehabilitation*, 21 pp. 675–685.

Holt, R., Weightman, A. and Gallagher, J. (2013) 'A System in the Wild: Deploying a Two Player Arm Rehabilitation System for Children With Cerebral Palsy in a School Environment.' *Journal of Usability ...*, 8(4) pp. 111–126.

Hughes, A. and Drury, B. (2013) 'Electric Motors and Drives: Fundamentals, Types and Applications .' GB : Newnes .

IJzerman, M. J., Renzenbrink, G. J. and Geurts, A. C. H. (2009) 'Neuromuscular stimulation after stroke: from technology to clinical deployment.' *Expert review of neurotherapeutics*, 9(4) pp. 541–552.

Intel Corportation (2016) *Intel Compute Stick*. [Online] [Accessed on 1st January 2016] http://www.intel.co.uk/content/www/uk/en/compute-stick/intel-compute-stick.html.

Interactive Motion Technologies (2016) *InMotion ARM^{TM} Interactive Therapy System*. [Online] [Accessed on 1st January 2016] http://interactive-motion.com/healthcarereform/upper-extremity-rehabilitiation/inmotion2-arm/.

Iosa, M., Morone, G., Cherubini, A. and Paolucci, S. (2016) 'The three laws of neurorobotics: A review on what neurorehabilitation robots should do for patients and clinicians.' *Journal of Medical and Biological Engineering*. Springer Berlin Heidelberg pp. 1–11.

Iosa, M., Morone, G., Ragaglini, M. R., Fusco, A. and Paolucci, S. (2013) 'Motor strategies and bilateral transfer in sensorimotor learning of patients with subacute stroke and healthy subjects. A randomized controlled trial.' *European Journal of Physical and Rehabilitation Medicine*, 49(3) pp. 291–299.

Israely, S. and Carmeli, E. (2015) 'Error augmentation as a possible technique for improving upper extremity motor performance after a stroke – a systematic review.' *Topics in Stroke Rehabilitation*, 9357(April) pp. 1–11.

Jackson, D., McCrone, P. and Turner-Stokes, L. (2013) 'Costs of caring for adults with long-term neurological conditions.' *Journal of rehabilitation medicine : official journal of the UEMS European Board of Physical and Rehabilitation Medicine*, 45(7) pp. 653–61.

Jette, A. (2006) 'Toward a common language for function, disability, and health.' *Physical Therapy* pp. 726–734.

Johansson, B. B. (2000) 'Brain Plasticity and Stroke Rehabilitation : The Willis Lecture.' *Stroke\rStroke*, 31(1) pp. 223–230.

Johnson, M. A. and Moradi, M. H. (2005) 'PID control: new identification and design methods .' New York;London; : Springer .

Johnson, M. J. (2006) 'Recent trends in robot-assisted therapy environments to improve real-life functional performance after stroke.' *Journal of NeuroEngineering and Rehabilitation*. Medical College of Wisconsin, Dept. of Physical Medicine and Rehabilitation, 9200 W. Wisconsin Ave, Milwaukee, WI 53226, United States, 3.

Kadivar, Z., Sullivan, J. L., Eng, D. P., Pehlivan, a U., O'Malley, M. K., Yozbatiran, N. and Francisco, G. E. (2011) 'Robotic training and kinematic analysis of arm and hand after incomplete spinal cord injury: a case study.' *IEEE ... International Conference on Rehabilitation Robotics : [proceedings]*, 2011, January, p. 5975429.

Kadivar, Z., Sung, C., Thompson, Z., O'Malley, M., Liebschner, M. and Deng, Z. (2011) 'Comparison of reaching kinematics during mirror and parallel robot assisted movements.' *In Studies in Health Technology and Informatics*. Department of Physical Medicine and Rehabilitation, Baylor College of Medicine, One Baylor Plaza, Houston, TX, 77082, United States (Medicine Meets Virtual Reality 18: NextMed, MMVR18), pp. 247–253.

Kahn, L. E., Rymer, W. Z. and Reinkensmeyer, D. J. (2004) 'Adaptive assistance for guided force training in chronic stroke.' *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, 4 pp. 2722–5.

Kahn, L. E., Zygman, M. L., Rymer, W. Z. and Reinkensmeyer, D. J. (2006) 'Robot-assisted reaching exercise promotes arm movement recovery in chronic hemiparetic stroke: a randomized controlled pilot study.' *Journal of neuroengineering and rehabilitation*, 3, January, p. 12.

Kelly-Hayes, P. M., Robertson, J. T., Broderick, J. P., Duncan, P. W., Hershey, L. a., Roth, E. J., Thies, W. H. and Trombly, C. a. (1998) *The American Heart Association Stroke Outcome Classification*. *Stroke*.

Kerr, C., McDowell, B. and McDonough, S. (2004) 'Electrical stimulation in cerebral palsy : a review of effects on strength and motor function.' *Developmental Medicine & Child Neurology*, 46(3) pp. 205–213.

Kirihara, K., Saga, N. and Saito, N. (2010) 'Design and control of an upper limb rehabilitation support device for disabled people using a pneumatic cylinder.' *Industrial Robot-an International Journal*, 37(4) pp. 354–363.

Kitago, T., Ryan, S. L., Mazzoni, P., Krakauer, J. W. and Haith, A. M. (2013) 'Unlearning versus savings in visuomotor adaptation: comparing effects of washout, passage of time, and removal of errors on motor memory.' *Frontiers in human neuroscience*. Frontiers Media SA, 7(June) p. 307.

Krabben, T., Molier, B. I., Houwink, A., Rietman, J. S., Buurke, J. H. and Prange, G. B. (2011) 'Circle drawing as evaluative movement task in stroke rehabilitation: an explorative study.' *Journal of NeuroEngineering and Rehabilitation*, 8(March) p. 15.

Krakauer, J. W. (2005) 'Arm function after stroke: from physiology to recovery.' *Seminars in neurology*, 25(4) pp. 384–95.

Krakauer, J. W. (2006) 'Motor learning: its relevance to stroke recovery and neurorehabilitation.' *Current opinion in neurology*, 19(1) pp. 84–90.

Krakauer, J. W., Ghez, C. and Ghilardi, M. F. (2005) 'Adaptation to visuomotor transformations: consolidation, interference, and forgetting.' *The Journal of neuroscience : the official journal of the Society for Neuroscience*, 25(2) pp. 473–8.

Krebs, H. and Hogan, N. (2006) 'Therapeutic robotics: A technology push.' *Proceedings of the IEEE*, 94(9).

Krebs, H. I., Dipietro, L., Volpe, B. T. and Hogan, N. (2003) 'Rehabilitation Robotics : Performance-Based Progressive Robot-Assisted Therapy.' *Autonomous Robots*, 15(1) pp. 7–20.

Krebs, H. I., Hogan, N., Aisen, M. L. and Volpe, B. T. (1998) 'Robot-aided neurorehabilitation.' *IEEE transactions on rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, 6(1) pp. 75–87.

Krebs, H. I., Krams, M., Agrafiotis, D. K., DiBernardo, A., Chavez, J. C., Littman, G. S., Yang, E., Byttebier, G., Dipietro, L., Rykman, A., McArthur, K., Hajjar, K., Lees, K. R. and Volpe, B. T. (2014) 'Robotic measurement of arm movements after stroke establishes biomarkers of motor recovery.' *Stroke; a journal of cerebral circulation*, 45(1) pp. 200–4.

Krebs, H. I., Volpe, B. and Hogan, N. (2009) 'A working model of stroke recovery from rehabilitation robotics practitioners.' *Journal of neuroengineering and rehabilitation*, 6 p. 6.

Kung, P.-C., Lin, C.-C. K. and Ju, M.-S. (2010) 'Neuro-rehabilitation robot-assisted assessments of synergy patterns of forearm, elbow and shoulder joints in chronic stroke patients.' *Clinical Biomechanics*, 25(7) pp. 647–654.

Kwakkel, G., Kollen, B. and Krebs, H. (2007) 'Effects of robot-assisted therapy on upper limb recovery after stroke: a systematic review.' *Neurorehabilitation and neural ...*, 22(2) pp. 111–121.

Lance, J. W. (1990) 'What is spasticity?' *Lancet (London, England)*. ENGLAND p. 606.

Lang, C. E., Bland, M. D., Bailey, R. R., Schaefer, S. Y. and Birkenmeir, R. L. (2013) ‘Assessment of upper extremity impairment, function, and activity following stroke: Foundations for clinical decision making’ pp. 1–21.

Langhorne, P., Coupar, F. and Pollock, A. (2009) ‘Motor recovery after stroke: a systematic review.’ *Lancet neurology*. Elsevier Ltd, 8(8) pp. 741–54.

Lee, J. and Choi, S. (2010) ‘Effects of haptic guidance and disturbance on motor learning: Potential advantage of haptic disturbance.’ *2010 IEEE Haptics Symposium, HAPTICS 2010* pp. 335–342.

Lee, T., Swinnen, S. and Serrien, D. (1994) ‘Cognitive effort and motor learning.’ *Quest*.

Lenzi, T., Vitiello, N., De Rossi, S. M. M., Roccella, S., Vecchi, F. and Carrozza, M. C. (2011) ‘NEUROExos: A variable impedance powered elbow exoskeleton.’ *2011 IEEE International Conference on Robotics and Automation*. Ieee, May, pp. 1419–1426.

Leuenberger, K., Gonzenbach, R., Wachter, S., Luft, A. and Gassert, R. (2016) ‘A method to qualitatively assess arm use in stroke survivors in the home environment.’ *Medical & Biological Engineering & Computing*. Springer Berlin Heidelberg, April, pp. 1–10.

Levin, M., Sveistrup, H. and Subramanian, S. (2010) ‘Feedback and virtual environments for motor learning and rehabilitation.’ *Schedae*. Presses universitaires de Caen, 2 pp. 19–36.

Levitt, S. (2010) *Treatment of cerebral palsy and motor delay, 5th ed.* Chichester: Wiley-Blackwell.

Li, C., Inoue, Y., Liu, T. and Sun, L. (2013) ‘Validation of bimanual-coordinated training supported by a new upper-limb rehabilitation robot: a near-infrared spectroscopy study.’ *Disability and rehabilitation. Assistive technology*, 8(1) pp. 38–48.

Li, S., Frisoli, A., Avizzano, C. A., Ruffaldi, E., Lugo-Villeda, L. I., Bergamasco, M. and Ieee (2009) *Bimanual Haptic-Desktop Platform for Upper-limb Post-Stroke Rehabilitation: Practical Trials*. *2009 Ieee International Conference on Robotics and Biomimetics*.

Li, Y., Ang, K. H. and Chong, G. C. Y. (2006) ‘PID control system analysis and design.’ *IEEE Control Systems*, 26(1) pp. 32–41.

Liao, W., Wu, C., Hsieh, Y., Lin, K. and Chang, W. (2012) ‘Effects of robot-assisted upper limb rehabilitation on daily function and real-world arm activity in patients with chronic stroke: a randomized controlled trial.’ *Clinical Rehabilitation*, 26(2) pp. 111–120.

Lin, H., Bae, H., Midkiff, S. P., Eigenmann, R. and Kim, S. P. (2013) ‘Languages and Compilers for Parallel Computing: 24th International Workshop, LCPC 2011, Fort Collins, CO, USA, September 8-10, 2011. Revised Selected Papers.’ *In* Rajopadhye, S. and Mills Strout, M. (eds). Berlin, Heidelberg: Springer Berlin Heidelberg, pp. 141–155.

Lo, H. S. and Xie, S. Q. (2012) ‘Exoskeleton robots for upper-limb rehabilitation: State of the art and future prospects.’ *Medical Engineering & Physics*, 34(3) pp. 261–268.

de los Reyes-Guzmán, A., Dimbwadyo-Terrer, I., Trincado-Alonso, F., Monasterio-Huelin, F., Torricelli, D. and Gil-Agudo, A. (2014) ‘Quantitative assessment based on kinematic measures of functional impairments during upper extremity movements: A review.’ *Clinical Biomechanics*, 29(7) pp. 719–727.

Loureiro, R. C. V, Harwin, W. S., Nagai, K. and Johnson, M. (2011) ‘Advances in upper limb stroke rehabilitation: a technology push.’ *Medical & Biological Engineering & Computing*, 49(10) pp. 1103–1118.

Lum, P. S., Burgar, C. G., Shor, P. C., Majmundar, M. and Van der Loos, M. (2002) ‘Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke.’ *Archives of Physical Medicine and Rehabilitation*, 83(7) pp. 952–959.

MacClellan, L. and Bradham, D. (2005) ‘Robotic upper-limb neurorehabilitation in chronic stroke patients.’ *Journal of …*, 42(6) pp. 717–722.

Maciejasz, P., Eschweiler, J., Gerlach-Hahn, K., Jansen-Troy, A. and Leonhardt, S. (2014) ‘A survey on robotic devices for upper limb rehabilitation.’ *Journal of neuroengineering and rehabilitation*, 11(1) p. 3.

Madgwick, S. O. H., Harrison, A. J. L. and Vaidyanathan, R. (2011) ‘Estimation of IMU and MARG orientation using a gradient descent algorithm.’ *IEEE International Conference on Rehabilitation Robotics*.

Majeed, Y. A., Abdollahi, F., Awadalla, S. and Patton, J. (2015) ‘Multivariate outcomes in a three week bimanual self-telerehabilitation with error augmentation post-stroke.’ *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS*, 2015–Novem pp. 1425–1431.

Marchal-Crespo, L. and Reinkensmeyer, D. J. (2009) ‘Review of control strategies for robotic movement training after neurologic injury.’ *Journal of neuroengineering and rehabilitation*, 6, January, p. 20.

Masia, L., Frascarelli, F., Morasso, P., Di Rosa, G., Petrarca, M., Castelli, E. and Cappa, P. (2011) ‘Reduced short term adaptation to robot generated dynamic environment in children affected by Cerebral Palsy.’ *Journal of neuroengineering and rehabilitation*. BioMed Central Ltd, 8(1) p. 28.

Masiero, S., Armani, M. and Rosati, G. (2011) ‘Upper-limb robot-assisted therapy in rehabilitation of acute stroke patients: Focused review and results of new randomized controlled trial.’ *Journal of Rehabilitation Research and Development*, 48(4) pp. 355–366.

Massey, E. W. (2014) ‘Diagnostic medical and surgical approaches to stroke management.’ *In* Singleton, M. C. and Branch, E. F. (eds) *Physical Therapy and the Stroke Patient*. New York: Routledge, pp. 1–20.

McCabe, J., Monkiewicz, M., Holcomb, J., Pundik, S. and Daly, J. J. (2015) ‘Comparison of robotics, functional electrical stimulation, and motor learning methods for treatment of persistent upper extremity dysfunction after stroke: A randomized controlled trial.’ *Archives of Physical Medicine and Rehabilitation*, 96(6) pp. 981–990.

McKerrow, P. (1991) *Introduction to robotics*. Sydney: Addison-Wesley.

Microsoft Coorporation (2016) *Microsoft Surface Pro 4*. [Online] [Accessed on 1st January 2016] https://www.microsoftstore.com/store/msuk/en_GB/pdp/productID.326546100?WT.mc_id=pointitsem+Google+Adwords+Surface+Pro+4+-+EN&s_kwcid=AL!4249!3!103489117605!e!!g!!surface pro 4&ef_id=V1iCNAAAASVTUh38:20160630132537:s.

Milot, M.-H., Marchal-Crespo, L., Green, C. S., Cramer, S. C. and Reinkensmeyer, D. J. (2010) ‘Comparison of error-amplification and haptic-guidance training techniques for learning of a timing-based motor task by healthy individuals.’ *Experimental brain research*, 201(2) pp. 119–31.

Molier, B. I., Van Asseldonk, E. H. F., Hermens, H. J. and Jannink, M. J. A. (2010) ‘Nature, timing, frequency and type of augmented feedback; does it influence motor relearning of the hemiparetic arm after stroke? A systematic review.’ *Disability and Rehabilitation*, 32(22) pp. 1799–1809.

Morales, R., Javier Badesa, F., Garcia-Aracil, N., Maria Sabater, J. and Perez-Vidal, C. (2011) ‘Pneumatic robotic systems for upper limb rehabilitation.’ *Medical & Biological Engineering & Computing*, 49(10) pp. 1145–1156.

Mousavi, H., Khademi, M. and Dodakian, L. (2013) ‘A Spatial Augmented Reality Rehab System for Post-Stroke Hand Rehabilitation’ pp. 279–286.

Nair, M. and Peate, I. (2012) *Fundamentals of Applied Pathophysiology: An Essential Guide for Nursing and Healthcare Students*. Wiley-Blackwell.

National Instruments (2010) *OPERATING INSTRUCTIONS AND SPECIFICATIONS CompactRIO NI cRIO-9022 Intelligent Real-Time Embedded Controller for CompactRIO*. [Online] http://www.ni.com/pdf/manuals/375102d.pdf.

National Instruments Corp. (2009) *NI 9505 Current Measurement Considerations (FPGA Interface)*. CompactRIO Reference and Procedures (FPGA Interface). [Online] [Accessed on 4th June 2014] http://zone.ni.com/reference/en-XX/help/370984R-01/target4devicehelp/9505_currentmeasurement/.

National Instruments Corp. (2010) ‘Operating Insturctions and specifications NI 9505’ p. 40.

National Instruments Corp. (2012) *Unexpected Current Reading on the NI 9505*. *National Instruments Corp.*

National Instruments Corp. (2015) *The NI TDMS File Format*. National Instruments Corp. [Online] [Accessed on 5th October 2015] http://www.ni.com/white-paper/3727/en/#toc2.

NDI Measurement Sciences (2016) *Optotrack Certus*. [Online] [Accessed on 1st January 2016] http://www.ndigital.com/msci/products/optotrak-certus/.

Nordin, N., Xie, S. and Burkhard, W. (2014) ‘Assessment of Movement Quality in Robot-assisted Upper Limb Rehabilitation : A Review.’ *Journal of NeuroEngineering and Rehabilitation*, 11(137).

Nordin, N., Xie, S. Q. and Wünsche, B. (2014) ‘Assessment of movement quality in robot- assisted upper limb rehabilitation after stroke: a review.’ *Journal of neuroengineering and rehabilitation*, 11 p. 137.

Novak, I., McIntyre, S., Morgan, C., Campbell, L., Dark, L., Morton, N., Stumbles, E., Wilson, S.-A. and Goldsmith, S. (2013) ‘A systematic review of interventions for children with cerebral palsy: state of the evidence.’ *Developmental medicine and child neurology*, 55(10) pp. 885–910.

Novakovic, V. and Sanguineti, V. (2011) ‘Adaptation to constant-magnitude assistive forces: kinematic and neural correlates.’ *Experimental Brain Research*, 209(3) pp. 425–436.

Oberg, E., Jones, F. D., Horton, H. L. and Ryffel, H. H. (2012) *Machinery’s Handbook (29th Edition) & Guide to Machinery’s Handbook*. *Industrial Press*. Industrial Press.

Oldfield, R. C. (1971) ‘The assessment and analysis of handedness: the Edinburgh inventory.’ *Neuropsychologia*, 9(1) pp. 97–113.

Oliveira, L. F., Simpson, D. M. and Nadal, J. (1996) ‘Calculation of area of stabilometric signals using principal component analysis.’ *Physiological measurement*, 17(4) pp. 305–12.

Ostensjø, S., Carlberg, E. B. and Vøllestad, N. K. (2004) ‘Motor impairments in young children with cerebral palsy: relationship to gross motor function and everyday activities.’ *Developmental medicine and child neurology*, 46(9) pp. 580–9.

Park, J. H., Shea, C. H. and Wright, D. L. (2000) ‘Reduced-frequency concurrent and terminal feedback: a test of the guidance hypothesis.’ *Journal of motor behavior*, 32(3) pp. 287–96.

Park, K., Kim, Y., Nagai, C. and Obinata, G. (2012) ‘Bilateral transfer in active and passive guidance-reproduction of upper limbs motion: Effect of proprioception and handedness.’ *Journal of Biomechanical Science and Engineering*, 7(2) pp. 141–155.

Park, K., Kim, Y. and Obinata, G. (2011) ‘Bilateral transfer in active and passive guidance-reproduction based bimanual tasks: effect of proprioception and handedness.’ *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, 2011 pp. 3127–3130.

Parker, J. (2011) ‘A review of the evidence underpinning the use of visual and auditory feedback for computer technology in post-stroke upper-limb rehabilitation.’ *Disability & Rehabilitation ...*, 6(November) pp. 465–472.

Patten, C., Dozono, J., Schmidt, S., Jue, M. and Lum, P. (2006) ‘Combined functional task practice and dynamic high intensity resistance training promotes recovery of upper-extremity motor function in post-stroke hemiparesis: a case study.’ *Journal of neurologic physical therapy : JNPT*, 30(3) pp. 99–115.

Patton, J. L., Kovic, M. and A, F. M.-I. (2006) ‘Custom-designed haptic training for restoring reaching ability to individuals with poststroke hemiparesis.’ *The Journal of Rehabilitation Research and Development*, 43(5) p. 643.

Patton, J. L. and Mussa-Ivaldi, F. a (2004) ‘Robot-Assisted Adaptive Training: Custom Force Fields for Teaching Movement Patterns.’ *IEEE Transactions on Biomedical Engineering*, 51(4) pp. 636–646.

Patton, J. L., Stoykov, M. E., Kovic, M. and Mussa-Ivaldi, F. a (2006) ‘Evaluation of robotic training forces that either enhance or reduce error in chronic hemiparetic stroke survivors.’ *Experimental brain research. Experimentelle Hirnforschung. Expérimentation cérébrale*, 168(3) pp. 368–83.

Patton, J., Wei, Y. J., Bajaj, P. and Scheidt, R. A. (2013) ‘Visuomotor learning enhanced by augmenting instantaneous trajectory error feedback during reaching.’ *PLoS One*. 2013/02/06, 8(1) p. e46466.

Pehlivan, A. U., Losey, D. P. and Omalley, M. K. (2016) ‘Minimal Assist-as-Needed Controller for Upper Limb Robotic Rehabilitation.’ *IEEE Transactions on Robotics*. IEEE, 32(1) pp. 113–124.

Pérez, R., Costa, Ú., Torrent, M., Solana, J., Opisso, E., Cáceres, C., Tormos, J. M., Medina, J. and Gómez, E. J. (2010) ‘Upper limb portable motion analysis system based on inertial technology for neurorehabilitation purposes.’ *Sensors (Basel, Switzerland)*, 10(12) pp. 10733–51.

Perry, J. and Andureu, J. (2010) ‘Effective game use in neurorehabilitation: user-centered perspectives.’ *... Educational Games, ...* pp. 1–44.

Platz, T., Winter, T., Müller, N., Pinkowski, C., Eickhof, C. and Mauritz, K.-H. (2001) ‘Arm ability training for stroke and traumatic brain injury patients with mild arm paresis: A single-blind, randomized, controlled trial.’ *Archives of Physical Medicine and Rehabilitation*. Elsevier, 82(7) pp. 961–968.

Posteraro, F., Mazzoleni, S., Aliboni, S., Cesqui, B., Battaglia, A., Carrozza, M. C., Dario, P. and Micera, S. (2010) ‘Upper Limb Spasticity Reduction Following Active Training: A Robot-Mediated Study In Patients With Chronic Hemiparesis.’ *Journal of Rehabilitation Medicine*, 42(3) pp. 279–281.

Preston, N., Weightman, A., Culmer, P., Levesley, M., Bhakta, B. and Mon-Williams, M. (2014) ‘The Cerebral Palsy Kinematic Assessment Tool (CPKAT): feasibility testing of a new portable tool for the objective evaluation of upper limb kinematics in children with cerebral palsy in the non-laboratory setting.’ *Disability and Rehabilitation: Assistive Technology* pp. 1–6.

Prior, S. and Warner, P. (1990) ‘A review of world rehabilitation robotics research.’ *High-Tech Help for the Handicapped, ….*

Proietti, T., Crocher, V., Roby-Brami, A. and Jarrasse, N. (2016) ‘Upper-limb robotic exoskeletons for neurorehabilitation: a review on control strategies.’ *IEEE Reviews in Biomedical Engineering*. IEEE, PP(99) pp. 1–1.

Rego, P., Moreira, P. M. and Reis, L. P. (2010) ‘Serious Games for Rehabilitation A Survey and a Classification Towards a Taxonomy.’ *5th Iberian Conference on Information Systems and Technologies*, (November 2015) pp. 1–6.

Rhudy, M. (2014) ‘Time Alignment Techniques for Experimental Sensor Data.’ *International Journal of Computer Science & Engineering Survey*, 5(2) pp. 1–14.

Robertson, J. V. G., Hoellinger, T., Lindberg, P., Bensmail, D., Hanneton, S. and Roby-Brami, A. (2009) ‘Effect of auditory feedback differs according to side of hemiparesis: a comparative pilot study.’ *Journal of neuroengineering and rehabilitation*, 6 p. 45.

Rohafza, M., Fluet, G. G., Qiu, Q. and Adamovich, S. (2014) ‘Correlation of reaching and grasping kinematics and clinical measures of upper extremity function in persons with stroke related hemiplegia.’ *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Annual Conference*, 2014 pp. 3610–3613.

Rohrer, B., Fasoli, S., Krebs, H. I., Hughes, R., Volpe, B., Frontera, W. R., Stein, J. and Hogan, N. (2002) ‘Movement smoothness changes during stroke recovery.’ *The Journal of neuroscience : the official journal of the Society for Neuroscience*, 22(18) pp. 8297–304.

Rohrer, B., Fasoli, S., Krebs, H. I., Volpe, B., Frontera, W. R., Stein, J. and Hogan, N. (2004) ‘Submovements grow larger, fewer, and more blended during stroke recovery.’ *Motor control*, 8(4) pp. 472–483.

Rønning, O. M. and Guldvog, B. (1998) ‘Outcome of subacute stroke rehabilitation: a randomized controlled trial.’ *Stroke; a journal of cerebral circulation*, 29(4) pp. 779–784.

van Roon, D., Steenbergen, B. and Meulenbroek, R. G. J. (2005) ‘Trunk use and co-contraction in cerebral palsy as regulatory mechanisms for accuracy control.’ *Neuropsychologia*, 43(4) pp. 497–508.

Rosati, G., Rod??, A., Avanzini, F. and Masiero, S. (2013) ‘On the role of auditory feedback in robot-assisted movement training after stroke: Review of the literature.’ *Computational Intelligence and Neuroscience* p. 586138.

Rosenbaum, P. (2003) ‘Cerebral palsy: what parents and doctors want to know.’ *Bmj*, 326(MAY).

Rotella, M. F., Koehler, M., Nisky, I., Bastian, A. J. and Okamura, A. M. (2013) ‘Adaptation to visuomotor rotation in isometric reaching is similar to movement adaptation.’ *IEEE International Conference on Rehabilitation Robotics*.

Rozario, S. and Housman, S. (2009) ‘Therapist-mediated post-stroke rehabilitation using haptic/graphic error augmentation.’ *... in Medicine and ….*

Rozario, S. V, Housman, S., Kovic, M., Kenyon, R. V and Patton, J. L. (2009) ‘Therapist-mediated post-stroke rehabilitation using haptic/graphic error augmentation.’ *Conf Proc IEEE Eng Med Biol Soc*. 2009/12/08, 2009 pp. 1151–1156.

Ryan, R. and Deci, E. (2000) ‘Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions.’ *Contemporary educational psychology*, 25(1) pp. 54–67.

Sacco, R. L., Kasner, S. E., Broderick, J. P., Caplan, L. R., Connors, J. J. B., Culebras, A., Elkind, M. S. V, George, M. G., Hamdan, A. D., Higashida, R. T., Hoh, B. L., Janis, L. S., Kase, C. S., Kleindorfer, D. O., Lee, J.-M., Moseley, M. E., Peterson, E. D., Turan, T. N., Valderrama, A. L. and Vinters, H. V (2013) ‘An updated definition of stroke for the 21st century: a statement for healthcare professionals from the American Heart Association/American Stroke Association.’ *Stroke; a journal of cerebral circulation*, 44(7) pp. 2064–89.

Safavynia, S. a, Torres-Oviedo, G. and Ting, L. H. (2011) ‘Muscle Synergies: Implications for Clinical Evaluation and Rehabilitation of Movement.’ *Topics in spinal cord injury rehabilitation*, 17(1) pp. 16–24.

Salkind, N. (2007) *Encyclopedia of Measurement and Statistics*. 2455 Teller Road, Thousand Oaks California 91320 United States of America : Sage Publications, Inc.

Sanchez, R. J., Wolbrecht, E., Smith, R., Liu, J., Rao, S., Cramer, S., Rahman, T., Bobrow, J. E., Reinkensmeyer, D. J. and Shah, P. (2005) ‘A pneumatic robot for re-training arm movement after stroke: Rationale and mechanical design.’ *Proceedings of the 2005 IEEE 9th International Conference on Rehabilitation Robotics*, 2005 pp. 500–504.

Sanguineti, V., Casadio, M., Vergaro, E., Squeri, V., Giannoni, P. and Morasso, P. G. (2009) 'Robot therapy for stroke survivors: proprioceptive training and regulation of assistance.' *Studies in health technology and informatics*, 145, January, pp. 126–42.

Santis, D. De, Zenzeri, J., Casadio, M., Masia, L., Squeri, V. and Morasso, P. (2014) 'Characterizing the human-robot haptic dyad in robot therapy of stroke survivors.' *International Journal of Intelligent Computing and Cybernetics*, 7(3) p. 4.

Santisteban, L., Térémetz, M., Bleton, J.-P., Baron, J.-C., Maier, M. A. and Lindberg, P. G. (2016) 'Upper Limb Outcome Measures Used in Stroke Rehabilitation Studies: A Systematic Literature Review.' *Plos One*, 11(5) p. e0154792.

Scarborough, P., Peto, V., Bhatnagar, P., Kaur, A., Leal, J., Luengo-, R., Gray, A., Rayner, M. and Allender, S. (2009) *Stroke statistics 2009 edition British Heart Foundation & Stroke Association*. Oxford,England.

Schiariti, V., Klassen, A. F., Cieza, A., Sauve, K., O'Donnell, M., Armstrong, R. and Mâsse, L. C. (2014) 'Comparing contents of outcome measures in cerebral palsy using the international classification of functioning (ICF-CY): A systematic review.' *European Journal of Paediatric Neurology*, 18(1) pp. 1–12.

Schmidt, R. and Lee, T. (2005) *Motor Control and Learning: A Behavioral Emphasis*. *Human Kinetics*. Human Kinetics.

Secoli, R., Milot, M.-H., Rosati, G. and Reinkensmeyer, D. J. (2011) 'Effect of visual distraction and auditory feedback on patient effort during robot-assisted movement training after stroke.' *Journal of neuroengineering and rehabilitation*. BioMed Central Ltd, 8(1) p. 21.

Seidler, R. D., Kwak, Y., Fling, B. W. and Bernard, J. A. (2013) 'Neurocognitive mechanisms of error-based motor learning.' *Advances in Experimental Medicine and Biology*, 782 pp. 39–60.

Shadmehr, R., Smith, M. A. and Krakauer, J. W. (2010) 'Error correction, sensory prediction, and adaptation in motor control.' *Annual review of neuroscience*, 33 pp. 89–108.

Sheng, B., Zhang, Y., Meng, W., Deng, C. and Xie, S. (2015) 'Bilateral robots for upper-limb stroke rehabilitation: State of the art and future prospects.' *Medical Engineering and Physics*.

Shirzad, N. and Van der Loos, H. F. M. (2012) 'Error amplification to promote motor learning and motivation in therapy robotics.' *Conference proceedings : ... Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference*, 2012, January, pp. 3907–10.

Shirzad, N. and Van der Loos, H. F. M. (2015) 'Evaluating the User Experience of Exercising Reaching Motions With a Robot That Predicts Desired Movement Difficulty.' *Journal of Motor Behavior*, (May 2015) pp. 1–16.

Shirzad, N. and Van Der Loos, H. F. M. (2013) 'Adaptation of task difficulty in rehabilitation exercises based on the user's motor performance and physiological responses.' *In IEEE International Conference on Rehabilitation Robotics*, p. 6650429.

Sigrist, R., Rauter, G., Riener, R. and Wolf, P. (2013) 'Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review.' *Psychonomic bulletin & review*, 20(1) pp. 21–53.

Simkins, M., Fedulow, I., Kim, H., Abrams, G., Byl, N. and Rosen, J. (2012) 'Robotic Rehabilitation Game Design for Chronic Stroke.' *Games for Health Journal*, 1(6) pp. 422–430.

Sivan, M. (2014) *Development of a home-based Computer Assisted Arm Rehabilitation (hCAAR) device for upper limb exercises in stroke patients*. University of Leeds.

Sivan, M., O'Connor, R. J., Makower, S., Levesley, M. and Bhakta, B. (2011) 'Systematic review of outcome measures used in the evaluation of robot-assisted upper limb exercise in stroke.' *Journal of Rehabilitation Medicine*, 43(3) pp. 181–189.

Song, Z. and Guo, S. (2012) 'Design Process of Exoskeleton Rehabilitation Device and Implementation of Bilateral Upper Limb Motor Movement.' *Journal of Medical and Biological …*, 32(5) pp. 323–330.

Squeri, V., Vergaro, E., Brichetto, G., Casadio, M., Morasso, P. G., Solaro, C. and Sanguineti, V. (2007) 'Adaptive robot training in the rehabilitation of incoordination in Multiple Sclerosis: A pilot study.' *In 2007 IEEE 10th International Conference on Rehabilitation Robotics, ICORR'07*. Dept. of Informatics, Systems and Telematics, University of Genova, Italy (2007 IEEE 10th International Conference on Rehabilitation Robotics, ICORR'07), pp. 364–370.

Stienen, A. H. A., Hekman, E. E. G., Van Der Helm, F. C. T., Prange, G. B., Jannink, M. J. A., Aalsma, A. M. M. and Van Kooij, H. Der (2007) 'Dampace: Dynamic force-coordination trainer for the upper extremities.' *In*

2007 IEEE 10th International Conference on Rehabilitation Robotics, ICORR'07, pp. 820–826.

Stienen, A. H. A., Hekman, E. E. G., Prange, G. B., Jannink, M. J. A., Aalsma, A. M. M., van der Helm, F. C. T. and van der Kooij, H. (2009) 'Dampace: Design of an Exoskeleton for Force-Coordination Training in Upper-Extremity Rehabilitation.' *Journal of Medical Devices-Transactions of the Asme*, 3(3).

Stienen, A. H. A. and Kooij, E. E. G. H. and F. C. T. V. der H. and G. B. P. and M. J. A. J. and A. M. M. A. and H. Van der (2007) 'Dampace : dynamic force-coordination trainer for the extremities.' *In International Conference on Rehabilitatoin Robotics ICORR 2007. ….*

Subramanian, S. K., Yamanaka, J., Chilingaryan, G. and Levin, M. F. (2010) 'Validity of movement pattern kinematics as measures of arm motor impairment poststroke.' *Stroke; a journal of cerebral circulation*, 41(10) pp. 2303–8.

Surman, G., Bonellie, S., Chalmers, J., Colver, A., Dolk, H., Hemming, K., King, A., Kurinczuk, J. J., Parkes, J. and Platt, M. J. (2006) 'UKCP: a collaborative network of cerebral palsy registers in the United Kingdom.' *Journal of public health (Oxford, England)*, 28(2) pp. 148–56.

Todorov, E. (2004) 'Optimality principles in sensorimotor control.' *Nature neuroscience*, 7(9) pp. 907–15.

Trlep, M., Mihelj, M. M., Puh, U. U. and Munih, M. (2011) 'Rehabilitation Robot with Patient-Cooperative Control for Bimanual Training of Hemiparetic Subjects.' *Advanced Robotics*, 25(February 2013) pp. 1949–1968.

Tropea, P., Cesqui, B., Monaco, V., Aliboni, S., Posteraro, F. and Micera, S. (2013) 'Effects of the Alternate Combination of "Error-Enhancing" and "Active Assistive" robot-mediated treatments on stroke patients.' *IEEE Journal of Translational Engineering in Health and Medicine*, 1(August) pp. 1–9.

Tseng, Y.-W., Diedrichsen, J., Krakauer, J. W., Shadmehr, R. and Bastian, A. J. (2007) 'Sensory prediction errors drive cerebellum-dependent adaptation of reaching.' *Journal of neurophysiology*, 98(1) pp. 54–62.

Turner-Stokes, L., Sykes, N. and Silber, E. (2008) 'Long-term neurological conditions: management at the interface between neurology, rehabilitation and palliative care.' *Clinical medicine*, (10).

Umemura, A., Saito, Y., Fujisaki, K. and Ieee (2009) 'A Study on Power-Assisted Rehabilitation Robot Arms Operated by Patient with Upper Limb Disabilities.' *In 2009 Ieee 11th International Conference on Rehabilitation Robotics, Vols 1 and 2*, pp. 525–530.

United Nations, Department of Economic and Social Affairs, P. D. (2013) 'World Population Ageing.' *United Nations* p. 114.

Utley, A. and Astill, S. (2008) 'Motor control, learning and development .' Abingdon : Taylor & Francis .

Vergaro, E., Squeri, V., Brichetto, G., Casadio, M., Morasso, P., Solaro, C. and Sanguineti, V. (2010) 'Adaptive robot training for the treatment of incoordination in Multiple Sclerosis.' *Journal of neuroengineering and rehabilitation*, 7, January, p. 37.

De Vito, L., Postolache, O. and Rapuano, S. (2014) 'Measurements and sensors for motion tracking in motor rehabilitation.' *IEEE Instrumentation and Measurement Magazine*, 17(3) pp. 30–38.

van Vliet, P. M. and Wulf, G. (2006) 'Extrinsic feedback for motor learning after stroke: what is the evidence?' *Disability and rehabilitation*, 28(13–14) pp. 831–40.

Waldner, A., Tomelleri, C. and Hesse, S. (2009) 'Transfer of scientific concepts to clinical practice: recent robot-assisted training studies.' *Functional Neurology*, 24(4) pp. 173–177.

Wang, F. (2012) 'Recent Research Advances in Upper-extremity Rehabilitation.' *Advances in Robotics & Automation*, 1(3) pp. 1–3.

Wang, F., Barkana, D. E. and Sarkar, N. (2010) 'Impact of visual error augmentation when integrated with assist-as-needed training method in robot-assisted rehabilitation.' *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, 18(5) pp. 571–9.

Weightman, A., Alexoulis-Chrysovergis, A. C., Cooper, G., Hodson-Tole, E. and Deconick, F. (2015) 'Novel rehabilitation robotic control strategies for promoting motor learning in the upper limb of the neurologically impaired.' *In Society for Research in Rehabiltation Summer Meeting*.

Weightman, A., Alexoulis-Chrysovergis, A. C. and Olsen, S. (2014) 'What should we consider when designing rehabilitation robots for the upper limb of the neurologically impaired ?' *Proceedings of the Australasian Conference on Robotics and Automation*.

Weightman, A., Preston, N., Levesley, M., Holt, R., Mon-Williams, M., Clarke, M., Cozens, A. J. and Bhakta, B. (2011) 'Home based computer-assisted upper limb exercise for young children with cerebral palsy: a feasibility study investigating impact on motor control and functional outcome.' *Journal of rehabilitation medicine : official journal of the UEMS European Board of Physical and Rehabilitation Medicine*, 43(4) pp. 359–63.

Weisstein, E. W. (2015) *Circle-Line Intesection*. MathWorld--A Wolfram Web Resource. [Online] [Accessed on 22nd October 2014] http://mathworld.wolfram.com/Circle-LineIntersection.html.

West, B. T., Welch, K. B. and Galecki, A. T. (2015) *Linear mixed models: a practical guide using statistical software*.

Wolbrecht, E. T., Reinkensmeyer, D. J. and Bobrow, J. E. (2010) 'Pneumatic Control of Robots for Rehabilitation.' *The International Journal of Robotics Research*, 29(1) pp. 23–38.

World Health Organization (WHO) (2001) *International Classification of Functioning, Disability and Health: ICF*. Geneva: World Health Organization (WHO).

Xsens Technologies B.V. (2013) 'MTw User Manual.'

Xu, G., Song, A. and Li, H. (2011) 'Control System Design for an Upper-Limb Rehabilitation Robot.' *Advanced Robotics*, 25(1–2) pp. 229–251.

Yoo, D. H. and Kim, S. Y. (2015) 'Effects of upper limb robot-assisted therapy in the rehabilitation of stroke patients.' *Journal of Physical Therapy Science,* 27(3) pp. 677–679.

Ziegler, J. G. and Nichols, N. B. (1942) 'Optimum Settings for Automatic Controllers.' *Transacction of the ASME* pp. 759–765.

Appendix A

A1 Development of the robotic rehabilitation system

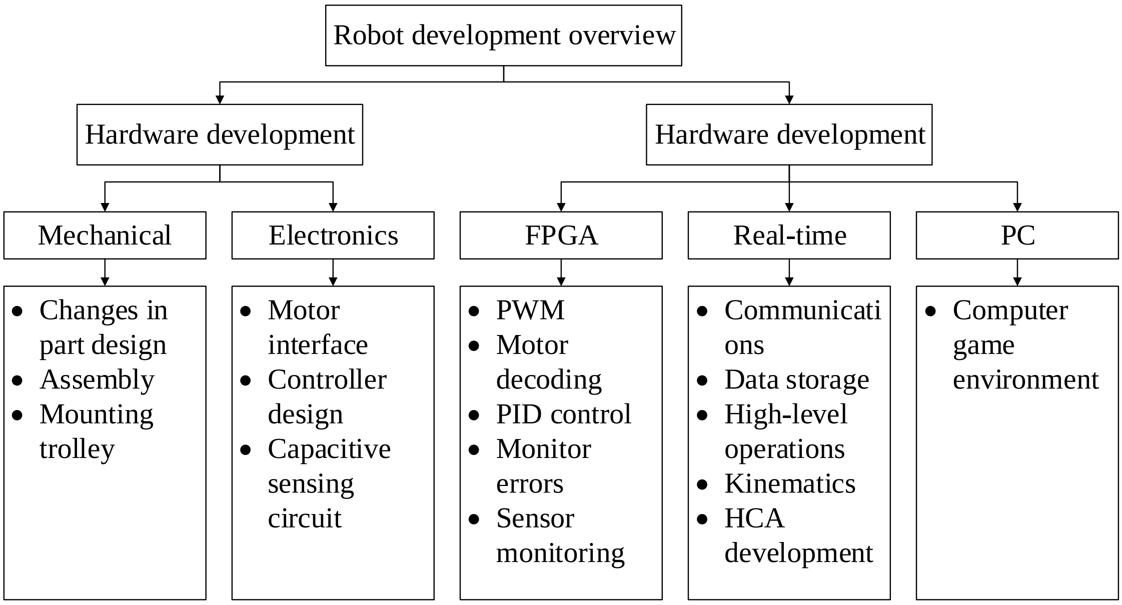


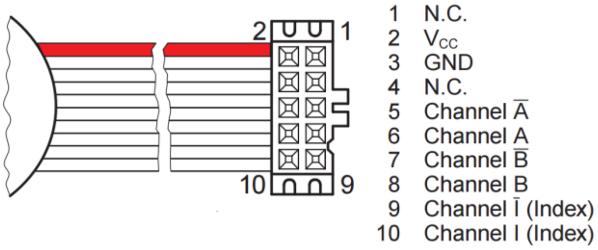
Figure A-1: Overview of the development of the robotic rehabilitation system

Modifications on the electronic design of the rehabilitation robot

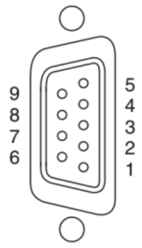
In the original design of the rehabilitation device a printed circuit board (PCB) was developed, to handle the differential signalling of the encoder, utilising a differential line receiver to add the respective signals from each encoder’s outputs while subtracting the noise. The inputs and outputs of the circuit board were then connected to a multiple high-speed digital input/output module.

To simplify the design of the rehabilitation robot and to enhance its capabilities each motor was directly connected to a National Instruments™ 9505 DC brushed motor servo drive module, which handled and outputs the Pulse Width Modulation (PWM) signals generated by the cRIO directly to the motor and provided an interface for direct connection of the quadrature encoder channels. The NI 9505 was externally powered by a power source and its output was connected to the two input terminals of the motor. To interface the motors' encoder (outputs female 2x5way receptacle) with the encoder on the NI 9505 a custom adapter was created as shown in Figure A-2 and Figure A-3. The benefits of this approach was that only one NI module was required per motor (Figure A-4) instead of two (high speed digital I/O and motor controller) and also it did not require the manufacture of custom PCBs which further reduced the complexity of the system. Finally, an added benefit was that the NI 9505 module had a current sensing circuit which allowed indirect measurement of the load on the motors.

a) Maxon motor encoder DIN interface



b) NI 9505encoder D-sub interface

Connector	Pin	Signal
	1	Encoder Phase A+
	2	Encoder Phase B+
	3	Encoder Index+ (Phase Z+)
	4	Emergency Stop (E-Stop)
	5	+5 V (output)
	6	Encoder Phase A–
	7	Encoder Phase B–
	8	Encoder Index– (Phase Z–)
	9	Common (COM)

c) DIN to D-sub adapter pin allocation

Motor Encoder· output pin number:	NI 9505 encoder input pin number:
1	N.C.
2	5
3	9
4	N.C.
5¤	6
6¤	1
7	7
8¤	2
9	8
10	3

Figure A-2: The different interfaces of the components and the DIN-d-SUB custom adapter pin allocation. Figures a, b from (Maxon Motor Worldwide 2014; National Instruments Corp. 2010)

Figure A-3: The 2x5 way DIN to 9-way d-Sub adapter

Figure A-4: Testing the interface between the motor and NI 9505

Furthermore, as a safety mechanism, the system incorporated a capacitive sensor inside the handle of the device. The system detected changes in capacitance when a hand was in proximity to the sensor. As such, the robot would apply forces only when the users were holding the handle. In the original design, a circuit board with capacitive sensing capabilities was developed and used to sense the presence of the hand on the handle of the robot. Responsible for the sensing was an Atmel™ QT-240-ISSG, which is a four channel capacitive sensing circuit. However, QT-240-ISSG was discontinued and a replacement was required. By researching the market as a suitable replacement, the Atmel™ AT42QT1011 was identified. AT42QT1011 was a single channel capacitance sensing integrated circuit (IC). The specific IC was selected because it did not incorporate the Max on-duration feature, a common feature among the capacitive sensing IC's which recalibrates the sensor when it is activated for a certain period of time (Atmel, 2013).

Due to the different layout of the new IC; a new Printed Circuit Board (PCB) was to be designed which would include the regulation circuitry to power the IC as well as the electronic elements (resistors, capacitors) needed for the correct operation of the system. The requirements for this new PCB were that it should have been small enough in order to fit inside the handle of the robot and that it should have been able to house at least two sensors (channels) for redundancy purposes, that is to ensure operation in the case that one sensor malfunctioned or received a false reading. As such, a PCB was designed (Figure A-5) and manufactured (Figure A-6) with the capability of housing three sensors and all the relevant circuitry and electronic components for their operation.

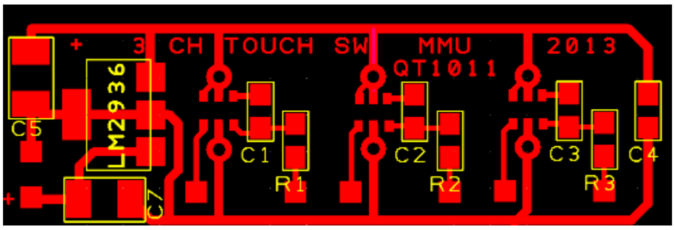
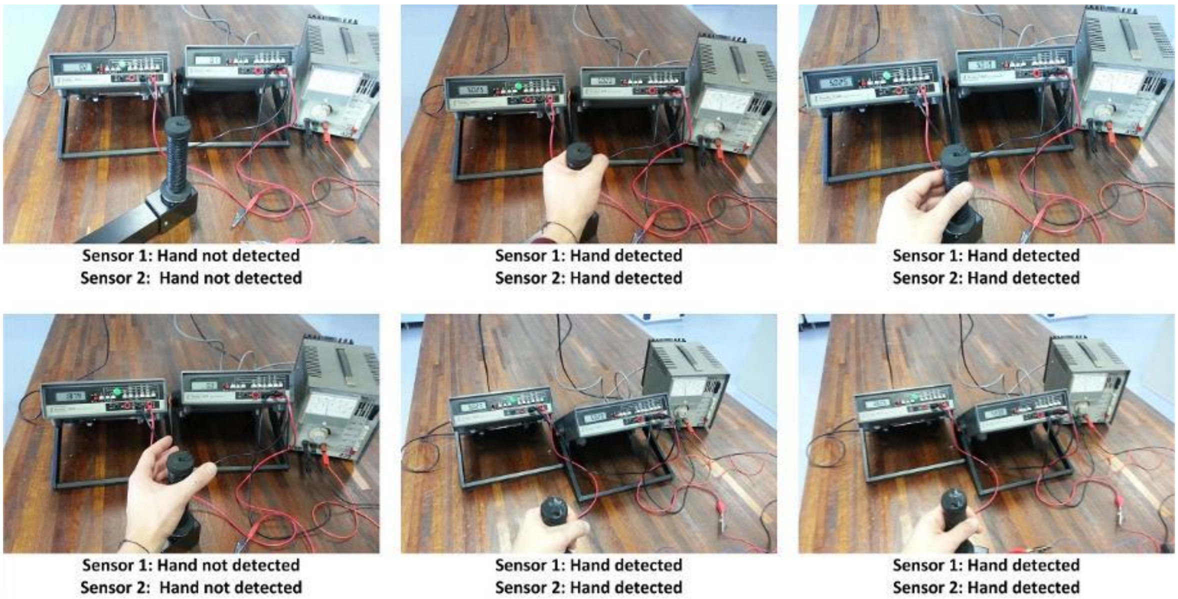


Figure A-5: The three channel capacitive sensing PCB layout

Figure A-6: The capacitive sensor board

Finally, two channels were used with the input of each sensor being connected to a long insulated copper wire, which performed as the sensor receiver. Both wires were wrapped around the outer perimeter of the handle in a coil configuration to ensure maximum coverage. The systems performance on detecting the human hand was tested for different grip positions. After the correct operation was ensured i.e. the sensor would correctly detect the presence of the hand, the handle was covered with a heat shrinking tube with a non-slip textured finish, for better grip, and then the system was tested again in order to verify that the addition of the heat shrinking sleeve did not affect its operation (Figure A-7).



Sensor 1: Hand not detected
Sensor 2: Hand not detected

Sensor 1: Hand detected
Sensor 2: Hand detected

Sensor 1: Hand detected
Sensor 2: Hand detected

Sensor 1: Hand not detected
Sensor 2: Hand not detected

Sensor 1: Hand detected
Sensor 2: Hand detected

Sensor 1: Hand detected
Sensor 2: Hand detected

Figure A-7: Testing the sensor with different grip patterns with and without the heat-shrinking sleeve

Modifications of the mechanical design of the rehabilitation robot

On the initiation of this project most of the components of the rehabilitation robot were either already manufactured/delivered or were on the process of being manufactured. During the assembly process of the robotic manipulandum several issues arose regarding different components that were either mismatching due to errors on the initial designs or needed further processing. Furthermore, there were other components that needed to be re-designed. It is out of the scope of this report to describe the numerous actions that were undertaken to resolve these issues in every detail but this section will provide an overview of some key points of the process.

1) All the components that were to be exposed into plain view were to be powder coated not only for aesthetic reasons but also to reduce the reflectivity of the aluminium surfaces so that the robotic device would be suitable to be used with the VICON motion tracking system whose performance can be affected by reflective surfaces (Figure A-8). Powder coating was chosen as a painting technique as it provides a harder finish than paint and hence makes the coloured surface more resistant to scratches and marks. To reduce the reflectivity to a

minimum all surfaces were painted in matt black. Before submitting the components for powder coating all surfaces that were not to be painted were covered with high temperature masking tape. Moreover, to avoid blockage from the painting material all holes were sealed.

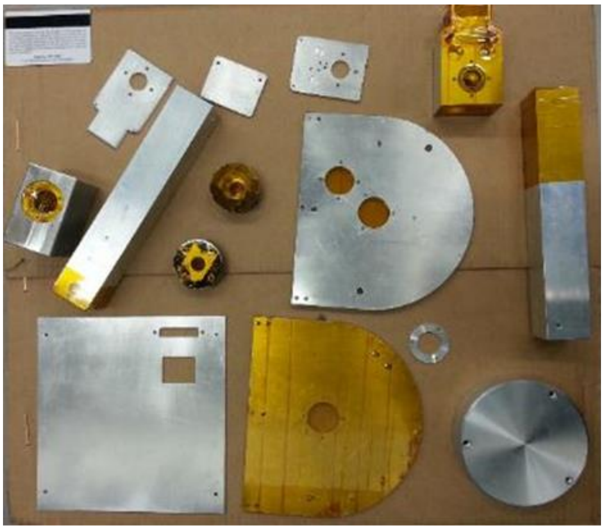


Figure A-8: Preparation of the components before being submitted for powder coating

2) Some components needed to be re-designed. For example, one of the rods, that formed the frame of the main body, had to be redesigned as the holes for the screws that connected the rod with the top and bottom cover plates were misaligned. Furthermore, all the rods were shorter than they should have by 2 mm. Instead of redesigning and manufacturing each rod to resolve this, custom washers for each rod were designed and manufactured in order to make up for the mismatch (Figure A-9). Such an approach saved time and material without compromising the structural integrity of the device.

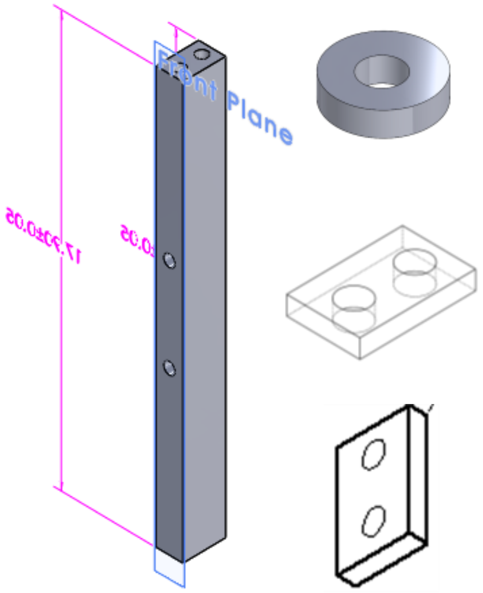


Figure A-9: Example of different parts that were re-designed

3) A number of components needed further processing after they were manufactured to ensure correct fit within the assembly (Figure A-10).

Figure A-10: Example of type of work undertaken to modify the design. The holes for the screws that attached the back plate to the main frame of the joystick were misaligned as such new holes were drilled

When all components were in place the device was assembled (Figure A-11) and then tested while being unpowered for smooth-unobstructed operation (Figure A-12).

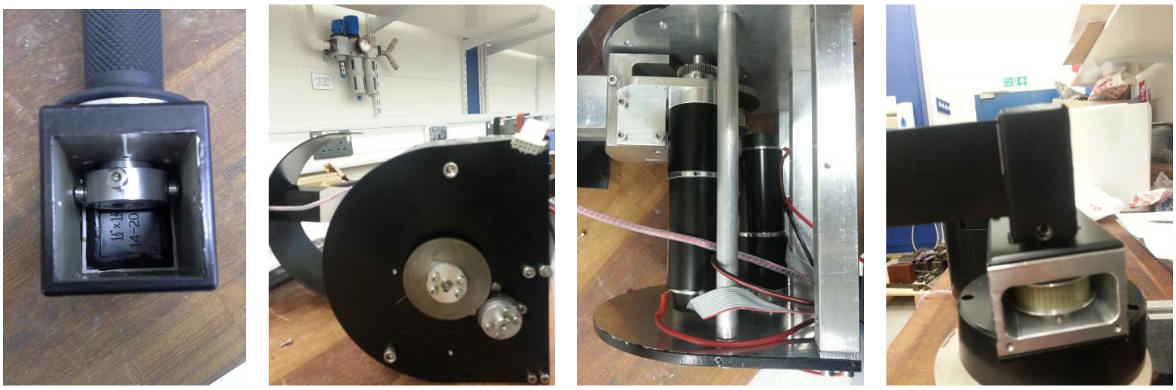


Figure A-11: Different stages of the assembly sequence

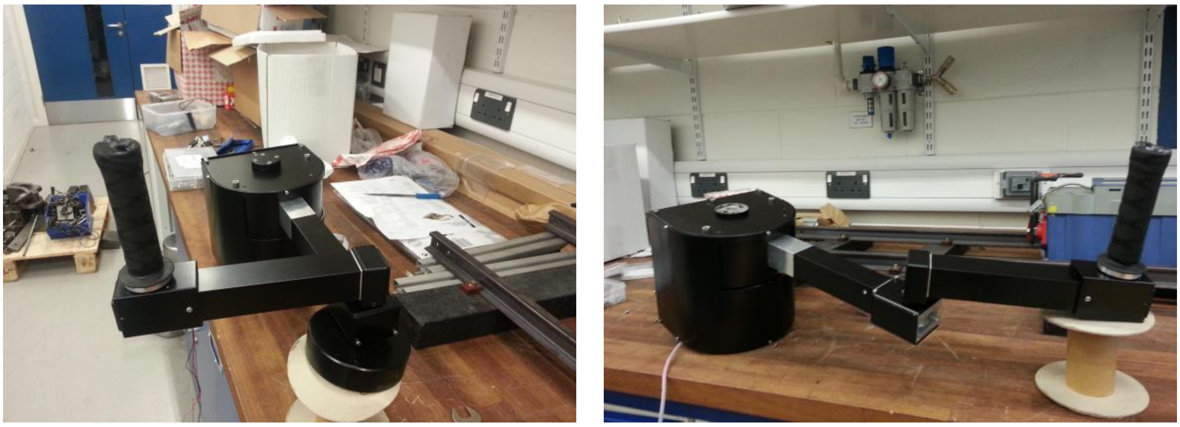


Figure A-12: The assembled rehabilitation device

4) To allow for the system to be portable a trolley was designed for the rehabilitation robot to be mounted on. The trolley also had to house a gaming PC (E-ATX size) and all the electronic hardware required for the rehabilitation robot i.e. the compact-RIO and the power supply. The overall footprint of the trolley was approximately 880 mm x 850 mm (Figure A-13). In this configuration the robot was fixed on the frame of the trolley with the tip of the joystick handle being 800 mm from the ground. Also, the system was designed to be interchangeable i.e. the screen and robot could be mounted on either side of the trolley.

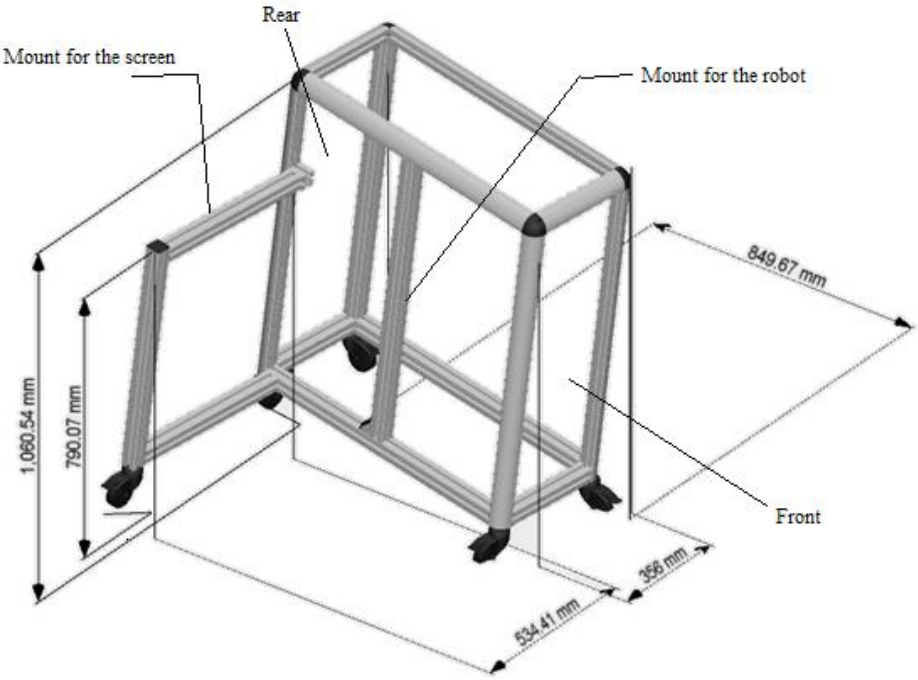


Figure A-13: Dimensional drawing of the trolley design where the robot was mounted

The trolley also needed to have a mounting for the computer screen. For health and safety reasons panels needed to be fitted to prevent the users from accessing components of the rehabilitation robot. To allow access to the inside of the trolley cut-outs were made to the panels with the rear opening being large enough to allow for an extended-advanced technology extended (E-ATX) computer case to fit inside (Figure A-13). Finally, a monitor mount was fitted to the rear using a mount with adjustable height pitch, yaw and roll (Figure A-14). The minimum height the computer screen could be placed was 800mm (from the floor to the centre of the screen).

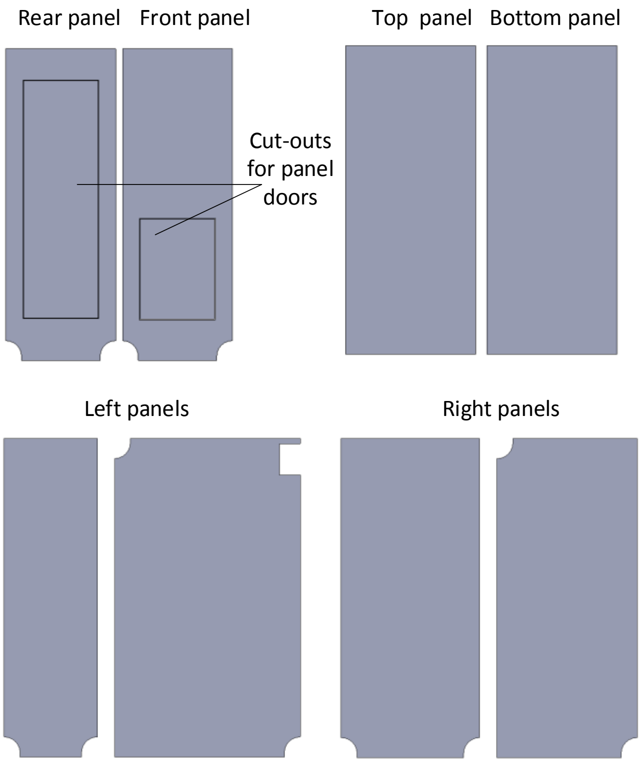


Figure A-14: Panel design for the rehabilitation robot trolley. The front and rear panels have opening for doors to be fitted.

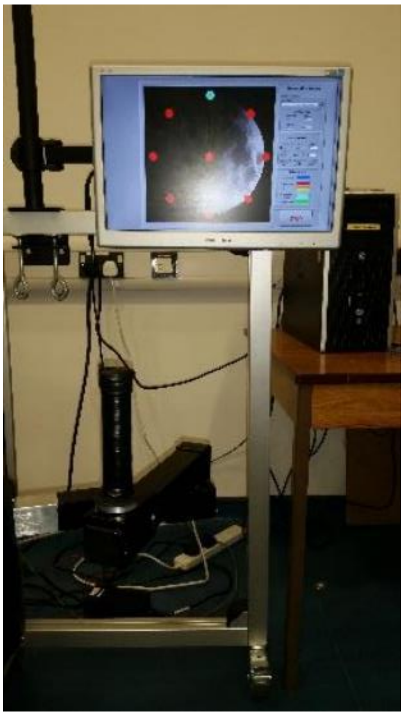


Figure A-15: The screen mount of the rehabilitation robot

Summary of the modifications performed to the robotic rehabilitation system

As described in the previous subsections certain changes were performed in the original design of the system. A flowchart with an overview of those changes is provided in Figure A-16.

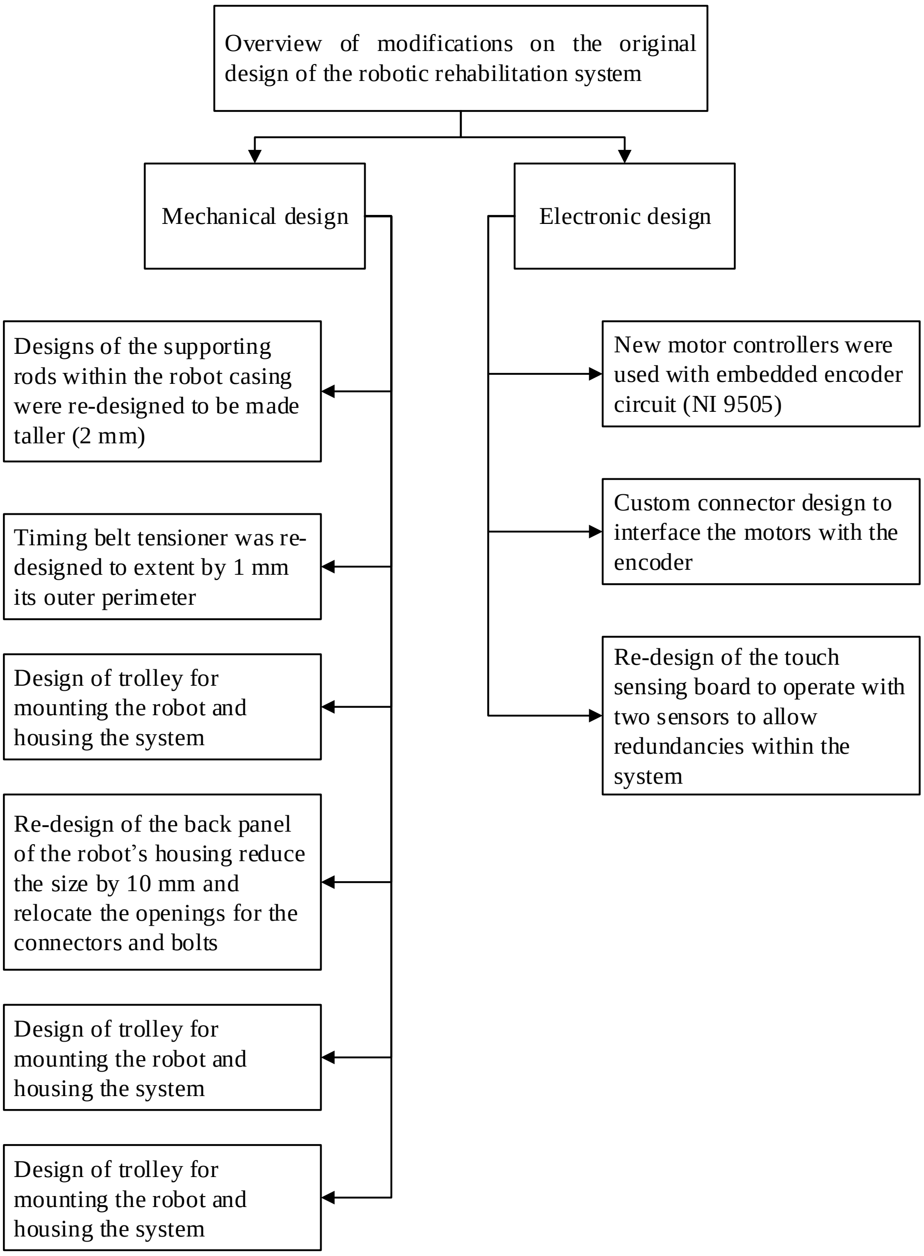


Figure A-16: Summary of modifications performed to the robotic rehabilitation system

A2 Forward and inverse kinematics for a two-link planar robotic manipulator

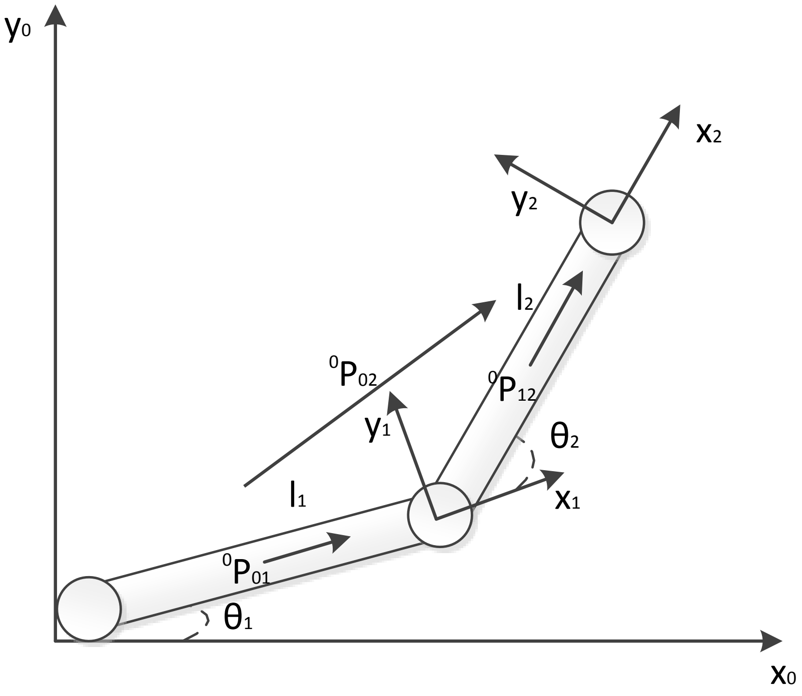


Figure A-17: Two link manipulator for a random position of the end-effector

Forward kinematics

The vector from the origin of frame 0 to frame 1 is given by (21) and the vector r from the origin of frame 1 to the origin of frame 2 is provided in (22).

$$p_{0,1}^0 = (l_1 \cos(\theta_1)\,, l_1 \sin(\theta_1))$$ *(21):*vector from frame 0 to frame 1

$$p_{1,2}^0 = (l_2 \cos(\theta_1 + \theta_2)\,, l_2 \sin(\theta_1 + \theta_2))$$ *(22):* vector from frame 1 to frame 2

$$p_{0,2}^{0} = \begin{bmatrix} p_x \\ p_y \end{bmatrix} = \begin{bmatrix} y \\ y \end{bmatrix}$$

(23): transformation matrix for the endpoint

$$= \begin{bmatrix} l_1 \cos(\theta_1) + l_2 \cos(\theta_1 + \theta_2) \\ l_1 \sin(\theta_1) + l_2 \cos(\theta_1 + \theta_2) \end{bmatrix}$$

Hence, the x-y coordinates of the position of the endpoint are given by (24) and (25)

$$p_x = (l_1 \cos(\theta_1) + l_2 \cos(\theta_1 + \theta_2))$$

(24) vector for the x coordinate of the endpoint

$$p_y = (l_1 \sin(\theta_1) + l_2 \sin(\theta_1 + \theta_2))$$

(25) vector for the y coordinate of the endpoint

Inverse kinematics

In the previous section, the vectors for the position of the endpoint were derived (24), (25).

$$p_x^2 + p_y^2 = (l_1 cos\theta_1 + \cos(\theta_1 + \theta_2))^2 + (l_1 sin\theta_1 + l_2 \sin(\theta_1 + \theta_2))^2 = ..$$

$$= l_1^2 + l_2^2 + 2 l_1 l_2 cos\theta_2$$

$$cos\theta_2 = (\frac{p_x^2 + p_y^2 - l_1^2 - l_2^2}{2 l_1 l_2}) \qquad (26)$$

$$sin^2\theta_2 + cos^2\theta_2 = 1 \Leftrightarrow \sin\theta_2 = \sqrt{1 - cos^2\theta_2} \qquad (27)$$

$$\theta_2 = \pm atan2(sin\theta_2, cos\theta_2) \qquad (28)$$

From the previous equations it is evident that θ_2 has two solutions; one for the positive result and one for the negative result of (28) To find θ_1*:*

$$
\begin{aligned}
p_x &= l_1 cos\theta_1 + l_2 cos(\theta_1 + \theta_2) \\
&= l_1 cos\theta_1 + l_2 cos\theta_1 cos\theta_2 - l_2 sin\theta_1 sin\theta_2 \\
&= (l_1 + l_2 cos\theta_2) cos\theta_1 - l_2 sin\theta_1 sin\theta_2
\end{aligned}
\tag{29}
$$

$$
\begin{aligned}
p_y &= l_1 sin\theta_1 + l_2 sin(\theta_1 + \theta_2) \\
&= l_1 sin\theta_1 + l_2 sin\theta_1 cos\theta_2 - l_2 cos\theta_1 sin\theta_2 \\
&= (l_1 + l_2 cos\theta_2) sin\theta_1 - l_2 cos\theta_1 sin\theta_2
\end{aligned}
\tag{30}
$$

By dividing (29) by (30):

$$
\begin{aligned}
\frac{p_y}{p_x} = \frac{(l_1 + l_2 cos\theta_2) sin\theta_1 - l_2 cos\theta_1 sin\theta_2}{(l_1 + l_2 cos\theta_2) cos\theta_1 - l_2 sin\theta_1 sin\theta_2} &= \frac{\frac{sin\theta_1}{cos\theta_2} + \frac{l_2 sin\theta_2}{(l_1 + l_2 cos\theta_2)}}{1 - \frac{l_2 sin\theta_1 sin\theta_2}{(l_1 + l_2 cos\theta_2) cos\theta_1}} \\
&= \frac{tan\theta_1 + \frac{l_2 sin\theta_2}{(l_1 + l_2 cos\theta_2)}}{1 - tan\theta_1 \frac{l_2 sin\theta_2}{(l_1 + l_2 cos\theta_2)}}
\end{aligned}
\tag{31}
$$

Because

$$
\tan(\varphi + \theta) = \frac{\tan\varphi + tan\theta}{1 - tan\varphi tan\theta}
$$

(31) becomes:

$$
\begin{aligned}
\tan^{-1}\frac{p_y}{p_x} = \tan^{-1}(tan\theta_1) \\
+ \tan^{-1}\left(\frac{l_2 sin\theta_2}{(l_1 + l_2 cos\theta_2)}\right)
\end{aligned}
\tag{32}
$$

By solving (32) for θ1:

$$\theta_1 = atan2\left(p_y, p_x\right) - atan2(l_2 sin\theta_2, l_1 + l_2 cos\theta_2) \qquad (33)$$

For the two solution of θ_2 there will be two respective solutions for θ_1. This is known as redundancy in robotics and it means there two different configurations for the manipulator's endpoint to reach a certain position (McKerrow, 1991). As for the specific application, there were no limitations on the design of the robot to indicate which angles should be selected and as such, either of the two sets of solutions is valid.

A3 Calculating the setpoint for error augmentation

To calculate the points of intersection of a circle and a line the following algorithm is used (Weisstein, 2015) :

Given a line that's defined by two points A(x_1,y_1) and B(x_2,y_2) and a circle $(x-a)^2+(y-b)^2 = r^2$

We define:

$$d_x = (x_2 + a) - (x_1 + a) = x_2 - x_1 \tag{34}$$

$$d_y = (y_2 + b) - (y_1 + b) = y_2 - y_1 \tag{35}$$

$$d_r = \sqrt{d_x^2 + d_y^2} \tag{36}$$

$$D = \begin{vmatrix} x_1 & x_2 \\ y_1 & y_2 \end{vmatrix} = (x_1 + a)(y_2 + b) - (x_2 + a)(y_1 + b) \tag{37}$$

The coordinates of the points of intersection x and y are given by Equations (13) and (14) respectively

$$X_{1,2} = \frac{Dd_y \pm s(d_y)d_x\sqrt{r^2 d_r^2 - D^2}}{d_r^2} \tag{38}$$

$$Y_{1,2} = \frac{-Dd_x \pm s|d_y|\sqrt{r^2 d_r^2 - D^2}}{d_r^2} \tag{39}$$

Where:

$$s(x) = \begin{cases} -1 \, for \; x < 0 \\ \;\, 1 \, for \; x \geq 0 \end{cases} \tag{40}$$

As such the two points of intersection between the perpendicular line and the circle around the endpoint are C(x_1,y_1) and D(x_2,y_2). To select the appropriate solution, the distances between the two points and the target B are calculated and compared. The solution that results in the greatest distance is selected as the endpoint as it will always be on the outermost section of the circle.

Given B(x_3,y_3) the coordinates of the target the distances from C and D are calculated

$$\overrightarrow{CB} = \sqrt{(x_1 - x_3)^2 + (y_1 - y_3)^2} \tag{41}$$

$$\overrightarrow{DB} = \sqrt{(x_2 - x_3)^2 + (y_2 - y_3)^2} \tag{42}$$

$$\text{Is } \overrightarrow{CB} > \overrightarrow{DB}\ ? \quad \begin{cases} Yes, Setpoint\ is\ C \\ No,\ Setpoint\ is\ D \end{cases} \tag{43}$$

Appendix B

This section contains work published from this research project.

Error Augmented Robotic Rehabilitation of the Upper Limb
A Review

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Keywords: Robotic, Rehabilitation, Upper, Limb, Haptic, Visual, Feedbacks, Augmented, Enhanced, Review.

Abstract: Objective: To collect and assess the available evidence for the efficacy of error augmentation in upper limb robotic rehabilitation.
Methods: A systematic literature search up to May 2013 was conducted in one citation index, the Web of Knowledge, and in two individual databases: PubMed and Scopus, for publications that utilized error augmented feedback as practice modality in robotic rehabilitation of the upper limb.
Results: The systematic search returned 12 studies that utilized error augmented feedback in trials to unimpaired and impaired individuals suffering from stroke, multiple sclerosis and primary dystonia. One additional study utilizing viscous force fields was included as the authors paid special merit to the effects of the field in directions where the error was amplified. In the studies that met the inclusion criteria two different types of error augmented feedback was used that is, haptic and visual feedback which were used either separately as rehabilitation modalities or in conjunction with each other. All studies but one report positive outcome regardless of the type(s) of feedback utilized.
Conclusions: Error augmentation in upper limb robotic rehabilitation is a relatively new area of study, counting almost nine years after the first relevant publication and rather understudied. Error augmentation in upper limb robotic rehabilitation should be further researched in more practice-intensive studies and with larger trial groups. The potential of error augmented upper limb rehabilitation should also be explored with conditions other than the ones described in this review.

1 INTRODUCTION

Neurological impairments resulting from conditions such as stroke and cerebral palsy are common. For example, stroke affects 150 000 people in the UK each year (2005/2006 S.S.C.A., 2001) and cerebral palsy is the commonest cause of childhood disability in Europe (Reinkensmeyer et al., 2004; Huang and Krakauer, 2009; Weightman et al., 2011). Neurological impairment, resulting from these pathologies, often influences upper limb function causing weakness, spasticity and loss of selective muscle activation. These in turn, cause difficulties with voluntary movements and affect the ability to reach, grasp transport and manipulate objects. Movements in affected individuals are therefore characterized by increased duration, reduced peak velocity, increased variability and fewer straight hand trajectories (Wu et al., 2000).

Improvement in upper limb function can lead to better performance in activities of daily living, increased social integration and can thus produce a better quality of life (Maher et al., 2007; Imms, 2008). Exercise of an impaired limb is known to improve function (Kluzik et al., 1990), with better performance observed with increased time and amount of practice devoted to learning a particular task (French et al., 2007). Traditionally such exercises are monitored by a trained clinical therapist. However, researchers have (recently) begun to investigate the application of robotics as a potential modality to support such rehabilitation.

The paradigm of upper limb rehabilitation robotics is a motivating computer environment, which promotes therapeutic movements of the impaired limb with a powered interface implementing a control algorithm to promote recovery (Prange et al., 2006; Scott and Dukelow, 2011). Such a system can provide patients with access to rehabilitation protocols, which do not require direct, time demanding, supervision of a clinical therapist. As such they can increase access to therapy with limited additional burden on healthcare provision. Furthermore, such systems enable the logging of valuable data regarding user's activity and performance for the therapist to closely monitor adaptation and provide feedback on progress to the user. Rehabilitation robotic therapy has demonstrated statistically significant benefits in improving upper limb function, with kinematic analysis revealing benefits in movement time, path and smoothness of reach (Fasoli et al., 2008; Huang and Krakauer, 2009; Fluet et al., 2010, Weightman et al., 2011, Norouzi-Gheidari et al., 2012).

Currently, three types of rehabilitation robot have been described: i) end point attachment; ii) multiple point attachment and iii) exoskeletons (Reinkensmeyer et al., 2004; Jackson et al., 2007, Scott and Dukelow, 2011; Weightman et al., 2011). End point attachment robots are limited in that they can only promote desirable trajectories (spatial and temporal characteristics) of the hand and cannot control the corresponding position of the elbow and shoulder. However, they are likely to be more cost effective than multiple point of attachment robots and exoskeletons. Multiple point of attachment robots and exoskeletons can control the full kinematics of the arm (end point, elbow, shoulder) but are usually significantly larger and more expensive and as such are less likely to be utilized outside the clinical environment; for example in home rehabilitation applications where size and price can be significant consideration factors for employing such technology.

The control strategy i.e. the manner of interaction between user and the powered joysticks/robotics, implemented is critical for the promotion of improved upper limb function (Reinkensmeyer et al., 2004; Marchal-Crespo and Reinkensmeyer, 2009) and different control strategies have been utilised in the current literature. Marchal-Crespo et al. (Marchal-Crespo and Reinkensmeyer, 2009) suggested they can broadly be divided into three groups. Firstly, assisting control strategies help to move the impaired upper limb in aiming type movements, this is similar to the "active assist" type exercises utilised by therapists (Marchal-Crespo and Reinkensmeyer, 2009; Weightman et al., 2011). Secondly, challenge based control strategies can make movements more difficult, for example augmenting error between actual and desired trajectory or promoting increased effort (resistance training) from the participant. Thirdly, haptic simulation strategies involve the user practising activities of daily living within a virtual haptic environment (Montagner et al., 2007, Marchal-Crespo and Reinkensmeyer, 2009).

Challenge based algorithms such as, error augmenting, are based on the concept that errors in performance and hence results of aiming and prehensile movements of the upper limb influence motor adaptation (Wolpert et al., 1995; *Patton et al., 2006b*). These strategies have been shown to improve motor function in adults suffering from stroke (Morris et al., 2004; Patton et al., 2006b). Moreover, there have been early indications that error augmented visual feedback can induce motor learning in able bodied and possibly in impaired individuals (Wei et al., 2005). In the last twenty years, substantial work has been done in robotic rehabilitation. Error augmentation seems to be a relatively new modality and to our knowledge there has not been an attempt to gather and collectively report the findings of such studies. Therefore, the purpose of this paper is to present a systematic literature review of research regarding the use of error augmented feedback in the robotic rehabilitation of the upper limb and determine its potential for promoting improved upper limb function in those who have suffered a neurological impairment.

2 METHODS

A systematic literature search up to May 2013 was conducted in one citation index, the Web of Knowledge, and in two individual databases: PubMed and Scopus. In order to ensure that the search would return as many results as possible two different sets of keywords were used in each database. No lower end in year was used in any search. The keywords for the first set were: robot, rehabilitation, upper, limb, error and the keywords for the second set were: rehabilitation, upper, limb, error. Papers identified in either search were included for further investigation. To make sure that significant publications were not missed during the initial search the references of the retrieved studies were checked for relevant publications. After identifying and excluding duplicates, all abstracts were reviewed and when necessary a full review of the manuscript was undertaken.

The inclusion criteria for the review were studies i) with upper limb robotic rehabilitation; ii) utilizing error augmentation as a training modality, including all types of distorted feedback (haptic or visual); iii) where trials on humans (impaired or able bodied) were performed. Only papers reporting new experimental data were included, however it should be noted that the systematic search returned two review papers referring to error augmented robotic therapy in upper limb rehabilitation (Johnson, 2006; Reinkensmeyer, 2009).

3 RESULTS

Out of 60 papers originally identified 12 met the inclusion criteria. An exception was made with study (Patton et al., 2006b) which didn't meet the set criteria for the review, because viscous force fields were used in the study not an error augmentation. However, the authors discussed the effects of the treatment in the directions of the movement where error was amplified. As such the study was considered suitable for the purposes of this review and therefore a total of 13 papers were reviewed.

An overview on the contents of the selected papers can be found in Table 1.

3.1 Overview of Selected Studies

Error augmented robotic therapy for the rehabilitation of the upper limb is a relatively new rehabilitation modality, as the first relevant study was undertaken in 2004 (Patton and Mussa-Ivaldi, 2004). Since then publications regarding this subject are published with an average rate of 1.5 publications per year (Figure 1).

3.1.1 Clinical Characteristics of the Participants

All included studies employed human participants for clinical trials. The conditions that were addressed varied significantly, with six studies focusing on upper limb rehabilitation in stroke patients (Patton et al., 2006a; Patton et al., 2006b; Cesqui et al., 2008; Rozario et al., 2009; Abdollahi et al., 2011; Molier et al., 2011), two studies employing participants with multiple sclerosis (Squeri et al., 2007b; Vergaro et al., 2010) and one study (Casellato *et al.*, 2012) employing error augmented robotic therapy in children with primary dystonia. Furthermore, four studies experimented in the effects of error augmented robotic therapy with the participation of only able bodied, healthy adults (Patton and Mussa-Ivaldi, 2004; Matsuoka et al., 2007; Wang et al., 2010; Shirzad et al., 2012).

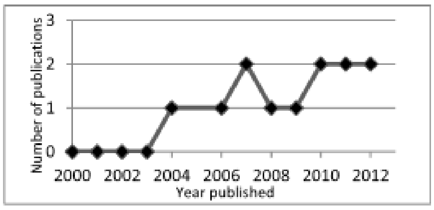

Figure 1: Number of publications on error augmented robotic therapy on the upper limb.

3.1.2 Types of Rehabilitation Robots

Interestingly all but two (Patton et al., 2006b; Molier et al., 2011), studies used single point of attachment robotic systems (endpoint). In one study two endpoint robotic devices were utilized to control the thumb and the index finger of the participants in pinching movements (Matsuoka et al., 2007) while in another study a multiple point of attachment system (exoskeleton) was used for the control of arm movements (Molier et al., 2011).

3.1.3 Types of Error augmented Feedback

Two different types of feedback, where error was augmented, were identified among the selected studies. The approaches can be categorized as: a) Error augmented haptic feedback, where forces perturbed upper limb movement when a certain level of error away from the desired trajectory was reached (Patton and Mussa-Ivaldi, 2004; Patton et al., 2006a; Patton et al., 2006b; Squeri et al., 2007b, Cesqui et al., 2008; Vergaro et al., 2010; Abdollahi et al., 2011; Molier et al., 2011; Casellato et al., 2012); b) Error augmented visual feedback, where the visual output of the system was distorted by a factor (ε) in order for the actual distance between the arm and the target, to differ from the one perceived by the user (Matsuoka et al., 2007; Wang et al., 2010); c) A combination of a and b where error in visual and haptic feedback was augmented (Rozario et al., 2009; Shirzad et al., 2012).

3.2 Intervention Modalities

The main concept of the intervention behind all the reviewed studies was that a user was positioned in front of a computer screen while a robotic manipulandum was attached to/held by the participant's upper limb. A target would be displayed while visual feedback about the current position of the arm was provided to the user. The user was asked to perform movements towards predefined targets while the system responded to the users' movement by augmenting any error.

In some of the reviewed studies (Patton and Mussa-Ivaldi, 2004; Squeri et al., 2007b; Cesqui et al., 2008; Vergaro et al., 2010; Casellato et al., 2012) haptic error augmenting algorithms were compared against other types of haptic algorithms namely, error reducing haptic algorithms. Error reducing algorithms are adaptive assistive algorithms which apply forces towards the optimal trajectory when a threshold of error is reached. In the aforementioned studies the two different types of haptic algorithms were either administered to different trial groups or in the same group but in different stages of the trial in order for a comparison between the two training modalities to be feasible. There was one study (Molier et al., 2011) where restraining forces only occurred when a certain amount of error was reached in order to provide position feedback to the user. In this case the forces were turned off when the user didn't exceed a predefined error threshold.

There was great variance in the number of sessions and the total exercise time the participants undertook, among the studies. In several cases the total intervention time was administered in one session (Johnson, 2006; Patton et al., 2006b; Matsuoka et al., 2007; Casellato et al., 2012; Shirzad et al., 2012) while in others the number of sessions varied from a minimum of 2 sessions (Wang et al., 2010; Molier et al., 2011) to a maximum 10 sessions (Cesqui *et al.*, 2008). Moreover, the total time of exercise administered varied significantly from as little as 90 minutes (Shirzad et al., 2012) to as much as 20hours (Cesqui et al., 2008). Additionally, some studies induced a washout component in the practice regime either by including a washout cycle in the practice session where the perturbative forces were gradually removed (Patton and Mussa-Ivaldi, 2004; Patton et al., 2006a; Casellato et al., 2012), or by setting a washout period between trials where no practice was undertaken (Cesqui et al., 2008; Rozario et al., 2009, Wang et al., 2010).

Table 2 provides an overview on the practice schemes administered in the reviewed studies.

3.3 Outcome Measures

The most common clinical measures among the studies that were used to evaluate outcome on stroke patients were the Fugl-Meyer scale, the Modified Ashworth scale for spasticity and the Box and Block test. Other clinical measures used can be found in Table 3. In the above-mentioned studies kinematic data were collected namely, error that is to say the deviation between the actual and desired trajectory, jerk index (Squeri et al., 2007a), Jerk (Teulings') index (Teulings et al., 1997), and strength (Patton et al., 2006a; Patton et al., 2006b; Cesqui et al., 2008; Rozario et al., 2009; Abdollahi et al., 2011; Molier et al., 2011).

Both studies that performed trials in patients with multiple sclerosis (Squeri et al., 2007a; Vergaro et al., 2010) evaluated performance with clinical measures such as Expanded Disability Status Scale (EDSS), Ataxia and Tremor scale, Nine Hole Peg Test, Visual Analogue Scale (VAS) and the Tremor and Activity of Daily Life (TADL) questionnaire as well as kinematic such as, lateral deviation (root mean square value) from the nominal path, movement duration (seconds), symmetry (ration between acceleration and deceleration phases) and smoothness.

Likewise, studies that employed only able-bodied participants used only kinematic measures like error (distance between actual and desired directory, lateral deviation etc.), mean lag (Matsuoka et al., 2007) and times needed assistance. The times needed assistance measure was used in one study (Wang et al., 2010) where visual error augmentation was utilized. In this studies training scheme the system would assist movement only when a threshold in error was reached. In one study (Shirzad et al., 2012) a Self-Assessment Manikin (SAM) affect questionnaire was administered. Finally, in the study where trials on children with primary dystonia were performed (Casellato et al., 2012) only clinical measures were used that is to say, Burke-Fahn-Marsden Dystonia Rating Scale (BFMDRS).

A more detailed overview of the outcome measures used according to condition can be found in Table 3.

3.4 Impact on Motor Learning and Upper Limb Function

Out of the 13 reviewed studies 12 report positive impact on upper limb function, five of which report conclusive results (Squeri et al., 2007a; Cesqui et al., 2008; Vergaro et al., 2010; Abdollahi et al., 2011; Molier et al., 2011) and seven (Patton and Mussa-Ivaldi, 2004; Patton et al., 2006a; Patton et al., 2006b; Matsuoka et al., 2007; Rozario et al., 2009; Wang et al., 2010; Casellato et al., 2012) report inconclusive but positive results (Table 1). Inconclusive results were considered as, those results where the experiment did not have significant statistical power for definitive conclusions to be drawn and the results where the authors couldn't definitively link improvements to the error augmented treatment.

In one study (Shirzad et al., 2012) the authors concluded that there was no significant impact of the intervention on motor learning but when the different training modes employed in the study were compared, motor learning was improved only when haptic error augmentation was combined with visual error augmentation. In the study where a viscous force field were used (Patton et al., 2006b), the authors concluded that significant positive effects were only encountered in the directions where error was amplified.

4 DISCUSSION

In this review 13 studies were qualitatively analysed regarding the effects of error augmented feedback on robotic rehabilitation of the upper limb. The reviewed studies employed error augmented therapy either in the form of haptic or visual feedback or a combination of the two. Trials were conducted on healthy participants or on adult participants suffering from the effects of stroke or multiple sclerosis or children with primary dystonia.

The first identified study utilizing error augmentation in the robotic rehabilitation of the upper limb was published in 2004 (Patton and Mussa-Ivaldi, 2004). In the nine years since this first study by Patton et. al was published we could only retrieve twelve additional studies regarding error augmentation in the rehabilitation of the upper limb.

4.1 Clinical Trial Protocols

The design of the trial protocols implemented in the reviewed studies varied significantly as did the intervention time and group formation. Five of the studies (Squeri et al., 2007a; Cesqui et al., 2008; Rozario et al., 2009; Vergaro et al., 2010, Abdollahi et al., 2011) employed a crossover protocol where the same group was exposed to different training modalities with a two week washout period between the two. Furthermore, six studies used single session trials (Patton and Mussa-Ivaldi, 2004; Patton et al., 2006a; Patton et al., 2006b; Matsuoka et al., 2007; Casellato et al., 2012; Shirzad et al., 2012) with the total practice time spanning from as little as 22 min (Patton and Mussa-Ivaldi, 2004) to as much as 96 min (Patton et al., 2006a). Interestingly, only one study utilized a randomized control clinical trial (RCT) protocol (Patton et al., 2006b).

Although, the reviewed studies have presented positive indications of the benefits of the error augmented robotic therapy to the rehabilitation of the upper limb, many of the authors argue that more conclusive outcomes could have been produced if their studies had larger numbers of participants and provided more sessions with more practice intensive protocols. Furthermore, the design of the trial protocols seems to be a significant factor that influences the trial outcome. As such trials designed under a Random Control Trial (RCT) protocol, where a well-established haptic control algorithm would be compared to an error augmenting haptic algorithm, could potentially provide more definitive results (Dobkin, 2004).

4.2 Error Augmented Feedback in Upper Limb Rehabilitation

4.2.1 Success of Error Augmented Haptic Feedback Trials

By studying the results of the trials that utilized haptic error augmentation one can conclude that the different conditions are affected differently by this modality. Stroke patients seem to be more positively affected by haptic error augmentation exercises as all studies that performed such experiments on stroke patients conclude that the group that received error augmented therapy showed improvement in the function of the paretic limb. However, such a statement cannot be definitively made as from the reviewed studies, the ones that performed trials on participants suffering from primary dystonia and multiple sclerosis were significantly less than the trials on stroke patients. Therefore, the reviewed studies cannot be compared directly in terms of the outcome for individuals with different conditions.

More specifically, studies (Cesqui et al., 2008, Abdollahi et al., 2011; Molier et al., 2011) conclusively report that the patients who received error augmented therapy were positively affected. In study (Rozario et al., 2009) the authors report that while the kinematic measures indicate improvement, clinical measures did not provide any measurable change in the performance and they suggest that results were probably hindered by the small trial group and the small number of sessions. The difference in the outcome of kinematic and the clinical measures may be due to the fact that kinematic measures in most cases provide better responsiveness, that is they are more capable of accurately detecting changes over time, than clinical scales (Sivan et al., 2011), hence are more sensitive detectors of change.

Both studies that employed participants with multiple sclerosis report positive outcomes. Study (Squeri et al., 2007a) concluded that at the end of the sessions the participants exhibited faster, smoother and more symmetric movement. On the other hand, study (Vergaro et al., 2010) presents similar results but did not indicate significant differences on the outcome between error reducing and error augmenting therapy, with the only exception being a reduction in a tremor related clinical measure which occurred only after error augmented therapy. As such, the improvement presented in both studies may be due to the fact that the participants experienced the positive effects of adaptation in a dynamic environment regardless of the conditions applied within that environment.

With regards to children suffering from primary dystonia (Casellato et al., 2012) results indicate improvement in terms of optimal path control which as the authors suggest may be due to a refinement in the existing sensorimotor patterns of the impaired participants rather than due to motor learning. In the trials involving participation of able bodied individuals (Patton and Mussa-Ivaldi, 2004; Shirzad et al., 2012), the participants could adapt their movement to the altered environment. However, in (Patton and Mussa-Ivaldi, 2004) there was no clear difference of the effects of error augmenting therapy when compared to those from error reducing therapy. Finally, subjects in (Shirzad et al., 2012) showed improved in satisfaction, attentiveness and dominance when they were introduced to augmented error conditions despite of the type of feedback where error was augmented, but didn't show improvements on their performance. Both trials utilized a single session training scheme with relatively small number of repetitions that may have not allowed significant changes in motor adaptation to occur.

4.2.2 Success of Error augmented Visual Feedback Trials

The studies that used error augmentation in visual feedback, were significantly less than the ones that made use of error augmented haptic feedback. It should be noted that in three out four studies where visual feedback distortion was used, only able bodied participants were employed as such it is difficult to draw conclusions on whether the results would transfer to the motor impaired.

Nevertheless, only one study (Matsuoka et al., 2007) reports positive outcome when error was augmented in the visual feedback as it allowed a new coordination pattern to transfer to the trials with no feedback distortion and reduced error. Study (Rozario et al., 2009) didn't provide statistically significant results but indicates that for some of the participants', error was reduced when they were exposed to error augmented training.

4.3 Comparison of Haptic Error Augmented Therapy to other Haptic Therapy

In the studies where the performance of haptic error augmented therapy was compared with haptic error reducing therapy (Squeri et al., 2007a; Cesqui et al., 2008; Vergaro et al., 2010) all studies report that there was no clear indication for the prevalence of one approach over the other. An interesting outcome came from the study where viscous force fields were used (Patton et al., 2006b) as the authors conclude that most of the improvement in function occurred in the directions of the field where errors where amplified.

5 CONCLUSSIONS

Error augmentation in upper limb robotic rehabilitation is a relatively new area of study, counting almost nine years since the first relevant publication, and a rather understudied one. Despite the small number of publications that have employed this modality, there are some clear indications about its potential benefits. The evidence gathered from this review indicate that stroke patients received the most benefit from haptic error augmented therapy but no clear conclusions were drawn whether this training modality has significant benefits on stroke patients, over other established modalities such as error reducing or assistive therapy.

We suggest that large scale randomized control trials be undertaken in order to explore the prospects of haptic error augmentation and fully evaluate its effectiveness on upper limb robotic rehabilitation. In these trials error augmented therapy should be compared against other, more established training schemes. Furthermore, we suggest that the impact of error augmented therapy should be explored in conditions that share similar symptoms related to neuromuscular control to stroke, such as cerebral palsy. Understanding the neurological mechanisms targeted by different therapies, in terms of both learning and motor performance, could provide greater insight into their potential efficacy in a range of different pathologies and is an important consideration for future studies. Likewise, we would like to encourage scientists to perform trials on impaired subjects where error augmentation on visual feedback will be implemented as the results of this review indicate that this modality hasn't been researched to its full capacity.

Guidelines on trial design and dose administration for rehabilitation of the upper limb in conditions such as stroke have been presented in literature (Dobkin, 2004). To the author's knowledge, reviews on the outcome measures for robotic rehabilitation of the upper limb in conditions such as cerebral palsy, primary dystonia and multiple sclerosis have not yet been conducted, while one review regarding such measures has been undertaken for the rehabilitation for the upper limb in stroke patients (Sivan et al., 2011).

This review has identified that there is no uniform condition-specific trial design or evaluation protocol as different intervention protocols and different measures have been used in trials with participants of the same condition. As a result of this a comparison between trials and their outcomes is difficult. Adoption of standard outcome measures would enable inter-study evaluation and help to progress this area of research significantly. As robotic rehabilitation of the upper limb is getting more and more accepted by the scientific community as a valid rehabilitation modality, we believe that uniform condition-specific trial protocol guidelines should be established, in order to enable researchers to easily evaluate the outcome of relevant studies in literature and allow them to compare the outcome of their studies against that of others.

REFERENCES

2005/2006 S.S.C.A., 2001 Stroke incidence and risk factors in a population based cohort study. *ONS Health Stats Quart (12)*.

Abdollahi, F., Rozario, S. V., Kenyon, R. V., Patton, J. L., Case, E., Kovic, M. & Listenberger, M., 2011. Arm control recovery enhanced by error augmentation. *IEEE Int Conf Rehabil Robot,* 2011, 5975504.

Casellato, C., Pedrocchi, A., Zorzi, G., Rizzi, G., Ferrigno, G. & Nardocci, N., 2012. Error-enhancing robot therapy to induce motor control improvement in childhood onset primary dystonia. *Journal of Neuroengineering and Rehabilitation,* 9.

Cesqui, B., Aliboni, S., Mazzoleni, S., Carrozza, M. C., Posteraro, F., Micera, S. & Ieee, 2008. On the Use of Divergent Force Fields in Robot-Mediated Neurorehabilitation. *2008 2nd Ieee Ras & Embs International Conference on Biomedical Robotics and Biomechatronics.* 942-949.

Dobkin, B. H., 2004. Strategies for stroke rehabilitation. *Lancet Neurology,* 3, 528-536.

Fasoli, S. E., Fragala-Pinkham, M., Hughes, R., Hogan, N., Krebs, H. I. & Stein, J., 2008. Upper limb robotic therapy for children with hemiplegia. *Am J Phys Med Rehabil,* 87, 929-36.

Fluet, G. G., Qiu, Q., Kelly, D., Parikh, H. D., Ramirez, D., Saleh, S. & Adamovich, S. V., 2010. Interfacing a haptic robotic system with complex virtual environments to treat impaired upper extremity motor function in children with cerebral palsy. *Dev Neurorehabil,* 13, 335-45.

French, B., Thomas, L. H., Leathley, M. J., Sutton, C. J., Mcadam, J., Forster, A., Langhorne, P., Price, C. I. M., Walker, A. & Watkins, C. L., 2007. Repetitive task training for improving functional ability after stroke. *Cochrane Database of Systematic Reviews.*

Huang, V. S. & Krakauer, J. W., 2009. Robotic neurorehabilitation: a computational motor learning perspective. *J Neuroeng Rehabil,* 6, 5.

Imms, C., 2008. Children with cerebral palsy participate: A review of the literature. *Disability and Rehabilitation,* 30, 1867-1884.

Jackson, A. E., Holt, R. J., Culmer, P. R., Makower, S. G., Levesley, M. C., Richardson, R.C., Cozens, J. A., Williams, M. M. & Bhakta, B. B., 2007. Dual robot system for upper limb rehabilitation after stroke: The design process. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science,* 221, 845-857.

Johnson, M. J., 2006. Recent trends in robot-assisted therapy environments to improve real-life functional performance after stroke. *Journal of Neuroengineering and Rehabilitation,* 3.

Kluzik, J., Fetters, L. & Coryell, J., 1990. Quantification of control: a preliminary study of effects of neurodevelopmental treatment on reaching in children with spastic Cerebral Palsy. *Physical Therapy,* 70, 65-76.

Maher, C. A., Williams, M. T., Olds, T. & Lane, A. E., 2007. Physical and sedentary activity in adolescents with cerebral palsy. *Developmental Medicine and Child Neurology,* 49, 450-457.

Marchal-Crespo, L. & Reinkensmeyer, D. J., 2009. Review of control strategies for robotic movement training after neurologic injury. *Journal of Neuroengineering and Rehabilitation,* 6.

Matsuoka, Y., Brewer, B. R. & Klatzky, R. L., 2007. Using visual feedback distortion to alter coordinated pinching patterns for robotic rehabilitation. *J Neuroeng Rehabil,* 4, 17.

Molier, B. I., Prange, G. B., Krabben, T., Stienen, A. H. A., Van Der Kooij, H., Buurke, J. H., Jannink, M. J. A. & Hermens, H. J., 2011. Effect of position feedback during task-oriented upper-limb training after stroke: Five-case pilot study. *Journal of Rehabilitation Research and Development,* 48, 1109-1117.

Montagner, A., Frisoli, A., Borelli, L., Procopio, C., Bergamasco, M., Carboncini, M. C. & Rossi, B., Year. A pilot clinical study on robotic assisted rehabilitation in VR with an arm exoskeleton deviceed.^eds. *Virtual Rehabilitation, 2007*, 57-64.

Morris, S. L., Dodd, K. J. & Morris, M. E., 2004. Outcomes of progressive resistance strength training following stroke: a systematic review. *Clin Rehabil,* 18, 27-39.

Norouzi-Gheidari, N., Archambault, P. S. & Fung, J., 2012. Effects of robot-assisted therapy on stroke rehabilitation in upper limbs: systematic review and meta-analysis of the literature. *Journal of Rehabilitation Research and Development,* 49, 479-96.

Patton, J. L., Kovic, M. & Mussa-Ivaldi, F. A., 2006a. Custom-designed haptic training for restoring reaching ability to individuals with poststroke hemiparesis. *J Rehabil Res Dev,* 43, 643-56.

Patton, J. L. & Mussa-Ivaldi, F. A., 2004. Robot-assisted adaptive training: custom force fields for teaching movement patterns. *IEEE Trans Biomed Eng,* 51, 636-46.

Patton, J. L., Stoykov, M. E., Kovic, M. & Mussa-Ivaldi, F. A., 2006b. Evaluation of robotic training forces that either enhance or reduce error in chronic hemiparetic stroke survivors. *Experimental Brain Research,* 168, 368-383.

Prange, G. B., Jannink, M. J. A., Groothuis-Oudshoorn, C. G. M., Hermens, H.J. & Ijzerman, M. J., 2006. Systematic review of the effect of robot-aided therapy on recovery of the hemiparetic arm after stroke. *Journal of Rehabilitation Research and Development,* 43, 171-183.

Reinkensmeyer, D. J., 2009. Robotic Assistance for Upper Extremity Training after Stroke. *In* A. Gaggioli, E. A. Keshner, P. L. Weiss & G. Riva (eds.) *Advanced Technologies in Rehabilitation: Empowering Cognitive, Physical, Social and Communicative Skills through Virtual Reality, Robots, Wearable Systems and Brain-Computer Interfaces.* 25-39.

Reinkensmeyer, D. J., Emken, J. L. & Cramer, S. C., 2004. Robotics, motor learning, and neurologic recovery. *Annual Review of Biomedical Engineering,* 6, 497-525.

Rozario, S. V., Housman, S., Kovic, M., Kenyon, R. V. & Patton, J. L., 2009. Therapist-mediated post-stroke rehabilitation using haptic/graphic error augmentation. *Conf Proc IEEE Eng Med Biol Soc,* 2009, 1151-6.

Scott, S. H. & Dukelow, S. P., 2011. Potential of robots as next-generation technology for clinical assessment of neurological disorders and upper-limb therapy. *Journal of Rehabilitation Research and Development,* 48, 335-353.

Shirzad, N., Van Der Loos, H. F. M. & Ieee, 2012. Error Amplification to Promote Motor Learning and Motivation in Therapy Robotics. *2012 Annual International Conference of the Ieee Engineering in Medicine and Biology Society.* 3907-3910.

Sivan, M., O'connor, R. J., Makower, S., Levesley, M. & Bhakta, B., 2011. Systematic review of outcome measures used in the evaluation of robot-assisted upper limb exercise in stroke. *J Rehabil Med,* 43, 181-9.

Squeri, V., Vergaro, E., Brichetto, G., Casadio, M., Morasso, P. G., Solaro, C. & Sanguineti, V., Year. Adaptive robot training in the rehabilitation of incoordination in Multiple Sclerosis: A pilot studyed.^eds., Noordwijk, 364-370.

Squeri, V., Vergaro, E., Brichetto, G., Casadio, M., Morasso, P. G., Solaro, C., Sanguineti, V. & Ieee, 2007b. Adaptive robot training in the rehabilitation of incoordination in Multiple Sclerosis: a pilot study. *2007 Ieee 10th International Conference on Rehabilitation Robotics, Vols 1 and 2.* 364-370.

Teulings, H. L., Contrerasvidal, J. L., Stelmach, G. E. & Adler, C. H., 1997. Parkinsonism reduces coordination of fingers, wrist, and arm in fine motor control. *Experimental Neurology,* 146, 159-170.

Vergaro, E., Squeri, V., Brichetto, G., Casadio, M., Morasso, P., Solaro, C. & Sanguineti, V., 2010. Adaptive robot training for the treatment of incoordination in Multiple Sclerosis. *J Neuroeng Rehabil,* 7, 37.

Wang, F., Barkana, D. E. & Sarkar, N., 2010. Impact of visual error augmentation when integrated with assist-as-needed training method in robot-assisted rehabilitation. *IEEE Trans Neural Syst Rehabil Eng,* 18, 571-9.

Wei, Y., Bajaj, P., Scheidt, R., Patton, J. & Ieee, 2005. Visual error augmentation for enhancing motor learning and rehabilitative relearning. *2005 Ieee 9th International Conference on Rehabilitation Robotics.* New York: Ieee, 505-510.

Weightman, A., Preston, N., Levesley, M., Holt, R., Mon-Williams, M., Clarke, M., Cozens, A. J. & Bhakta, B., 2011. Home based computer-assisted upper limb exercise for young children with cerebral palsy: a feasibility study investigating impact on motor control and functional outcome. *Journal of Rehabilitation Medicine,* 43, 359-363.

Wolpert, D. M., Ghahramani, Z. & Jordan, M. I., 1995. An internal model for sensorimotor integration. *Science,* 269, 1880-1882.

Wu, C. Y., Trombly, C. A., Lin, K. C. & Tickle-Degnen, L., 2000. A kinematic study of contextual effects on reaching performance in persons with and without stroke: Influences of object availability. *Archives of Physical Medicine and Rehabilitation,* 81, 95-101.

APPENDIX

Table 1: Overview of the contents of the reviewed studies.

Study	**Year published**	**Type of Condition**	**Type of Robot**	**Type of control**	**Type of feedback altered**	**Number of participants (N)** *(E = experimental group C = control group)*	**Time post-stroke (months)**	**Amount of practice**	**Impact on upper limb function**
(Patton and Mussa-Ivaldi, 2004)	2004	n/a	endpoint	error reducing error enhancing	haptic	8 able bodied	n/a	Total movements: 871 (1 session) Total time practiced: 22 min (1 session for 22 min)	positive inconclusive
(Patton *et al.*, 2006a)	2006	stroke	endpoint	error enhancing	haptic	15 impaired E: 12 C: 9	19-132	Total movements: 742 movements (1 session) Total time practiced: 180 min (1 session of 80 min)	positive inconclusive
(Patton *et al.*, 2006b)	2006	stroke	endpoint	viscous force field	haptic	Total: 31 E:27 impaired C:4 able bodied	16-173	Total movements: 834 (1 session) Total time practiced: 57 min (1 session of 57 min)	positive inconclusive
(Matsuoka *et al.*, 2007)	2007	n/a	endpoint (fingers)	n/a	visual	51 able bodied	n/a	Total movements: 920 movements (1 session) Total time practiced: Unknown	positive inconclusive
(Squeri *et al.*, 2007a)	2007	Multiple sclerosis	endpoint	error enhancing error reducing	haptic	4 impaired	n/a	Total movements: 3680 (4 sessions) Total time practiced: 240 min (4 sessions of 60 min)	positive
(Cesqui *et al.*, 2008)	2008	stroke	endpoint	active assistive error enhancing	haptic	15 impaired	n/a	Total movements: Unknown Total time practiced: 600 min (10 sessions of 60 min)	positive
(Rozario *et al.*, 2009)	2009	stroke	endpoint	error enhancing	haptic/ visual	5 impaired	≥6 months	Total movements: Unknown Total time practiced: 240 min (6 sessions of 40 min)	positive inconclusive
(Vergaro *et al.*, 2010)	2010	Multiple sclerosis	endpoint	error enhancing error reducing	haptic	8 impaired	n/a	Total movements: 1992 (4 sessions) Total time practiced: 240 min (4 sessions of 60 min)	positive
(Wang *et al.*, 2010)	2010	n/a	endpoint	assistive	visual	20 able bodied	n/a	Total movements: 50 (2 sessions) Total time practiced: Unknown	positive inconclusive
(Abdollahi *et al.*, 2011)	2011	stroke	endpoint	error enhancing	haptic	19 impaired	6-259	Total movements: Unknown Total time practiced: 360 min (6 sessions of 60 min)	positive
(Molier *et al.*, 2011)	2011	stroke	exoskeleton	none (haptic feedback for error)	haptic	5 impaired	20-51	Total movements: Unknown (2 sessions) Total time practiced: 540 (18 sessions of 30 min)	positive
(Casellato *et al.*, 2012)	2012	primary dystonia	endpoint	null additive force constant disturbing force	haptic	Total: 22 11 impaired 11 able bodied	n/a	Total movements: 55 (1 session)	positive inconclusive
(Shirzad *et al.*, 2012)	2012	n/a	Endpoint	error enhancing	haptic/ visual	10 able bodied	n/a	Total movements: 129 (1 session) Total time practiced: 90 minutes (1 session of 90 min)	no effect

Table 2: Overview of the contents of the reviewed studies.

Study	**Number of sessions**	**Interven tion time in a session**	**Total number of movements in a session**	**Number of repetitions under feedback distortion *(haptic, visual or both)* generation in a session**	**Time trained in error augmentation in a session**	**Washout**
(Patton and Mussa-Ivaldi, 2004)	1	21.95 min	871	a) with intermittent perturbations = 298 b) constant exposure = 330 c) random intermittent removal of the force field Total = 748	a) 7.50 min b) 8.33 min c) 3.00 min Total = 18.83 min	75 movements (1.83 min) at the end of the session
(Patton *et al.*, 2006a)	1	95.75 min	742	a) machine learning = 200 b) learning (opposite to the learned forces) = 222 c) aftereffects catch intermittent removal of the force field = 80 d) sane as c = 80 e) same as b = 2 Total = 584	a) 25.00 min b) 30.00 min c) 20.00 min d) 10.00 min e) 0.25 min Total = 85.25 min	50 movements (3.00 min) at the end of the session
(Patton *et al.*, 2006b)	1	57.00 min	834	n/a	n/a	120 movements (8.00 min) at the end of the session
(Matsuoka *et al.*, 2007)	1	n/a	920	a) Index-Thumb-Both (ITB) distortion =120 b) Thumb-Index-Both distortion (TIB) =120 c) Thumb only condition mirroring ITB = 40 d) Thumb only condition mirroring TIB =40 Total = 320	n/a	n/a
(Squeri *et al.*, 2007a)	4	60.00 min	498	a) Robot learning = 120 b) Trial = 120 c) Training and catch trials = 168 Total = 408	approx. 49.00 min	45 movements at the end of the session 2 weeks after 4 sessions before protocol change
(Cesqui *et al.*, 2008)	20	60.00 min	n/a	n/a	60.00 min	2 weeks after 10 sessions before protocol change
(Rozario *et al.*, 2009)	6	40.00 min	n/a	n/a	35.00 min	2 weeks after 6 sessions before protocol change
(Vergaro *et al.*, 2010)	8	60.00 min	498	a) Robot training = 120 b) Subject training = 288	approx. 37.00 min	2 weeks after 4 sessions before protocol change
(Wang *et al.*, 2010)	2	n/a	25	Total = 25	n/a	n/a
(Abdollahi *et al.*, 2011)	12	60.00 min	n/a	n/a	30.00 min	2 weeks after 6 sessions before protocol change
(Molier *et al.*, 2011)	18	30.00 min	n/a	n/a	30.00 min	n/a
(Casellato *et al.*, 2012)	1	n/a	55	a) Null additive force = 15 b) Disturbing force =15 c) Deactivation of additive external force = 15 Total = 45	n/a	n/a
(Shirzad *et al.*, 2012)	1	90.00 min	129	Total = 65	approx. 45.00 min	10 movements at the beginning every training block (5 cycles/session)

Table 3: Overview of the practice administered in the reviewed studies.

Study	**Type of control**	**Type of Condition**	**Outcome measures**	**Statistical measurable impact**	**Author conclusions**
(Patton and Mussa-Ivaldi, 2004)	error enhancing	n/a	**Kinematic**: Error, speed	• The subjects' trajectories shifted significantly towards the desired trajectories ($p < 0.05$)	• Clinical improvement for adaptive therapy • No clear difference between error reducing and error enhancing therapy
(Patton *et al.*, 2006a)	error enhancing	stroke	**Clinical**: Fugl-Meyer, MAS **Kinematics**: Error	• All but one of the treatment groups movements showed beneficial aftereffects • Average reduction in error of –54%, ($p < 0.05$) • Treatment group, FM scores marginally increased an average of 1.6 ($p = 0.06$). No such improvement was seen in the control group ($p > 0.27$).	• The stroke group: movements showed beneficial aftereffects after training (error decreased) that persisted in all but three patients • This persistence was twice as long as for nondisabled people
(Patton *et al.*, 2006b)	viscous force field	stroke	**Clinical**: Chedoke stage of Arm, Elbow modified Ashworth Spasticity scale, F-M	• The after-effect was significant but 26% smaller that the healthy subjects (confidence 95%) • Significant improvements occurred only when the training forces magnified the original errors $F(1,13) = 4{,}29$ ($p<0.001$)	• For movement directions that begin with significant errors, significant improvement occurred only when the training forces magnified the original errors
(Matsuoka *et al.*, 2007)	n/a	n/a	n/a	• The mean total absolute error for at the first training block was significantly different for the last block ($p = 0.001$) • No significant results for final performance change at the end of the trial ($p = 0.99$)	• Training under visual feedback allowed new coordination pattern to transfer to no-feedback trials • Feedback distortion changed the amount of error reduced for each finger separately, and altogether • Distorting individual fingers separately (or together) did not affect the overall speed of learning in movement error reduction.
(Squeri *et al.*, 2007a)	error enhancing error reducing	Multiple sclerosis	**Clinical**: MMSE, EDSS, NRS, Scripps', Aswhorth, Ataxia and Tremor scale, NHPT, VAS, TADL **Kinematic**: Max lateral deviation, movement duration, symmetry, jerk index	• First to last session: highly significant ($p=0{,}000027$) decrease in duration and significant increase ($p=0.031$) in speed profile symmetry • Error enhancing vs error reducing: first-last sessions profile symmetry ($p= 0.006$) and trajectory smoothness ($p = 0.05$) increased in error enhancing • Decrease in NHPT score overall $F(1,3)=42.133$ ($p=0.007$)	• Analysis of motor performance reveals that, at the end of a training session, movements are faster, smoother and have a more symmetric speed profile • Smoothness improved over sessions
(Cesqui *et al.*, 2008)	active assistive error enhancing	stroke	**Clinical**: MSS, MAS, ROM, Mc-Master Stroke Assessment **Kinematic**: Smoothness, accuracy, path length ratio, movements direction variability	• Robotic-aided therapy led to a significant reduction in impairment of the hemiparetic limbs, as shown by the evolution of the MSS and MAS throughout the therapy (no p-value was provided) • Group I: final metric indexes were no different ($F=1.61$, $p = 0.194$) • Group II: final metric indexes were significantly different ($F=9{,}46$, $p = 0.006$)	• Post-stroke patients were able to contrast the perturbation field, i.e., they could reach the target, and perform the exercise (varies dependent on the severity of the impairment) • Improvements were higher depending on the admission upper limb severity level
(Rozario *et al.*, 2009)	error enhancing	stroke	**Clinical**: FM, WFMT, FAS, box and blocks **Kinematic**: Range of motion error	• ROM assessment exhibited a floor effect, where subjects that initially demonstrated fairly low reaching errors did not significantly improve their accuracy in reaching to target • ROM test did reduce for three subjects in the error augmented and control treatment groups. • Error for two of the three subjects was significantly decreased following error augmentation treatment compared to control treatment. • Subjects provided with error augmentation during the first phase of treatment produced greater performance improvements • No significant improvement, deterioration, or notable trends were demonstrated with the clinical measures. *(no statistical analysis was performed*	• the two week treatment blocks might not be sufficient to provide any measurable change clinically, small number of subjects (five) is not sufficient to draw any definitive conclusion • control treatment, while not providing error-augmentation, still improved functionality • MS subjects adapt to unfamiliar dynamic environments • Improvements from error measures don't correlate with clinical measures

Table 4: Overview of the practice administered in the reviewed studies (cont.).

Study	**Type of control**	**Type of Condition**	**Outcome measures**	**Statistical measurable impact**	**Author conclusions**
(Vergaro *et al.*, 2010)	error enhancing error reducing	Multiple sclerosis	**Clinical**: EDSS and Functional Systems Score, Scripps' ,NRS, Ashworth scale, Ataxia and Tremor scales, NHPT, VAS,TADL **Kinematic**: Lateral deviation, duration, Symmetry, Jerk	• Significant effect of period ($F(1,6) = 16.004$; $p = 0.00283$). • NHPT change from baseline (T0) to the end of the treatment (T3), irrespective of the training mode. NHPT score decreased from 61 ± 14 s to 48 ± 20 s, a 24% change ($F(1,6) = 16.495$, $p = 0.007$); • Ataxia score decreased from T0 and T3, irrespective of the training mode ($F(1,6) = 6.1935$, $p = 0.04725$). The decrease occurred during the first four sessions ($F(1,6) = 10.500$, $p = 0.01768$); • Tremor: TADL score decreased in the first four sessions, but only with error augmented training ($F(1,6) = 14.087$, $p = 0.00947$); • TADL secondary outcome that significantly decreased only in error augmented training ($F(1,6) = 14.087$, $p = 0.00947$).	• Adaptive robot training improves upper limb function. • No significant differences- neither short-term (within session) nor long term (between sessions) - between error-enhancing and error-reducing training.
(Wang *et al.*, 2010)	assistive	n/a	**Kinematic**: Times needed assistance, position error	• Significant improvements were observed in both AAN Session and INT Session ($p < 0.001$) • 19/20 participants needed fewer times of robotic assistance (no p-value provided) • Tracking performances improved with error augmented therapy ($p = 0.0014$)	• Participants became more capable of executing the task when the visual error augmentation training method had been integrated with the assist-as-needed training method/no statistically significant difference in carryover effects was observed between the two groups
(Abdollahi *et al.*, 2011)	error enhancing	stroke	**Clinical**: Fugl-Meyer, WMFT, ASFR, Box and blocks **Kinematic**: Rom reach value/rom error	• Six of nineteen subjects showed significant improvement in ROM either immediately following treatment ($p = 0.04854$) or at the follow-up phase of error-augmented treatment ($p = 0.07056$) • Error augmentation elicited varied degrees of performance improvement as measured by the AMFM scores based on percentage change from pre-treatment base line values to the follow-up evaluation (95% confidence intervals) • Fugl-Meyer score improved (95% confidence intervals)	• On average, subjects performed better in 1-week follow-up evaluations than they did at the end of the two weeks of training. It may be that the impaired nervous system does not react to nor does it try to learn from smaller errors, and the EA approach may promote learning by simply intensifying the signal-to-noise ratio for sensory systems, making errors more noticeable
(Molier *et al.*, 2011)	none (haptic feedback for error)	stroke	**Clinical**: FMA-UL, Motoricity index MI/ARAT **Kinematic**: Circulant arm movements, isometric strength	• Four subjects improved on the FMA-UL by between 1.0 and 9.5 points. • MI, two subjects improved by 8 and 13 points each • Four subjects improved on the ARAT by between 0.5 and 5.0 points. • Three subjects increased workspace by between 20.2% - 63.4% *(no statistical analysis was performed)*	• Emphasis on errors at the moment they occur may possibly stimulate motor learning when patients perform movement tasks with sufficiently high difficulty levels.
(Casellato *et al.*, 2012)	null additive force constant disturbing force	primary dystonia	**Clinical**: BFMDRS	• Disturbing force affected significantly the movement outcomes in healthy but not in dystonic subjects • In the dystonic population the altered dynamic exposure seems to induce a subsequent improvement, i.e. a beneficial after-effect in terms of optimal path control, compared with the correspondent reference movement outcome ($p = 0.05$)	• The short-time error-enhancing training in dystonia could represent an effective approach for motor performance improvement, since the exposure to controlled dynamic alterations induces a refining of the existing but strongly imprecise motor scheme and sensorimotor patterns.
(Shirzad *et al.*, 2012)	error enhancing	n/a	**Clinical**: Self-Assessment Mankin questionnaire **Kinematic**: Absolute deviation of trajectory, mean of max deviation	• Increased satisfaction and attentiveness in error augmented therapy and even more in visual and haptic mode (no p-values provided) • the means of each affect measure are significantly different between almost all pairs of conditions ($p<0.05$) • High-gain visual plus haptic EA leads to a significantly larger amount of learning a, in comparison with both of the visual EA methods ($p<0.1$)	• Significant differences in effect (specifically: satisfaction, attentiveness and dominance) between progressively more exaggerated error amplification conditions, even when presented in random order to subject

What should we consider when designing rehabilitation robots for the upper limb of the neurologically impaired?

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Abstract

Rehabilitation robotics has the potential to significantly increase access to useful therapeutic upper limb exercise for those suffering from neurological impairment. In order to maximise the potential of such technology to promote motor learning/relearning clearly we must consider carefully how it is designed, and who should be engaged in its development. In this paper we present our perspective on some important design considerations and highlight relevant literature. Our findings have implications for the development and optimisation of rehabilitation robotic technology for improving upper limb function in the neurologically impaired.

1 Introduction

Neurological impairment including stroke, the commonest form of adult disability in the USA, and cerebral palsy (CP), the commonest form of severe childhood disability in Europe (Hagberg and Hagberg, 1993), are a significant burden on healthcare providers with both conditions often affecting the volitional control of one or both upper limbs. Restorative technologies, such as rehabilitation robotics, aim to accelerate skill acquisition to increase the functional abilities of the neurologically impaired without device assistance. A benefit of rehabilitation robotics to healthcare providers is increased patient access to rehabilitation treatment as existing rehabilitation treatment is predominately delivered by therapy staff and as such is resource limited. Improved access to therapy maximises the potential of recovery and as a consequence a better quality of life whilst resulting in a more cost efficient healthcare provider.

The paradigm of upper limb rehabilitation robotics is a motivating computer environment, which promotes therapeutic movements of the impaired limb with a powered interface implementing a control algorithm to promote recovery. Rehabilitation robotic therapy for the upper limb has demonstrated statistically significant benefits, with improvements in kinematic parameters including movement time, path and smoothness of reach observed (Fasoli, et al., 2008, Huang and Krakauer, 2009, Fluet, et al., 2010, Weightman, et al., 2011, Norouzi-Gheidari, et al., 2012, Chen and Howard, 2014).

Rehabilitation robotics have demonstrated potential benefits and large scale trials to further evaluate their efficacy are on-going, for example in the United Kingdom (UK) The Northumbria Healthcare National Health Service (NHS) trust is undertaking a 5 year trial with stroke patients using the MIT-MANUS to evaluate improvement in upper limb function. In such a multidisciplinary area of research there is the potential to develop rehabilitation robots, which have not drawn upon the research previously conducted in this area or related disciplines. This can lead to sub-optimal systems, which do not maximise the quality of therapeutic exercise or worse still are not utilised because of poor design. Furthermore, as a community are we confident that rehabilitation robotic technology is suitably mature to conduct large scale efficacy trials? The danger in evaluating technology before suitable maturity is that it is set up to fail and as such starved of investment and development stifled. Clearly we need to consider carefully the design requirements for upper limb rehabilitation robotic technology drawing on our current knowledge.

In this paper we aim to highlight some important design considerations for upper limb rehabilitation robots and highlight relevant literature with the objective of stimulating discussion with the community and providing a resource for those interested in developing such technology. We do not intend on providing an exhaustive list of design considerations but instead present our opinion of important design factors and highlight where we believe our focus should be.

2 What to consider when designing rehabilitation robots

2.1 The need for a multidisciplinary team

Rehabilitation robotics is a multidisciplinary field and as such if this technology is to successfully develop it will require specialists from a number of disciplines to be involved in its design. Figure 1 illustrates the discipline's that have specialist knowledge/skills that will benefit the development of rehabilitation technology. Without input from a number of disciplines, key requirements of the system may be omitted in its design.

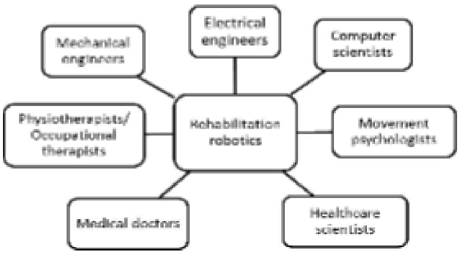


Figure 1: Illustrating the disciplines that have specialist knowledge/skills that can benefit the development of rehabilitation robotics.

2.2 Engage the end users in the design process

The User Centred Design (UCD) process involves engagement with end-users to determine their desires, requirements and limitations through a variety of methodologies to successfully develop technology that meets these requirements. The term end-user refers to the people who will utilise the technology, in the case of rehabilitation robotics; this includes the neurologically impaired, therapists and medical doctors. However in this context this term is often extended to include anyone associated with the utilisation of this technology, for example family members of the neurologically impaired.

In the UK the NHS, and the wider healthcare community, we have seen an increased emphasis on the need for user involvement within healthcare research to ensure the issues of importance to end users, and not just those of academic or clinical interest are addressed (Lightfoot and Sloper, 2003, Shah and Robinson, 2006, Hogg, 2007, Lamey and Bristow, 2007). Shah & Robinson, 2006, from the Multidisciplinary Assessment of Technology Centre for Healthcare (MATCH), emphasise that gathering users' needs has been shown to determine both the success/failure of the development of technology (Shaw, 1998), and the quality associated with the product (Keiser and Smith, 1993). Furthermore, researchers such as Bridgelal, et al., 2008 go on to say that involving users throughout the cycle of device development, "…increases the likelihood of producing devices that are safe, usable, clinically effective and appropriate to cultural context".

Rehabilitation robotics requires the merging and integration of the technical capabilities of the technology with the desires of the end users in order for it to be successful. Shah and Robinson, 2006 highlighted a number of methods that have been utilised for medical device development, including usability tests, focus groups, observation, and simulations.

Several authors have utilised a UCD approach with end users to identify design issues in rehabilitation robotics including (Lee, et al., 2005, Holt, et al., 2007, Lu, et al., 2011). Lee *et al.,* 2005 conducted a survey with physiotherapists to identify design issues, highlighting the importance of safety, cost, privacy of patient information and intuitive usability, concluding that in general therapists respond positively to the idea of rehabilitation robotics. Lu *et al.,* 2011a presented a UCD approach for the development of a robot for upper limb rehabilitation of adults with stroke whilst Holt *et al.,* 2007 suggest that user involvement for developing rehabilitation robotics is an essential requirement.

The development of rehabilitation robotics for children presents a unique design challenge that can make conventional methods to engage users challenging. There is a sparsity of literature for the development of rehabilitation robotics for children using a UCD approach; however research by Holt *et al.,* 2013, Weightman *et al.,* 2010 present useful methodologies and highlight their opinion of the importance of such an approach.

In summary, analysis of the literature illustrates that adopting a user centred design approach is beneficial in developing effective rehabilitation robotic technology.

2.3 Consider the required functionality

We have already considered the importance of UCD, in this section we will consider some important functionality of rehabilitation robots identified using this technique. We can categorise the functionality for rehabilitation robots into five areas, therapeutic functionality, mechanical functionality, safety, motivational factors, user friendliness and social acceptability (Weightman, et al., 2010). We will consider rehabilitation robotic control in a later section of this paper.

Therapeutic functionality

The type of arm exercise the rehabilitation robot should promote and how these match the movements physiotherapists would encourage should be considered. Brewer et al., 2007 advocate further research comparing physiotherapy and rehabilitation robotics. However there is research that can aid us in designing rehabilitation robots with consideration to therapeutic functionality.

The versatility of the rehabilitation robot which allows for different patient positions, different arm movements, and different types of exercise is important. Maintaining adequate joint alignment and providing assistive forces proportional to the needs of the patient are two other important functional features. Pain and muscle fatigue detection, could also be used to personalise therapy (Lee, et al., 2005, Lu, et al., 2011).

Mechanical functionality

The mechanical functionality of a rehabilitation robot will be coupled to the required therapeutic functionality. However, the performance including the functional workspace, smoothness of movement and robustness should be considered (Weightman, et al., 2010).

In order to achieve therapeutic adaptability it has been proposed that users prefer for the robot to have an increased number of degrees of freedom and be able to move in different planes (Lee, et al., 2005, Lu, et al., 2011), however this could increase mechanical complexity, weight, size and cost.

Safety

Safety standards can be divided into hardware and software based (Weightman, et al., 2010). Hardware safety design functions include: limiting the range of motion, safe movement protocols implemented because of emergency or danger (Lee, et al., 2005) and having accessible and effective emergency stop switches and buttons.

Software safety features include safe control algorithms that adapt therapy to patient needs and limits, automatic safety checks, having audio-visual warnings in case of danger or failure (Lee, et al., 2005), effective information sharing between machine and user (Tejima, 2000) and security over personal data of the patient (Lee, et al., 2005).

Other good design practices and recommendations regarding safety include quantitatively evaluating the effectiveness of safety strategies and working towards safety oriented design based on human pain tolerance. (Tejima, 2000)

Motivational factors

Several factors can influence patient motivation, including patient age and preferences, and as such improve adherence to prescribed exercise. (Maclean, et al., 2002, Colombo, et al., 2007) Other motivational features can be valuable: providing audio or visual positive feedback for encouragement alongside progress visualisation (Lee, et al., 2005). Computer game motivational factors will be considered in more detail later.

User friendliness and social acceptability

User friendliness is a key component in the design of rehabilitation robots. For example in home or school environments poor user friendliness is likely to lead to poor utilisation (Holt, et al., 2013, Preston, et al., 2014). User friendliness can be considered the ease with which the device is utilised. Factors that affect this include the size and set up time. Research would indicate a preference for a set up time less than 5 minutes, allowing for portability, and having a simple to use software and user interface. (Brewer, et al., 2007, Weightman, et al., 2010, Holt, et al., 2013)

Social acceptability in this context is how the rehabilitation robots are perceived by users and others. This is of particular relevance for rehabilitation robots for children with cerebral palsy, children with a perception that the device is for rehabilitation may not want to use it. (Weightman, et al., 2010)

2.4 Design for the environment the rehabilitation robot will be used in and consider the cost/benefit trade offs

Robotic devices for upper limb rehabilitation

A recent review by Maciejasz, et al., 2014 highlighted the plethora of rehabilitation robots that have been developed. Classification of the type of robot has been based on the type of actuation (Gopura and Kiguchi, 2009) and the manner in which the robot attaches/guides the arm (Maciejasz, et al., 2014). The wide variety of rehabilitation robots is a reflection of the differing requirements in terms of the clinical condition they are designed to provide therapy for and also the environment in which the therapy will be delivered.

What environment will the robot be used in

The environment in which the robot will be used is important in its design. Important parameters to consider include the size, weight, usability, portability and power requirements, as this will be subject to the environmental constraints. For example a home environment will place more of a constraint on size than a rehabilitation robot designed for a clinical environment.

Researchers in this field seeking a more detailed analysis may find the work of Jackson, et al., 2007, Weightman, et al., 2011, Holt, et al., 2013 who have deployed rehabilitation robots in clinical, home and school environments respectively.

The environment in which the rehabilitation robot will be used will influence the type of actuation of the robot. There are three different types of actuation being used in the robotic rehabilitation systems namely, electric motors (Krebs and Hogan, 2006), pneumatic actuators (Secoli, et al., 2011) and hydraulic actuators (Stienen, 2007). Electric actuators are the most popular choice for such applications (Maciejasz, et al., 2014). This is mostly due to the fact that electric motors have a relatively higher power output and they are easy to power and control.

Conversely, pneumatic actuators are lighter and have lower impedance but they are hard to control due to their non-linear nature (Harwin, et al., 1995, Morales, et al., 2011). In addition, despite the small size of the actuators the overall size of a pneumatic system is dramatically increased by the size of the compressor needed to provide them with pressurised air (Maciejasz, et al., 2014). For all the aforementioned reasons such systems are most suitable for application where they remain stationary such as clinical environments.

Finally, hydraulic actuators have been the less popular choice amongst all three. Such actuators have a high torque output and are very sensitive and responsive (Maciejasz, et al., 2014). On the other hand they require frequent maintenance, are prone to oil spillages and they require a lot of space thus making them unsuitable for robotic rehabilitating applications (Gopura, et al., 2011).

The physical interface between robot and patient

The manner in which the robot attaches to the patient is important as it will determine if the robot promotes desirable spatial and temporal characteristics of the end point (hand) or the arm. We should consider the environment in which the robot is to be deployed as large multiple point of attachment systems are suited to clinical environments and not home based rehabilitation. Similarly end point of attachment robots may be better suited to home based rehabilitation but in clinical environments the advantage of promoting desirable movements of the whole arm and not just the end point may be favourable.

Single point of attachment systems

The most common design of such systems are end effector/endpoint systems. These systems are usually attached to/held by the patients hand (Loureiro, et al., 2011). Such systems are usually more simplistic, less expensive, are usually portable and have a smaller footprint hence making them ideal for home rehabilitation applications. Furthermore, due to their simple configuration such systems require less complicated control algorithms. On the other hand, such systems can only control the position of the hand and not the corresponding position of the elbow and shoulder hence allowing configuration that may potentially injure the arm (Loureiro, et al., 2011, Maciejasz, et al., 2014).

A recently conducted review of robotic devices used in upper limb rehabilitation by Maciejasz *et al.,* 2014 identified that the majority of the single point of attachment systems developed, allow movement in three dimensions. However, several systems have been developed that only allow movement in a single plane. Such systems, are very simple and economical and when combined with carefully selected control algorithms allow similarly effective movements with their three dimensional counterparts (Loureiro, et al., 2011).

Multiple point of attachment systems and exoskeletons

Such systems can control the full kinematics of the human arm. They allow the control of posture during movement and control of the synergies between the joints by allowing or prohibiting certain configurations (Gopura, et al., 2011). Furthermore, because of their ability to very accurately follow the movement of the human arm they provide very efficient means to collect kinematic data in real time. Conversely, such systems are usually big, utilise multiple actuators, are more complicated to design and control and hence are more expensive than single point of attachment systems. For all the aforementioned reasons such systems are more suitable for the clinical environment such as hospitals and rehabilitation centres. (Lo and Xie, 2012, Maciejasz, et al., 2014).

Cost/Benefit trade offs

As we have seen there are advantages and disadvantages to different robot configurations and corresponding actuation systems which define their suitability for different environments. As such when we consider the design requirements for this technology they will be different depending on the intended environment it will operate in. Hence cost/benefit analysis in terms of the selection of the type of robot configuration and actuation system should be considered. For example, if we are striving as a community to develop rehabilitation robotic technology for home use should we not consider the choice of components, benefit of additional degrees of freedom and complexity with respect to cost. Home based rehabilitation robotic systems have to be economically viable for healthcare providers so, as a community, should we not be integrating this into our design requirements?

2.5 Design a motivational game

Development of rehabilitation robotic systems has mainly focused on the hardware development of the system and not the game element (Shah, et al., 2014). Developing the motivational game component of a rehabilitation robot can increase the amount of therapy undertaken by the patient and conversely a poorly motivating game is likely to reduce the amount of therapy undertaken (Colombo, et al., 2007). Should we not review out focus on the software element as without it the most advanced hardware will not be utilised.

Unlike therapy utilising the Nintendo Wii or XBOX Kinect rehabilitation robotics cannot utilise commercially available games as the controller implemented to determine the forces applied to the patient applies more constraints. As such the design of rehabilitation robots needs to consider the type of motivational game developed carefully. Several researchers have highlighted the need for a better computer game element for rehabilitation robotics systems (Dickey, 2005, Colombo, et al., 2007, Fluet, et al., 2010, Weightman, et al., 2011, Preston, et al., 2014, Shah, et al., 2014)

Lohse et al., 2013 state that designing a video game for rehabilitation purposes is a multidisciplinary task including game design, neuroscience of motivation and principles of motor learning. Several key considerations have been identified in the literature which the designers of computer games for rehabilitation robots should be aware of:

Game interface

Cook, et al., 2002 highlighted the easier the gaming interface the better understood by the patient in their research with children with severe disabilities.

Set clear goals

Both long-term and short-term goals are essential in providing an objective to strive for and can divide a lengthy task into manageable sections (Fullerton, 2008). Gameplay can be considered as offering two major categories of goals, self-improvement or survival (Lohse, et al., 2013). Self-improvement can be considered as reaching a new stage ("level") of a character/avatar and acquiring fictive material goods. Survival goals can be considered as a consequence of failing a given task, leading to reattempting the task or restarting the game. Some studies suggest that the lack of long-term consequences may lead to increased perseverance, provoking users to use different strategies. (Hoffman and Nadelson, 2010)

It has been shown that goal oriented tasks lead to an increased motivation and engagement. (Lohse, et al., 2013)

Rewards and achievements

Rewards and achievements (feedback) act as positive recognition for finishing a given task and are common to computer games. It has been observed that after being presented with a reward or acknowledgement after a challenging action, users feel a sense of gratification and are more likely to continue playing the game. (Lohse, et al., 2013, Shah, et al., 2014)

Difficulty/Challenge

The level of difficulty of a game can greatly affect the willingness to continue playing (Colombo, et al., 2007, Shah, et al., 2014). If the level of challenge is too low the player can lose motivation and conversely if the task is too challenging the user is more likely to abandon playing altogether. (Hoffman and Nadelson, 2010)

So what is an appropriate level of challenge? (Lohse, et al., 2013) define the concept of "positive failure" stating that it is more motivating to fail just before accomplishing a task as the user is more likely to reattempt it. Lohse et al., (2013) suggest steadily increasing the level of difficulty of a task allowing for greater transfer of skills from one challenge to the next, finally leading to a transfer to everyday activities. They also suggest this can be accomplished by maintaining the user at the limit of his/her ability throughout the game.

Furthermore using steadily increasing levels of difficulty allows for a greater transfer of skills from one challenge to the next, finally leading to a transfer to everyday activities. This can be done by maintaining the user at the limit of his ability throughout the game. (Lohse, et al., 2013)

Choice, Interactivity and Control

Choice (options) within computer games refers to the ability of taking different paths or strategies in order to attain a desired result. This can lead to players attempting to replay a game after completing it, in order to try a new perspective. (Lohse, et al., 2013) suggest that there is a strong link between exploring new possibilities in-game and physiological rewards. However this may be difficult to implement as the control of the robot may impose constraints.

(Hoffman and Nadelson, 2010) suggest free control of the game environment is also important. The ability to make decisions offers positive feedback irrespective of failure or success.

Socialisation

Lohse, et al., 2013 emphasise the importance of creating a social environment around games, and identify three types, competition, feedback and presence. The first two provide a direct interaction between users, either competing or supporting each other in order to achieve the given goals. The latter does not require contact, the existence of other players in the same environment provides comfort (Holt, et al., 2013).

Lohse, et al., 2013 suggest that when considering rehabilitation, socialisation through an online community can lead to an increased amount of time spent using the device.

Context

Hoffman and Nadelson, 2010 highlight the importance of, but not essential, high end graphics and an appealing story line. The authors state that a focus on function related features should gain priority.

2.6 What control strategy should be used?

The control strategy can be considered as the manner of interaction between the user and the rehabilitation robot. The control strategy used for rehabilitation robotics is critical (Reinkensmeyer, et al., 2004, Marchal-Crespo and Reinkensmeyer, 2009, Alexoulis-Chrysovergis, et al., 2013) as its function is to promote motor learning/relearning of the upper limb. Analysis of the literature illustrates a variety of different control strategies have been utilised, Marchal-Crespo and Reinkensmeyer, 2009 suggests the control strategies can be characterised into three groups, see Figure 2.

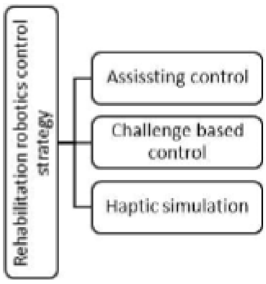


Figure 2: Illustrating the categorization of control strategies as proposed by (Marchal-Crespo and Reinkensmeyer, 2009)

Assisting control

Assisting control strategies are similar to "active assist" type exercises that physiotherapists utilise that help to move the impaired limb in aiming type movements, they are the most predominately utilised control strategy (Marchal-Crespo and Reinkensmeyer, 2009). However, literature has highlighted that this type of controller can reduce the amount of volitional control from the patient leading to a decreased effort (Wolbrecht, et al., 2007). To overcome this problem "assistance as needed' controllers aim to only assist as much as needed encouraging the patient to increase effort levels. Methods used to implement this include triggering assistance at set force/velocity thresholds and dead bands, that is areas in which no assistance is provided.

Challenge based control

Challenge based control strategies augment the error between the actual and desired trajectories or promote increased effort. This type of strategy includes providing resistance to the patient's movement (Hesse, et al., 2003) promoting increased effort. Furthermore error augmenting control algorithms (Alexoulis-Chrysovergis, et al., 2013) have been shown to influence motor adaptation (Wolpert, et al., 1995) and improve motor function in adults suffering from stroke (Morris, et al., 2004, Patton, et al., 2006).

Haptic simulation

Haptic simulation strategies involve the practice of activities of daily living within a virtual haptic environment (Montagner, et al., 2007, Marchal-Crespo and Reinkensmeyer, 2009). These types of environment can create many simulations of real life situations giving an appropriate context to the movements being practiced and automatically grade the level of difficulty. (Patton, et al., 2004, Nef, et al., 2007)

Summary

Rehabilitation robotic control is an on-going area of research, currently research is being conducted with a number of different strategies, although it is not clear which is the optimal for promoting motor learning/re-learning. It is plausible that different controllers will be more suited to different levels of severity of neurological impairment. In the authors opinion further research is required in this area before large scale clinical trials are conducted.

2.7 Consider feedback that may improve performance

Although different approaches have been undertaken by different research groups the main concept behind rehabilitation robotics is that a robotic system interfaces with is the patient's impaired limb then, the patient is asked to perform predefined tasks, usually interacting with a computer interface. The system provides visual, auditory or audio-visual feedback in the form of a computer game while a control algorithm determines the systems response to the patient's movement, given the information provided by a setup of different sensors, such as accelerometers, dynamometers, EMG signals etc.

A significant amount of research in this field has focused on the controller design as we have discussed in the previous section. However, an equally important aspect is the selection of the type and form of feedback that is provided to the user. Appropriate feedback can motivate the user reducing abandonment and also provide the user with useful information about their performance. In this section we will present relevant literature relating to the different types of feedback that can be used in upper limb rehabilitation robotics and its effect on motor learning for the impaired.

Feedback can be categorised as intrinsic and extrinsic. Intrinsic feedback is a result of the sensory information generated by an individual's own movement while extrinsic or augmented feedback is information externally given to the individual. The latter can be provided in different forms namely visually, acoustically or haptically (Van Vliet and Wulf, 2006). There has been sufficient evidence that extrinsic feedback can improve motor function, promote motor learning and increase retention of an acquired skill (Van Vliet and Wulf, 2006). However, the positive effect of extrinsic feedback on improving upper limb function is influenced by the type of feedback, the stage of the trial that this is provided and the information that is provided to the user with as illustrated in Figure 3.

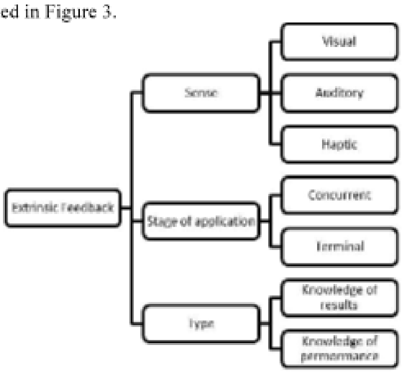


Figure 3: Different parameters of extrinsic feedback on upper limb rehabilitation

Type of feedback

Visual feedback, via a computer screen, virtual reality system, or augmented reality system, is the most commonly used type of feedback and is sometime used in conjunction with auditory feedback. There has been evidence of the benefits of visual feedback when provided in a carefully selected manner (Molier, et al., 2010, Parker, et al., 2011, Patton, et al., 2013)

Auditory feedback has been a rather understudied source of feedback. Recently there has been sufficient evidence presented in literature that auditory feedback promotes brain plasticity through mechanisms that are fundamental for the recovery from neurological injury (Rosati, et al., 2013).

Sigrist, et al., 2013 state that "haptic feedback is defined as any kind of haptic perception that teaches the necessary features that guide the subject toward, and not necessarily through, the desired motion". Haptic feedback has been found to enhance participation and cooperation and promote motor learning (Sigrist, et al., 2013)

When should feedback be given

An important factor to consider is whether augmented feedback should be provided during (concurrent) or at the end of each trial (terminal). Concurrent feedback has been shown to have a positive effect on motor learning and skill acquisition. However, it has been observed that when only real-time concurrent feedback was provided the performance has reduced on follow-up retention tests (Park, et al., 2000). This is has been attributed to patients becoming highly dependent on the feedback provided (Sigrist, et al., 2013).

Park, et al., 2000 suggest that concurrent feedback may only be useful in the early stages of a training scheme where the patient needs assistance in understanding the task needed to be performed and that it should be switched off in the subsequent trials. An alternative is to only provide feedback at the end of a trial. This has been shown to reduce dependency but not eliminate it. As such, trials where no feedback is provided are required in order to strengthen the internal movement representation. (Sigrist, et al., 2013)

Information

Another important aspect of feedback is the information it communicates to the user. This information can be categorised as Knowledge of Results (KR) and Knowledge of Performance (KP). Knowledge of results is information about the outcome of performing a skill or about achieving the goal of the performance. Knowledge of performance is information about movement characteristics that led to the performance (Timmermans, et al., 2009). In early stages of therapy prescriptive KP seems to be more beneficial, while in more advanced stages of therapy descriptive KP appears to be more constructive (Molier, et al., 2010).

The literature demonstrates that designers of rehabilitation robots should consider the manner in which feedback is given in order to potentially improve performance.

3 Discussion

The aim of this paper was to highlight some important considerations in the design of rehabilitation robots for the neurologically impaired. Analysis of the literature has demonstrated there are several important areas of current interest.

Analysis of the literature has illustrated that rehabilitation robotics designed by multidisciplinary groups utilising a UCD approach have been successfully deployed in clinical, home and school environments.

This paper has presented a number of key functionalities that have been highlighted in previous literature that designers of rehabilitation robots should be aware of and consider in the design of future technology.

Furthermore we have highlighted the importance of designing a rehabilitation robot for the environment it will be used in and to focus on the cost/benefit trade offs. If as a community we wish to promote the commercialisation and hence adoption of such technology, should we not be designing rehabilitation robots that are focussed on both improved performance and reduced cost? The cost of the technology will be a crucial factor in the decision making process of healthcare providers in determining its feasibility.

We have presented literature which supports our opinion that we should focus on the development of motivational computer games as well as the rehabilitation robotic hardware. State of the art effective rehabilitation robotic hardware will not be utilised by patients unless there is a motivational computer game to encourage adherence with prescribed therapy.

This paper has demonstrated the significant research that is on-going in the development of control algorithms for promoting motor learning/relearning through rehabilitation robotics. This is a challenging area of research as significant time and funding is required to trial control algorithms with rehabilitation robotics with the neurologically impaired. Furthermore, it is even more challenging to assess the effectiveness of one control strategy in relation to another. The problem is further compounded when we consider that for neurological impairments such as stroke or CP we cannot consider this population as a group with a homogenous type of impairment, each individual will have their own specific characteristic neurological and physiological impairments with varying degrees of severity. In the authors opinion we must investigate this area in breadth and depth before we can expect efficient effective rehabilitation robotic technology for the neurologically impaired.

Finally we have presented literature that illustrates the importance of providing feedback to patients utilising rehabilitation robotics and how it can be used to improve outcomes.

3.1 Future directions

We have highlighted essential literature that should be considered for the design and development of rehabilitation robotics. There are numerous challenges to the future development of rehabilitation robotics if they are to be effective and economically viable for healthcare providers. The following paragraphs highlight some areas of importance for the future development of rehabilitation robotics.

Home based systems

Predominately rehabilitation robotic systems have focussed on the development of systems for use in clinical environments. These systems have demonstrated benefit for improving upper limb function of the neurologically impaired. However the inherent problem with these systems is that patients have to travel to hospitals to use them and as such this reduces access to a large volume of useful therapy. The development of home-based rehabilitation robotic systems has its own challenges including the trade off between functionality and cost as well as the logisitcal support of patients using the home based systems. However, these systems would enable a greater volume of useful therapeutic exercise to be undertaken in comparison to clinically based systems.

Methodological quality of research

There are several measures of methodological quality that have been developed for assessing the quality of published research in the healthcare domain. However these measures are predominately focussed on the trial of medicines and are ill suited for assessing the quality of literature in the area of rehabilitation robotics. Without a more appropriate measure of the quality of research it is more problematic to assess the contribution of research studies and as such more difficult to draw valid conclusions from the available literature.

Adoption and Integration of rehabilitation robotics

Although there is limited literature in the area, the adoption of upper limb rehabilitation robotics into healthcare provision has been limited, concerns about the cost of the technology are not straightforward according to economic analysis [Turchetti, et al., 2014]. We believe there is another barrier to the technology that should be considered, namely how will such technology integrate into existing healthcare provision structures? If the technology is to be home based then it may be that additional technical support will be required to support the implementation of the therapist prescribed interventions. Where will this technical support come from and how will this role integrate into existing infrastructures? As a community do we need to develop a suggested model for adoption to inform decision makers?

4 Conclusions

Rehabilitation robotics has shown potential for providing increased access to rehabilitation for improving arm function in the neurologically impaired whilst also being economically viable for healthcare providers. It would seem sensible to continue our efforts as a community in seeking answers to important design considerations, such as those highlighted in this paper, before embarking on evaluating the overall efficacy of rehabilitation robotics for promoting motor learning/relearning in the neurologically impaired.

References

[Alexoulis-Chrysovergis, et al., 2013] A. Alexoulis-chrysovergis, A. Weightman, E. Hodson-Tole and F. Deconinck. Error augmented robotic rehabilitation of the upper limb a review., *NEUROTECHNIX 2013 - First International Congress on Neurotechnology Electronics and Informatics,* Vilamoura, Algarve, Portugal.

[Brewer et al., 2007] B. Brewer, S. McDowell and L. Worthan-Chaudhariet. Poststroke upper extremity rehabilitation: a review of robotic systems and clinical results. *Topics in stroke rehabilitation*, 14(2):22-44, 2007.

[Bridgelal, et al., 2008] R. Bridgelal, P. Grocott and H Weir. Issues and challenges of involving users in medical device development. *Health Expect*, 11(1):63-71, 2008.

[Chen and Howard, 2014] Y. Chen and A. Howard. Effects of robotic therapy on upper-extremity function in children with cerebral palsy: a systematic review. *Dev neurorehabil*, Early online Apr 11. 2014.

[Colombo, et al., 2007] R. Colombo, F. Pisano, A. Mazzone, C. Delconte, S. Micera. C. Carrozza, P. Dario, G. Minuco. Design strategies to improve patient motivation during robot-aided rehabilitation. *Journal of Neuroengineering and Rehabilitation*, 4(1):1-12. 2007.

[Cook, et al., 2002] M. Cook, M. Meng, J. Gu, K. Howery. Development of a robotic device for facilitating learning by children who have severe disabilities. *IEEE Trans Neural Syst Rehabil Eng*, 10(3):178-87. 2002.

[Dickey, 2005] M. Dickey. Engaging by design: how engagement strategies in popular computer and video games can inform instructional design. *Educational Technology Research and Development*, 53(2):67-83. 2005.

[Fasoli, et al., 2008] S. Fasoli, M. Fragala-Pinkham, R. Hughes, H. Krebs, J. Stein. Upper limb robotic therapy for children with hemiplegia. *Am J Phys Med Rehabil*, 87(11):929-36. 2008.

[Fluet, et al., 2010] G. Fluet, Q. Qiu, D. Kelly, H. Parikh, S. Saleh, S. adamovich. Interfacing a haptic robotic system with complex virtual environments to treat impaired upper extremity motor function in children with cerebral palsy. *Dev Neurorehabil*, 13(5):335-45. 2010.

[Fullerton, 2008] T. Fullerton, *Game design workshop: a playcentric approach to creating innovative games*. CRC press. 2008.

[Gopura and Kiguchi, 2009] R. Gopura, and K. kiguchi. Mechanical designs of active upper-limb exoskeleton robots: state-of-the-art and design difficulties. *IEEE international conference on Rehabilitation Robotics, ICORR 2009.* pages 178-187, Kyoto, Japan 23-26 june 2009.

[Goupura, et al., 2011] R. Gopura, K. Kazuo and D. Bandara. A brief review on upper extremity robotic exoskeleton systems. *6th IEEE International Conference on Industrial and Information Systems ICIIS 2011.* pages 346-351, Kandy, Sri Lanka *2011,* 16-19 Aug 2011.

[Hagberg and Hagber, 1993] B. Hagberg and G. Hagberg. 1993. Origins of cerebral palsy. *In:* T, David, (Ed.), *Recent Advances in Paediatrics,* vol. 11. Churchill Livingstone, pp. 67-83.

[Harwin, et al., 1995] W. Harwin, T. Rahman and R. Foulds. A review of design issues in rehabilitation robotics with reference to north american research. *IEEE Transactions on Rehabilitation Engineering*, 3(1):3-13, 1995.

[Hesse, et al., 2003] S. Hesse, G. Schulte-Tigges, M. Konrad, A. Bardeleben, C. Werner. Robot-assisted arm trainer for the passive and active practice of bilateral forearm and wrist movements in hemiparetic subjects.

Arch Phys Med Rehabil, 84(6):915-20, 2003.

[Hoffman and Nadelson, 2010] B. Hoffman and L. Nadelson. Motivational engagement and video gaming: a mixed methods study. *Educational Technology Research and Development*, 58(3):245-270, 2010.

[Hogg, 2007] C. Hogg. Patient and public involvement: what next for the NHS? *Health Expectations*, 10(2):129-138, 2007.

[Holt, et al., 2007] R. Holt, S. Makower, A. Jackson, P. Culmer. User involvement in developing rehabilitation robotic devices: an essential requirement. *IEEE 10th International Conference on Rehabilitation robotics, ICORR 2007, pages* 196-204. *Noordwijk, The Netherlands* 13-15 june 2007.

[Holt, et al., 2013] R. Holt, A. Weightman, J. Gallagher, N. Preston, M. Levesley, M. Mon-Williams, B. Bhakta. A system in the wild: deploying a two player arm rehabilitation system for children with cerebral palsy in a school environment. *Journal of Usability Studies,* 8: 111-126, 2013.

[Huang and Krakauer, 2009] V. Huang, and J. krakauer. Robotic neurorehabilitation: a computational motor learning perspective. *J Neuroeng Rehabil*, 6(5):497-525, 2009.

[Jackson, et al., 2007] A. Jackson, R. Holt, P. Culmer, S. Makower, M. Levesley, R. Richardson, J. Cozens. Dual robot system for upper limb rehabilitation after stroke: the design process. *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, 221(7):845-857, 2007.

[Keiser and Smoth, 1993] T. Keiser, and D. Smith. Customer-driven strategies: moving from talk to action. *Strategy & Leadership*, 21(5):25-32, 1993.

[Krebs and Hogan, 2006] H. Krebs and N. Hogan. Therapeutic Robotics: a technology push. *Proceedings of the IEEE*, 94(9):1727-1738. 2006.

[Lamey and Bristow, 2007] B. Lamey and C. Bristow. 2007. The design of a mental healthcare low secure unit: the meaningful involvement of service user in the design process. *International Conference on Inclusive Design*, INCLUDE, London, UK, 2007.

[Lee, et al., 2005] M. Lee, M. Rittenhouse and H. Abdullah. Design issues for therapeutic robot systems: results from a survey of physiotherapists. *Journal of Intelligent and Robotic Systems*, 42(3):239-252, 2005.

[Lightfoot and Sloper, 2003] J. Lightfoot and P. Sloper. Having a say in health: involving young people with a chronic illness or physical disability in local health services development. *Children and Society*, 17(4):277-290, 2003.

[Lo and Xie, 2012] H. Lo and S. Xie. Exoskeleton robots for upper-limb rehabilitation: state of the art and future prospects. *Medical Engineering & Physics*, 34(3):261-268, 2012.

[Lohse, et al., 2013] K. Lohse, N. Shirzad, A. Verster, N. Hodges, H. Van der Loos. Video games and rehabilitation: using design principles to enhance engagement in physical therapy. *J Neurol Phys Ther*, 37(4):166-75, 2013.

[Loureiro, et al., 2011] R. Loureiro, W. Harwin, K. Nagai, M. Johnson. Advances in upper limb stroke rehabilitation: a technology push. *Medical & Biological Engineering & Computing*, 49(10):1103-1118. 2011.

[Lu, et al., 2011a] E. Lu, R. Wang, R. Huq, D. Gardner, P. Karam, K. Zabjek, D. Hebert, J. Boger, A. Mihailidis. Development of a robotic device for upper limb stroke rehabilitation: a user-centered design approach. *Paladyn*, 2(4):176-184, 2011.

[Lu et al., 2011b] E. Lu, R. Wang, D. Hebert, J. Boger, M. Galea, A. Mihailidis. The development of an upper limb stroke rehabilitation robot: identification of clinical practices and design requirements through a survey of therapists. *Disability and Rehabilitation: Assistive Technology*, 6(5):420-431, 2011.

[Maciejasz, et al., 2014] P. Maciejasz, J. Eschweiler, K. Gerlach-Hahn, A. Jansen-Troy, S. Leonhardt. A survey on robotic devices for upper limb rehabilitation. *Journal of Neuroengineering and Rehabilitation*, 11(3):1-29, 2014.

[Maclean, et al., 2002] N. Maclean, P. Pound, C. Wolfe, A. Rudd. The concept of patient motivation: a qualitative analysis of stroke professionals' attitudes. *Stroke*, 33(2):444-8, 2002.

[Marchal-crespo and Reinkensmeyer, 2009] L. Marchal-crespo, and D. Reinkensmeyer. Review of control strategies for robotic movement training after neurologic injury. *Journal of Neuroengineering and Rehabilitation*, 6(20): 2009.

[Molier, et al.,] B. Molier, E. Van Asseldonk, H. Hermens, M. Jannink. Nature, timing, frequency and type of augmented feedback; does it influence motor relearning of the hemiparetic arm after stroke? A systematic review. *Disability and Rehabilitation*, 32(22):1799-1809, 2010.

[Montagner, et al., 2007] A. Montagner, A. Frisoli, C. Procopio. A pilot clinical study on robotic assisted rehabilitation in VR with an arm exoskeleton device. *Virtual Rehabilitation 2007,* pages 57-64, Venice, Italy, 27-29 Sept, 2007.

[Morales, et al., 2011] R. Morales, F. Badesa, N. Garcia-Aracil, J. Sabater, C. Perez-Vidal. Pneumatic robotic systems for upper limb rehabilitation. *Medical & Biological Engineering & Computing*, 49(10):1145-1156, 2011.

[Morris, et al., 2004] S. Morris, K. Dodd, M. Morris. Outcomes of progressive resistance strength training following stroke: a systematic review. *Clin Rehabil*, 18(1):27-39, 2004.

[Nef, et al., 2007] T. Nef, M. Mihelj, R. Riener. ARMin: a robot for patient-cooperative arm therapy. *Med Biol Eng Comput*, 45(9):887-900, 2007.

[Norouzi-Gheidari, et al., 2012] N. Norouzi-Gheidari, P. Archambault, J. Fung. Effects of robot-assisted therapy on stroke rehabilitation in upper limbs: systematic review and meta-analysis of the literature. *Journal of Rehabilitation Research and Development*, 49(4):479-96, 2012.

[Park, et al., 2000] J. Park, C. Shea, D. Wright, Reduced-frequency concurrent and terminal feedback: a test of the guidance hypothesis. *J Mot Behav*, 32(3):287-96, 2000.

[Parker, et al., 2011] J. Parker, G. Mountain, J. Hammerton. A review of the evidence underpinning the use of visual and auditory feedback for computer technology in post-stroke upper-limb rehabilitation. *Disabil Rehabil Assist Technol*, 6(6):465-72, 2011.

[Patton, et al., 2004] J. Patton, G, Dawe, F. Mussa-Ivaldi, R. Kenyon. Robotics and virtual reality: the development of a life-sized 3-D system for the rehabilitation of motor function. *Conf proc IEEE Eng Med Biol Soc 2004*, 7:4840-3, 2004.

[Patton, et al., 2006] J. Patton, M. Stoykov, M. Kovic, F. Mussa-Ivaldi. Evaluation of robotic training forces that either enhance or reduce error in chronic hemiparetic stroke survivors. *Experimental Brain Research*, 168(3):368-383, 2006.

[Patton, et al., 2013] J. Patton, Y. Wei, P. Bajaj, R. Scheidt. Visuomotor learning enhanced by augmenting instantaneous trajectory error feedback during reaching. *PLOS One*, 8(1):E46466, 2013.

[Preston, et al., 2014] N. Preston, A. Weightman, J. Gallagher, R. Holt, M. Clarke, M. Mon-Williams, M. Levesley, B. Bhakta. Feasibility of school-based computer-assisted robotic gaming technology for upper limb rehabilitation of children with cerebral palsy. *Disabil Rehabil Assist Technol*, early online 25 June, 2014.

[Reinkensmeyer, et al., 2004] D. Reinkensmeyer, J. Emken, S. Cramer. Robotics, motor learning, and neurologic recovery. *Annual Review of Biomedical Engineering*, 6:497-525, 2004.

[Rosati, et al., 2013] G. Rosati, A. Roda, F. Avanzini, S. Masiero. On the role of auditory feedback in robot-assisted movement training after stroke: review of the literature. *Computational Intelligence and Neuroscience*, ArticleID 586138, 2013.

[Secoli, et al., 2011] R. Secoli, M. Milot, G. Rosati, D. Reinkensmeyer. Effect of visual distraction and auditory feedback on patient effort during robot-assisted movement training after stroke. *J Neuroeng Rehabil*, 8:21, 2011.

[Shah, et al., 2014] N. Shah, A. Basteris, F. Amirabdollahian. Design parameters in multimodal games for rehabilitation. *Games Health J*, 3(1):13-20, 2014.

[Shah, et al., 2006] S. Shah, and I. Robinson. User involvement in healthcare technology development and assessment: structured literature review. *Int J Health Care Qual Assur Inc Leadersh Health Serv*, 19(6-7):500-15, 2006.

[Shaw, 1998] B. Shaw, Innovation and new product development in the UK medical equipment industry. *International Journal of Technology Management*, 15(3-5):433-445, 1998.

[Sigrist, et al., 2013] R. Sigrist, G. Rauter, R. Riener, P. Wolf. Augmented visual, auditory, haptic, and multimodal feedback in motor learning: a review. *Psychon Bull Rev*, 20(1):21-53, 2013.

[Stienen, et al., 2007] A. Stienen, E. Hekman, G. Prange, M. Jannink A. Aalsma, F. Van der Helm, H. Van der Kooij. Dampace: dynamic force-coordination trainer for the upper extremities. *Journal of Medical Devices*, 3(3):031003-1-10, 2007.

[Tejiman, et al., 2000] N. Tejima. Rehabilitation robotics: a review. *Advanced Robotics*, 14(7):551-564, 2000.

[Timmermans, 2009] A. Timmermans, H. Seelen, R. Willmann, H. Kingma. Technology-assisted training of arm-hand skills in stroke: concepts on reacquisition of motor control and therapist guidelines for rehabilitation technology design. *Journal of Neuroengineering and Rehabilitation*, 20(6):1, 2009.

[Turchetti, et al., 2014] G. Turchetti, N. Vitiello, L. Trieste, S. Romiti. Why effectiveness of robot-mediated neurorehabilitation does not necessarily influence its adoption. *IEEE Reviews in Biomedical Engineering*, 7:143-153, 2014.

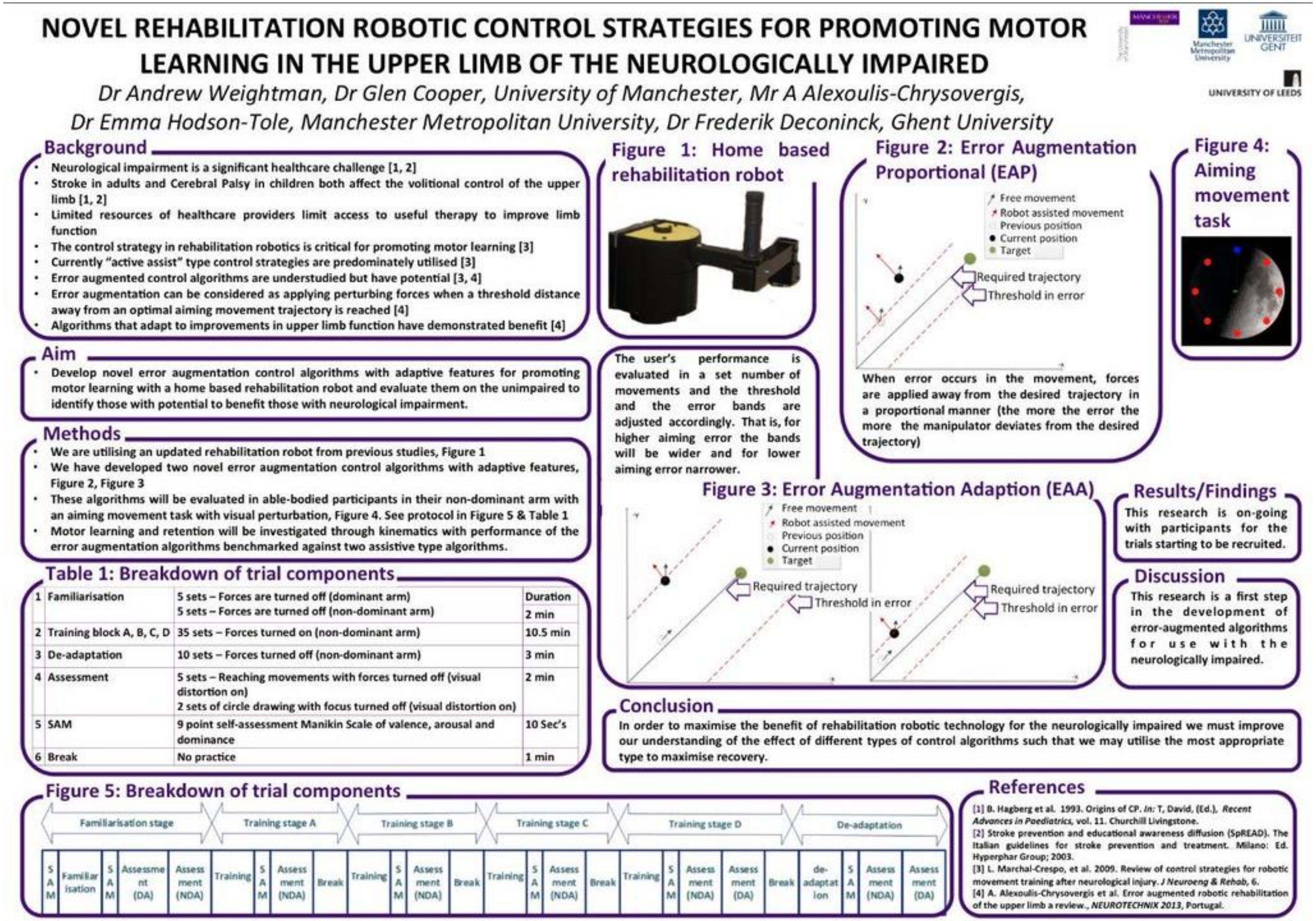
[Van Vilet 2006] P. Van Vliet and G. Wulf. Extrinsic feedback for motor learning after stroke: what is the evidence? *Disabil Rehabil*, 28(13-14):831-40, 2006.

[Weightman, et al., 2011] A. Weightman, N. Preston, M. Levesley, R. Holt, M. Mon-Williams, M. Clarke, A. Cozens, B. Bhakta. Home based computer-assisted upper limb exercise for young children with cerebral palsy: a feasibility study investigating impact on motor control and functional outcome. *Journal of Rehabilitation Medicine*, 43(4):359-363, 2011.

[Weightman, et al., 2010] A. Weightman, N. Preston, R. Holt, M. Allsop, M. Levesley, B. Bhakta. Engaging children in healthcare technology design: developing rehabilitation technology for children with cerebral palsy. *Journal of Engineering Design*, 21(5):579-600, 2010.

[Wolbrecht, et al., 2007] E. Wolbrecht, V. Chan, V. Le, S. Cramer, D. Reinkensmeyer, J. Bobrow. Real-time computer modeling of weakness following stroke optimizes robotic assistance for movement therapy. *Neural Engineering, 2007. CNE '07. 3rd international IEEE/EMBS conference on,* pages 152-158, 2-5 May 2007.

[Wolpert, et al., 1995] D. Wolpert, Z. Ghahramani, M. Jordan. An internal model for sensorimotor integration. *Science*, 269(5232):1880-1882, 1995.



NOVEL REHABILITATION ROBOTIC CONTROL STRATEGIES FOR PROMOTING MOTOR LEARNING IN THE UPPER LIMB OF THE NEUROLOGICALLY IMPAIRED

Dr Andrew Weightman, Dr Glen Cooper, University of Manchester, Mr A Alexoulis-Chrysovergis,
Dr Emma Hodson-Tole, Manchester Metropolitan University, Dr Frederik Deconinck, Ghent University

Background

- Neurological impairment is a significant healthcare challenge [1, 2]
- Stroke in adults and Cerebral Palsy in children both affect the volitional control of the upper limb [1, 2]
- Limited resources of healthcare providers limit access to useful therapy to improve limb function
- The control strategy in rehabilitation robotics is critical for promoting motor learning [3]
- Currently "active assist" type control strategies are predominately utilised [3]
- Error augmented control algorithms are understudied but have potential [3, 4]
- Error augmentation can be considered as applying perturbing forces when a threshold distance away from an optimal aiming movement trajectory is reached [4]
- Algorithms that adapt to improvements in upper limb function have demonstrated benefit [4]

Aim

- Develop novel error augmentation control algorithms with adaptive features for promoting motor learning with a home based rehabilitation robot and evaluate them on the unimpaired to identify those with potential to benefit those with neurological impairment.

Methods

- We are utilising an updated rehabilitation robot from previous studies, Figure 1
- We have developed two novel error augmentation control algorithms with adaptive features, Figure 2, Figure 3
- These algorithms will be evaluated in able-bodied participants in their non-dominant arm with an aiming movement task with visual perturbation, Figure 4. See protocol in Figure 5 & Table 1
- Motor learning and retention will be investigated through kinematics with performance of the error augmentation algorithms benchmarked against two assistive type algorithms.

Table 1: Breakdown of trial components

			Duration
1	Familiarisation	5 sets – Forces are turned off (dominant arm) 5 sets – Forces are turned off (non-dominant arm)	2 min
2	Training block A, B, C, D	35 sets – Forces turned on (non-dominant arm)	10.5 min
3	De-adaptation	10 sets – Forces turned off (non-dominant arm)	3 min
4	Assessment	5 sets – Reaching movements with forces turned off (visual distortion on) 2 sets of circle drawing with focus turned off (visual distortion on)	2 min
5	SAM	9 point self-assessment Manikin Scale of valence, arousal and dominance	10 Sec's
6	Break	No practice	1 min

Figure 5: Breakdown of trial components

Familiarisation stage					Training stage A				Training stage B				Training stage C				Training stage D					De-adaptation			
SAM	Familiarisation	SAM	Assessment (DA)	Assessment (NDA)	Training	SAM	Assessment (NDA)	Break	Training	SAM	Assessment (NDA)	Break	Training	SAM	Assessment (NDA)	Break	Training	SAM	Assessment (NDA)	Assessment (DA)	Break	de-adaptation	SAM	Assessment (NDA)	Assessment (DA)

Figure 1: Home based rehabilitation robot

The user's performance is evaluated in a set number of movements and the threshold and the error bands are adjusted accordingly. That is, for higher aiming error the bands will be wider and for lower aiming error narrower.

Figure 2: Error Augmentation Proportional (EAP)

When error occurs in the movement, forces are applied away from the desired trajectory in a proportional manner (the more the error the more the manipulator deviates from the desired trajectory)

Figure 3: Error Augmentation Adaption (EAA)

Conclusion

In order to maximise the benefit of rehabilitation robotic technology for the neurologically impaired we must improve our understanding of the effect of different types of control algorithms such that we may utilise the most appropriate type to maximise recovery.

Figure 4: Aiming movement task

Results/Findings

This research is on-going with participants for the trials starting to be recruited.

Discussion

This research is a first step in the development of error-augmented algorithms for use with the neurologically impaired.

References

[1] B. Hagberg et al. 1993. Origins of CP. *In:* T, David, (Ed.), *Recent Advances in Paediatrics*, vol. 11. Churchill Livingstone.

[2] Stroke prevention and educational awareness diffusion (SpREAD). The Italian guidelines for stroke prevention and treatment. Milano: Ed. Hyperphar Group; 2003.

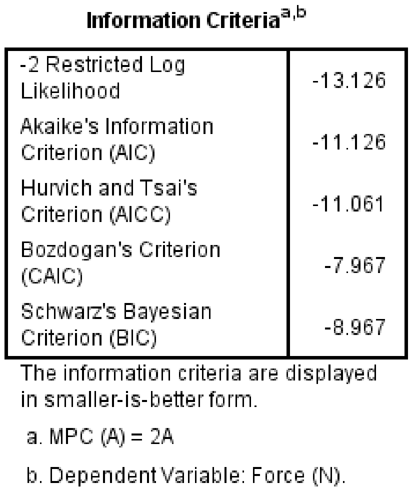
[3] L. Marchal-Crespo, et al. 2009. Review of control strategies for robotic movement training after neurological injury. *J Neuroeng & Rehab*, 6.

[4] A. Alexoulis-Chrysovergis et al. Error augmented robotic rehabilitation of the upper limb a review., *NEUROTECHNIX 2013*, Portugal.

Appendix C

Chapter 3: Force measurement mapping

MPC = 2 A,



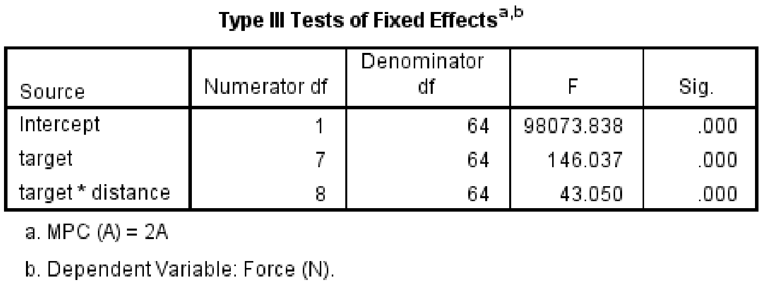
Information Criteria[a,b]

-2 Restricted Log Likelihood	-13.126
Akaike's Information Criterion (AIC)	-11.126
Hurvich and Tsai's Criterion (AICC)	-11.061
Bozdogan's Criterion (CAIC)	-7.967
Schwarz's Bayesian Criterion (BIC)	-8.967

The information criteria are displayed in smaller-is-better form.

a. MPC (A) = 2A

b. Dependent Variable: Force (N).

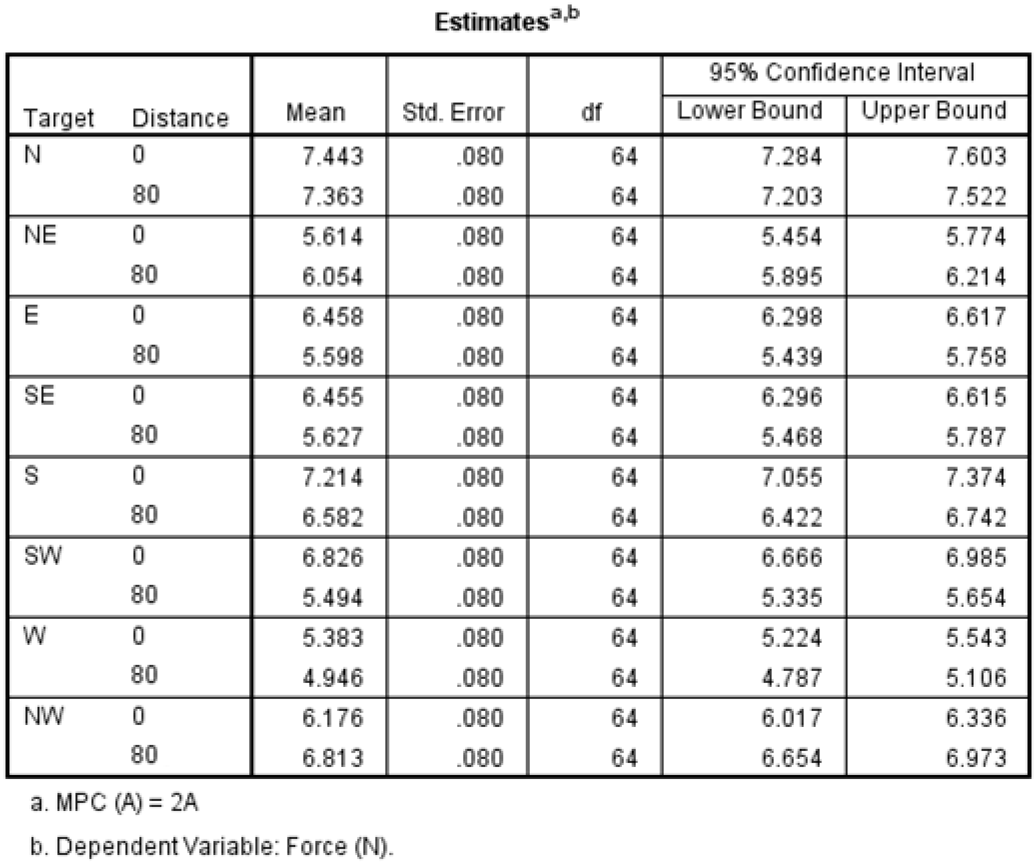


Type III Tests of Fixed Effects[a,b]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	64	98073.838	.000
target	7	64	146.037	.000
target * distance	8	64	43.050	.000

a. MPC (A) = 2A

b. Dependent Variable: Force (N).

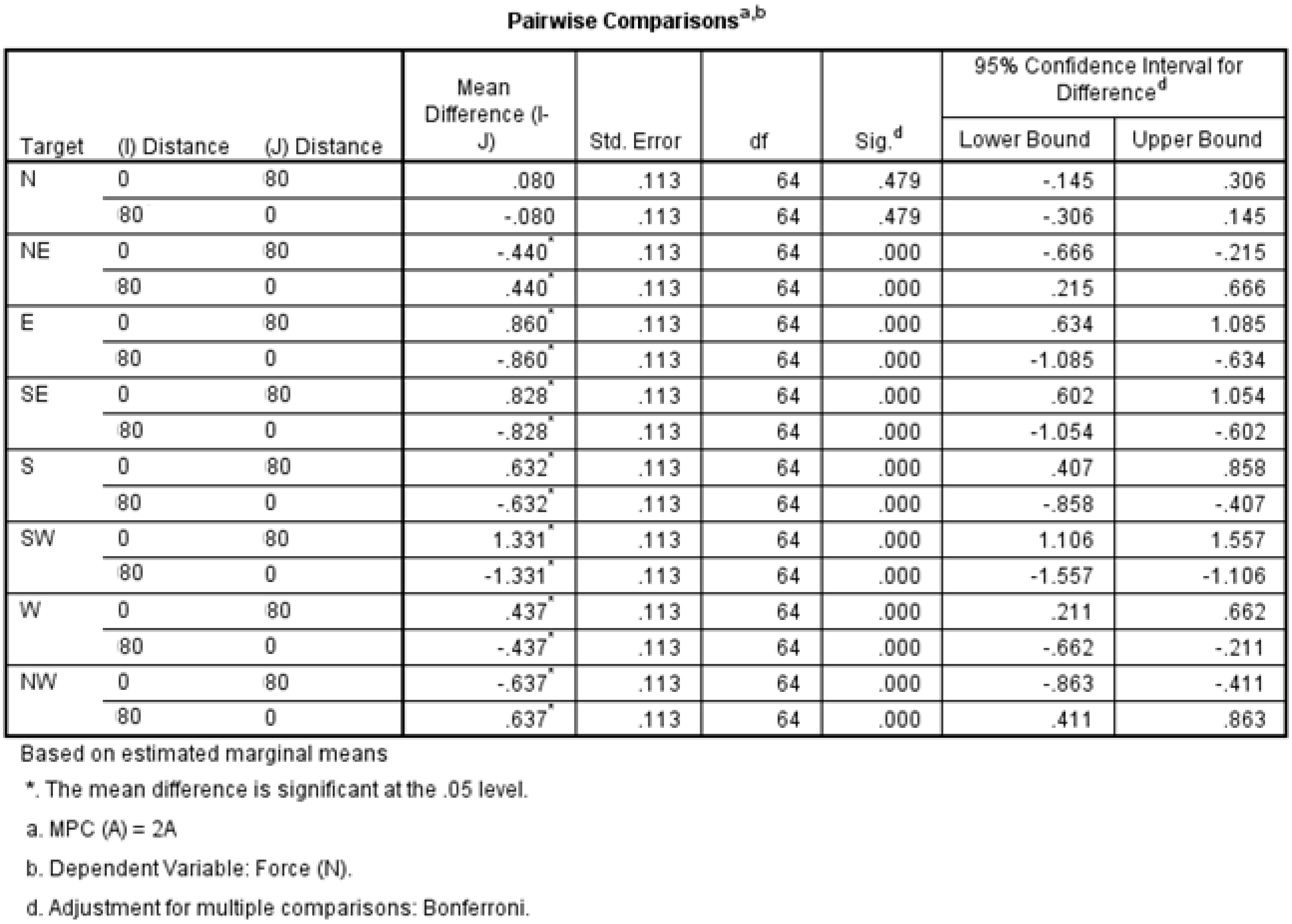


Estimates[a,b]

Target	Distance	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
N	0	7.443	.080	64	7.284	7.603
	80	7.363	.080	64	7.203	7.522
NE	0	5.614	.080	64	5.454	5.774
	80	6.054	.080	64	5.895	6.214
E	0	6.458	.080	64	6.298	6.617
	80	5.598	.080	64	5.439	5.758
SE	0	6.455	.080	64	6.296	6.615
	80	5.627	.080	64	5.468	5.787
S	0	7.214	.080	64	7.055	7.374
	80	6.582	.080	64	6.422	6.742
SW	0	6.826	.080	64	6.666	6.985
	80	5.494	.080	64	5.335	5.654
W	0	5.383	.080	64	5.224	5.543
	80	4.946	.080	64	4.787	5.106
NW	0	6.176	.080	64	6.017	6.336
	80	6.813	.080	64	6.654	6.973

a. MPC (A) = 2A

b. Dependent Variable: Force (N).



Pairwise Comparisons[a,b]

Target	(I) Distance	(J) Distance	Mean Difference (I-J)	Std. Error	df	Sig.[d]	95% Confidence Interval for Difference[d]	
							Lower Bound	Upper Bound
N	0	80	.080	.113	64	.479	-.145	.306
	80	0	-.080	.113	64	.479	-.306	.145
NE	0	80	-.440*	.113	64	.000	-.666	-.215
	80	0	.440*	.113	64	.000	.215	.666
E	0	80	.860*	.113	64	.000	.634	1.085
	80	0	-.860*	.113	64	.000	-1.085	-.634
SE	0	80	.828*	.113	64	.000	.602	1.054
	80	0	-.828*	.113	64	.000	-1.054	-.602
S	0	80	.632*	.113	64	.000	.407	.858
	80	0	-.632*	.113	64	.000	-.858	-.407
SW	0	80	1.331*	.113	64	.000	1.106	1.557
	80	0	-1.331*	.113	64	.000	-1.557	-1.106
W	0	80	.437*	.113	64	.000	.211	.662
	80	0	-.437*	.113	64	.000	-.662	-.211
NW	0	80	-.637*	.113	64	.000	-.863	-.411
	80	0	.637*	.113	64	.000	.411	.863

Based on estimated marginal means

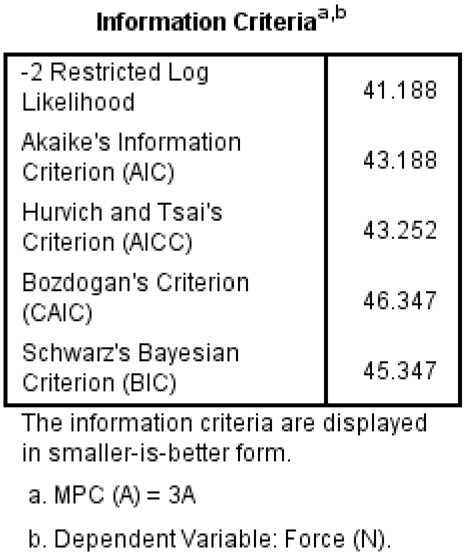
*. The mean difference is significant at the .05 level.

a. MPC (A) = 2A

b. Dependent Variable: Force (N).

d. Adjustment for multiple comparisons: Bonferroni.

MPC = 3 A



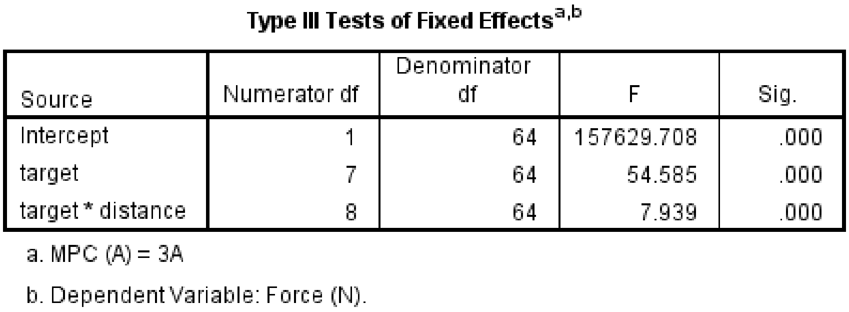
Information Criteria[a,b]

-2 Restricted Log Likelihood	41.188
Akaike's Information Criterion (AIC)	43.188
Hurvich and Tsai's Criterion (AICC)	43.252
Bozdogan's Criterion (CAIC)	46.347
Schwarz's Bayesian Criterion (BIC)	45.347

The information criteria are displayed in smaller-is-better form.

a. MPC (A) = 3A

b. Dependent Variable: Force (N).

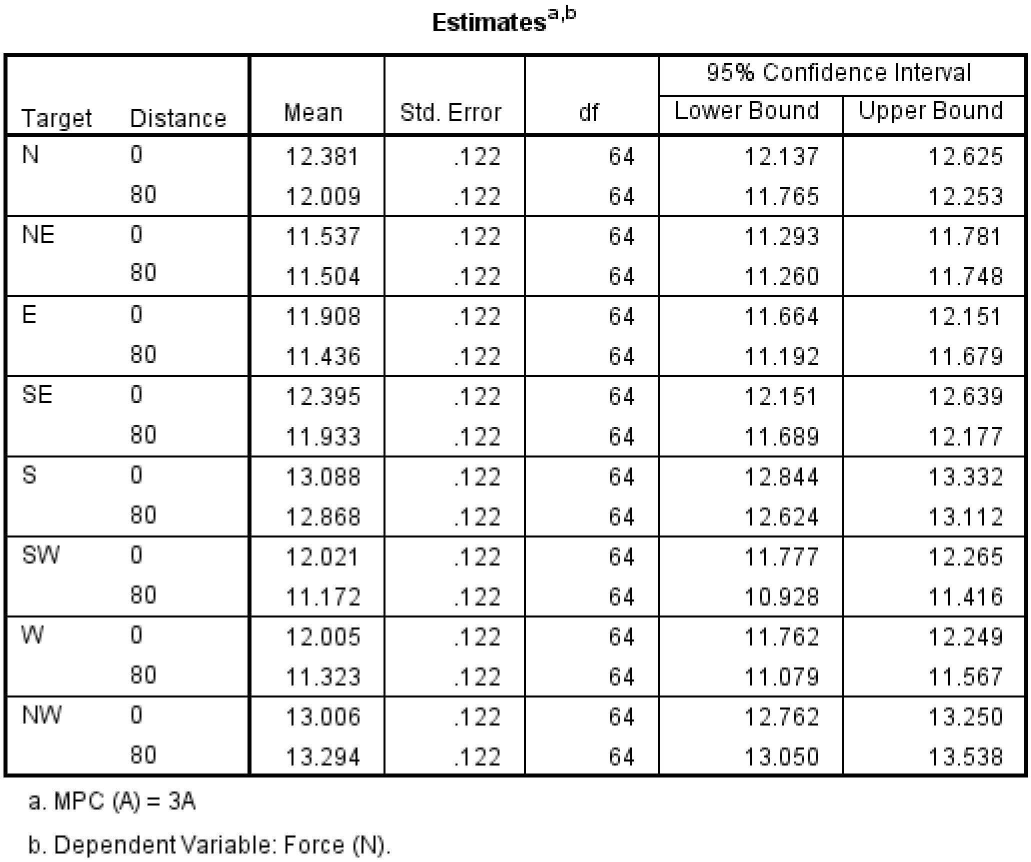


Type III Tests of Fixed Effects[a,b]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	64	157629.708	.000
target	7	64	54.585	.000
target * distance	8	64	7.939	.000

a. MPC (A) = 3A

b. Dependent Variable: Force (N).

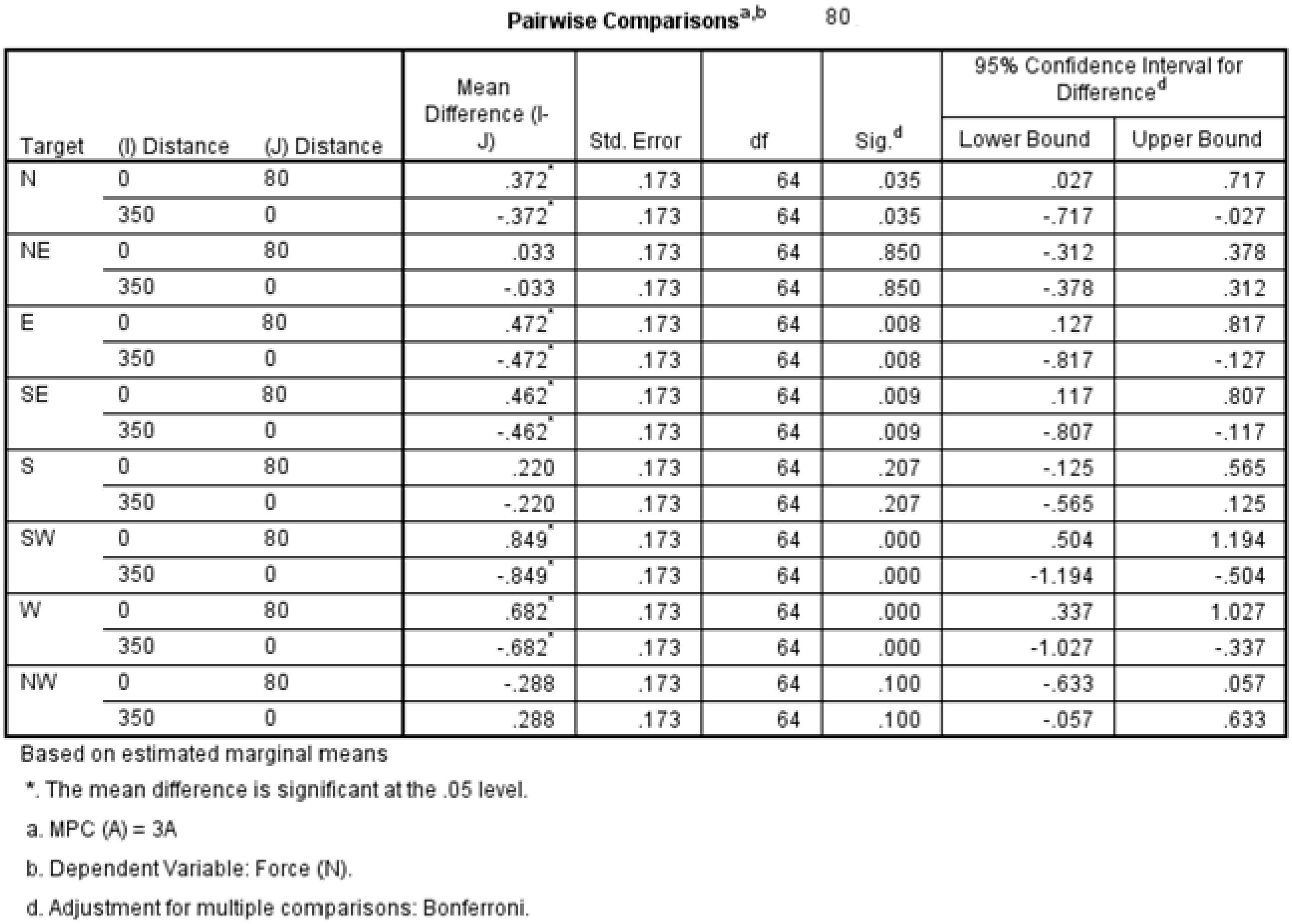


Estimates[a,b]

Target	Distance	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
N	0	12.381	.122	64	12.137	12.625
	80	12.009	.122	64	11.765	12.253
NE	0	11.537	.122	64	11.293	11.781
	80	11.504	.122	64	11.260	11.748
E	0	11.908	.122	64	11.664	12.151
	80	11.436	.122	64	11.192	11.679
SE	0	12.395	.122	64	12.151	12.639
	80	11.933	.122	64	11.689	12.177
S	0	13.088	.122	64	12.844	13.332
	80	12.868	.122	64	12.624	13.112
SW	0	12.021	.122	64	11.777	12.265
	80	11.172	.122	64	10.928	11.416
W	0	12.005	.122	64	11.762	12.249
	80	11.323	.122	64	11.079	11.567
NW	0	13.006	.122	64	12.762	13.250
	80	13.294	.122	64	13.050	13.538

a. MPC (A) = 3A

b. Dependent Variable: Force (N).



Pairwise Comparisons[a,b] 80

Target	(I) Distance	(J) Distance	Mean Difference (I-J)	Std. Error	df	Sig.[d]	95% Confidence Interval for Difference[d]	
							Lower Bound	Upper Bound
N	0	80	.372*	.173	64	.035	.027	.717
	350	0	-.372*	.173	64	.035	-.717	-.027
NE	0	80	.033	.173	64	.850	-.312	.378
	350	0	-.033	.173	64	.850	-.378	.312
E	0	80	.472*	.173	64	.008	.127	.817
	350	0	-.472*	.173	64	.008	-.817	-.127
SE	0	80	.462*	.173	64	.009	.117	.807
	350	0	-.462*	.173	64	.009	-.807	-.117
S	0	80	.220	.173	64	.207	-.125	.565
	350	0	-.220	.173	64	.207	-.565	.125
SW	0	80	.849*	.173	64	.000	.504	1.194
	350	0	-.849*	.173	64	.000	-1.194	-.504
W	0	80	.682*	.173	64	.000	.337	1.027
	350	0	-.682*	.173	64	.000	-1.027	-.337
NW	0	80	-.288	.173	64	.100	-.633	.057
	350	0	.288	.173	64	.100	-.057	.633

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. MPC (A) = 3A

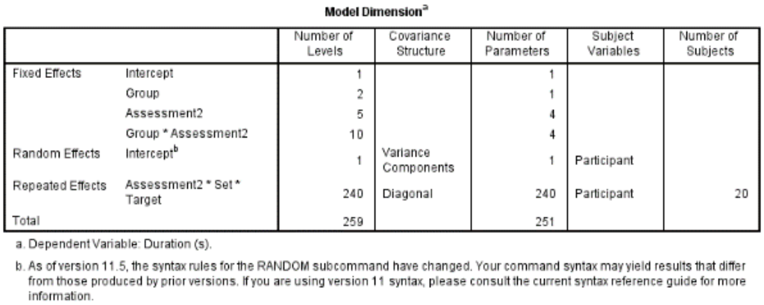
b. Dependent Variable: Force (N).

d. Adjustment for multiple comparisons: Bonferroni.

Chapter 5: Results of the statistical analysis

Analysis of the NDA

Duration

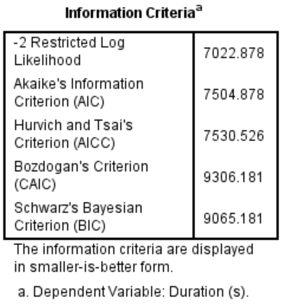


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Duration (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

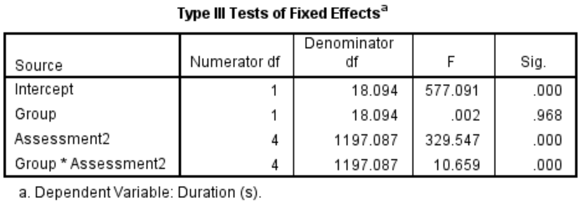


Information Criteria[a]

-2 Restricted Log Likelihood	7022.878
Akaike's Information Criterion (AIC)	7504.878
Hurvich and Tsai's Criterion (AICC)	7530.526
Bozdogan's Criterion (CAIC)	9306.181
Schwarz's Bayesian Criterion (BIC)	9065.181

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration (s).

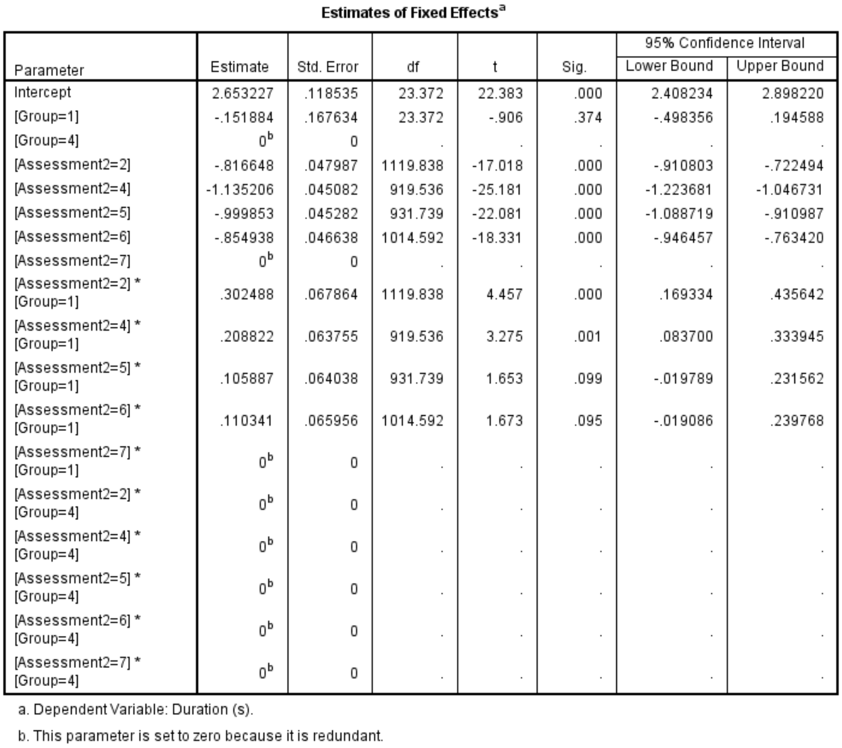


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.094	577.091	.000
Group	1	18.094	.002	.968
Assessment2	4	1197.087	329.547	.000
Group * Assessment2	4	1197.087	10.659	.000

a. Dependent Variable: Duration (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

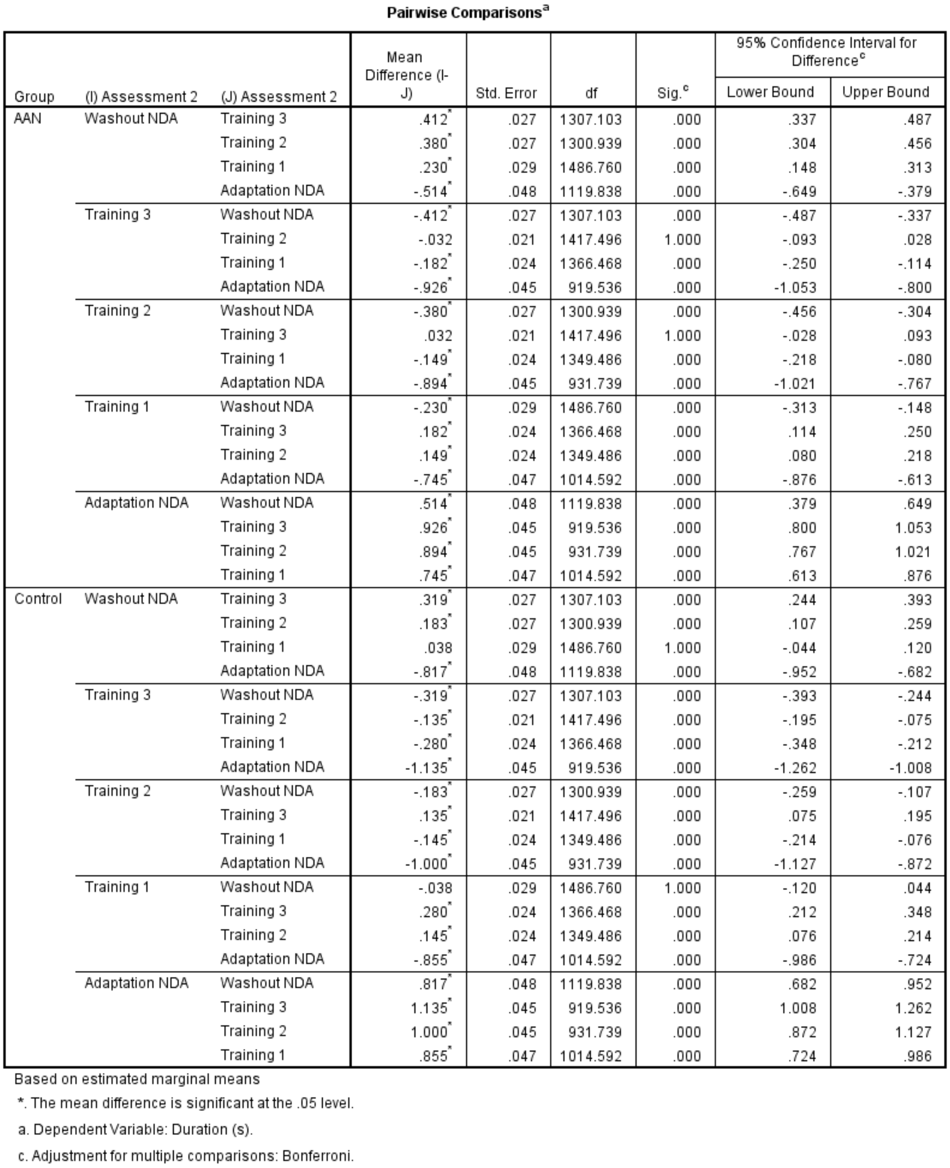


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	2.653227	.118535	23.372	22.383	.000	2.408234	2.898220
[Group=1]	-.151884	.167634	23.372	-.906	.374	-.498356	.194588
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.816648	.047987	1119.838	-17.018	.000	-.910803	-.722494
[Assessment2=4]	-1.135206	.045082	919.536	-25.181	.000	-1.223681	-1.046731
[Assessment2=5]	-.999853	.045282	931.739	-22.081	.000	-1.088719	-.910987
[Assessment2=6]	-.854938	.046638	1014.592	-18.331	.000	-.946457	-.763420
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	.302488	.067864	1119.838	4.457	.000	.169334	.435642
[Assessment2=4] * [Group=1]	.208822	.063755	919.536	3.275	.001	.083700	.333945
[Assessment2=5] * [Group=1]	.105887	.064038	931.739	1.653	.099	-.019789	.231562
[Assessment2=6] * [Group=1]	.110341	.065956	1014.592	1.673	.095	-.019086	.239768
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
AAN	Washout NDA	Training 3	.412*	.027	1307.103	.000	.337	.487
		Training 2	.380*	.027	1300.939	.000	.304	.456
		Training 1	.230*	.029	1486.760	.000	.148	.313
		Adaptation NDA	-.514*	.048	1119.838	.000	-.649	-.379
	Training 3	Washout NDA	-.412*	.027	1307.103	.000	-.487	-.337
		Training 2	-.032	.021	1417.496	1.000	-.093	.028
		Training 1	-.182*	.024	1366.468	.000	-.250	-.114
		Adaptation NDA	-.926*	.045	919.536	.000	-1.053	-.800
	Training 2	Washout NDA	-.380*	.027	1300.939	.000	-.456	-.304
		Training 3	.032	.021	1417.496	1.000	-.028	.093
		Training 1	-.149*	.024	1349.486	.000	-.218	-.080
		Adaptation NDA	-.894*	.045	931.739	.000	-1.021	-.767
	Training 1	Washout NDA	-.230*	.029	1486.760	.000	-.313	-.148
		Training 3	.182*	.024	1366.468	.000	.114	.250
		Training 2	.149*	.024	1349.486	.000	.080	.218
		Adaptation NDA	-.745*	.047	1014.592	.000	-.876	-.613
	Adaptation NDA	Washout NDA	.514*	.048	1119.838	.000	.379	.649
		Training 3	.926*	.045	919.536	.000	.800	1.053
		Training 2	.894*	.045	931.739	.000	.767	1.021
		Training 1	.745*	.047	1014.592	.000	.613	.876
Control	Washout NDA	Training 3	.319*	.027	1307.103	.000	.244	.393
		Training 2	.183*	.027	1300.939	.000	.107	.259
		Training 1	.038	.029	1486.760	1.000	-.044	.120
		Adaptation NDA	-.817*	.048	1119.838	.000	-.952	-.682
	Training 3	Washout NDA	-.319*	.027	1307.103	.000	-.393	-.244
		Training 2	-.135*	.021	1417.496	.000	-.195	-.075
		Training 1	-.280*	.024	1366.468	.000	-.348	-.212
		Adaptation NDA	-1.135*	.045	919.536	.000	-1.262	-1.008
	Training 2	Washout NDA	-.183*	.027	1300.939	.000	-.259	-.107
		Training 3	.135*	.021	1417.496	.000	.075	.195
		Training 1	-.145*	.024	1349.486	.000	-.214	-.076
		Adaptation NDA	-1.000*	.045	931.739	.000	-1.127	-.872
	Training 1	Washout NDA	-.038	.029	1486.760	1.000	-.120	.044
		Training 3	.280*	.024	1366.468	.000	.212	.348
		Training 2	.145*	.024	1349.486	.000	.076	.214
		Adaptation NDA	-.855*	.047	1014.592	.000	-.986	-.724
	Adaptation NDA	Washout NDA	.817*	.048	1119.838	.000	.682	.952
		Training 3	1.135*	.045	919.536	.000	1.008	1.262
		Training 2	1.000*	.045	931.739	.000	.872	1.127
		Training 1	.855*	.047	1014.592	.000	.724	.986

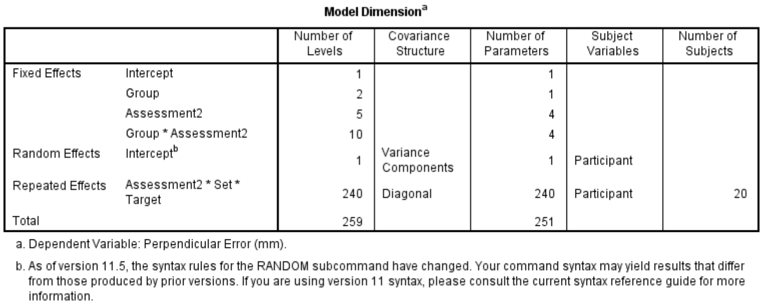
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration (s).

c. Adjustment for multiple comparisons: Bonferroni.

Perpendicular error

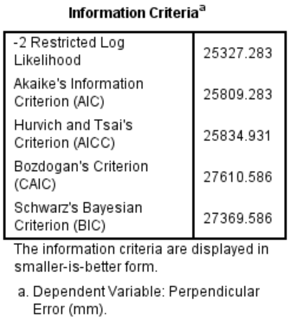


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Perpendicular Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

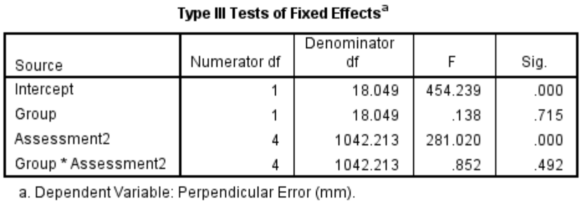


Information Criteria[a]

-2 Restricted Log Likelihood	25327.283
Akaike's Information Criterion (AIC)	25809.283
Hurvich and Tsai's Criterion (AICC)	25834.931
Bozdogan's Criterion (CAIC)	27610.586
Schwarz's Bayesian Criterion (BIC)	27369.586

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Perpendicular Error (mm).

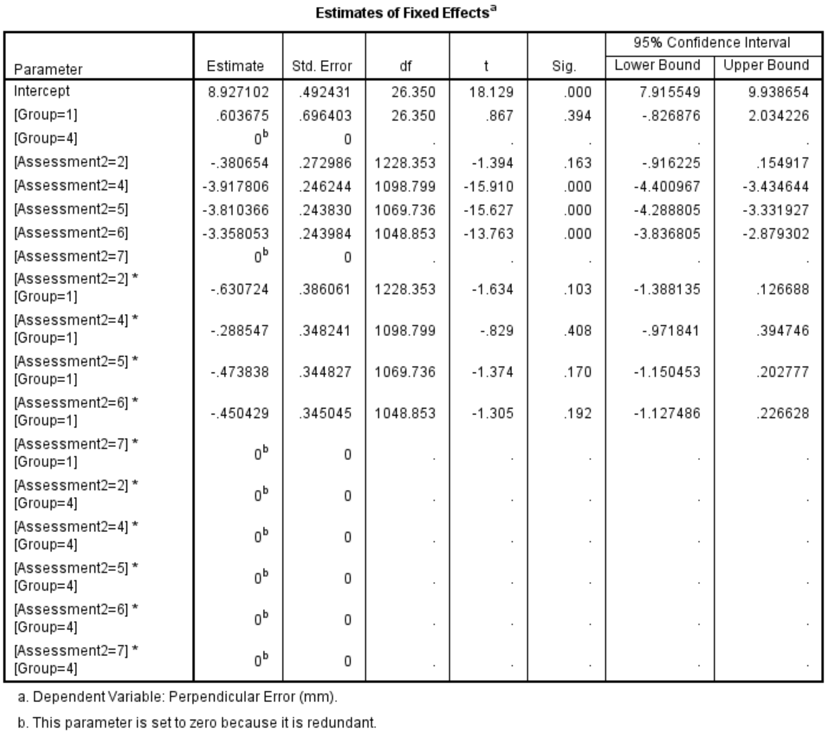


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.049	454.239	.000
Group	1	18.049	.138	.715
Assessment2	4	1042.213	281.020	.000
Group * Assessment2	4	1042.213	.852	.492

a. Dependent Variable: Perpendicular Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

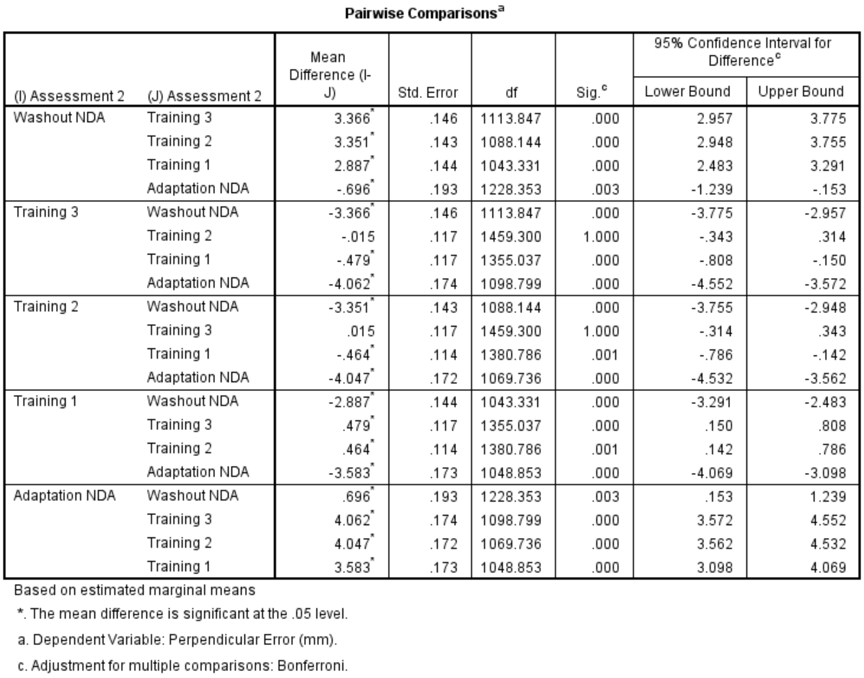


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	8.927102	.492431	26.350	18.129	.000	7.915549	9.938654
[Group=1]	.603675	.696403	26.350	.867	.394	-.826876	2.034226
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.380654	.272986	1228.353	-1.394	.163	-.916225	.154917
[Assessment2=4]	-3.917806	.246244	1098.799	-15.910	.000	-4.400967	-3.434644
[Assessment2=5]	-3.810366	.243830	1069.736	-15.627	.000	-4.288805	-3.331927
[Assessment2=6]	-3.358053	.243984	1048.853	-13.763	.000	-3.836805	-2.879302
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	-.630724	.386061	1228.353	-1.634	.103	-1.388135	.126688
[Assessment2=4] * [Group=1]	-.288547	.348241	1098.799	-.829	.408	-.971841	.394746
[Assessment2=5] * [Group=1]	-.473838	.344827	1069.736	-1.374	.170	-1.150453	.202777
[Assessment2=6] * [Group=1]	-.450429	.345045	1048.853	-1.305	.192	-1.127486	.226628
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Perpendicular Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	3.366*	.146	1113.847	.000	2.957	3.775
	Training 2	3.351*	.143	1088.144	.000	2.948	3.755
	Training 1	2.887*	.144	1043.331	.000	2.483	3.291
	Adaptation NDA	-.696*	.193	1228.353	.003	-1.239	-.153
Training 3	Washout NDA	-3.366*	.146	1113.847	.000	-3.775	-2.957
	Training 2	-.015	.117	1459.300	1.000	-.343	.314
	Training 1	-.479*	.117	1355.037	.000	-.808	-.150
	Adaptation NDA	-4.062*	.174	1098.799	.000	-4.552	-3.572
Training 2	Washout NDA	-3.351*	.143	1088.144	.000	-3.755	-2.948
	Training 3	.015	.117	1459.300	1.000	-.314	.343
	Training 1	-.464*	.114	1380.786	.001	-.786	-.142
	Adaptation NDA	-4.047*	.172	1069.736	.000	-4.532	-3.562
Training 1	Washout NDA	-2.887*	.144	1043.331	.000	-3.291	-2.483
	Training 3	.479*	.117	1355.037	.000	.150	.808
	Training 2	.464*	.114	1380.786	.001	.142	.786
	Adaptation NDA	-3.583*	.173	1048.853	.000	-4.069	-3.098
Adaptation NDA	Washout NDA	.696*	.193	1228.353	.003	.153	1.239
	Training 3	4.062*	.174	1098.799	.000	3.572	4.552
	Training 2	4.047*	.172	1069.736	.000	3.562	4.532
	Training 1	3.583*	.173	1048.853	.000	3.098	4.069

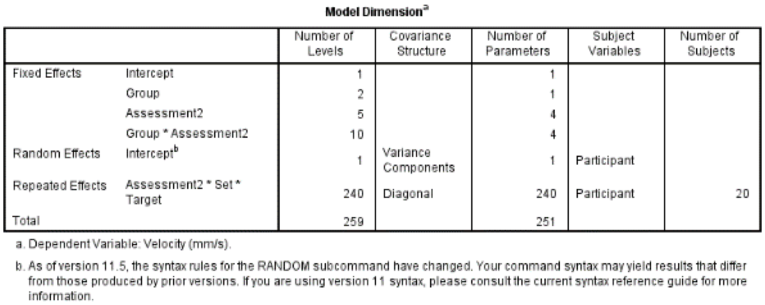
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Perpendicular Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Mean velocity

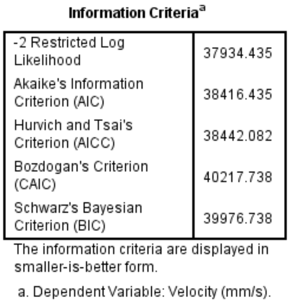


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Velocity (mm/s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

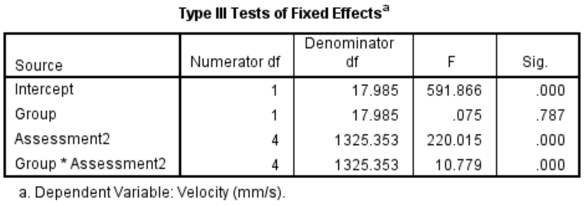


Information Criteria[a]

-2 Restricted Log Likelihood	37934.435
Akaike's Information Criterion (AIC)	38416.435
Hurvich and Tsai's Criterion (AICC)	38442.082
Bozdogan's Criterion (CAIC)	40217.738
Schwarz's Bayesian Criterion (BIC)	39976.738

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Velocity (mm/s).

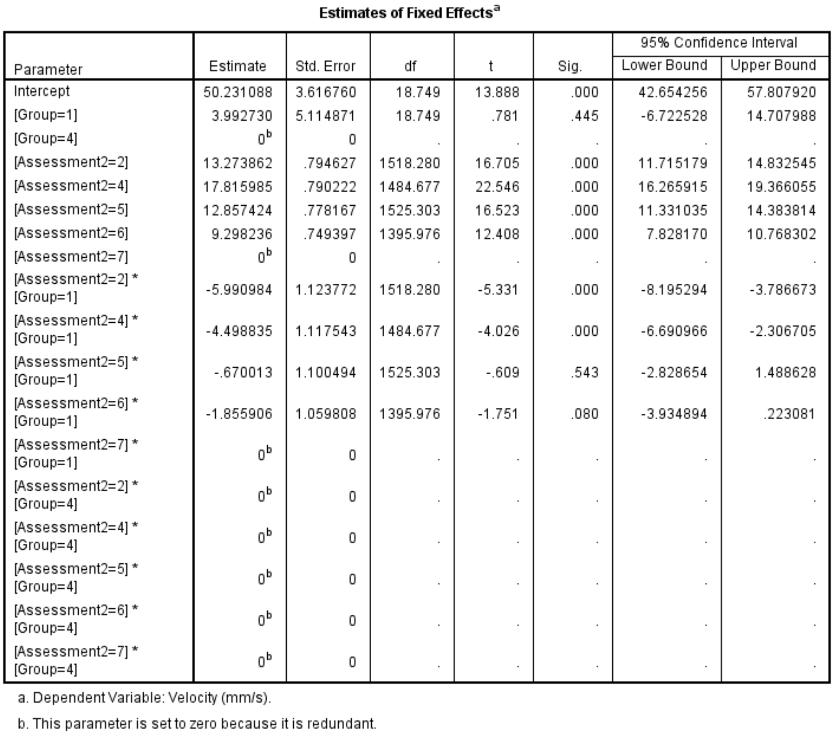


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.985	591.866	.000
Group	1	17.985	.075	.787
Assessment2	4	1325.353	220.015	.000
Group * Assessment2	4	1325.353	10.779	.000

a. Dependent Variable: Velocity (mm/s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

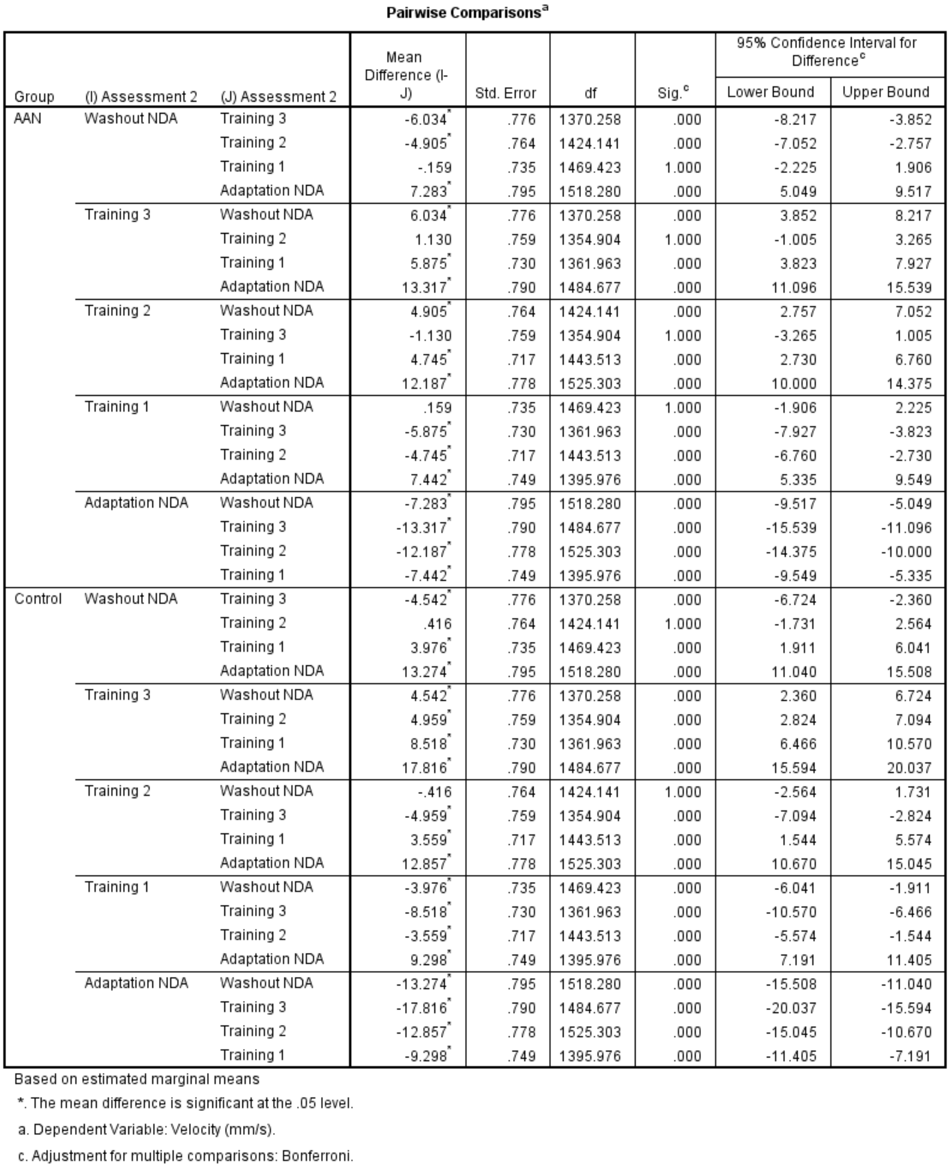


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	50.231088	3.616760	18.749	13.888	.000	42.654256	57.807920
[Group=1]	3.992730	5.114871	18.749	.781	.445	-6.722528	14.707988
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	13.273862	.794627	1518.280	16.705	.000	11.715179	14.832545
[Assessment2=4]	17.815985	.790222	1484.677	22.546	.000	16.265915	19.366055
[Assessment2=5]	12.857424	.778167	1525.303	16.523	.000	11.331035	14.383814
[Assessment2=6]	9.298236	.749397	1395.976	12.408	.000	7.828170	10.768302
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	-5.990984	1.123772	1518.280	-5.331	.000	-8.195294	-3.786673
[Assessment2=4] * [Group=1]	-4.498835	1.117543	1484.677	-4.026	.000	-6.690966	-2.306705
[Assessment2=5] * [Group=1]	-.670013	1.100494	1525.303	-.609	.543	-2.828654	1.488628
[Assessment2=6] * [Group=1]	-1.855906	1.059808	1395.976	-1.751	.080	-3.934894	.223081
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Velocity (mm/s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
AAN	Washout NDA	Training 3	-6.034*	.776	1370.258	.000	-8.217	-3.852
		Training 2	-4.905*	.764	1424.141	.000	-7.052	-2.757
		Training 1	-.159	.735	1469.423	1.000	-2.225	1.906
		Adaptation NDA	7.283*	.795	1518.280	.000	5.049	9.517
	Training 3	Washout NDA	6.034*	.776	1370.258	.000	3.852	8.217
		Training 2	1.130	.759	1354.904	1.000	-1.005	3.265
		Training 1	5.875*	.730	1361.963	.000	3.823	7.927
		Adaptation NDA	13.317*	.790	1484.677	.000	11.096	15.539
	Training 2	Washout NDA	4.905*	.764	1424.141	.000	2.757	7.052
		Training 3	-1.130	.759	1354.904	1.000	-3.265	1.005
		Training 1	4.745*	.717	1443.513	.000	2.730	6.760
		Adaptation NDA	12.187*	.778	1525.303	.000	10.000	14.375
	Training 1	Washout NDA	.159	.735	1469.423	1.000	-1.906	2.225
		Training 3	-5.875*	.730	1361.963	.000	-7.927	-3.823
		Training 2	-4.745*	.717	1443.513	.000	-6.760	-2.730
		Adaptation NDA	7.442*	.749	1395.976	.000	5.335	9.549
	Adaptation NDA	Washout NDA	-7.283*	.795	1518.280	.000	-9.517	-5.049
		Training 3	-13.317*	.790	1484.677	.000	-15.539	-11.096
		Training 2	-12.187*	.778	1525.303	.000	-14.375	-10.000
		Training 1	-7.442*	.749	1395.976	.000	-9.549	-5.335
Control	Washout NDA	Training 3	-4.542*	.776	1370.258	.000	-6.724	-2.360
		Training 2	.416	.764	1424.141	1.000	-1.731	2.564
		Training 1	3.976*	.735	1469.423	.000	1.911	6.041
		Adaptation NDA	13.274*	.795	1518.280	.000	11.040	15.508
	Training 3	Washout NDA	4.542*	.776	1370.258	.000	2.360	6.724
		Training 2	4.959*	.759	1354.904	.000	2.824	7.094
		Training 1	8.518*	.730	1361.963	.000	6.466	10.570
		Adaptation NDA	17.816*	.790	1484.677	.000	15.594	20.037
	Training 2	Washout NDA	-.416	.764	1424.141	1.000	-2.564	1.731
		Training 3	-4.959*	.759	1354.904	.000	-7.094	-2.824
		Training 1	3.559*	.717	1443.513	.000	1.544	5.574
		Adaptation NDA	12.857*	.778	1525.303	.000	10.670	15.045
	Training 1	Washout NDA	-3.976*	.735	1469.423	.000	-6.041	-1.911
		Training 3	-8.518*	.730	1361.963	.000	-10.570	-6.466
		Training 2	-3.559*	.717	1443.513	.000	-5.574	-1.544
		Adaptation NDA	9.298*	.749	1395.976	.000	7.191	11.405
	Adaptation NDA	Washout NDA	-13.274*	.795	1518.280	.000	-15.508	-11.040
		Training 3	-17.816*	.790	1484.677	.000	-20.037	-15.594
		Training 2	-12.857*	.778	1525.303	.000	-15.045	-10.670
		Training 1	-9.298*	.749	1395.976	.000	-11.405	-7.191

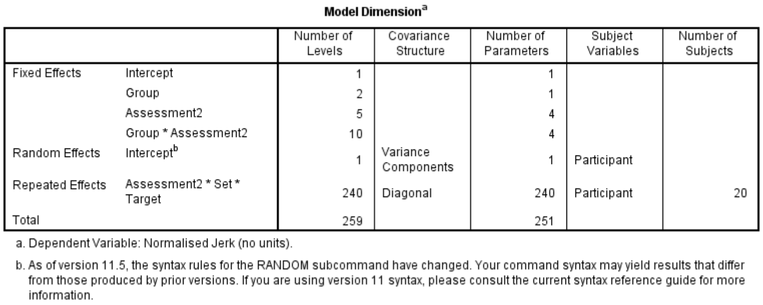
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Velocity (mm/s).

c. Adjustment for multiple comparisons: Bonferroni.

Normalised jerk

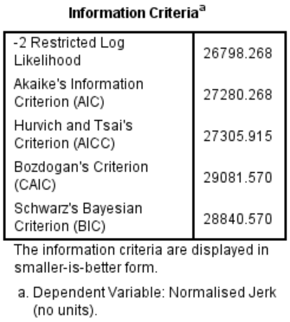


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Normalised Jerk (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

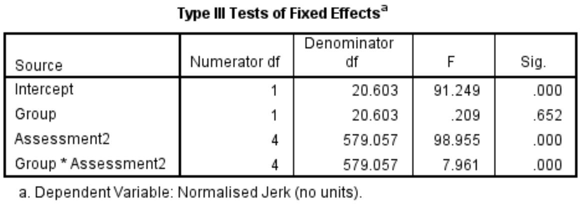


Information Criteria[a]

-2 Restricted Log Likelihood	26798.268
Akaike's Information Criterion (AIC)	27280.268
Hurvich and Tsai's Criterion (AICC)	27305.915
Bozdogan's Criterion (CAIC)	29081.570
Schwarz's Bayesian Criterion (BIC)	28840.570

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Normalised Jerk (no units).

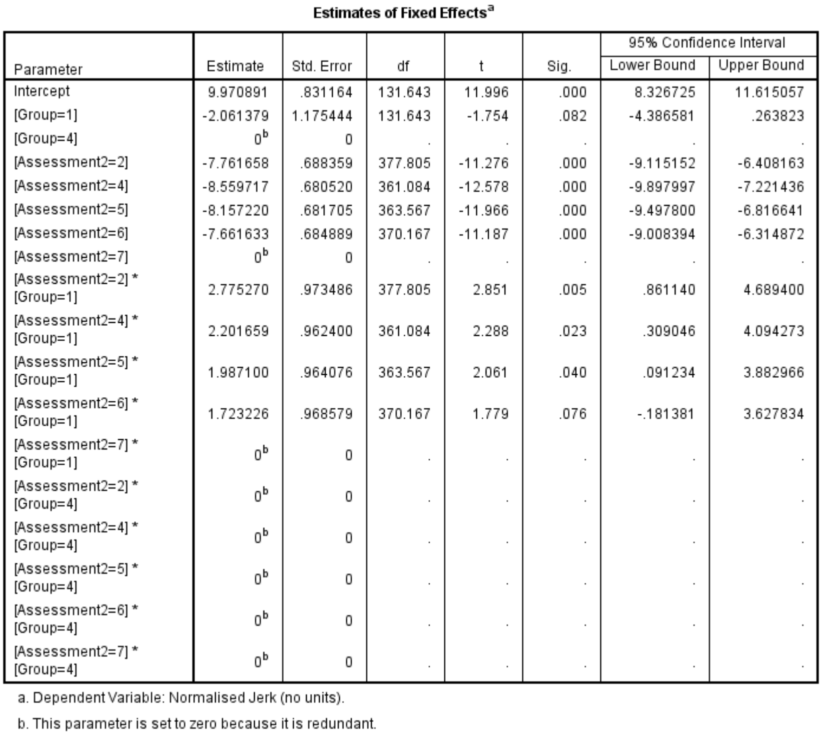


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	20.603	91.249	.000
Group	1	20.603	.209	.652
Assessment2	4	579.057	98.955	.000
Group * Assessment2	4	579.057	7.961	.000

a. Dependent Variable: Normalised Jerk (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

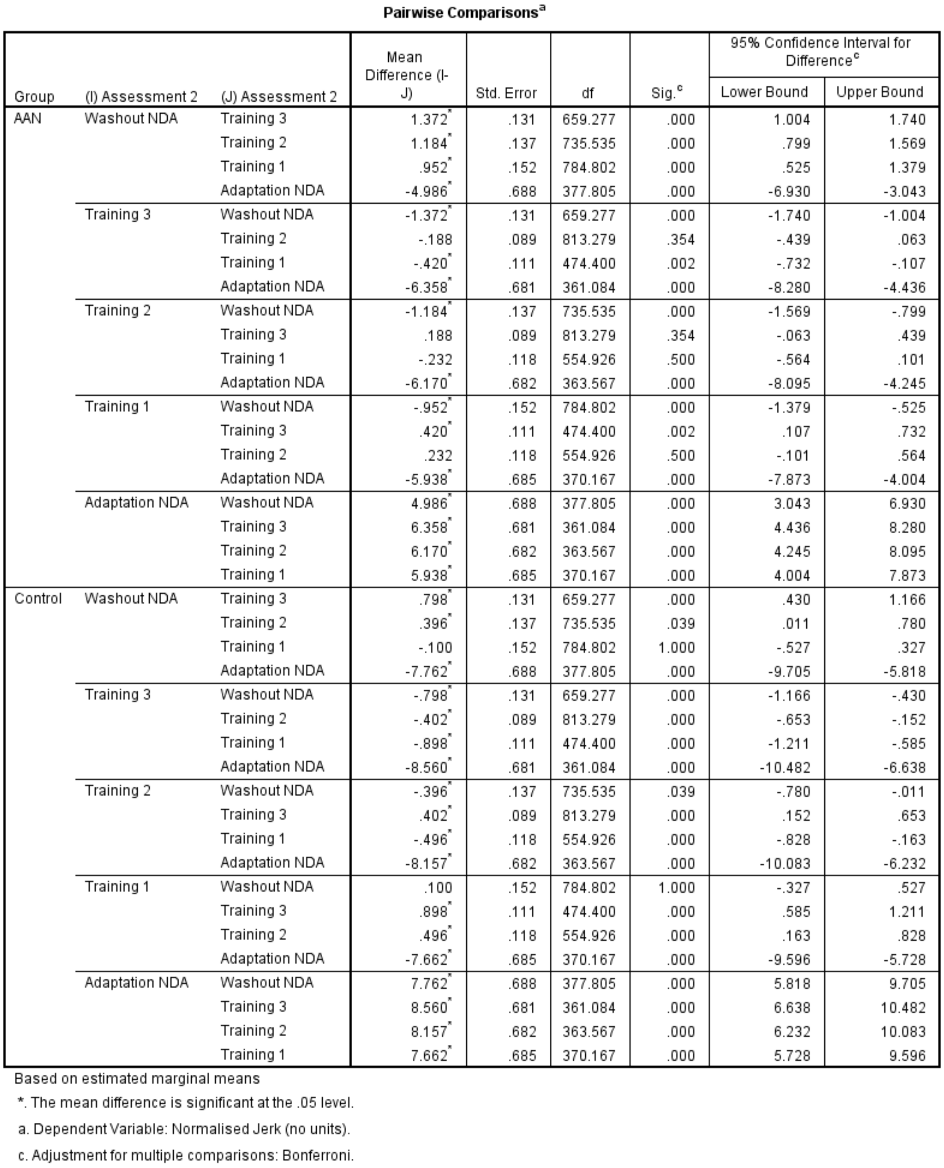


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	9.970891	.831164	131.643	11.996	.000	8.326725	11.615057
[Group=1]	-2.061379	1.175444	131.643	-1.754	.082	-4.386581	.263823
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-7.761658	.688359	377.805	-11.276	.000	-9.115152	-6.408163
[Assessment2=4]	-8.559717	.680520	361.084	-12.578	.000	-9.897997	-7.221436
[Assessment2=5]	-8.157220	.681705	363.567	-11.966	.000	-9.497800	-6.816641
[Assessment2=6]	-7.661633	.684889	370.167	-11.187	.000	-9.008394	-6.314872
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	2.775270	.973486	377.805	2.851	.005	.861140	4.689400
[Assessment2=4] * [Group=1]	2.201659	.962400	361.084	2.288	.023	.309046	4.094273
[Assessment2=5] * [Group=1]	1.987100	.964076	363.567	2.061	.040	.091234	3.882966
[Assessment2=6] * [Group=1]	1.723226	.968579	370.167	1.779	.076	-.181381	3.627834
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Normalised Jerk (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c] Lower Bound	Upper Bound
AAN	Washout NDA	Training 3	1.372*	.131	659.277	.000	1.004	1.740
		Training 2	1.184*	.137	735.535	.000	.799	1.569
		Training 1	.952*	.152	784.802	.000	.525	1.379
		Adaptation NDA	-4.986*	.688	377.805	.000	-6.930	-3.043
	Training 3	Washout NDA	-1.372*	.131	659.277	.000	-1.740	-1.004
		Training 2	-.188	.089	813.279	.354	-.439	.063
		Training 1	-.420*	.111	474.400	.002	-.732	-.107
		Adaptation NDA	-6.358*	.681	361.084	.000	-8.280	-4.436
	Training 2	Washout NDA	-1.184*	.137	735.535	.000	-1.569	-.799
		Training 3	.188	.089	813.279	.354	-.063	.439
		Training 1	-.232	.118	554.926	.500	-.564	.101
		Adaptation NDA	-6.170*	.682	363.567	.000	-8.095	-4.245
	Training 1	Washout NDA	-.952*	.152	784.802	.000	-1.379	-.525
		Training 3	.420*	.111	474.400	.002	.107	.732
		Training 2	.232	.118	554.926	.500	-.101	.564
		Adaptation NDA	-5.938*	.685	370.167	.000	-7.873	-4.004
	Adaptation NDA	Washout NDA	4.986*	.688	377.805	.000	3.043	6.930
		Training 3	6.358*	.681	361.084	.000	4.436	8.280
		Training 2	6.170*	.682	363.567	.000	4.245	8.095
		Training 1	5.938*	.685	370.167	.000	4.004	7.873
Control	Washout NDA	Training 3	.798*	.131	659.277	.000	.430	1.166
		Training 2	.396*	.137	735.535	.039	.011	.780
		Training 1	-.100	.152	784.802	1.000	-.527	.327
		Adaptation NDA	-7.762*	.688	377.805	.000	-9.705	-5.818
	Training 3	Washout NDA	-.798*	.131	659.277	.000	-1.166	-.430
		Training 2	-.402*	.089	813.279	.000	-.653	-.152
		Training 1	-.898*	.111	474.400	.000	-1.211	-.585
		Adaptation NDA	-8.560*	.681	361.084	.000	-10.482	-6.638
	Training 2	Washout NDA	-.396*	.137	735.535	.039	-.780	-.011
		Training 3	.402*	.089	813.279	.000	.152	.653
		Training 1	-.496*	.118	554.926	.000	-.828	-.163
		Adaptation NDA	-8.157*	.682	363.567	.000	-10.083	-6.232
	Training 1	Washout NDA	.100	.152	784.802	1.000	-.327	.527
		Training 3	.898*	.111	474.400	.000	.585	1.211
		Training 2	.496*	.118	554.926	.000	.163	.828
		Adaptation NDA	-7.662*	.685	370.167	.000	-9.596	-5.728
	Adaptation NDA	Washout NDA	7.762*	.688	377.805	.000	5.818	9.705
		Training 3	8.560*	.681	361.084	.000	6.638	10.482
		Training 2	8.157*	.682	363.567	.000	6.232	10.083
		Training 1	7.662*	.685	370.167	.000	5.728	9.596

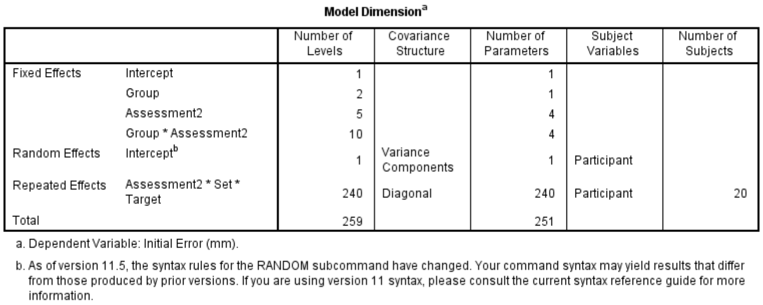
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Normalised Jerk (no units).

c. Adjustment for multiple comparisons: Bonferroni.

Initial error

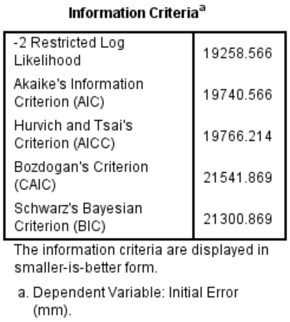


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Initial Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

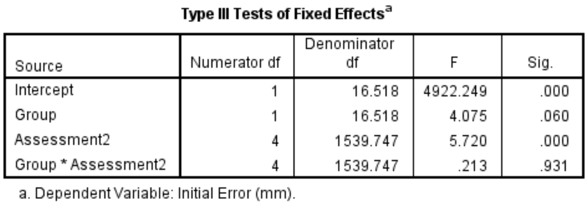


Information Criteria[a]

-2 Restricted Log Likelihood	19258.566
Akaike's Information Criterion (AIC)	19740.566
Hurvich and Tsai's Criterion (AICC)	19766.214
Bozdogan's Criterion (CAIC)	21541.869
Schwarz's Bayesian Criterion (BIC)	21300.869

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Initial Error (mm).

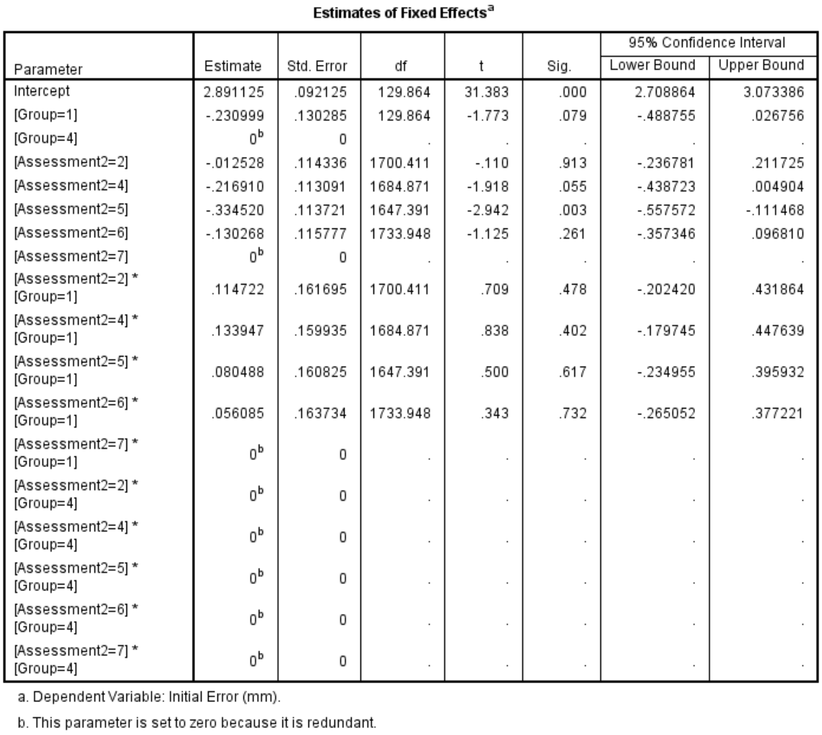


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	16.518	4922.249	.000
Group	1	16.518	4.075	.060
Assessment2	4	1539.747	5.720	.000
Group * Assessment2	4	1539.747	.213	.931

a. Dependent Variable: Initial Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

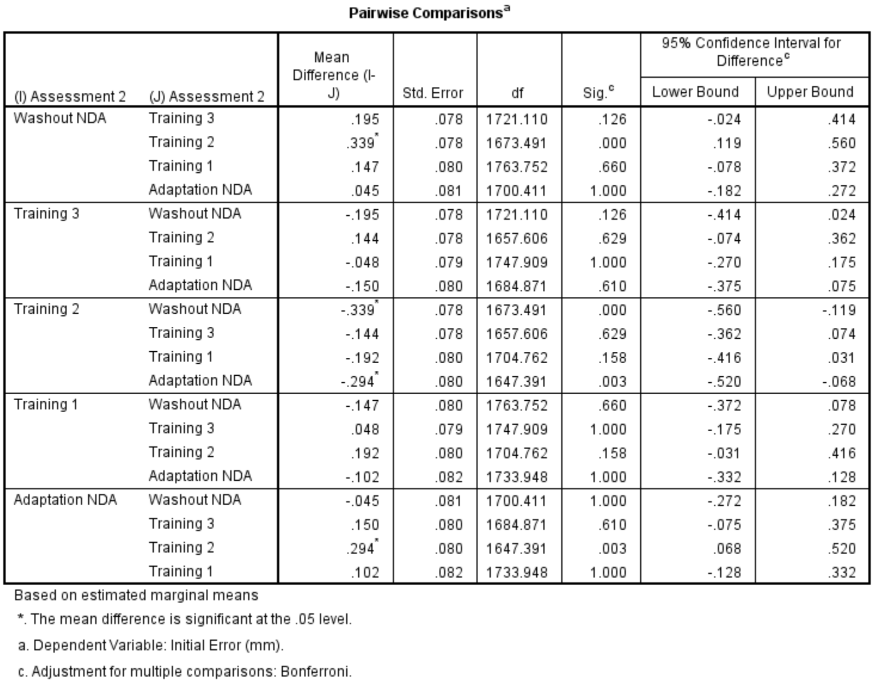


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.891125	.092125	129.864	31.383	.000	2.708864	3.073386
[Group=1]	-.230999	.130285	129.864	-1.773	.079	-.488755	.026756
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.012528	.114336	1700.411	-.110	.913	-.236781	.211725
[Assessment2=4]	-.216910	.113091	1684.871	-1.918	.055	-.438723	.004904
[Assessment2=5]	-.334520	.113721	1647.391	-2.942	.003	-.557572	-.111468
[Assessment2=6]	-.130268	.115777	1733.948	-1.125	.261	-.357346	.096810
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	.114722	.161695	1700.411	.709	.478	-.202420	.431864
[Assessment2=4] * [Group=1]	.133947	.159935	1684.871	.838	.402	-.179745	.447639
[Assessment2=5] * [Group=1]	.080488	.160825	1647.391	.500	.617	-.234955	.395932
[Assessment2=6] * [Group=1]	.056085	.163734	1733.948	.343	.732	-.265052	.377221
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Initial Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	.195	.078	1721.110	.126	-.024	.414
	Training 2	.339*	.078	1673.491	.000	.119	.560
	Training 1	.147	.080	1763.752	.660	-.078	.372
	Adaptation NDA	.045	.081	1700.411	1.000	-.182	.272
Training 3	Washout NDA	-.195	.078	1721.110	.126	-.414	.024
	Training 2	.144	.078	1657.606	.629	-.074	.362
	Training 1	-.048	.079	1747.909	1.000	-.270	.175
	Adaptation NDA	-.150	.080	1684.871	.610	-.375	.075
Training 2	Washout NDA	-.339*	.078	1673.491	.000	-.560	-.119
	Training 3	-.144	.078	1657.606	.629	-.362	.074
	Training 1	-.192	.080	1704.762	.158	-.416	.031
	Adaptation NDA	-.294*	.080	1647.391	.003	-.520	-.068
Training 1	Washout NDA	-.147	.080	1763.752	.660	-.372	.078
	Training 3	.048	.079	1747.909	1.000	-.175	.270
	Training 2	.192	.080	1704.762	.158	-.031	.416
	Adaptation NDA	-.102	.082	1733.948	1.000	-.332	.128
Adaptation NDA	Washout NDA	-.045	.081	1700.411	1.000	-.272	.182
	Training 3	.150	.080	1684.871	.610	-.075	.375
	Training 2	.294*	.080	1647.391	.003	.068	.520
	Training 1	.102	.082	1733.948	1.000	-.128	.332

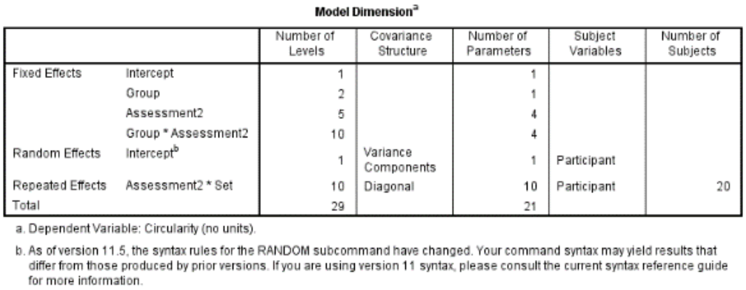
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Initial Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Circularity

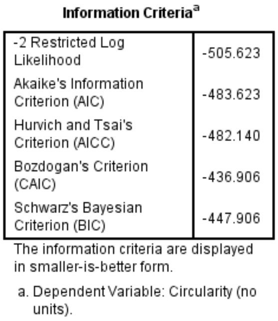


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	10	Diagonal	10	Participant	20
Total		29		21		

a. Dependent Variable: Circularity (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

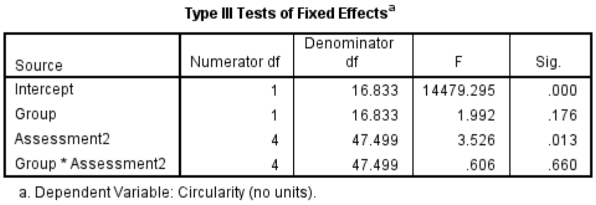


Information Criteria[a]

-2 Restricted Log Likelihood	-505.623
Akaike's Information Criterion (AIC)	-483.623
Hurvich and Tsai's Criterion (AICC)	-482.140
Bozdogan's Criterion (CAIC)	-436.906
Schwarz's Bayesian Criterion (BIC)	-447.906

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Circularity (no units).

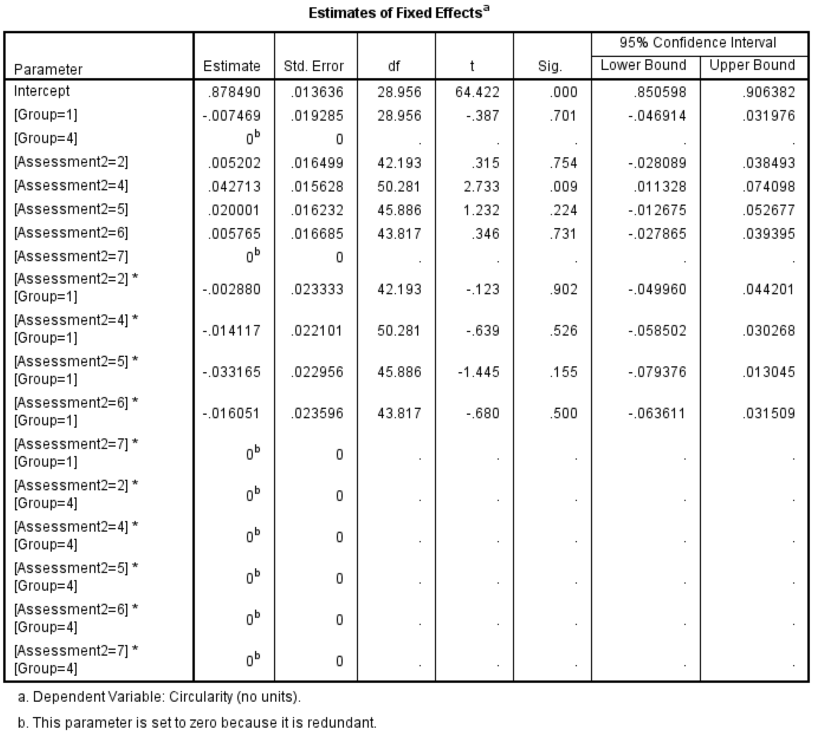


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	16.833	14479.295	.000
Group	1	16.833	1.992	.176
Assessment2	4	47.499	3.526	.013
Group * Assessment2	4	47.499	.606	.660

a. Dependent Variable: Circularity (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

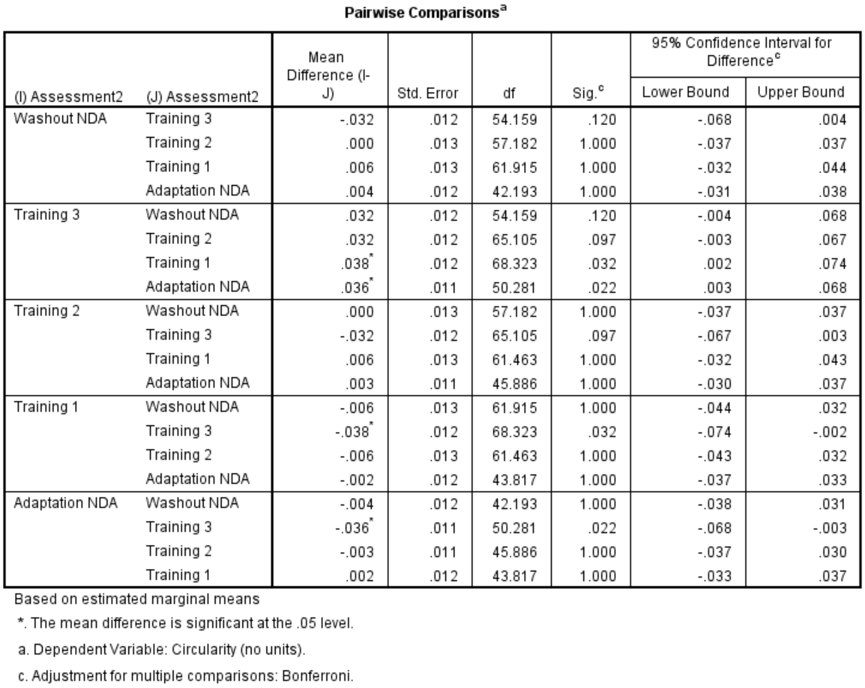


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.878490	.013636	28.956	64.422	.000	.850598	.906382
[Group=1]	-.007469	.019285	28.956	-.387	.701	-.046914	.031976
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	.005202	.016499	42.193	.315	.754	-.028089	.038493
[Assessment2=4]	.042713	.015628	50.281	2.733	.009	.011328	.074098
[Assessment2=5]	.020001	.016232	45.886	1.232	.224	-.012675	.052677
[Assessment2=6]	.005765	.016685	43.817	.346	.731	-.027865	.039395
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	-.002880	.023333	42.193	-.123	.902	-.049960	.044201
[Assessment2=4] * [Group=1]	-.014117	.022101	50.281	-.639	.526	-.058502	.030268
[Assessment2=5] * [Group=1]	-.033165	.022956	45.886	-1.445	.155	-.079376	.013045
[Assessment2=6] * [Group=1]	-.016051	.023596	43.817	-.680	.500	-.063611	.031509
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Circularity (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment2	(J) Assessment2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c] Lower Bound	Upper Bound
Washout NDA	Training 3	-.032	.012	54.159	.120	-.068	.004
	Training 2	.000	.013	57.182	1.000	-.037	.037
	Training 1	.006	.013	61.915	1.000	-.032	.044
	Adaptation NDA	.004	.012	42.193	1.000	-.031	.038
Training 3	Washout NDA	.032	.012	54.159	.120	-.004	.068
	Training 2	.032	.012	65.105	.097	-.003	.067
	Training 1	.038*	.012	68.323	.032	.002	.074
	Adaptation NDA	.036*	.011	50.281	.022	.003	.068
Training 2	Washout NDA	.000	.013	57.182	1.000	-.037	.037
	Training 3	-.032	.012	65.105	.097	-.067	.003
	Training 1	.006	.013	61.463	1.000	-.032	.043
	Adaptation NDA	.003	.011	45.886	1.000	-.030	.037
Training 1	Washout NDA	-.006	.013	61.915	1.000	-.044	.032
	Training 3	-.038*	.012	68.323	.032	-.074	-.002
	Training 2	-.006	.013	61.463	1.000	-.043	.032
	Adaptation NDA	-.002	.012	43.817	1.000	-.037	.033
Adaptation NDA	Washout NDA	-.004	.012	42.193	1.000	-.038	.031
	Training 3	-.036*	.011	50.281	.022	-.068	-.003
	Training 2	-.003	.011	45.886	1.000	-.037	.030
	Training 1	.002	.012	43.817	1.000	-.033	.037

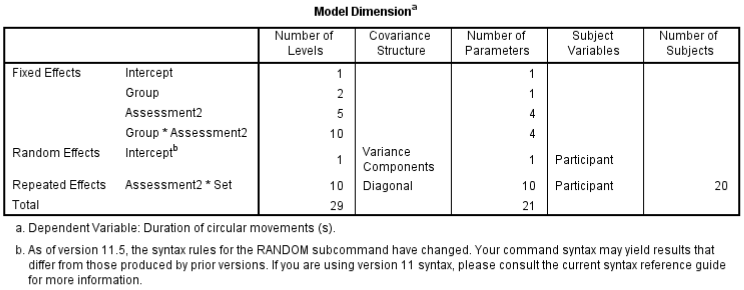
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Circularity (no units).

c. Adjustment for multiple comparisons: Bonferroni.

Duration of circular movements

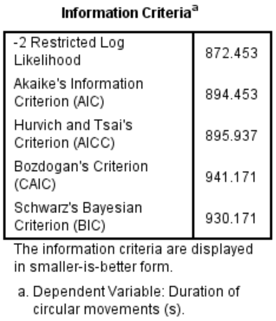


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	10	Diagonal	10	Participant	20
Total		29		21		

a. Dependent Variable: Duration of circular movements (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

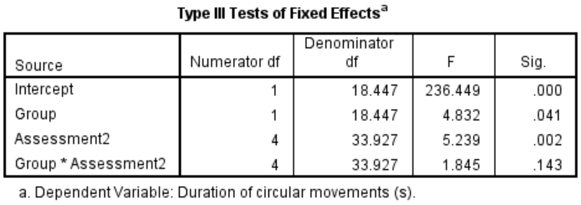


Information Criteria[a]

-2 Restricted Log Likelihood	872.453
Akaike's Information Criterion (AIC)	894.453
Hurvich and Tsai's Criterion (AICC)	895.937
Bozdogan's Criterion (CAIC)	941.171
Schwarz's Bayesian Criterion (BIC)	930.171

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration of circular movements (s).

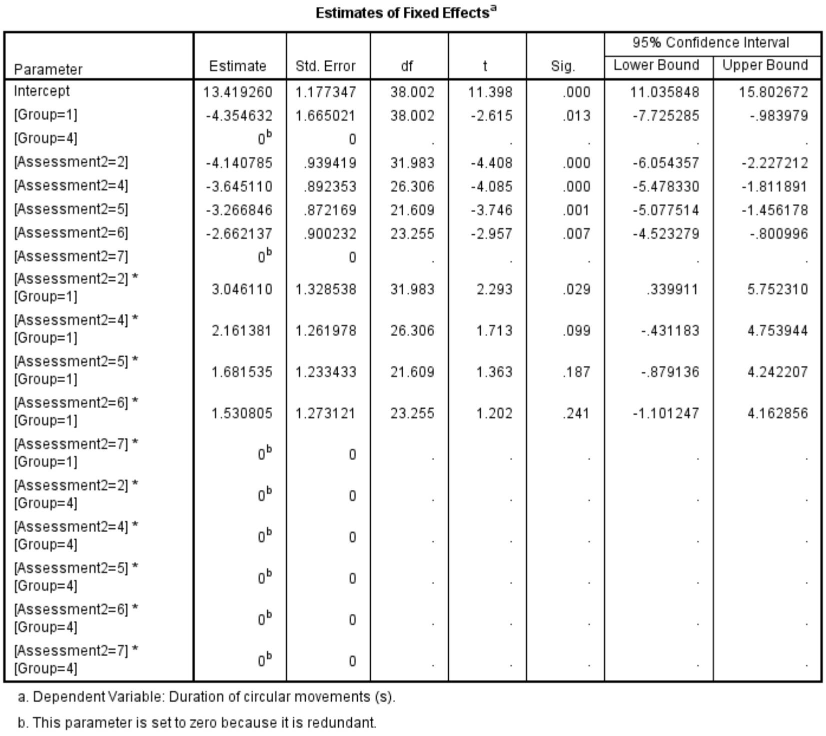


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.447	236.449	.000
Group	1	18.447	4.832	.041
Assessment2	4	33.927	5.239	.002
Group * Assessment2	4	33.927	1.845	.143

a. Dependent Variable: Duration of circular movements (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

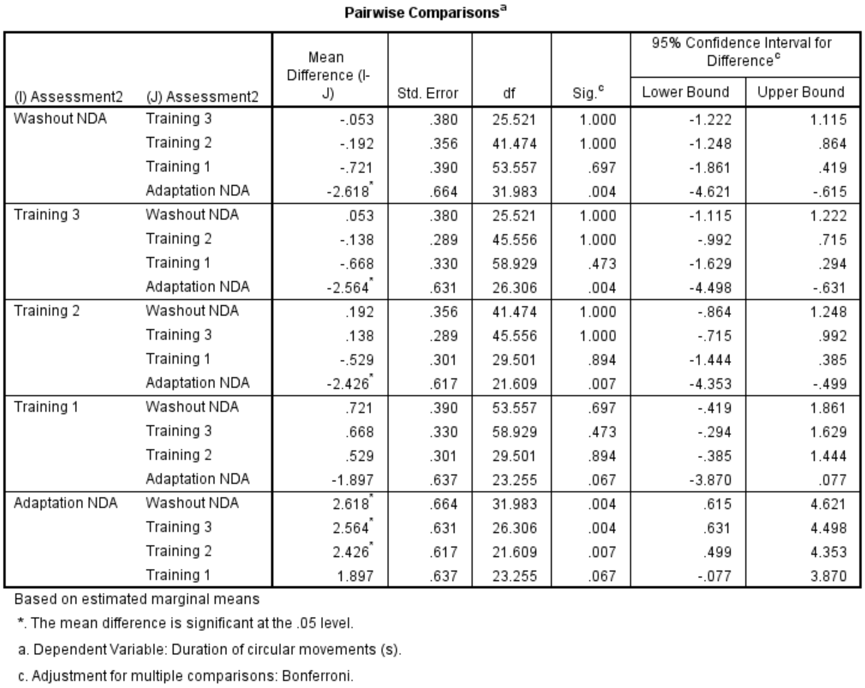


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	13.419260	1.177347	38.002	11.398	.000	11.035848	15.802672
[Group=1]	-4.354632	1.665021	38.002	-2.615	.013	-7.725285	-.983979
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-4.140785	.939419	31.983	-4.408	.000	-6.054357	-2.227212
[Assessment2=4]	-3.645110	.892353	26.306	-4.085	.000	-5.478330	-1.811891
[Assessment2=5]	-3.266846	.872169	21.609	-3.746	.001	-5.077514	-1.456178
[Assessment2=6]	-2.662137	.900232	23.255	-2.957	.007	-4.523279	-.800996
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	3.046110	1.328538	31.983	2.293	.029	.339911	5.752310
[Assessment2=4] * [Group=1]	2.161381	1.261978	26.306	1.713	.099	-.431183	4.753944
[Assessment2=5] * [Group=1]	1.681535	1.233433	21.609	1.363	.187	-.879136	4.242207
[Assessment2=6] * [Group=1]	1.530805	1.273121	23.255	1.202	.241	-1.101247	4.162856
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration of circular movements (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment2	(J) Assessment2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	-.053	.380	25.521	1.000	-1.222	1.115
	Training 2	-.192	.356	41.474	1.000	-1.248	.864
	Training 1	-.721	.390	53.557	.697	-1.861	.419
	Adaptation NDA	-2.618*	.664	31.983	.004	-4.621	-.615
Training 3	Washout NDA	.053	.380	25.521	1.000	-1.115	1.222
	Training 2	-.138	.289	45.556	1.000	-.992	.715
	Training 1	-.668	.330	58.929	.473	-1.629	.294
	Adaptation NDA	-2.564*	.631	26.306	.004	-4.498	-.631
Training 2	Washout NDA	.192	.356	41.474	1.000	-.864	1.248
	Training 3	.138	.289	45.556	1.000	-.715	.992
	Training 1	-.529	.301	29.501	.894	-1.444	.385
	Adaptation NDA	-2.426*	.617	21.609	.007	-4.353	-.499
Training 1	Washout NDA	.721	.390	53.557	.697	-.419	1.861
	Training 3	.668	.330	58.929	.473	-.294	1.629
	Training 2	.529	.301	29.501	.894	-.385	1.444
	Adaptation NDA	-1.897	.637	23.255	.067	-3.870	.077
Adaptation NDA	Washout NDA	2.618*	.664	31.983	.004	.615	4.621
	Training 3	2.564*	.631	26.306	.004	.631	4.498
	Training 2	2.426*	.617	21.609	.007	.499	4.353
	Training 1	1.897	.637	23.255	.067	-.077	3.870

Based on estimated marginal means

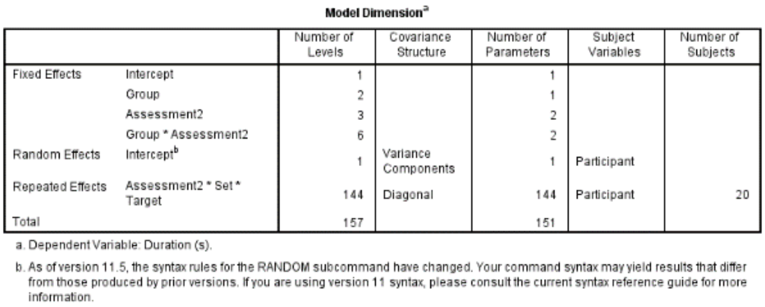
*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration of circular movements (s).

c. Adjustment for multiple comparisons: Bonferroni.

Analysis of the DA

Duration

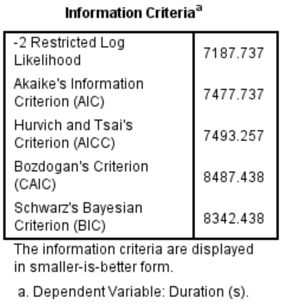


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Duration (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

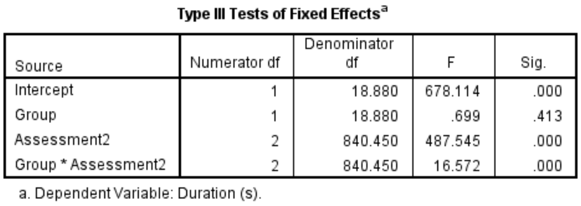


Information Criteria[a]

-2 Restricted Log Likelihood	7187.737
Akaike's Information Criterion (AIC)	7477.737
Hurvich and Tsai's Criterion (AICC)	7493.257
Bozdogan's Criterion (CAIC)	8487.438
Schwarz's Bayesian Criterion (BIC)	8342.438

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration (s).

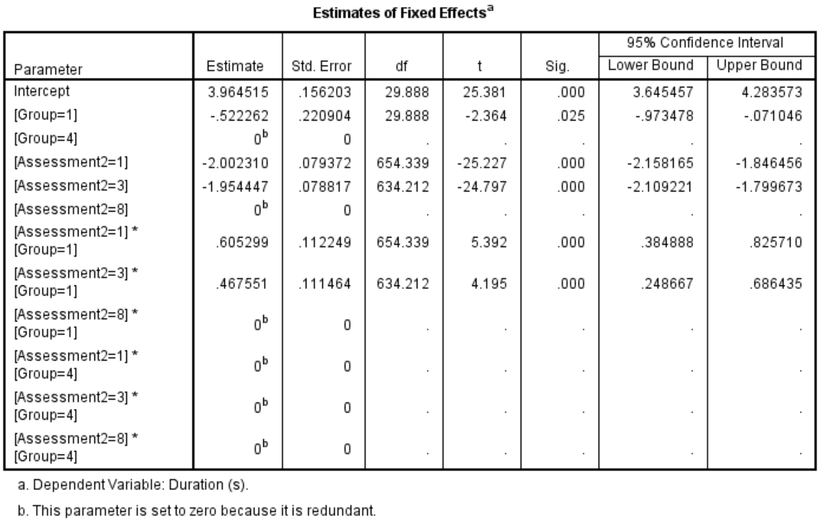


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.880	678.114	.000
Group	1	18.880	.699	.413
Assessment2	2	840.450	487.545	.000
Group * Assessment2	2	840.450	16.572	.000

a. Dependent Variable: Duration (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

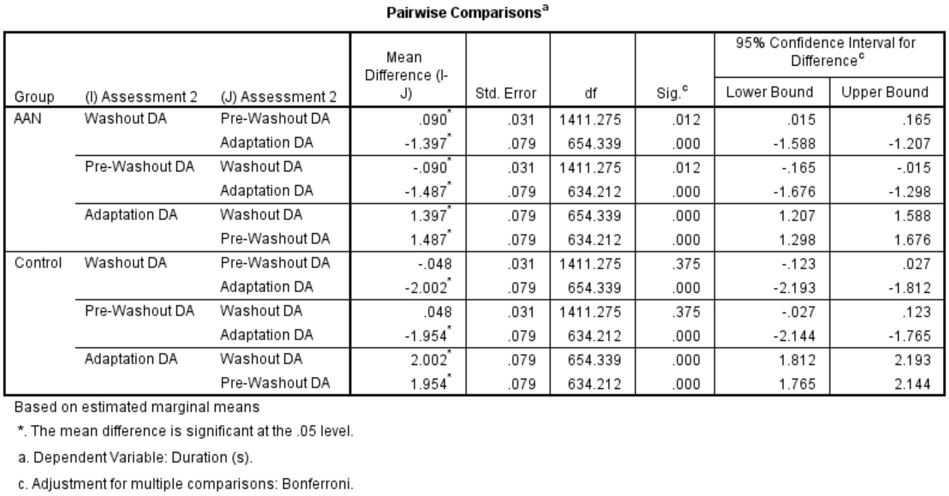


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	3.964515	.156203	29.888	25.381	.000	3.645457	4.283573
[Group=1]	-.522262	.220904	29.888	-2.364	.025	-.973478	-.071046
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-2.002310	.079372	654.339	-25.227	.000	-2.158165	-1.846456
[Assessment2=3]	-1.954447	.078817	634.212	-24.797	.000	-2.109221	-1.799673
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	.605299	.112249	654.339	5.392	.000	.384888	.825710
[Assessment2=3] * [Group=1]	.467551	.111464	634.212	4.195	.000	.248667	.686435
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
AAN	Washout DA	Pre-Washout DA	.090*	.031	1411.275	.012	.015	.165
		Adaptation DA	-1.397*	.079	654.339	.000	-1.588	-1.207
	Pre-Washout DA	Washout DA	-.090*	.031	1411.275	.012	-.165	-.015
		Adaptation DA	-1.487*	.079	634.212	.000	-1.676	-1.298
	Adaptation DA	Washout DA	1.397*	.079	654.339	.000	1.207	1.588
		Pre-Washout DA	1.487*	.079	634.212	.000	1.298	1.676
Control	Washout DA	Pre-Washout DA	-.048	.031	1411.275	.375	-.123	.027
		Adaptation DA	-2.002*	.079	654.339	.000	-2.193	-1.812
	Pre-Washout DA	Washout DA	.048	.031	1411.275	.375	-.027	.123
		Adaptation DA	-1.954*	.079	634.212	.000	-2.144	-1.765
	Adaptation DA	Washout DA	2.002*	.079	654.339	.000	1.812	2.193
		Pre-Washout DA	1.954*	.079	634.212	.000	1.765	2.144

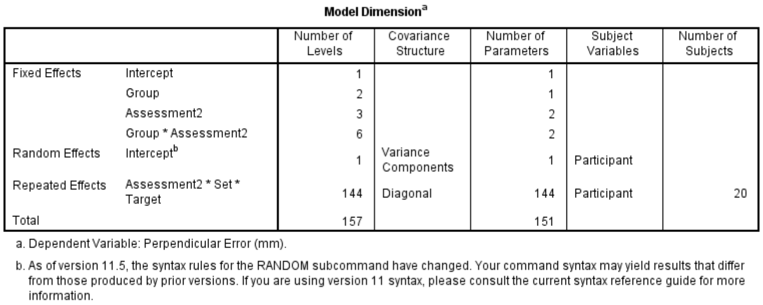
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration (s).

c. Adjustment for multiple comparisons: Bonferroni.

Perpendicular error

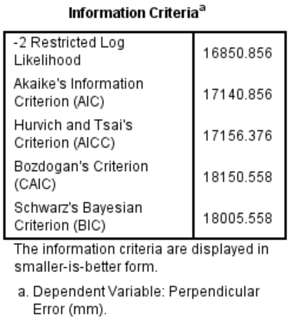


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Perpendicular Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

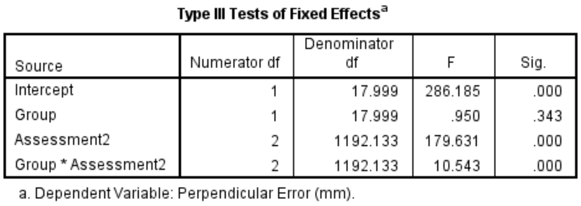


Information Criteria[a]

-2 Restricted Log Likelihood	16850.856
Akaike's Information Criterion (AIC)	17140.856
Hurvich and Tsai's Criterion (AICC)	17156.376
Bozdogan's Criterion (CAIC)	18150.558
Schwarz's Bayesian Criterion (BIC)	18005.558

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Perpendicular Error (mm).

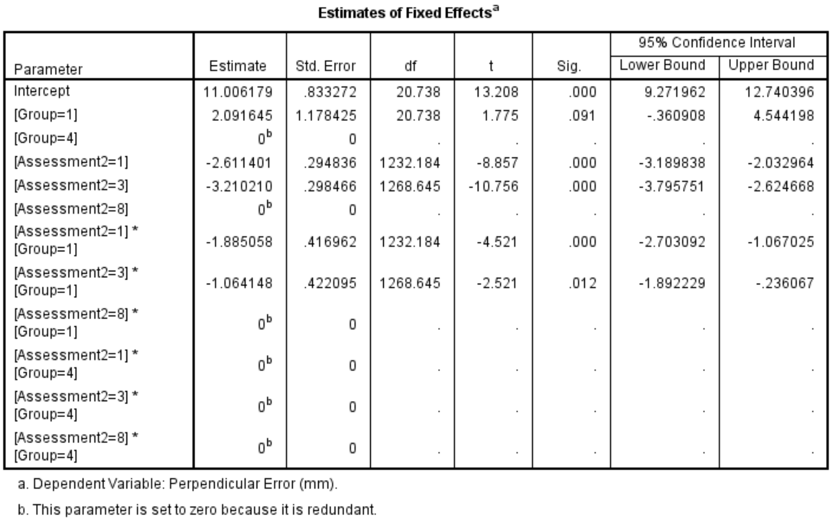


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.999	286.185	.000
Group	1	17.999	.950	.343
Assessment2	2	1192.133	179.631	.000
Group * Assessment2	2	1192.133	10.543	.000

a. Dependent Variable: Perpendicular Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

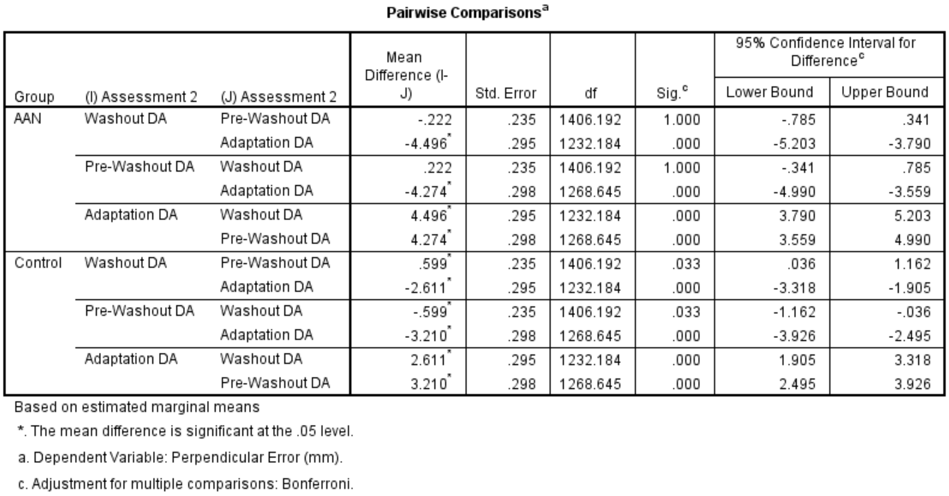


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	11.006179	.833272	20.738	13.208	.000	9.271962	12.740396
[Group=1]	2.091645	1.178425	20.738	1.775	.091	-.360908	4.544198
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-2.611401	.294836	1232.184	-8.857	.000	-3.189838	-2.032964
[Assessment2=3]	-3.210210	.298466	1268.645	-10.756	.000	-3.795751	-2.624668
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	-1.885058	.416962	1232.184	-4.521	.000	-2.703092	-1.067025
[Assessment2=3] * [Group=1]	-1.064148	.422095	1268.645	-2.521	.012	-1.892229	-.236067
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Perpendicular Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
AAN	Washout DA	Pre-Washout DA	-.222	.235	1406.192	1.000	-.785	.341
		Adaptation DA	-4.496*	.295	1232.184	.000	-5.203	-3.790
	Pre-Washout DA	Washout DA	.222	.235	1406.192	1.000	-.341	.785
		Adaptation DA	-4.274*	.298	1268.645	.000	-4.990	-3.559
	Adaptation DA	Washout DA	4.496*	.295	1232.184	.000	3.790	5.203
		Pre-Washout DA	4.274*	.298	1268.645	.000	3.559	4.990
Control	Washout DA	Pre-Washout DA	.599*	.235	1406.192	.033	.036	1.162
		Adaptation DA	-2.611*	.295	1232.184	.000	-3.318	-1.905
	Pre-Washout DA	Washout DA	-.599*	.235	1406.192	.033	-1.162	-.036
		Adaptation DA	-3.210*	.298	1268.645	.000	-3.926	-2.495
	Adaptation DA	Washout DA	2.611*	.295	1232.184	.000	1.905	3.318
		Pre-Washout DA	3.210*	.298	1268.645	.000	2.495	3.926

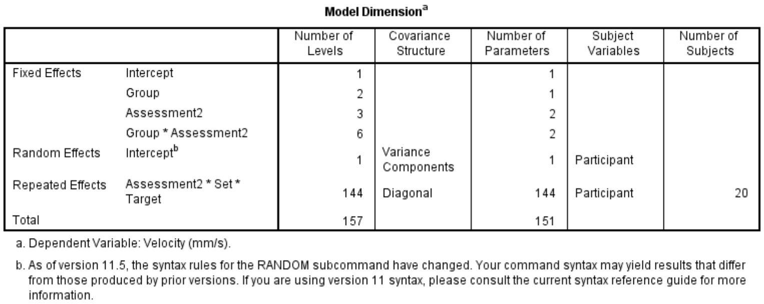
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Perpendicular Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Mean velocity

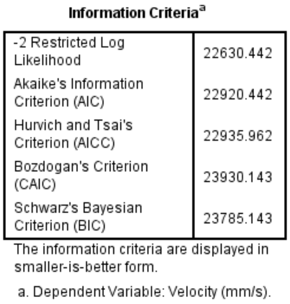


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Velocity (mm/s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

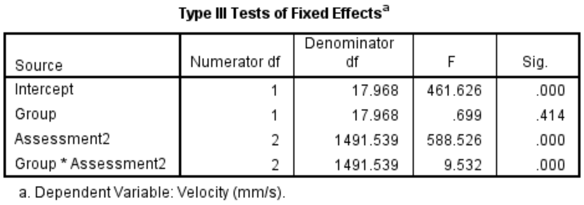


Information Criteria[a]

-2 Restricted Log Likelihood	22630.442
Akaike's Information Criterion (AIC)	22920.442
Hurvich and Tsai's Criterion (AICC)	22935.962
Bozdogan's Criterion (CAIC)	23930.143
Schwarz's Bayesian Criterion (BIC)	23785.143

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Velocity (mm/s).

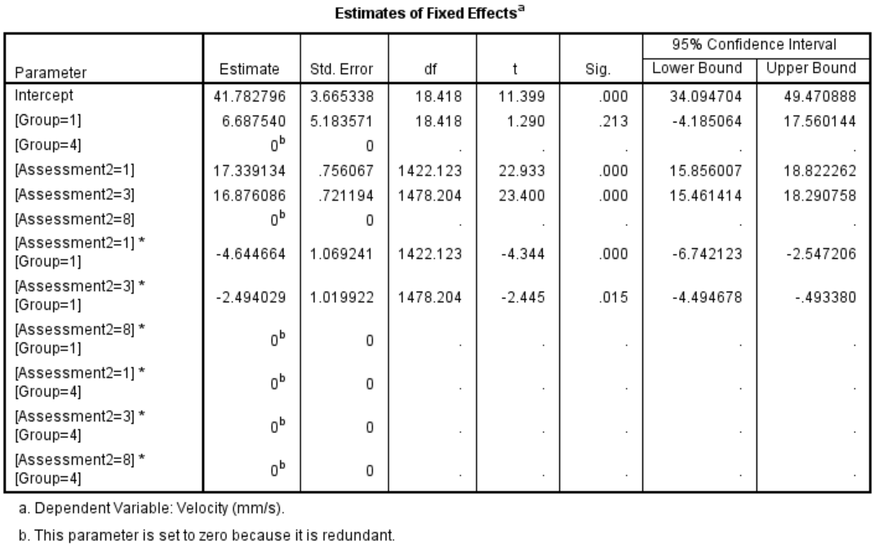


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.968	461.626	.000
Group	1	17.968	.699	.414
Assessment2	2	1491.539	588.526	.000
Group * Assessment2	2	1491.539	9.532	.000

a. Dependent Variable: Velocity (mm/s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

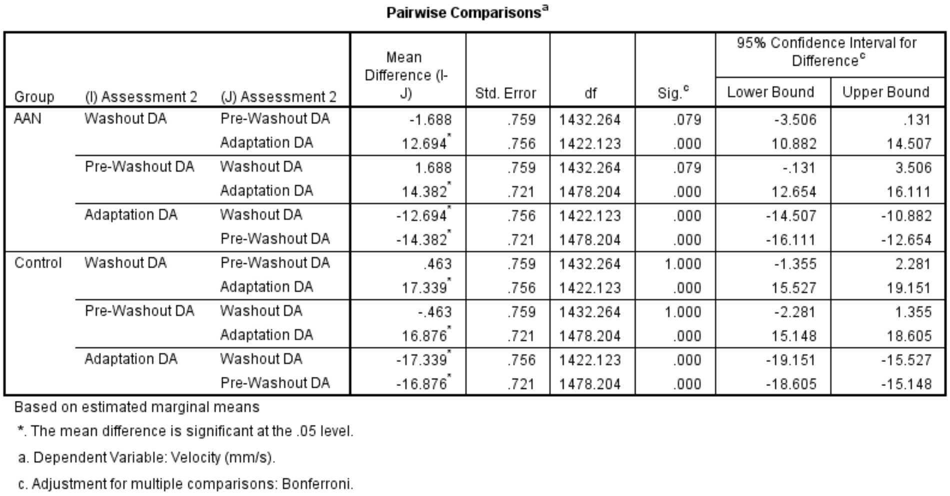


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	41.782796	3.665338	18.418	11.399	.000	34.094704	49.470888
[Group=1]	6.687540	5.183571	18.418	1.290	.213	-4.185064	17.560144
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	17.339134	.756067	1422.123	22.933	.000	15.856007	18.822262
[Assessment2=3]	16.876086	.721194	1478.204	23.400	.000	15.461414	18.290758
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	-4.644664	1.069241	1422.123	-4.344	.000	-6.742123	-2.547206
[Assessment2=3] * [Group=1]	-2.494029	1.019922	1478.204	-2.445	.015	-4.494678	-.493380
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Velocity (mm/s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
AAN	Washout DA	Pre-Washout DA	-1.688	.759	1432.264	.079	-3.506	.131
		Adaptation DA	12.694*	.756	1422.123	.000	10.882	14.507
	Pre-Washout DA	Washout DA	1.688	.759	1432.264	.079	-.131	3.506
		Adaptation DA	14.382*	.721	1478.204	.000	12.654	16.111
	Adaptation DA	Washout DA	-12.694*	.756	1422.123	.000	-14.507	-10.882
		Pre-Washout DA	-14.382*	.721	1478.204	.000	-16.111	-12.654
Control	Washout DA	Pre-Washout DA	.463	.759	1432.264	1.000	-1.355	2.281
		Adaptation DA	17.339*	.756	1422.123	.000	15.527	19.151
	Pre-Washout DA	Washout DA	-.463	.759	1432.264	1.000	-2.281	1.355
		Adaptation DA	16.876*	.721	1478.204	.000	15.148	18.605
	Adaptation DA	Washout DA	-17.339*	.756	1422.123	.000	-19.151	-15.527
		Pre-Washout DA	-16.876*	.721	1478.204	.000	-18.605	-15.148

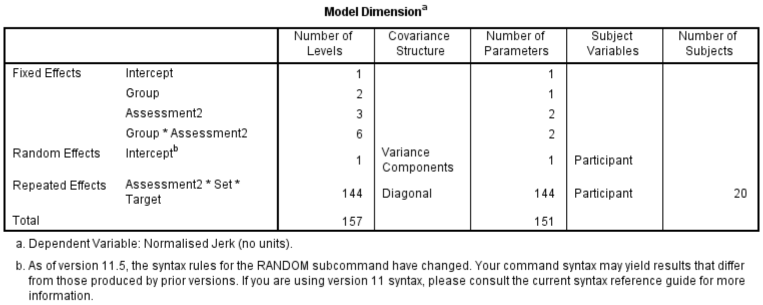
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Velocity (mm/s).

c. Adjustment for multiple comparisons: Bonferroni.

Normalised jerk

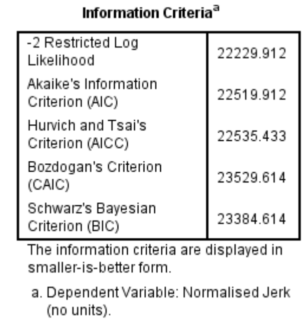


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Normalised Jerk (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

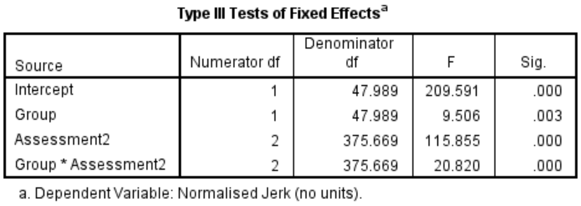


Information Criteria[a]

-2 Restricted Log Likelihood	22229.912
Akaike's Information Criterion (AIC)	22519.912
Hurvich and Tsai's Criterion (AICC)	22535.433
Bozdogan's Criterion (CAIC)	23529.614
Schwarz's Bayesian Criterion (BIC)	23384.614

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Normalised Jerk (no units).

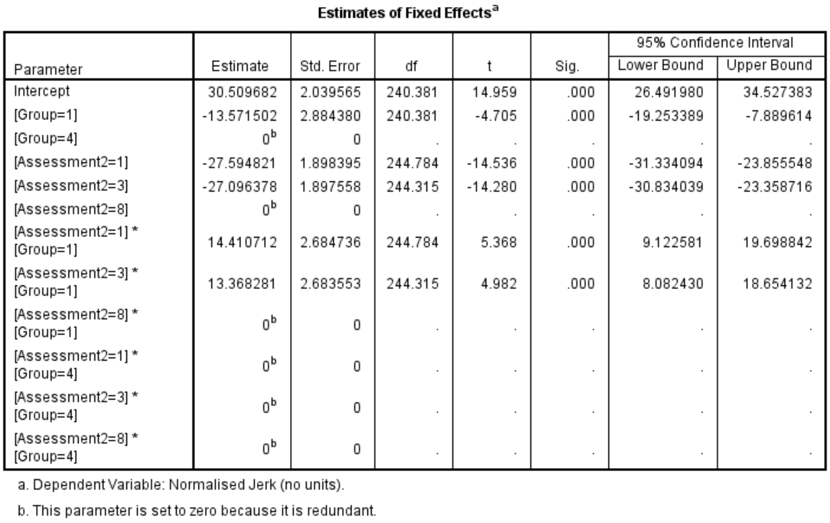


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	47.989	209.591	.000
Group	1	47.989	9.506	.003
Assessment2	2	375.669	115.855	.000
Group * Assessment2	2	375.669	20.820	.000

a. Dependent Variable: Normalised Jerk (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

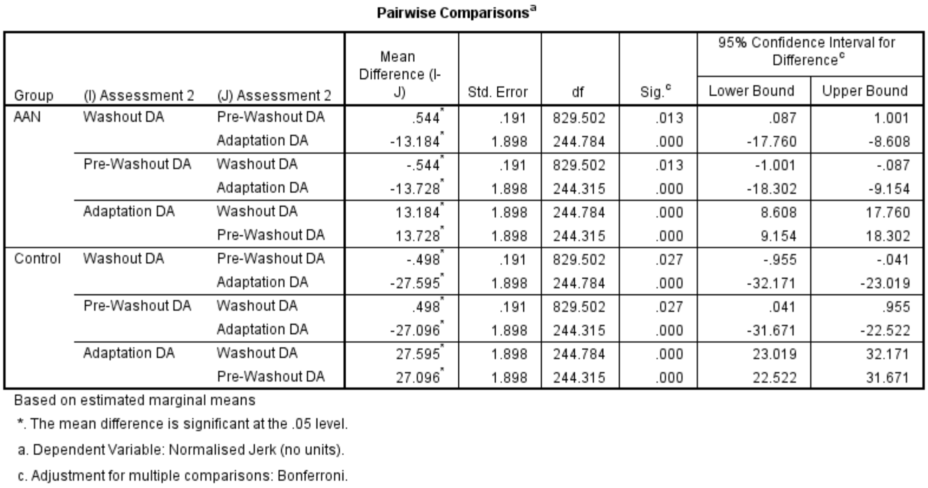


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	30.509682	2.039565	240.381	14.959	.000	26.491980	34.527383
[Group=1]	-13.571502	2.884380	240.381	-4.705	.000	-19.253389	-7.889614
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-27.594821	1.898395	244.784	-14.536	.000	-31.334094	-23.855548
[Assessment2=3]	-27.096378	1.897558	244.315	-14.280	.000	-30.834039	-23.358716
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	14.410712	2.684736	244.784	5.368	.000	9.122581	19.698842
[Assessment2=3] * [Group=1]	13.368281	2.683553	244.315	4.982	.000	8.082430	18.654132
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Normalised Jerk (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
AAN	Washout DA	Pre-Washout DA	.544*	.191	829.502	.013	.087	1.001
		Adaptation DA	-13.184*	1.898	244.784	.000	-17.760	-8.608
	Pre-Washout DA	Washout DA	-.544*	.191	829.502	.013	-1.001	-.087
		Adaptation DA	-13.728*	1.898	244.315	.000	-18.302	-9.154
	Adaptation DA	Washout DA	13.184*	1.898	244.784	.000	8.608	17.760
		Pre-Washout DA	13.728*	1.898	244.315	.000	9.154	18.302
Control	Washout DA	Pre-Washout DA	-.498*	.191	829.502	.027	-.955	-.041
		Adaptation DA	-27.595*	1.898	244.784	.000	-32.171	-23.019
	Pre-Washout DA	Washout DA	.498*	.191	829.502	.027	.041	.955
		Adaptation DA	-27.096*	1.898	244.315	.000	-31.671	-22.522
	Adaptation DA	Washout DA	27.595*	1.898	244.784	.000	23.019	32.171
		Pre-Washout DA	27.096*	1.898	244.315	.000	22.522	31.671

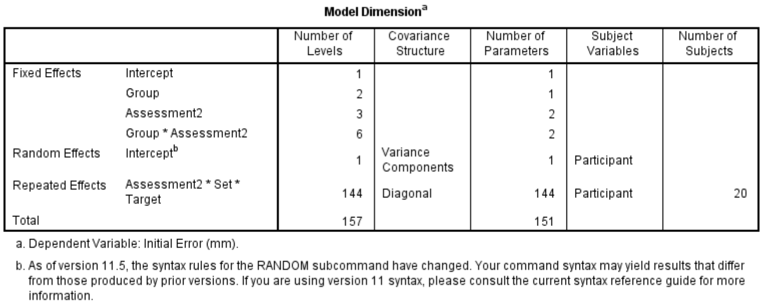
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Normalised Jerk (no units).

c. Adjustment for multiple comparisons: Bonferroni.

Initial error

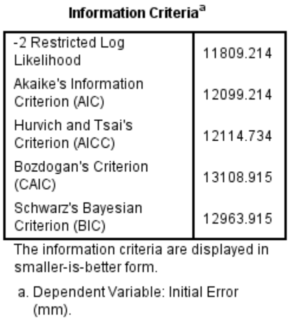


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Initial Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

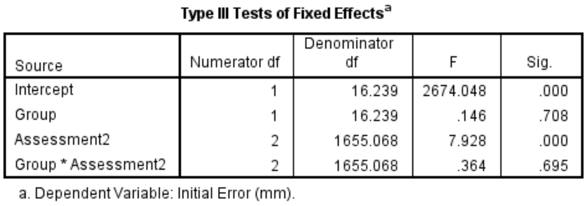


Information Criteria[a]

-2 Restricted Log Likelihood	11809.214
Akaike's Information Criterion (AIC)	12099.214
Hurvich and Tsai's Criterion (AICC)	12114.734
Bozdogan's Criterion (CAIC)	13108.915
Schwarz's Bayesian Criterion (BIC)	12963.915

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Initial Error (mm).

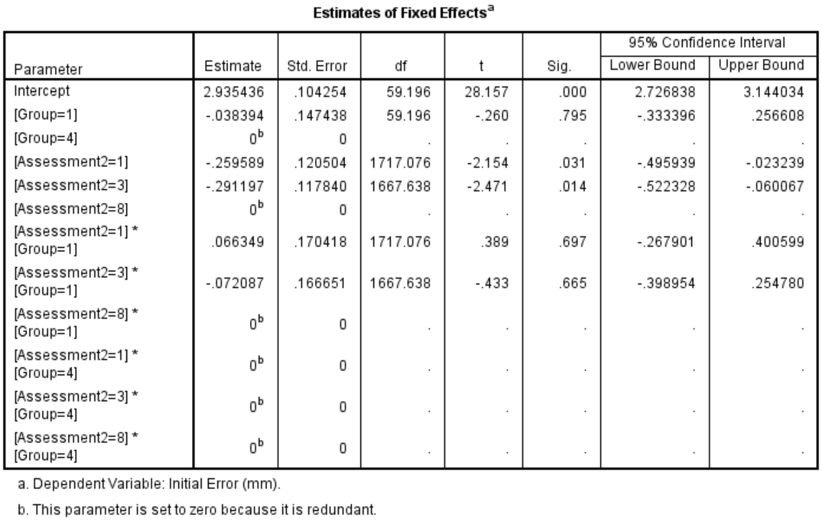


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	16.239	2674.048	.000
Group	1	16.239	.146	.708
Assessment2	2	1655.068	7.928	.000
Group * Assessment2	2	1655.068	.364	.695

a. Dependent Variable: Initial Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

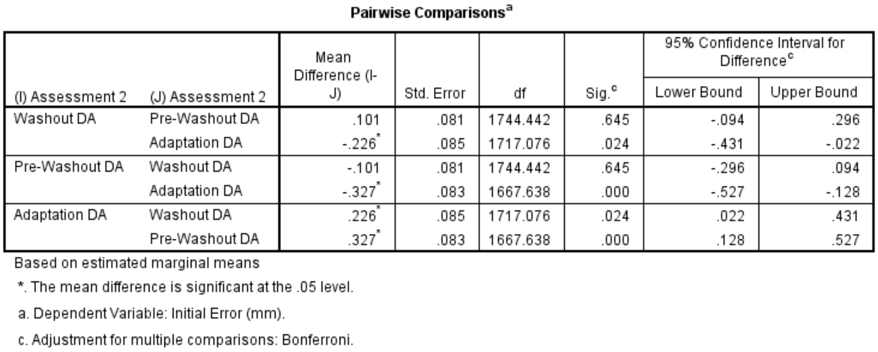


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.935436	.104254	59.196	28.157	.000	2.726838	3.144034
[Group=1]	-.038394	.147438	59.196	-.260	.795	-.333396	.256608
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-.259589	.120504	1717.076	-2.154	.031	-.495939	-.023239
[Assessment2=3]	-.291197	.117840	1667.638	-2.471	.014	-.522328	-.060067
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	.066349	.170418	1717.076	.389	.697	-.267901	.400599
[Assessment2=3] * [Group=1]	-.072087	.166651	1667.638	-.433	.665	-.398954	.254780
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Initial Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c] Lower Bound	95% Confidence Interval for Difference[c] Upper Bound
Washout DA	Pre-Washout DA	.101	.081	1744.442	.645	-.094	.296
	Adaptation DA	-.226*	.085	1717.076	.024	-.431	-.022
Pre-Washout DA	Washout DA	-.101	.081	1744.442	.645	-.296	.094
	Adaptation DA	-.327*	.083	1667.638	.000	-.527	-.128
Adaptation DA	Washout DA	.226*	.085	1717.076	.024	.022	.431
	Pre-Washout DA	.327*	.083	1667.638	.000	.128	.527

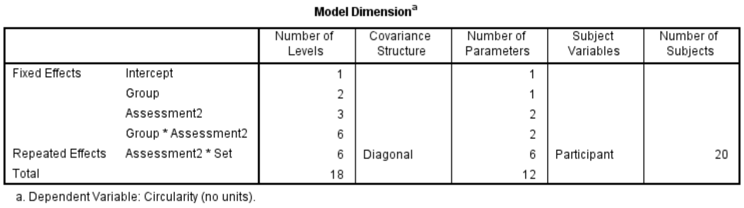
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Initial Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

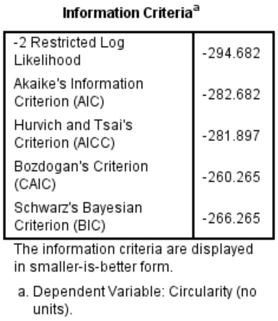
Circularity



Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Repeated Effects	Assessment2 * Set	6	Diagonal	6	Participant	20
Total		18		12		

a. Dependent Variable: Circularity (no units).

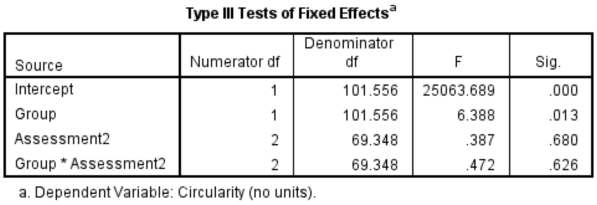


Information Criteria[a]

-2 Restricted Log Likelihood	-294.682
Akaike's Information Criterion (AIC)	-282.682
Hurvich and Tsai's Criterion (AICC)	-281.897
Bozdogan's Criterion (CAIC)	-260.265
Schwarz's Bayesian Criterion (BIC)	-266.265

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Circularity (no units).

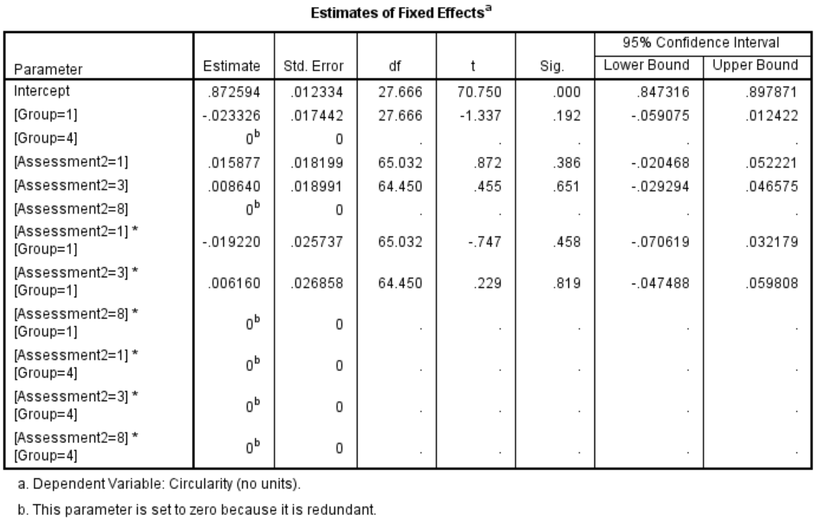


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	101.556	25063.689	.000
Group	1	101.556	6.388	.013
Assessment2	2	69.348	.387	.680
Group * Assessment2	2	69.348	.472	.626

a. Dependent Variable: Circularity (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

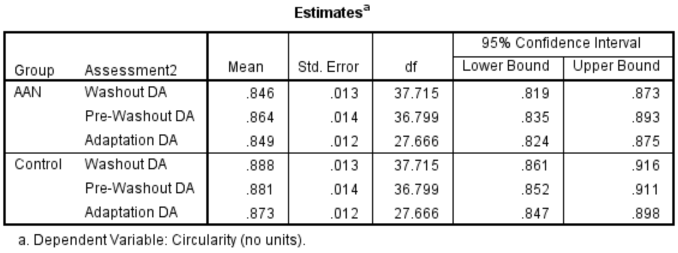


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.872594	.012334	27.666	70.750	.000	.847316	.897871
[Group=1]	-.023326	.017442	27.666	-1.337	.192	-.059075	.012422
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	.015877	.018199	65.032	.872	.386	-.020468	.052221
[Assessment2=3]	.008640	.018991	64.450	.455	.651	-.029294	.046575
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	-.019220	.025737	65.032	-.747	.458	-.070619	.032179
[Assessment2=3] * [Group=1]	.006160	.026858	64.450	.229	.819	-.047488	.059808
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Circularity (no units).

b. This parameter is set to zero because it is redundant.

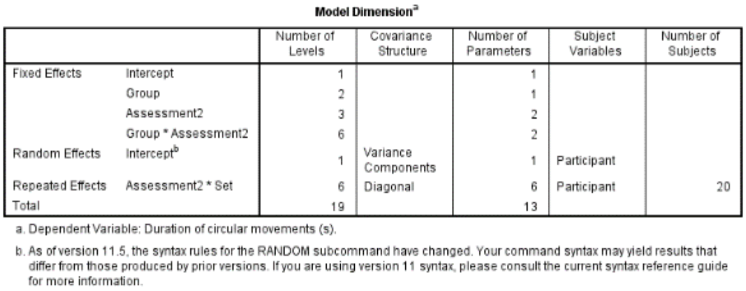


Estimates[a]

Group	Assessment2	Mean	Std. Error	df	95% Confidence Interval	
					Lower Bound	Upper Bound
AAN	Washout DA	.846	.013	37.715	.819	.873
	Pre-Washout DA	.864	.014	36.799	.835	.893
	Adaptation DA	.849	.012	27.666	.824	.875
Control	Washout DA	.888	.013	37.715	.861	.916
	Pre-Washout DA	.881	.014	36.799	.852	.911
	Adaptation DA	.873	.012	27.666	.847	.898

a. Dependent Variable: Circularity (no units).

Duration of circular movements

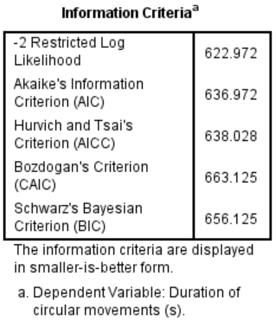


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	6	Diagonal	6	Participant	20
Total		19		13		

a. Dependent Variable: Duration of circular movements (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

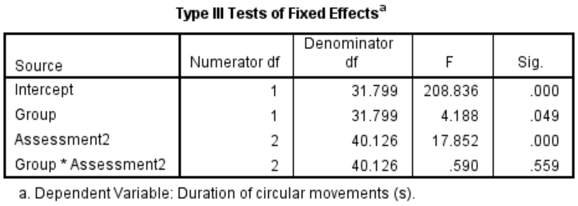


Information Criteria[a]

-2 Restricted Log Likelihood	622.972
Akaike's Information Criterion (AIC)	636.972
Hurvich and Tsai's Criterion (AICC)	638.028
Bozdogan's Criterion (CAIC)	663.125
Schwarz's Bayesian Criterion (BIC)	656.125

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration of circular movements (s).

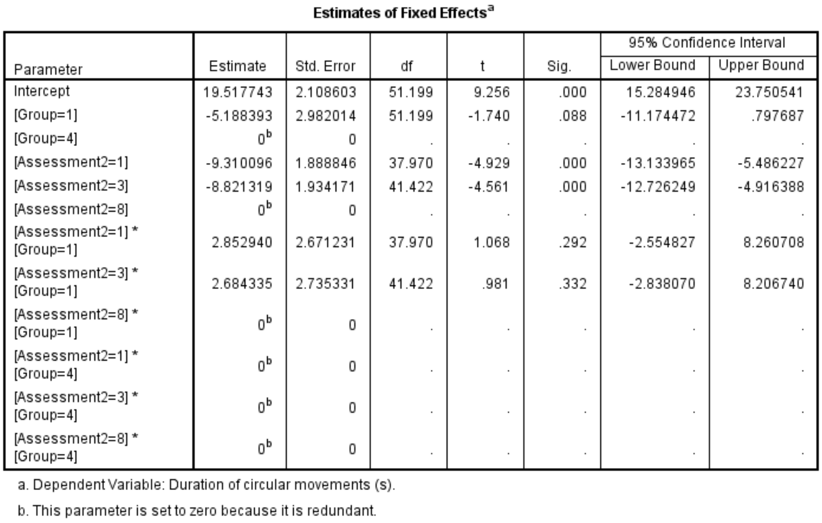


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	31.799	208.836	.000
Group	1	31.799	4.188	.049
Assessment2	2	40.126	17.852	.000
Group * Assessment2	2	40.126	.590	.559

a. Dependent Variable: Duration of circular movements (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



Estimates of Fixed Effects[a]

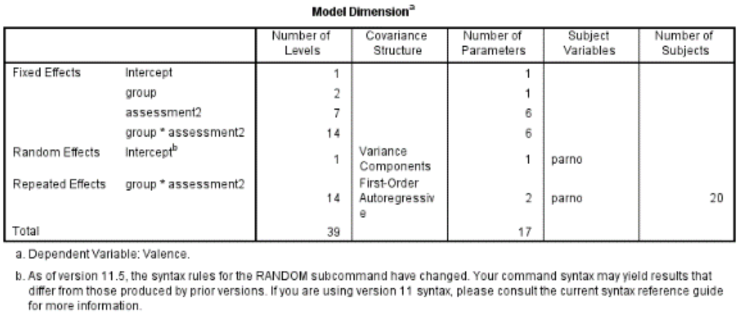
Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	19.517743	2.108603	51.199	9.256	.000	15.284946	23.750541
[Group=1]	-5.188393	2.982014	51.199	-1.740	.088	-11.174472	.797687
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-9.310096	1.888846	37.970	-4.929	.000	-13.133965	-5.486227
[Assessment2=3]	-8.821319	1.934171	41.422	-4.561	.000	-12.726249	-4.916388
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	2.852940	2.671231	37.970	1.068	.292	-2.554827	8.260708
[Assessment2=3] * [Group=1]	2.684335	2.735331	41.422	.981	.332	-2.838070	8.206740
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration of circular movements (s).

b. This parameter is set to zero because it is redundant.

Analysis of the SAM questionnaire

Valence

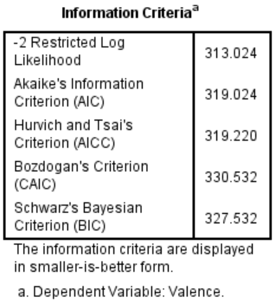


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	2		1		
	assessment2	7		6		
	group * assessment2	14		6		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	14	First-Order Autoregressive	2	parno	20
Total		39		17		

a. Dependent Variable: Valence.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

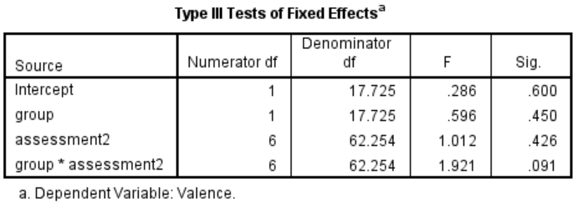


Information Criteria[a]

-2 Restricted Log Likelihood	313.024
Akaike's Information Criterion (AIC)	319.024
Hurvich and Tsai's Criterion (AICC)	319.220
Bozdogan's Criterion (CAIC)	330.532
Schwarz's Bayesian Criterion (BIC)	327.532

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Valence.

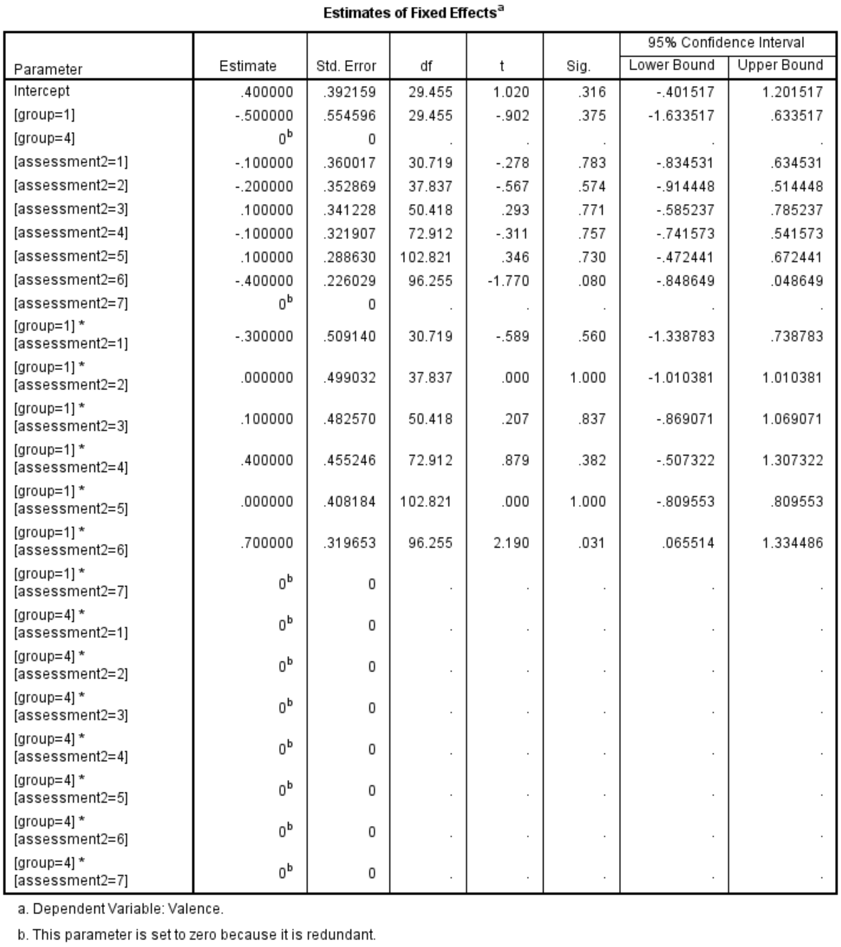


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.725	.286	.600
group	1	17.725	.596	.450
assessment2	6	62.254	1.012	.426
group * assessment2	6	62.254	1.921	.091

a. Dependent Variable: Valence.

Group 0: EAA	Assessment 8: Adaptation DA
Group 1: AAN	Assessment 7: Adaptation NDA
Group 2: EAP	Assessment 6: Training 1
Group 4: Control	Assessment 5: Training 2
	Assessment 4: Training 3
	Assessment 3: Pre-washout
	Assessment 2: Washout NDA
	Assessment 1: Washout DA



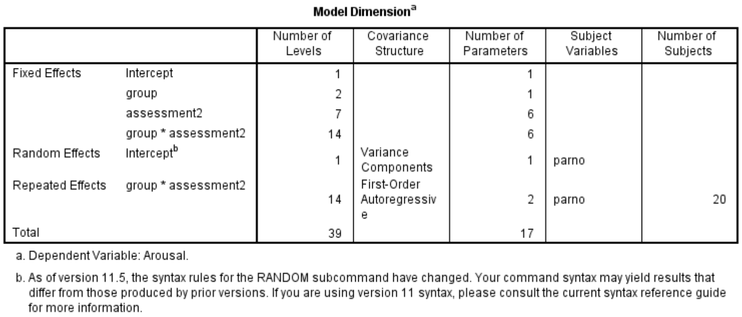
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.400000	.392159	29.455	1.020	.316	-.401517	1.201517
[group=1]	-.500000	.554596	29.455	-.902	.375	-1.633517	.633517
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	-.100000	.360017	30.719	-.278	.783	-.834531	.634531
[assessment2=2]	-.200000	.352869	37.837	-.567	.574	-.914448	.514448
[assessment2=3]	.100000	.341228	50.418	.293	.771	-.585237	.785237
[assessment2=4]	-.100000	.321907	72.912	-.311	.757	-.741573	.541573
[assessment2=5]	.100000	.288630	102.821	.346	.730	-.472441	.672441
[assessment2=6]	-.400000	.226029	96.255	-1.770	.080	-.848649	.048649
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=1] * [assessment2=1]	-.300000	.509140	30.719	-.589	.560	-1.338783	.738783
[group=1] * [assessment2=2]	.000000	.499032	37.837	.000	1.000	-1.010381	1.010381
[group=1] * [assessment2=3]	.100000	.482570	50.418	.207	.837	-.869071	1.069071
[group=1] * [assessment2=4]	.400000	.455246	72.912	.879	.382	-.507322	1.307322
[group=1] * [assessment2=5]	.000000	.408184	102.821	.000	1.000	-.809553	.809553
[group=1] * [assessment2=6]	.700000	.319653	96.255	2.190	.031	.065514	1.334486
[group=1] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Valence.

b. This parameter is set to zero because it is redundant.

Arousal

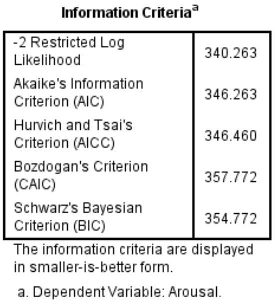


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	2		1		
	assessment2	7		6		
	group * assessment2	14		6		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	14	First-Order Autoregressive	2	parno	20
Total		39		17		

a. Dependent Variable: Arousal.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

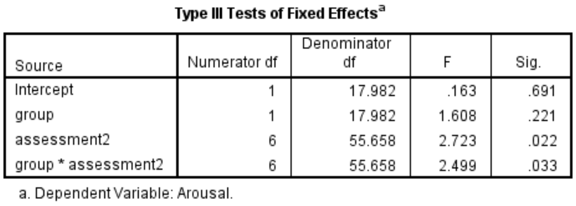


Information Criteria[a]

-2 Restricted Log Likelihood	340.263
Akaike's Information Criterion (AIC)	346.263
Hurvich and Tsai's Criterion (AICC)	346.460
Bozdogan's Criterion (CAIC)	357.772
Schwarz's Bayesian Criterion (BIC)	354.772

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Arousal.

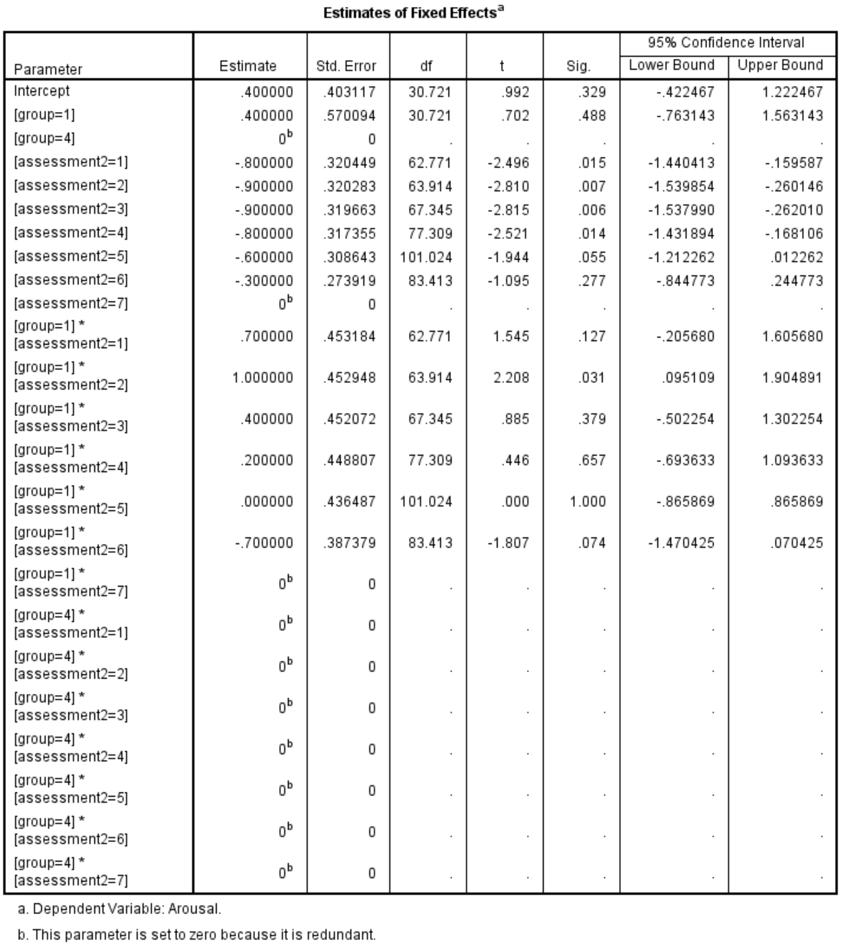


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.982	.163	.691
group	1	17.982	1.608	.221
assessment2	6	55.658	2.723	.022
group * assessment2	6	55.658	2.499	.033

a. Dependent Variable: Arousal.

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

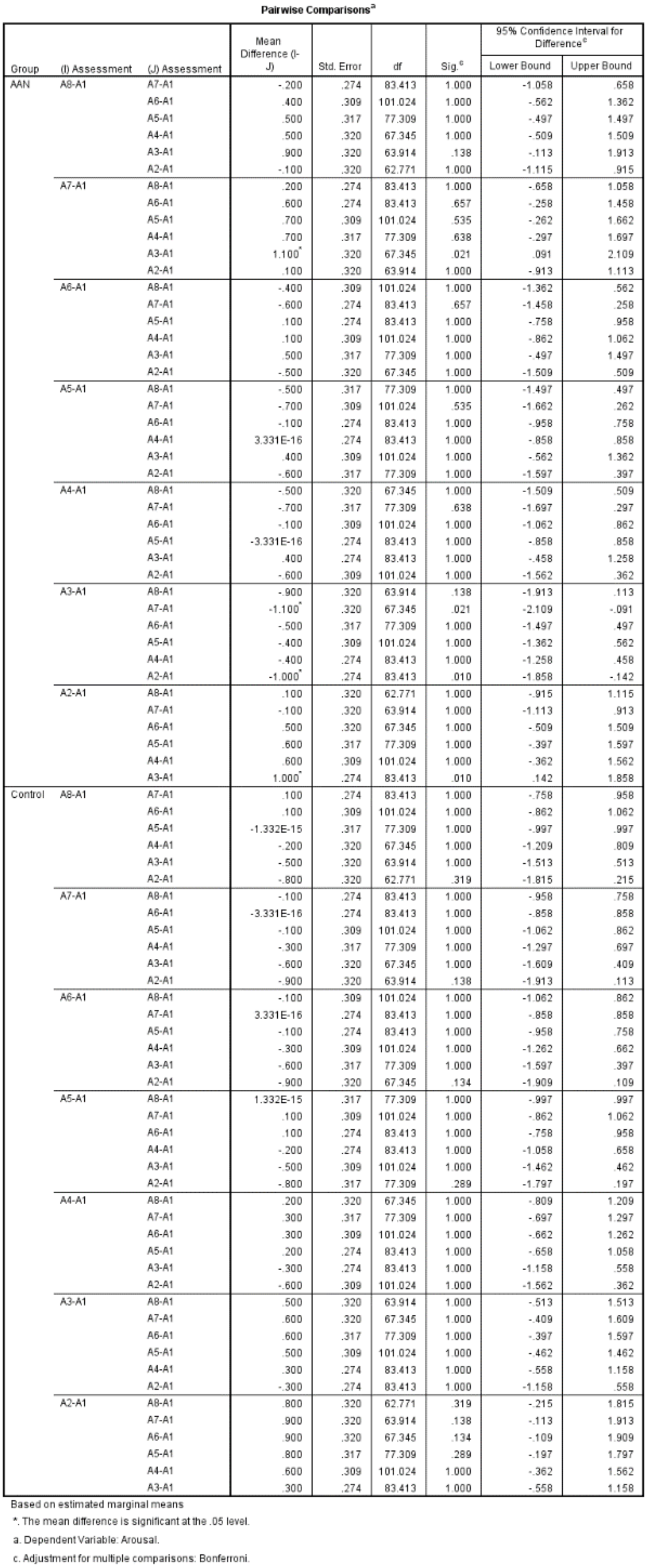


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.400000	.403117	30.721	.992	.329	-.422467	1.222467
[group=1]	.400000	.570094	30.721	.702	.488	-.763143	1.563143
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	-.800000	.320449	62.771	-2.496	.015	-1.440413	-.159587
[assessment2=2]	-.900000	.320283	63.914	-2.810	.007	-1.539854	-.260146
[assessment2=3]	-.900000	.319663	67.345	-2.815	.006	-1.537990	-.262010
[assessment2=4]	-.800000	.317355	77.309	-2.521	.014	-1.431894	-.168106
[assessment2=5]	-.600000	.308643	101.024	-1.944	.055	-1.212262	.012262
[assessment2=6]	-.300000	.273919	83.413	-1.095	.277	-.844773	.244773
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=1] * [assessment2=1]	.700000	.453184	62.771	1.545	.127	-.205680	1.605680
[group=1] * [assessment2=2]	1.000000	.452948	63.914	2.208	.031	.095109	1.904891
[group=1] * [assessment2=3]	.400000	.452072	67.345	.885	.379	-.502254	1.302254
[group=1] * [assessment2=4]	.200000	.448807	77.309	.446	.657	-.693633	1.093633
[group=1] * [assessment2=5]	.000000	.436487	101.024	.000	1.000	-.865869	.865869
[group=1] * [assessment2=6]	-.700000	.387379	83.413	-1.807	.074	-1.470425	.070425
[group=1] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Arousal.

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment	(J) Assessment	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
AAN	A8-A1	A7-A1	-.200	.274	83.413	1.000	-1.058	.658
		A6-A1	.400	.309	101.024	1.000	-.562	1.362
		A5-A1	.500	.317	77.309	1.000	-.497	1.497
		A4-A1	.500	.320	67.345	1.000	-.509	1.509
		A3-A1	.900	.320	63.914	.138	-.113	1.913
		A2-A1	-.100	.320	62.771	1.000	-1.115	.915
	A7-A1	A8-A1	.200	.274	83.413	1.000	-.658	1.058
		A6-A1	.600	.274	83.413	.657	-.258	1.458
		A5-A1	.700	.309	101.024	.535	-.262	1.662
		A4-A1	.700	.317	77.309	.638	-.297	1.697
		A3-A1	1.100*	.320	67.345	.021	.091	2.109
		A2-A1	.100	.320	63.914	1.000	-.913	1.113
	A6-A1	A8-A1	-.400	.309	101.024	1.000	-1.362	.562
		A7-A1	-.600	.274	83.413	.657	-1.458	.258
		A5-A1	.100	.274	83.413	1.000	-.758	.958
		A4-A1	.100	.309	101.024	1.000	-.862	1.062
		A3-A1	.500	.317	77.309	1.000	-.497	1.497
		A2-A1	-.500	.320	67.345	1.000	-1.509	.509
	A5-A1	A8-A1	-.500	.317	77.309	1.000	-1.497	.497
		A7-A1	-.700	.309	101.024	.535	-1.662	.262
		A6-A1	-.100	.274	83.413	1.000	-.958	.758
		A4-A1	3.331E-16	.274	83.413	1.000	-.858	.858
		A3-A1	.400	.309	101.024	1.000	-.562	1.362
		A2-A1	-.600	.317	77.309	1.000	-1.597	.397
	A4-A1	A8-A1	-.500	.320	67.345	1.000	-1.509	.509
		A7-A1	-.700	.317	77.309	.638	-1.697	.297
		A6-A1	-.100	.309	101.024	1.000	-1.062	.862
		A5-A1	-3.331E-16	.274	83.413	1.000	-.858	.858
		A3-A1	.400	.274	83.413	1.000	-.458	1.258
		A2-A1	-.600	.309	101.024	1.000	-1.562	.362
	A3-A1	A8-A1	-.900	.320	63.914	.138	-1.913	.113
		A7-A1	-1.100*	.320	67.345	.021	-2.109	-.091
		A6-A1	-.500	.317	77.309	1.000	-1.497	.497
		A5-A1	-.400	.309	101.024	1.000	-1.362	.562
		A4-A1	-.400	.274	83.413	1.000	-1.258	.458
		A2-A1	-1.000*	.274	83.413	.010	-1.858	-.142
	A2-A1	A8-A1	.100	.320	62.771	1.000	-.915	1.115
		A7-A1	-.100	.320	63.914	1.000	-1.113	.913
		A6-A1	.500	.320	67.345	1.000	-.509	1.509
		A5-A1	.600	.317	77.309	1.000	-.397	1.597
		A4-A1	.600	.309	101.024	1.000	-.362	1.562
		A3-A1	1.000*	.274	83.413	.010	.142	1.858
Control	A8-A1	A7-A1	.100	.274	83.413	1.000	-.758	.958
		A6-A1	.100	.309	101.024	1.000	-.862	1.062
		A5-A1	-1.332E-15	.317	77.309	1.000	-.997	.997
		A4-A1	-.200	.320	67.345	1.000	-1.209	.809
		A3-A1	-.500	.320	63.914	1.000	-1.513	.513
		A2-A1	-.800	.320	62.771	.319	-1.815	.215
	A7-A1	A8-A1	-.100	.274	83.413	1.000	-.958	.758
		A6-A1	-3.331E-16	.274	83.413	1.000	-.858	.858
		A5-A1	-.100	.309	101.024	1.000	-1.062	.862
		A4-A1	-.300	.317	77.309	1.000	-1.297	.697
		A3-A1	-.600	.320	67.345	1.000	-1.609	.409
		A2-A1	-.900	.320	63.914	.138	-1.913	.113
	A6-A1	A8-A1	-.100	.309	101.024	1.000	-1.062	.862
		A7-A1	3.331E-16	.274	83.413	1.000	-.858	.858
		A5-A1	-.100	.274	83.413	1.000	-.958	.758
		A4-A1	-.300	.309	101.024	1.000	-1.262	.662
		A3-A1	-.600	.317	77.309	1.000	-1.597	.397
		A2-A1	-.900	.320	67.345	.134	-1.909	.109
	A5-A1	A8-A1	1.332E-15	.317	77.309	1.000	-.997	.997
		A7-A1	.100	.309	101.024	1.000	-.862	1.062
		A6-A1	.100	.274	83.413	1.000	-.758	.958
		A4-A1	-.200	.274	83.413	1.000	-1.058	.658
		A3-A1	-.500	.309	101.024	1.000	-1.462	.462
		A2-A1	-.800	.317	77.309	.289	-1.797	.197
	A4-A1	A8-A1	.200	.320	67.345	1.000	-.809	1.209
		A7-A1	.300	.317	77.309	1.000	-.697	1.297
		A6-A1	.300	.309	101.024	1.000	-.662	1.262
		A5-A1	.200	.274	83.413	1.000	-.658	1.058
		A3-A1	-.300	.274	83.413	1.000	-1.158	.558
		A2-A1	-.600	.309	101.024	1.000	-1.562	.362
	A3-A1	A8-A1	.500	.320	63.914	1.000	-.513	1.513
		A7-A1	.600	.320	67.345	1.000	-.409	1.609
		A6-A1	.600	.317	77.309	1.000	-.397	1.597
		A5-A1	.500	.309	101.024	1.000	-.462	1.462
		A4-A1	.300	.274	83.413	1.000	-.558	1.158
		A2-A1	-.300	.274	83.413	1.000	-1.158	.558
	A2-A1	A8-A1	.800	.320	62.771	.319	-.215	1.815
		A7-A1	.900	.320	63.914	.138	-.113	1.913
		A6-A1	.900	.320	67.345	.134	-.109	1.909
		A5-A1	.800	.317	77.309	.289	-.197	1.797
		A4-A1	.600	.309	101.024	1.000	-.362	1.562
		A3-A1	.300	.274	83.413	1.000	-.558	1.158

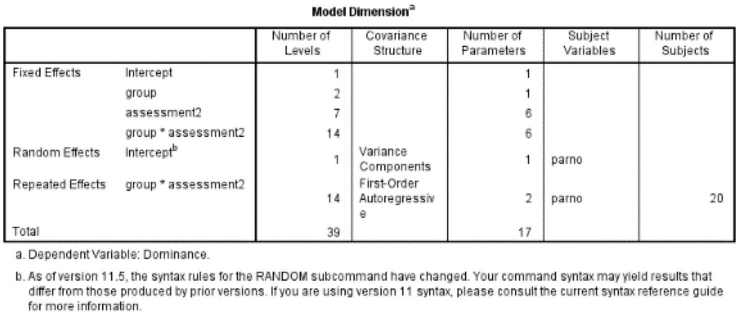
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Arousal.

c. Adjustment for multiple comparisons: Bonferroni.

Dominance

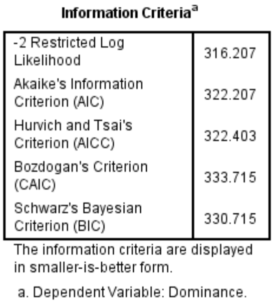


Model Dimension^{a}

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	2		1		
	assessment2	7		6		
	group * assessment2	14		6		
Random Effects	Intercept^{b}	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	14	First-Order Autoregressive	2	parno	20
Total		39		17		

a. Dependent Variable: Dominance.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

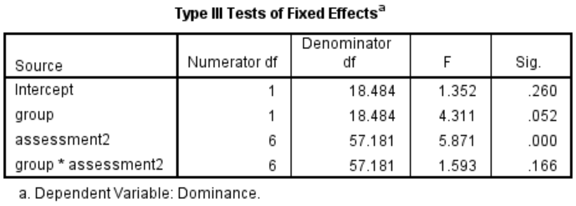


Information Criteria^{a}

-2 Restricted Log Likelihood	316.207
Akaike's Information Criterion (AIC)	322.207
Hurvich and Tsai's Criterion (AICC)	322.403
Bozdogan's Criterion (CAIC)	333.715
Schwarz's Bayesian Criterion (BIC)	330.715

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Dominance.

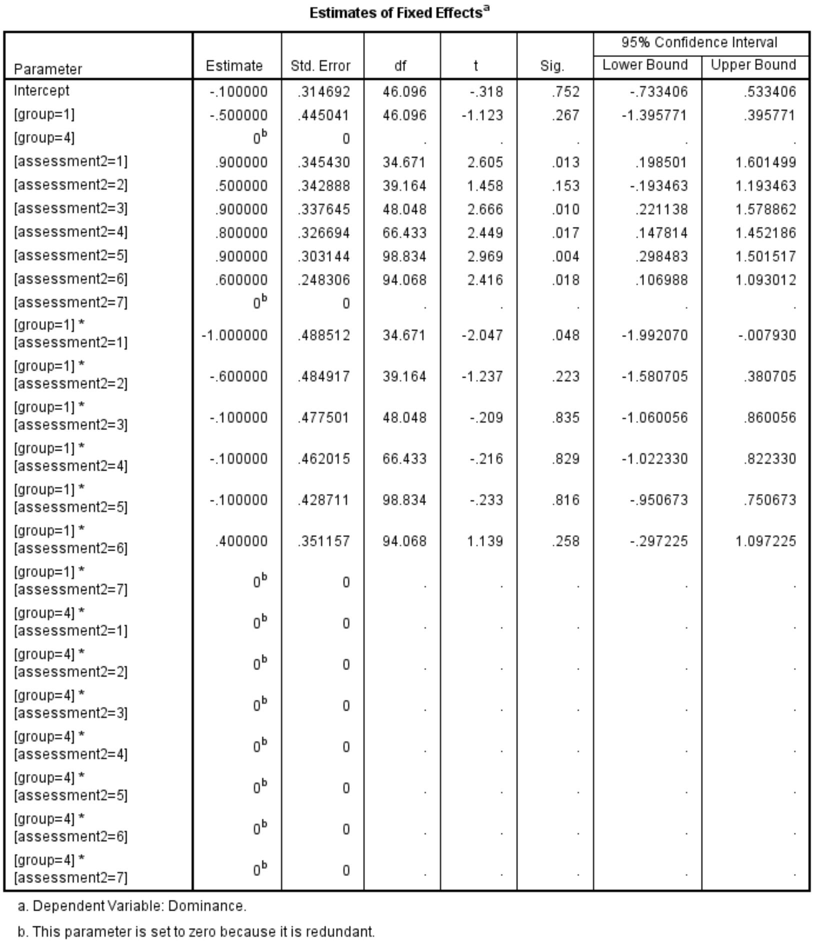


Type III Tests of Fixed Effects^{a}

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.484	1.352	.260
group	1	18.484	4.311	.052
assessment2	6	57.181	5.871	.000
group * assessment2	6	57.181	1.593	.166

a. Dependent Variable: Dominance.

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



Estimates of Fixed Effects^{a}

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	-.100000	.314692	46.096	-.318	.752	-.733406	.533406
[group=1]	-.500000	.445041	46.096	-1.123	.267	-1.395771	.395771
[group=4]	0^{b}	0	.	.	.	.	.
[assessment2=1]	.900000	.345430	34.671	2.605	.013	.198501	1.601499
[assessment2=2]	.500000	.342888	39.164	1.458	.153	-.193463	1.193463
[assessment2=3]	.900000	.337645	48.048	2.666	.010	.221138	1.578862
[assessment2=4]	.800000	.326694	66.433	2.449	.017	.147814	1.452186
[assessment2=5]	.900000	.303144	98.834	2.969	.004	.298483	1.501517
[assessment2=6]	.600000	.248306	94.068	2.416	.018	.106988	1.093012
[assessment2=7]	0^{b}	0	.	.	.	.	.
[group=1] * [assessment2=1]	-1.000000	.488512	34.671	-2.047	.048	-1.992070	-.007930
[group=1] * [assessment2=2]	-.600000	.484917	39.164	-1.237	.223	-1.580705	.380705
[group=1] * [assessment2=3]	-.100000	.477501	48.048	-.209	.835	-1.060056	.860056
[group=1] * [assessment2=4]	-.100000	.462015	66.433	-.216	.829	-1.022330	.822330
[group=1] * [assessment2=5]	-.100000	.428711	98.834	-.233	.816	-.950673	.750673
[group=1] * [assessment2=6]	.400000	.351157	94.068	1.139	.258	-.297225	1.097225
[group=1] * [assessment2=7]	0^{b}	0	.	.	.	.	.
[group=4] * [assessment2=1]	0^{b}	0	.	.	.	.	.
[group=4] * [assessment2=2]	0^{b}	0	.	.	.	.	.
[group=4] * [assessment2=3]	0^{b}	0	.	.	.	.	.
[group=4] * [assessment2=4]	0^{b}	0	.	.	.	.	.
[group=4] * [assessment2=5]	0^{b}	0	.	.	.	.	.
[group=4] * [assessment2=6]	0^{b}	0	.	.	.	.	.
[group=4] * [assessment2=7]	0^{b}	0	.	.	.	.	.

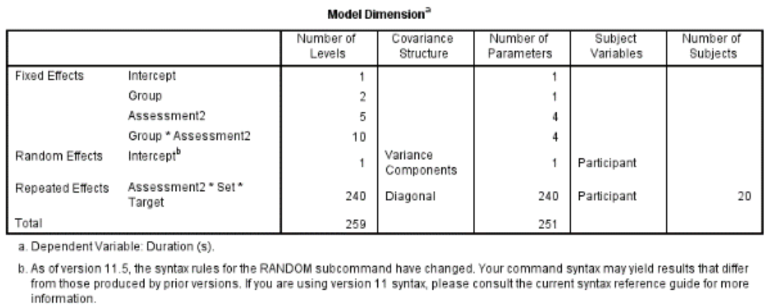
a. Dependent Variable: Dominance.

b. This parameter is set to zero because it is redundant.

Chapter 6: Results of the statistical analysis

Analysis of the NDA

Duration

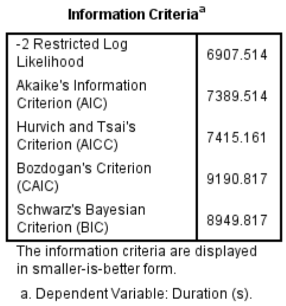


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Duration (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

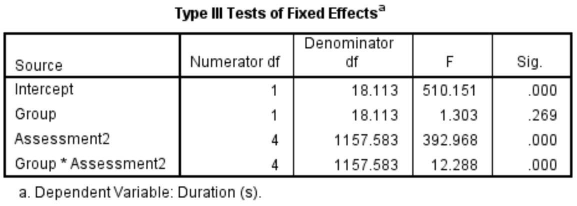


Information Criteria[a]

-2 Restricted Log Likelihood	6907.514
Akaike's Information Criterion (AIC)	7389.514
Hurvich and Tsai's Criterion (AICC)	7415.161
Bozdogan's Criterion (CAIC)	9190.817
Schwarz's Bayesian Criterion (BIC)	8949.817

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration (s).

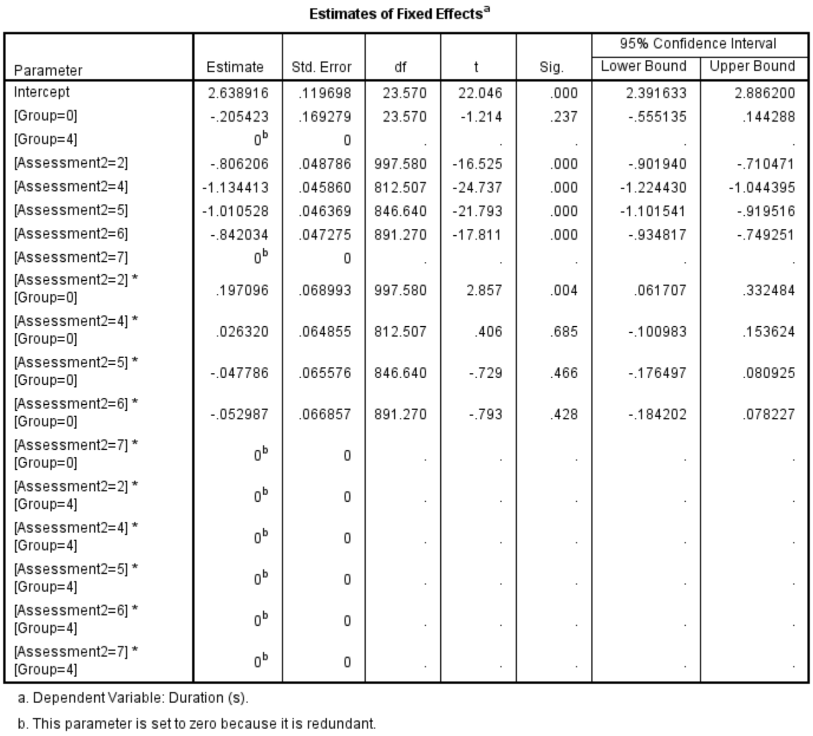


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.113	510.151	.000
Group	1	18.113	1.303	.269
Assessment2	4	1157.583	392.968	.000
Group * Assessment2	4	1157.583	12.288	.000

a. Dependent Variable: Duration (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

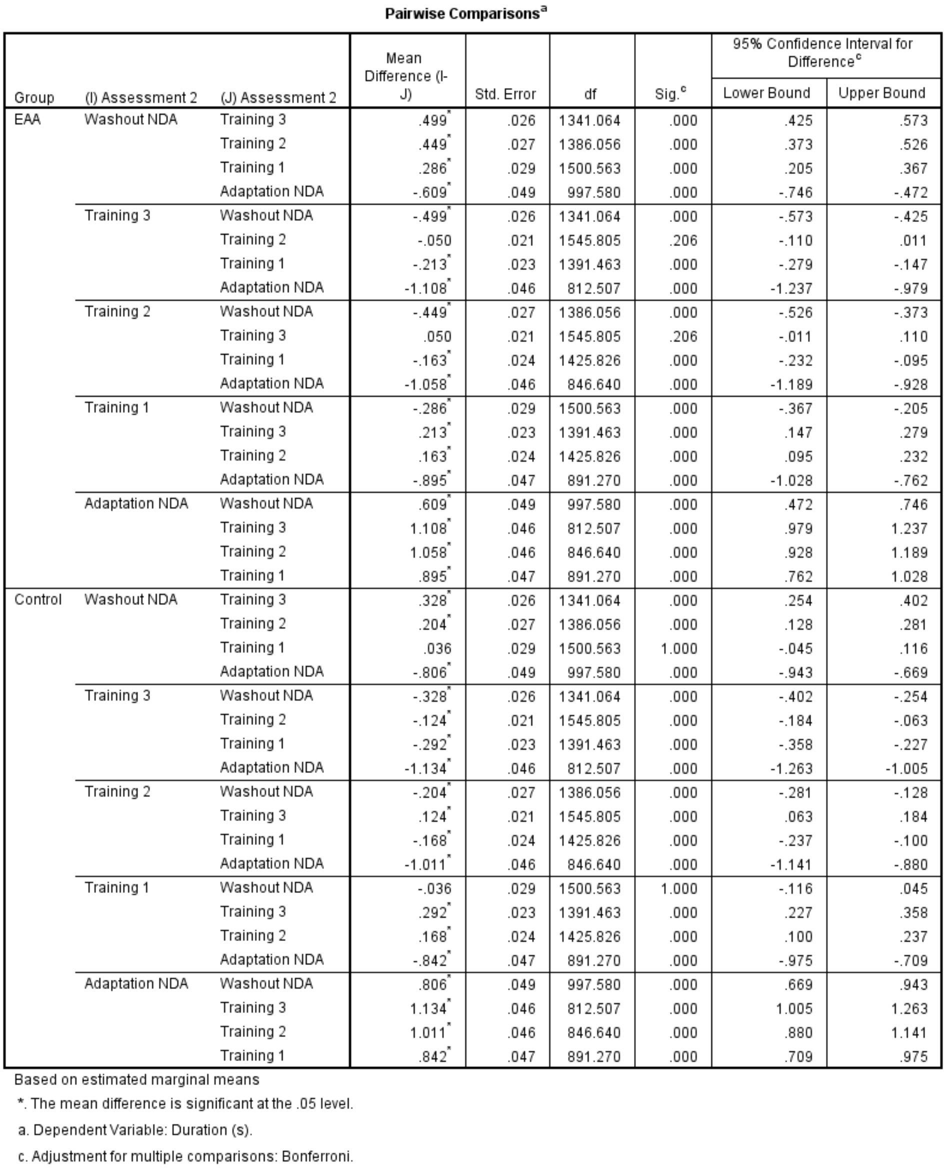


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	2.638916	.119698	23.570	22.046	.000	2.391633	2.886200
[Group=0]	-.205423	.169279	23.570	-1.214	.237	-.555135	.144288
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.806206	.048786	997.580	-16.525	.000	-.901940	-.710471
[Assessment2=4]	-1.134413	.045860	812.507	-24.737	.000	-1.224430	-1.044395
[Assessment2=5]	-1.010528	.046369	846.640	-21.793	.000	-1.101541	-.919516
[Assessment2=6]	-.842034	.047275	891.270	-17.811	.000	-.934817	-.749251
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	.197096	.068993	997.580	2.857	.004	.061707	.332484
[Assessment2=4] * [Group=0]	.026320	.064855	812.507	.406	.685	-.100983	.153624
[Assessment2=5] * [Group=0]	-.047786	.065576	846.640	-.729	.466	-.176497	.080925
[Assessment2=6] * [Group=0]	-.052987	.066857	891.270	-.793	.428	-.184202	.078227
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout NDA	Training 3	.499*	.026	1341.064	.000	.425	.573
		Training 2	.449*	.027	1386.056	.000	.373	.526
		Training 1	.286*	.029	1500.563	.000	.205	.367
		Adaptation NDA	-.609*	.049	997.580	.000	-.746	-.472
	Training 3	Washout NDA	-.499*	.026	1341.064	.000	-.573	-.425
		Training 2	-.050	.021	1545.805	.206	-.110	.011
		Training 1	-.213*	.023	1391.463	.000	-.279	-.147
		Adaptation NDA	-1.108*	.046	812.507	.000	-1.237	-.979
	Training 2	Washout NDA	-.449*	.027	1386.056	.000	-.526	-.373
		Training 3	.050	.021	1545.805	.206	-.011	.110
		Training 1	-.163*	.024	1425.826	.000	-.232	-.095
		Adaptation NDA	-1.058*	.046	846.640	.000	-1.189	-.928
	Training 1	Washout NDA	-.286*	.029	1500.563	.000	-.367	-.205
		Training 3	.213*	.023	1391.463	.000	.147	.279
		Training 2	.163*	.024	1425.826	.000	.095	.232
		Adaptation NDA	-.895*	.047	891.270	.000	-1.028	-.762
	Adaptation NDA	Washout NDA	.609*	.049	997.580	.000	.472	.746
		Training 3	1.108*	.046	812.507	.000	.979	1.237
		Training 2	1.058*	.046	846.640	.000	.928	1.189
		Training 1	.895*	.047	891.270	.000	.762	1.028
Control	Washout NDA	Training 3	.328*	.026	1341.064	.000	.254	.402
		Training 2	.204*	.027	1386.056	.000	.128	.281
		Training 1	.036	.029	1500.563	1.000	-.045	.116
		Adaptation NDA	-.806*	.049	997.580	.000	-.943	-.669
	Training 3	Washout NDA	-.328*	.026	1341.064	.000	-.402	-.254
		Training 2	-.124*	.021	1545.805	.000	-.184	-.063
		Training 1	-.292*	.023	1391.463	.000	-.358	-.227
		Adaptation NDA	-1.134*	.046	812.507	.000	-1.263	-1.005
	Training 2	Washout NDA	-.204*	.027	1386.056	.000	-.281	-.128
		Training 3	.124*	.021	1545.805	.000	.063	.184
		Training 1	-.168*	.024	1425.826	.000	-.237	-.100
		Adaptation NDA	-1.011*	.046	846.640	.000	-1.141	-.880
	Training 1	Washout NDA	-.036	.029	1500.563	1.000	-.116	.045
		Training 3	.292*	.023	1391.463	.000	.227	.358
		Training 2	.168*	.024	1425.826	.000	.100	.237
		Adaptation NDA	-.842*	.047	891.270	.000	-.975	-.709
	Adaptation NDA	Washout NDA	.806*	.049	997.580	.000	.669	.943
		Training 3	1.134*	.046	812.507	.000	1.005	1.263
		Training 2	1.011*	.046	846.640	.000	.880	1.141
		Training 1	.842*	.047	891.270	.000	.709	.975

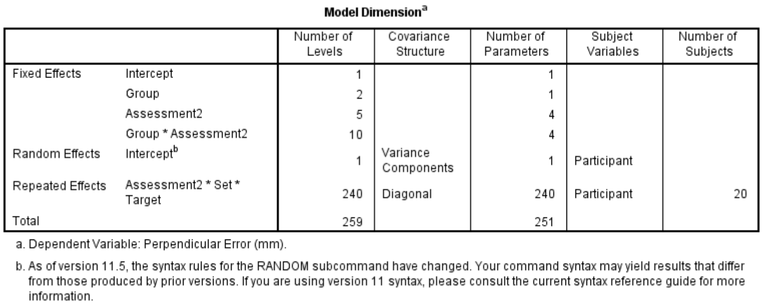
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration (s).

c. Adjustment for multiple comparisons: Bonferroni.

Perpendicular error

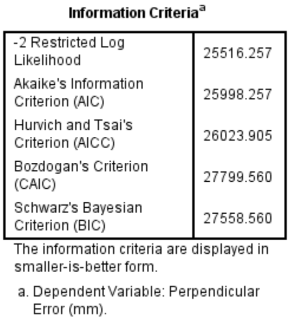


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Perpendicular Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

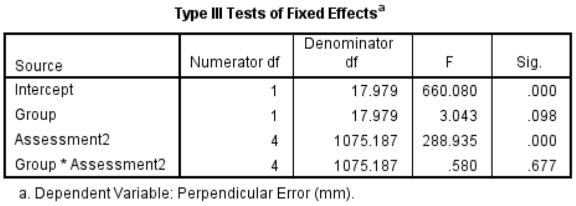


Information Criteria[a]

-2 Restricted Log Likelihood	25516.257
Akaike's Information Criterion (AIC)	25998.257
Hurvich and Tsai's Criterion (AICC)	26023.905
Bozdogan's Criterion (CAIC)	27799.560
Schwarz's Bayesian Criterion (BIC)	27558.560

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Perpendicular Error (mm).

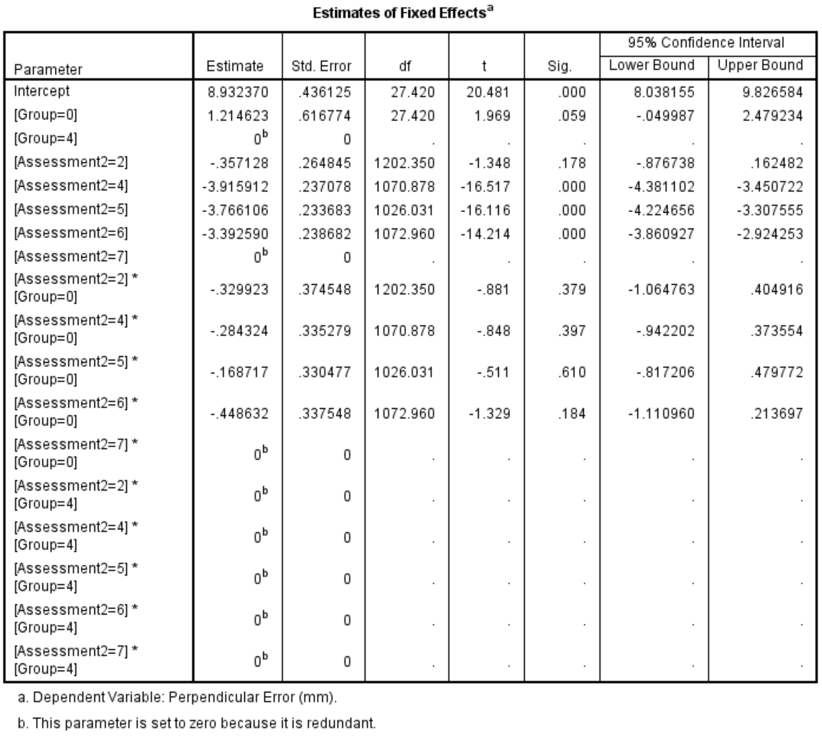


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.979	660.080	.000
Group	1	17.979	3.043	.098
Assessment2	4	1075.187	288.935	.000
Group * Assessment2	4	1075.187	.580	.677

a. Dependent Variable: Perpendicular Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

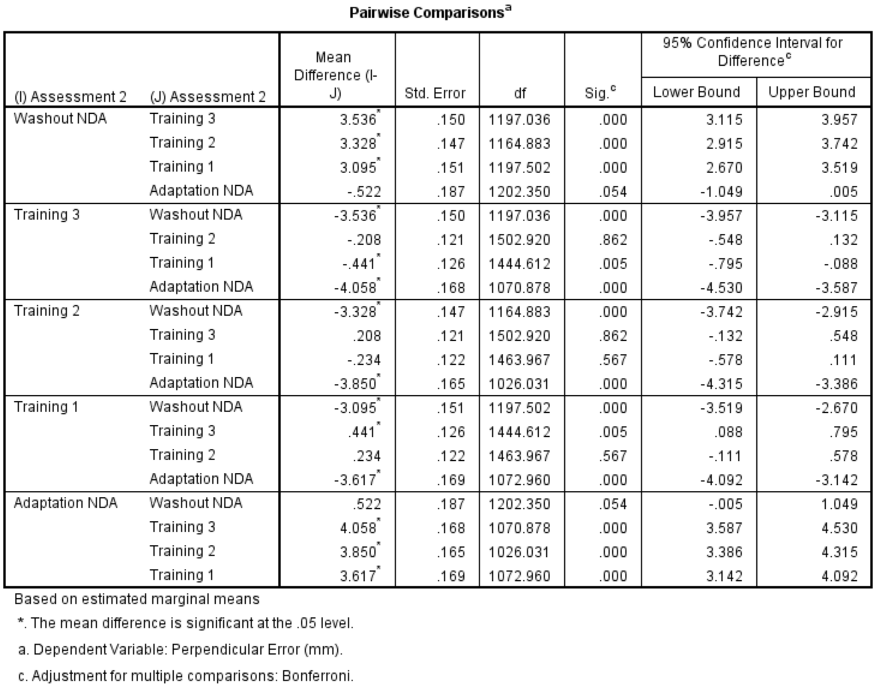


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	Upper Bound
Intercept	8.932370	.436125	27.420	20.481	.000	8.038155	9.826584
[Group=0]	1.214623	.616774	27.420	1.969	.059	-.049987	2.479234
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.357128	.264845	1202.350	-1.348	.178	-.876738	.162482
[Assessment2=4]	-3.915912	.237078	1070.878	-16.517	.000	-4.381102	-3.450722
[Assessment2=5]	-3.766106	.233683	1026.031	-16.116	.000	-4.224656	-3.307555
[Assessment2=6]	-3.392590	.238682	1072.960	-14.214	.000	-3.860927	-2.924253
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	-.329923	.374548	1202.350	-.881	.379	-1.064763	.404916
[Assessment2=4] * [Group=0]	-.284324	.335279	1070.878	-.848	.397	-.942202	.373554
[Assessment2=5] * [Group=0]	-.168717	.330477	1026.031	-.511	.610	-.817206	.479772
[Assessment2=6] * [Group=0]	-.448632	.337548	1072.960	-1.329	.184	-1.110960	.213697
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Perpendicular Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	3.536*	.150	1197.036	.000	3.115	3.957
	Training 2	3.328*	.147	1164.883	.000	2.915	3.742
	Training 1	3.095*	.151	1197.502	.000	2.670	3.519
	Adaptation NDA	-.522	.187	1202.350	.054	-1.049	.005
Training 3	Washout NDA	-3.536*	.150	1197.036	.000	-3.957	-3.115
	Training 2	-.208	.121	1502.920	.862	-.548	.132
	Training 1	-.441*	.126	1444.612	.005	-.795	-.088
	Adaptation NDA	-4.058*	.168	1070.878	.000	-4.530	-3.587
Training 2	Washout NDA	-3.328*	.147	1164.883	.000	-3.742	-2.915
	Training 3	.208	.121	1502.920	.862	-.132	.548
	Training 1	-.234	.122	1463.967	.567	-.578	.111
	Adaptation NDA	-3.850*	.165	1026.031	.000	-4.315	-3.386
Training 1	Washout NDA	-3.095*	.151	1197.502	.000	-3.519	-2.670
	Training 3	.441*	.126	1444.612	.005	.088	.795
	Training 2	.234	.122	1463.967	.567	-.111	.578
	Adaptation NDA	-3.617*	.169	1072.960	.000	-4.092	-3.142
Adaptation NDA	Washout NDA	.522	.187	1202.350	.054	-.005	1.049
	Training 3	4.058*	.168	1070.878	.000	3.587	4.530
	Training 2	3.850*	.165	1026.031	.000	3.386	4.315
	Training 1	3.617*	.169	1072.960	.000	3.142	4.092

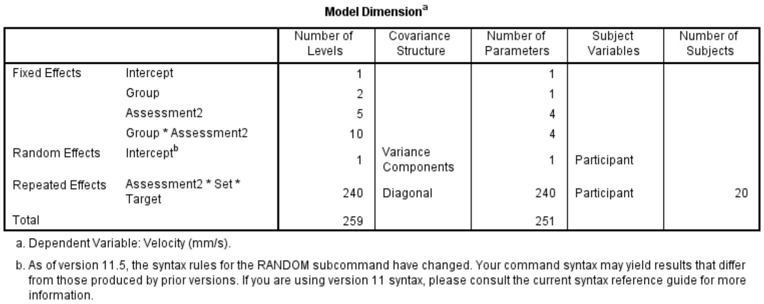
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Perpendicular Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Mean velocity

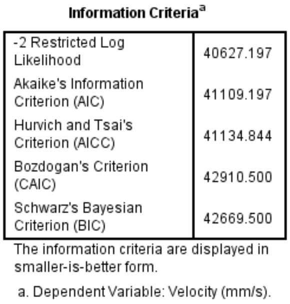


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Velocity (mm/s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

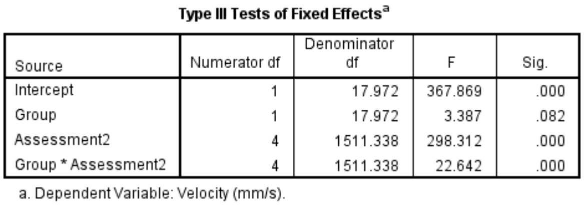


Information Criteria[a]

-2 Restricted Log Likelihood	40627.197
Akaike's Information Criterion (AIC)	41109.197
Hurvich and Tsai's Criterion (AICC)	41134.844
Bozdogan's Criterion (CAIC)	42910.500
Schwarz's Bayesian Criterion (BIC)	42669.500

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Velocity (mm/s).

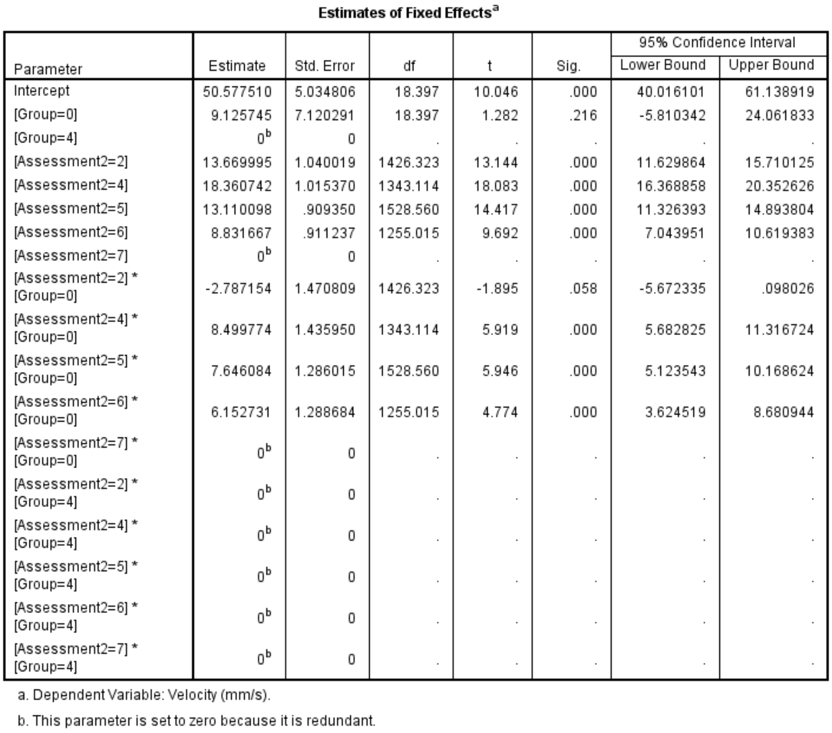


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.972	367.869	.000
Group	1	17.972	3.387	.082
Assessment2	4	1511.338	298.312	.000
Group * Assessment2	4	1511.338	22.642	.000

a. Dependent Variable: Velocity (mm/s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

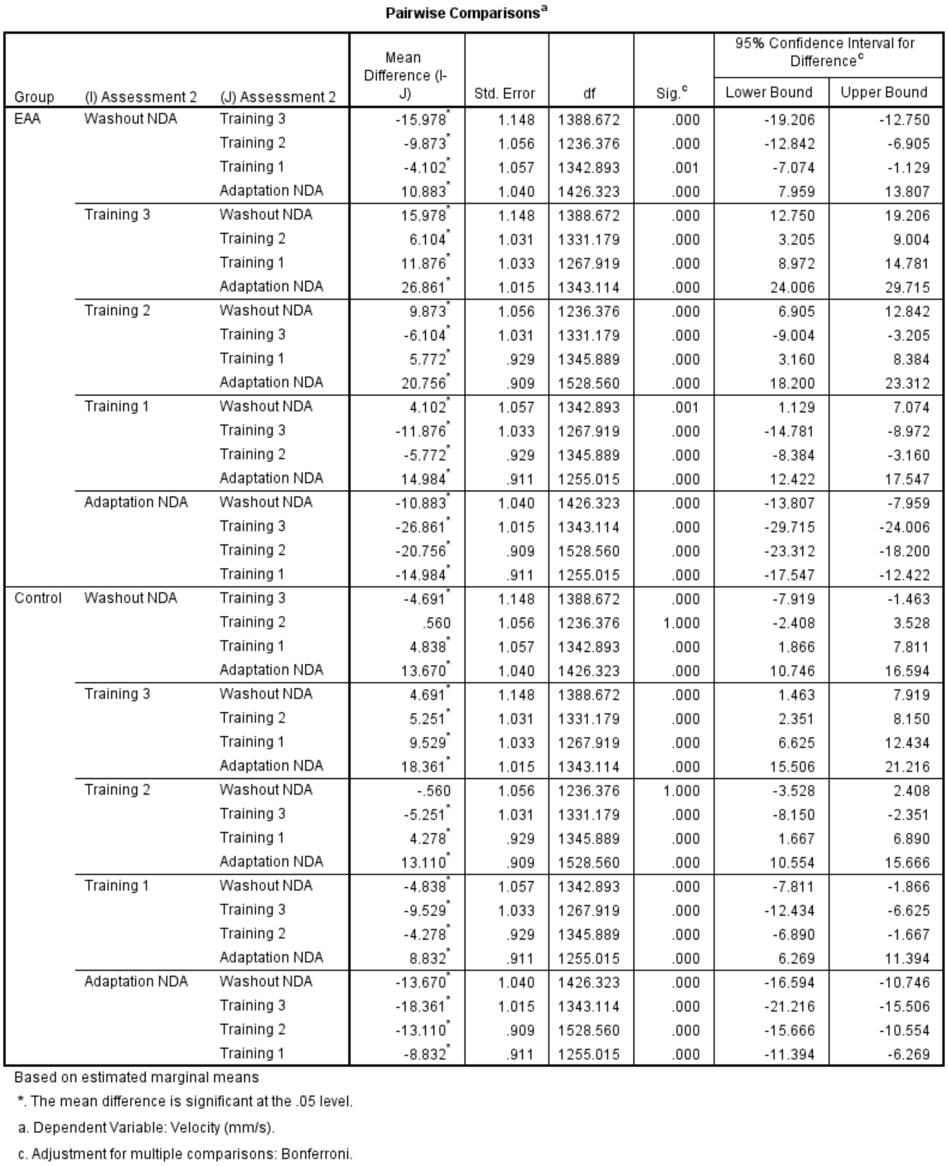


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	50.577510	5.034806	18.397	10.046	.000	40.016101	61.138919
[Group=0]	9.125745	7.120291	18.397	1.282	.216	-5.810342	24.061833
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	13.669995	1.040019	1426.323	13.144	.000	11.629864	15.710125
[Assessment2=4]	18.360742	1.015370	1343.114	18.083	.000	16.368858	20.352626
[Assessment2=5]	13.110098	.909350	1528.560	14.417	.000	11.326393	14.893804
[Assessment2=6]	8.831667	.911237	1255.015	9.692	.000	7.043951	10.619383
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	-2.787154	1.470809	1426.323	-1.895	.058	-5.672335	.098026
[Assessment2=4] * [Group=0]	8.499774	1.435950	1343.114	5.919	.000	5.682825	11.316724
[Assessment2=5] * [Group=0]	7.646084	1.286015	1528.560	5.946	.000	5.123543	10.168624
[Assessment2=6] * [Group=0]	6.152731	1.288684	1255.015	4.774	.000	3.624519	8.680944
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Velocity (mm/s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout NDA	Training 3	-15.978*	1.148	1388.672	.000	-19.206	-12.750
		Training 2	-9.873*	1.056	1236.376	.000	-12.842	-6.905
		Training 1	-4.102*	1.057	1342.893	.001	-7.074	-1.129
		Adaptation NDA	10.883*	1.040	1426.323	.000	7.959	13.807
	Training 3	Washout NDA	15.978*	1.148	1388.672	.000	12.750	19.206
		Training 2	6.104*	1.031	1331.179	.000	3.205	9.004
		Training 1	11.876*	1.033	1267.919	.000	8.972	14.781
		Adaptation NDA	26.861*	1.015	1343.114	.000	24.006	29.715
	Training 2	Washout NDA	9.873*	1.056	1236.376	.000	6.905	12.842
		Training 3	-6.104*	1.031	1331.179	.000	-9.004	-3.205
		Training 1	5.772*	.929	1345.889	.000	3.160	8.384
		Adaptation NDA	20.756*	.909	1528.560	.000	18.200	23.312
	Training 1	Washout NDA	4.102*	1.057	1342.893	.001	1.129	7.074
		Training 3	-11.876*	1.033	1267.919	.000	-14.781	-8.972
		Training 2	-5.772*	.929	1345.889	.000	-8.384	-3.160
		Adaptation NDA	14.984*	.911	1255.015	.000	12.422	17.547
	Adaptation NDA	Washout NDA	-10.883*	1.040	1426.323	.000	-13.807	-7.959
		Training 3	-26.861*	1.015	1343.114	.000	-29.715	-24.006
		Training 2	-20.756*	.909	1528.560	.000	-23.312	-18.200
		Training 1	-14.984*	.911	1255.015	.000	-17.547	-12.422
Control	Washout NDA	Training 3	-4.691*	1.148	1388.672	.000	-7.919	-1.463
		Training 2	.560	1.056	1236.376	1.000	-2.408	3.528
		Training 1	4.838*	1.057	1342.893	.000	1.866	7.811
		Adaptation NDA	13.670*	1.040	1426.323	.000	10.746	16.594
	Training 3	Washout NDA	4.691*	1.148	1388.672	.000	1.463	7.919
		Training 2	5.251*	1.031	1331.179	.000	2.351	8.150
		Training 1	9.529*	1.033	1267.919	.000	6.625	12.434
		Adaptation NDA	18.361*	1.015	1343.114	.000	15.506	21.216
	Training 2	Washout NDA	-.560	1.056	1236.376	1.000	-3.528	2.408
		Training 3	-5.251*	1.031	1331.179	.000	-8.150	-2.351
		Training 1	4.278*	.929	1345.889	.000	1.667	6.890
		Adaptation NDA	13.110*	.909	1528.560	.000	10.554	15.666
	Training 1	Washout NDA	-4.838*	1.057	1342.893	.000	-7.811	-1.866
		Training 3	-9.529*	1.033	1267.919	.000	-12.434	-6.625
		Training 2	-4.278*	.929	1345.889	.000	-6.890	-1.667
		Adaptation NDA	8.832*	.911	1255.015	.000	6.269	11.394
	Adaptation NDA	Washout NDA	-13.670*	1.040	1426.323	.000	-16.594	-10.746
		Training 3	-18.361*	1.015	1343.114	.000	-21.216	-15.506
		Training 2	-13.110*	.909	1528.560	.000	-15.666	-10.554
		Training 1	-8.832*	.911	1255.015	.000	-11.394	-6.269

Based on estimated marginal means

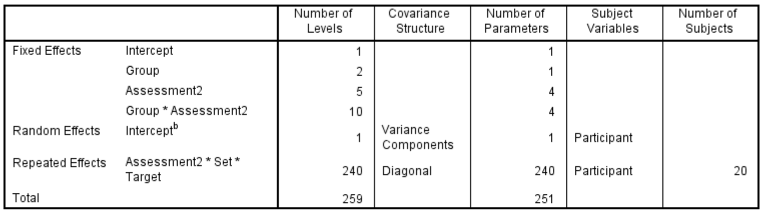
*. The mean difference is significant at the .05 level.

a. Dependent Variable: Velocity (mm/s).

c. Adjustment for multiple comparisons: Bonferroni.

Normalised jerk

Model Dimension[a]

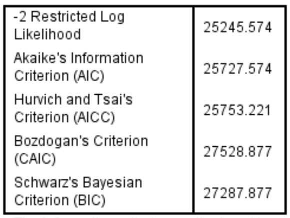


		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Normalised Jerk (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Information Criteria[a]

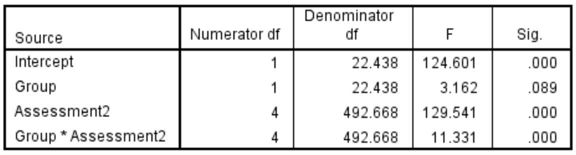


-2 Restricted Log Likelihood	25245.574
Akaike's Information Criterion (AIC)	25727.574
Hurvich and Tsai's Criterion (AICC)	25753.221
Bozdogan's Criterion (CAIC)	27528.877
Schwarz's Bayesian Criterion (BIC)	27287.877

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Normalised Jerk (no units).

Type III Tests of Fixed Effects[a]

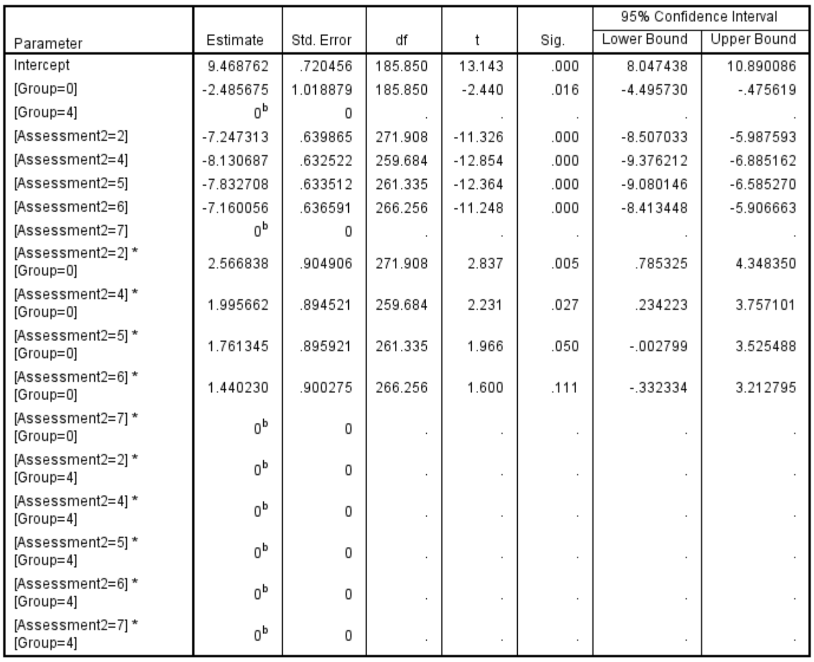


Source	Numerator df	Denominator df	F	Sig.
Intercept	1	22.438	124.601	.000
Group	1	22.438	3.162	.089
Assessment2	4	492.668	129.541	.000
Group * Assessment2	4	492.668	11.331	.000

a. Dependent Variable: Normalised Jerk (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

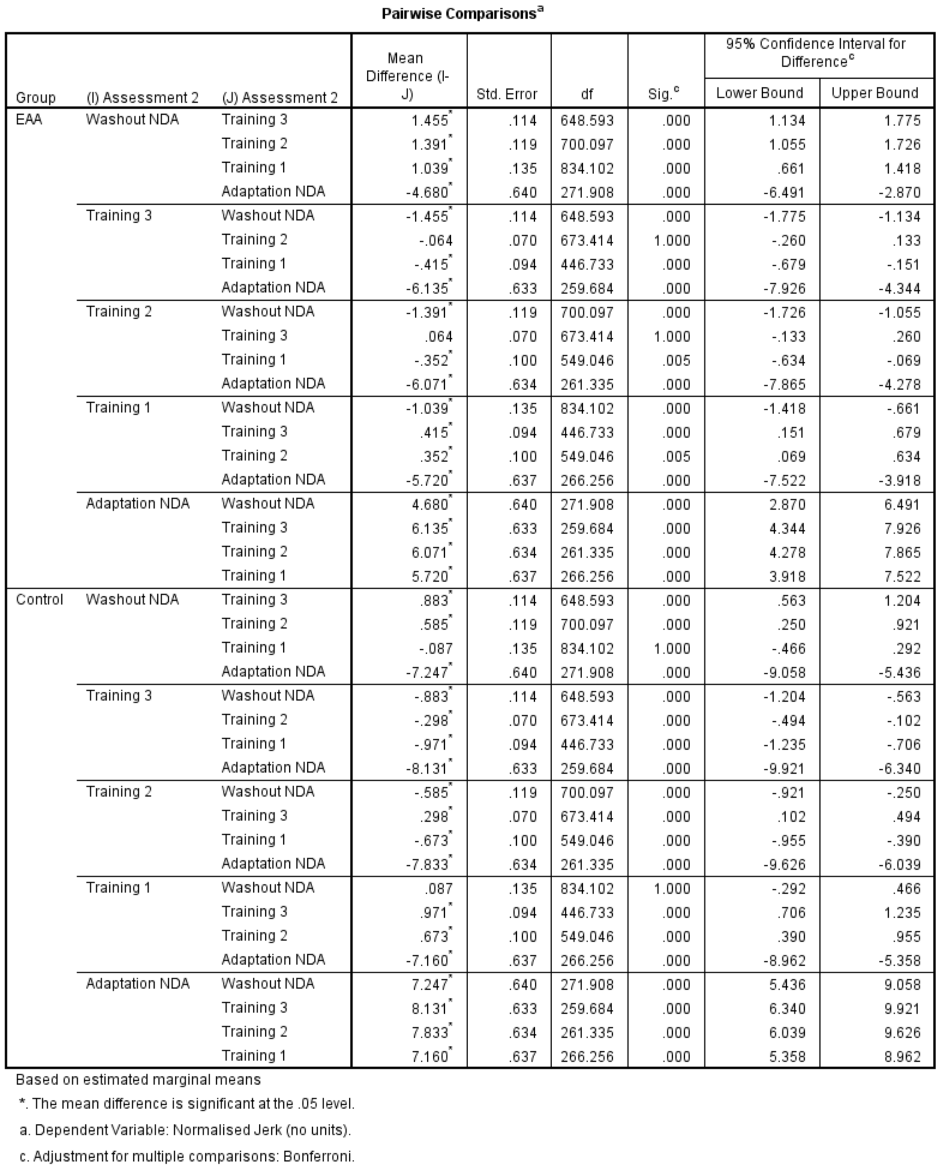
Estimates of Fixed Effects[a]



Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	9.468762	.720456	185.850	13.143	.000	8.047438	10.890086
[Group=0]	-2.485675	1.018879	185.850	-2.440	.016	-4.495730	-.475619
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-7.247313	.639865	271.908	-11.326	.000	-8.507033	-5.987593
[Assessment2=4]	-8.130687	.632522	259.684	-12.854	.000	-9.376212	-6.885162
[Assessment2=5]	-7.832708	.633512	261.335	-12.364	.000	-9.080146	-6.585270
[Assessment2=6]	-7.160056	.636591	266.256	-11.248	.000	-8.413448	-5.906663
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	2.566838	.904906	271.908	2.837	.005	.785325	4.348350
[Assessment2=4] * [Group=0]	1.995662	.894521	259.684	2.231	.027	.234223	3.757101
[Assessment2=5] * [Group=0]	1.761345	.895921	261.335	1.966	.050	-.002799	3.525488
[Assessment2=6] * [Group=0]	1.440230	.900275	266.256	1.600	.111	-.332334	3.212795
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Normalised Jerk (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout NDA	Training 3	1.455*	.114	648.593	.000	1.134	1.775
		Training 2	1.391*	.119	700.097	.000	1.055	1.726
		Training 1	1.039*	.135	834.102	.000	.661	1.418
		Adaptation NDA	-4.680*	.640	271.908	.000	-6.491	-2.870
	Training 3	Washout NDA	-1.455*	.114	648.593	.000	-1.775	-1.134
		Training 2	-.064	.070	673.414	1.000	-.260	.133
		Training 1	-.415*	.094	446.733	.000	-.679	-.151
		Adaptation NDA	-6.135*	.633	259.684	.000	-7.926	-4.344
	Training 2	Washout NDA	-1.391*	.119	700.097	.000	-1.726	-1.055
		Training 3	.064	.070	673.414	1.000	-.133	.260
		Training 1	-.352*	.100	549.046	.005	-.634	-.069
		Adaptation NDA	-6.071*	.634	261.335	.000	-7.865	-4.278
	Training 1	Washout NDA	-1.039*	.135	834.102	.000	-1.418	-.661
		Training 3	.415*	.094	446.733	.000	.151	.679
		Training 2	.352*	.100	549.046	.005	.069	.634
		Adaptation NDA	-5.720*	.637	266.256	.000	-7.522	-3.918
	Adaptation NDA	Washout NDA	4.680*	.640	271.908	.000	2.870	6.491
		Training 3	6.135*	.633	259.684	.000	4.344	7.926
		Training 2	6.071*	.634	261.335	.000	4.278	7.865
		Training 1	5.720*	.637	266.256	.000	3.918	7.522
Control	Washout NDA	Training 3	.883*	.114	648.593	.000	.563	1.204
		Training 2	.585*	.119	700.097	.000	.250	.921
		Training 1	-.087	.135	834.102	1.000	-.466	.292
		Adaptation NDA	-7.247*	.640	271.908	.000	-9.058	-5.436
	Training 3	Washout NDA	-.883*	.114	648.593	.000	-1.204	-.563
		Training 2	-.298*	.070	673.414	.000	-.494	-.102
		Training 1	-.971*	.094	446.733	.000	-1.235	-.706
		Adaptation NDA	-8.131*	.633	259.684	.000	-9.921	-6.340
	Training 2	Washout NDA	-.585*	.119	700.097	.000	-.921	-.250
		Training 3	.298*	.070	673.414	.000	.102	.494
		Training 1	-.673*	.100	549.046	.000	-.955	-.390
		Adaptation NDA	-7.833*	.634	261.335	.000	-9.626	-6.039
	Training 1	Washout NDA	.087	.135	834.102	1.000	-.292	.466
		Training 3	.971*	.094	446.733	.000	.706	1.235
		Training 2	.673*	.100	549.046	.000	.390	.955
		Adaptation NDA	-7.160*	.637	266.256	.000	-8.962	-5.358
	Adaptation NDA	Washout NDA	7.247*	.640	271.908	.000	5.436	9.058
		Training 3	8.131*	.633	259.684	.000	6.340	9.921
		Training 2	7.833*	.634	261.335	.000	6.039	9.626
		Training 1	7.160*	.637	266.256	.000	5.358	8.962

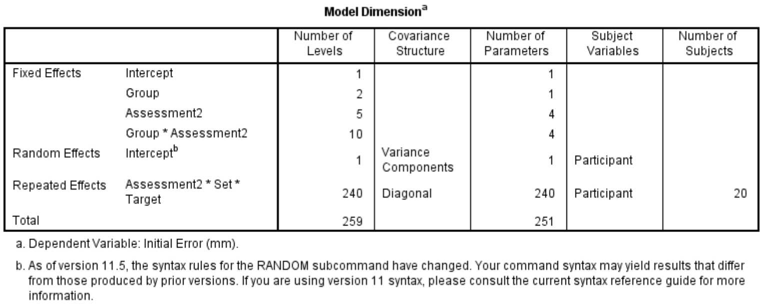
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Normalised Jerk (no units).

c. Adjustment for multiple comparisons: Bonferroni.

Initial error

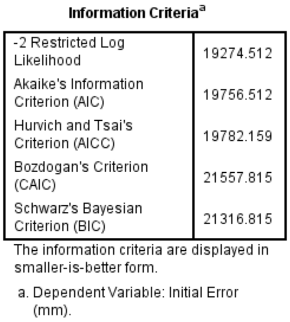


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Initial Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

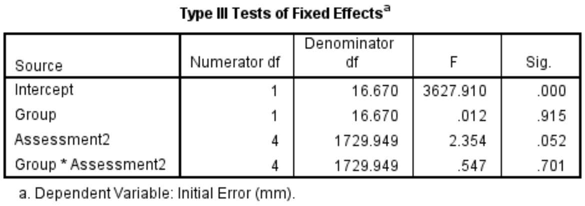


Information Criteria[a]

-2 Restricted Log Likelihood	19274.512
Akaike's Information Criterion (AIC)	19756.512
Hurvich and Tsai's Criterion (AICC)	19782.159
Bozdogan's Criterion (CAIC)	21557.815
Schwarz's Bayesian Criterion (BIC)	21316.815

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Initial Error (mm).

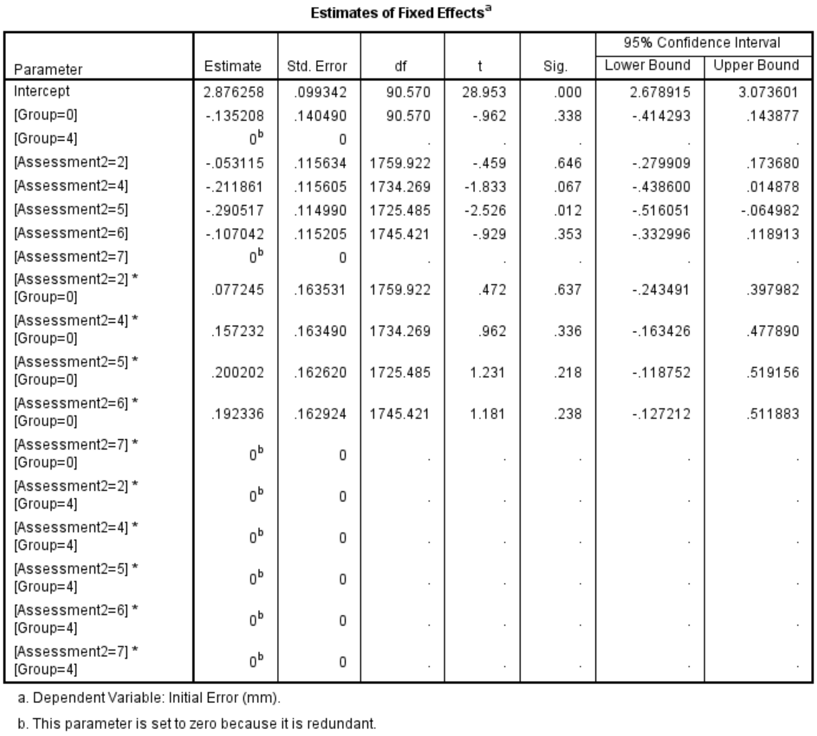


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	16.670	3627.910	.000
Group	1	16.670	.012	.915
Assessment2	4	1729.949	2.354	.052
Group * Assessment2	4	1729.949	.547	.701

a. Dependent Variable: Initial Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

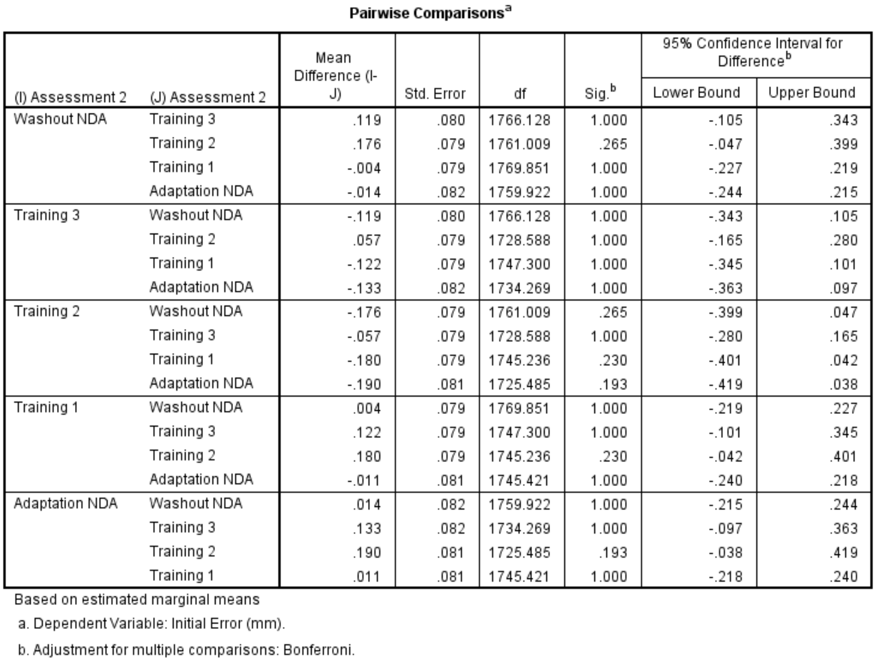


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	2.876258	.099342	90.570	28.953	.000	2.678915	3.073601
[Group=0]	-.135208	.140490	90.570	-.962	.338	-.414293	.143877
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.053115	.115634	1759.922	-.459	.646	-.279909	.173680
[Assessment2=4]	-.211861	.115605	1734.269	-1.833	.067	-.438600	.014878
[Assessment2=5]	-.290517	.114990	1725.485	-2.526	.012	-.516051	-.064982
[Assessment2=6]	-.107042	.115205	1745.421	-.929	.353	-.332996	.118913
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	.077245	.163531	1759.922	.472	.637	-.243491	.397982
[Assessment2=4] * [Group=0]	.157232	.163490	1734.269	.962	.336	-.163426	.477890
[Assessment2=5] * [Group=0]	.200202	.162620	1725.485	1.231	.218	-.118752	.519156
[Assessment2=6] * [Group=0]	.192336	.162924	1745.421	1.181	.238	-.127212	.511883
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Initial Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[b]	95% Confidence Interval for Difference[b]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	.119	.080	1766.128	1.000	-.105	.343
	Training 2	.176	.079	1761.009	.265	-.047	.399
	Training 1	-.004	.079	1769.851	1.000	-.227	.219
	Adaptation NDA	-.014	.082	1759.922	1.000	-.244	.215
Training 3	Washout NDA	-.119	.080	1766.128	1.000	-.343	.105
	Training 2	.057	.079	1728.588	1.000	-.165	.280
	Training 1	-.122	.079	1747.300	1.000	-.345	.101
	Adaptation NDA	-.133	.082	1734.269	1.000	-.363	.097
Training 2	Washout NDA	-.176	.079	1761.009	.265	-.399	.047
	Training 3	-.057	.079	1728.588	1.000	-.280	.165
	Training 1	-.180	.079	1745.236	.230	-.401	.042
	Adaptation NDA	-.190	.081	1725.485	.193	-.419	.038
Training 1	Washout NDA	.004	.079	1769.851	1.000	-.219	.227
	Training 3	.122	.079	1747.300	1.000	-.101	.345
	Training 2	.180	.079	1745.236	.230	-.042	.401
	Adaptation NDA	-.011	.081	1745.421	1.000	-.240	.218
Adaptation NDA	Washout NDA	.014	.082	1759.922	1.000	-.215	.244
	Training 3	.133	.082	1734.269	1.000	-.097	.363
	Training 2	.190	.081	1725.485	.193	-.038	.419
	Training 1	.011	.081	1745.421	1.000	-.218	.240

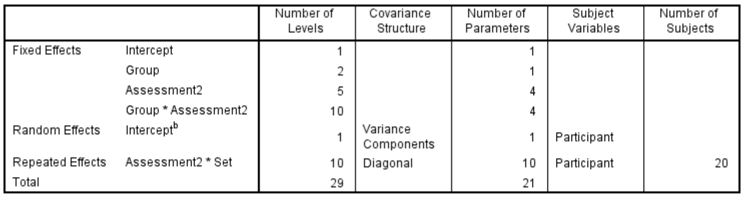
Based on estimated marginal means

a. Dependent Variable: Initial Error (mm).

b. Adjustment for multiple comparisons: Bonferroni.

Circularity

Model Dimension[a]

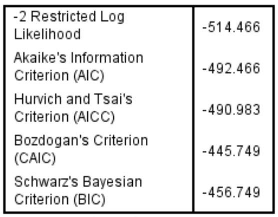


		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	10	Diagonal	10	Participant	20
Total		29		21		

a. Dependent Variable: Circularity (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Information Criteria[a]

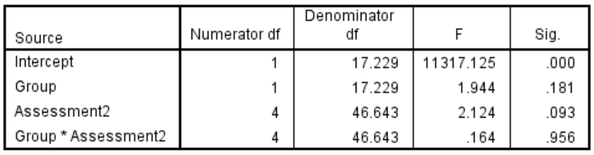


-2 Restricted Log Likelihood	-514.466
Akaike's Information Criterion (AIC)	-492.466
Hurvich and Tsai's Criterion (AICC)	-490.983
Bozdogan's Criterion (CAIC)	-445.749
Schwarz's Bayesian Criterion (BIC)	-456.749

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Circularity (no units).

Type III Tests of Fixed Effects[a]

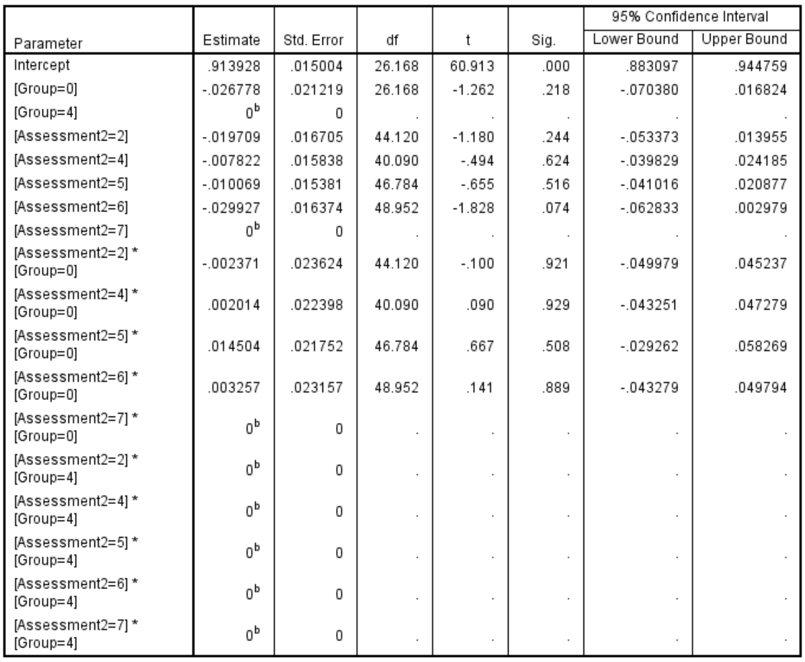


Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.229	11317.125	.000
Group	1	17.229	1.944	.181
Assessment2	4	46.643	2.124	.093
Group * Assessment2	4	46.643	.164	.956

a. Dependent Variable: Circularity (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

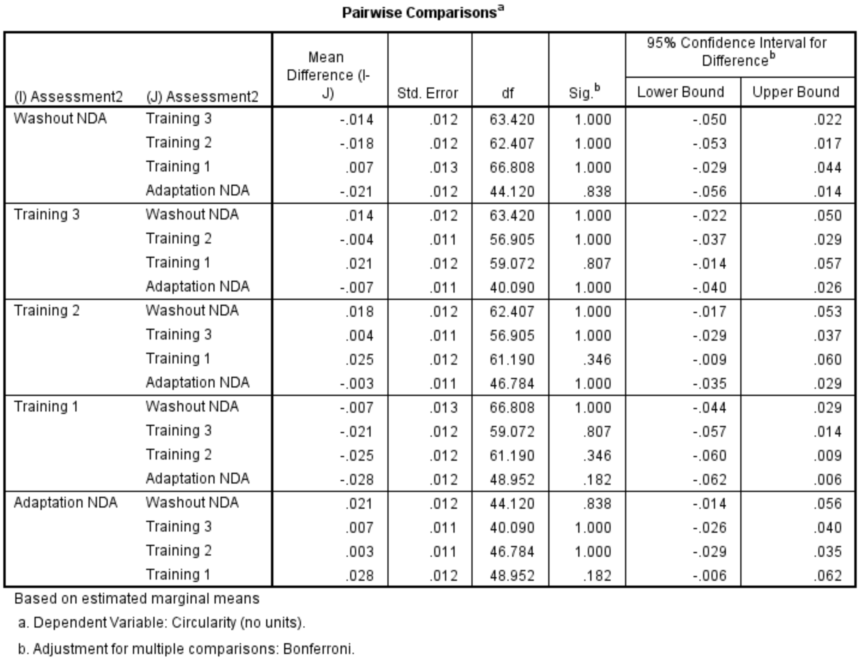
Estimates of Fixed Effects[a]



Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.913928	.015004	26.168	60.913	.000	.883097	.944759
[Group=0]	-.026778	.021219	26.168	-1.262	.218	-.070380	.016824
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.019709	.016705	44.120	-1.180	.244	-.053373	.013955
[Assessment2=4]	-.007822	.015838	40.090	-.494	.624	-.039829	.024185
[Assessment2=5]	-.010069	.015381	46.784	-.655	.516	-.041016	.020877
[Assessment2=6]	-.029927	.016374	48.952	-1.828	.074	-.062833	.002979
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	-.002371	.023624	44.120	-.100	.921	-.049979	.045237
[Assessment2=4] * [Group=0]	.002014	.022398	40.090	.090	.929	-.043251	.047279
[Assessment2=5] * [Group=0]	.014504	.021752	46.784	.667	.508	-.029262	.058269
[Assessment2=6] * [Group=0]	.003257	.023157	48.952	.141	.889	-.043279	.049794
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Circularity (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

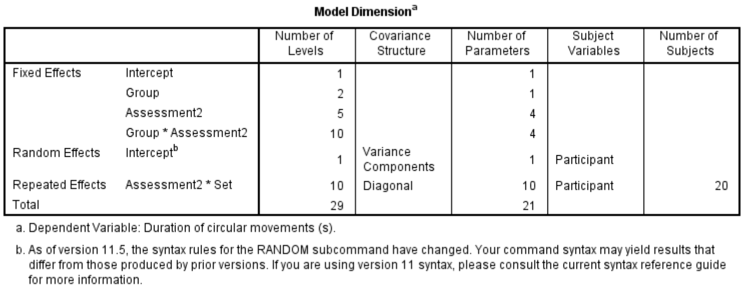
(I) Assessment2	(J) Assessment2	Mean Difference (I-J)	Std. Error	df	Sig.[b]	95% Confidence Interval for Difference[b]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	-.014	.012	63.420	1.000	-.050	.022
	Training 2	-.018	.012	62.407	1.000	-.053	.017
	Training 1	.007	.013	66.808	1.000	-.029	.044
	Adaptation NDA	-.021	.012	44.120	.838	-.056	.014
Training 3	Washout NDA	.014	.012	63.420	1.000	-.022	.050
	Training 2	-.004	.011	56.905	1.000	-.037	.029
	Training 1	.021	.012	59.072	.807	-.014	.057
	Adaptation NDA	-.007	.011	40.090	1.000	-.040	.026
Training 2	Washout NDA	.018	.012	62.407	1.000	-.017	.053
	Training 3	.004	.011	56.905	1.000	-.029	.037
	Training 1	.025	.012	61.190	.346	-.009	.060
	Adaptation NDA	-.003	.011	46.784	1.000	-.035	.029
Training 1	Washout NDA	-.007	.013	66.808	1.000	-.044	.029
	Training 3	-.021	.012	59.072	.807	-.057	.014
	Training 2	-.025	.012	61.190	.346	-.060	.009
	Adaptation NDA	-.028	.012	48.952	.182	-.062	.006
Adaptation NDA	Washout NDA	.021	.012	44.120	.838	-.014	.056
	Training 3	.007	.011	40.090	1.000	-.026	.040
	Training 2	.003	.011	46.784	1.000	-.029	.035
	Training 1	.028	.012	48.952	.182	-.006	.062

Based on estimated marginal means

a. Dependent Variable: Circularity (no units).

b. Adjustment for multiple comparisons: Bonferroni.

Duration of circular movements

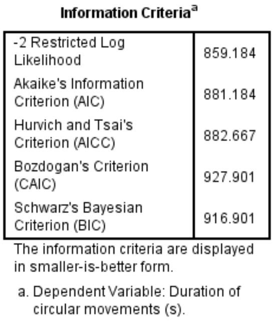


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	10	Diagonal	10	Participant	20
Total		29		21		

a. Dependent Variable: Duration of circular movements (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

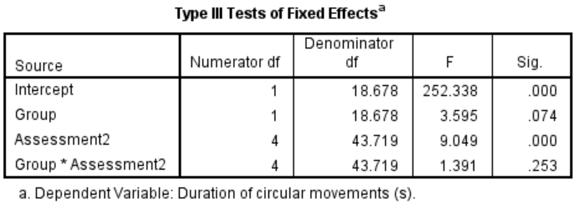


Information Criteria[a]

-2 Restricted Log Likelihood	859.184
Akaike's Information Criterion (AIC)	881.184
Hurvich and Tsai's Criterion (AICC)	882.667
Bozdogan's Criterion (CAIC)	927.901
Schwarz's Bayesian Criterion (BIC)	916.901

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration of circular movements (s).

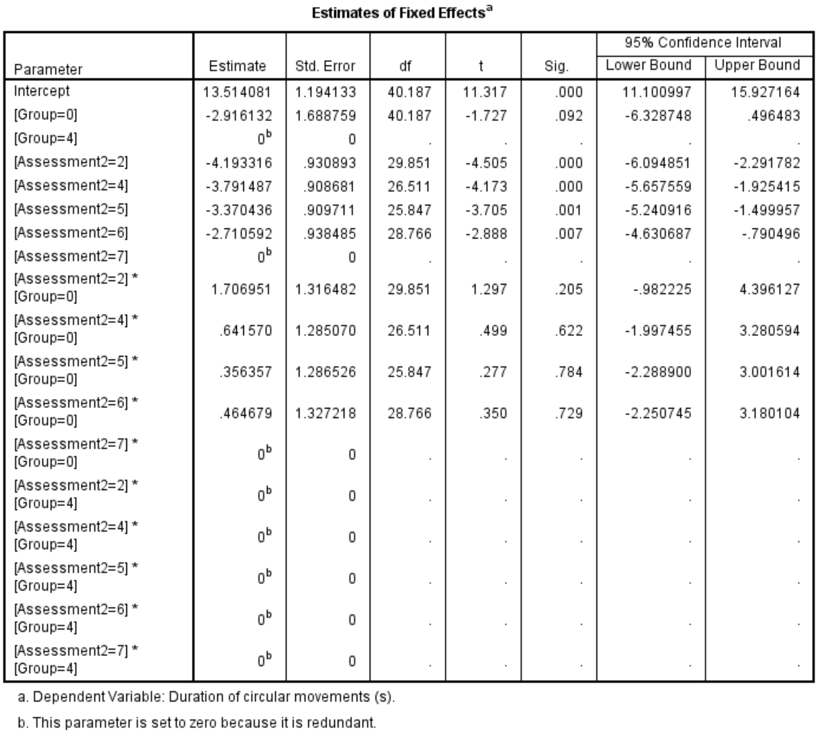


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.678	252.338	.000
Group	1	18.678	3.595	.074
Assessment2	4	43.719	9.049	.000
Group * Assessment2	4	43.719	1.391	.253

a. Dependent Variable: Duration of circular movements (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

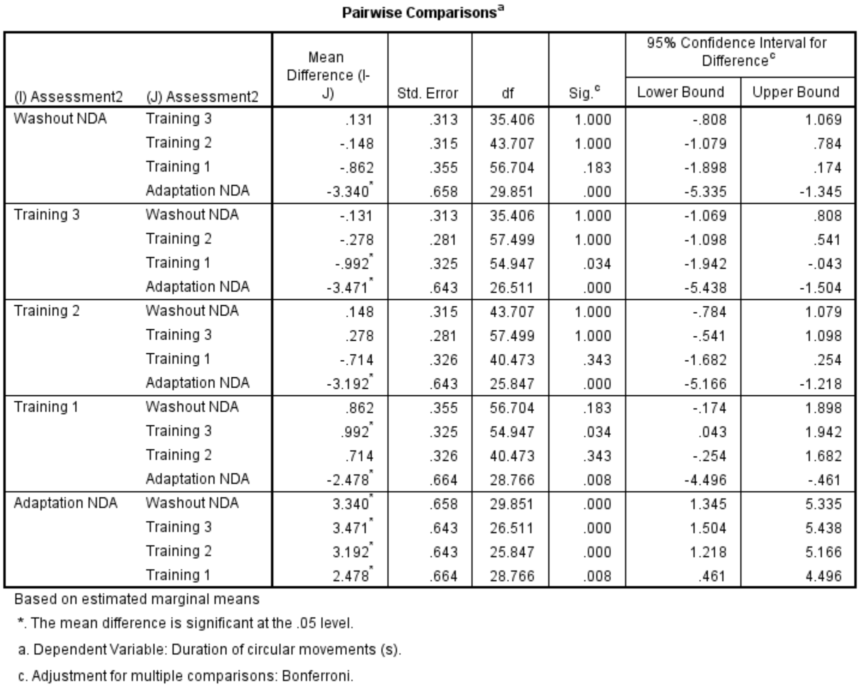


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	13.514081	1.194133	40.187	11.317	.000	11.100997	15.927164
[Group=0]	-2.916132	1.688759	40.187	-1.727	.092	-6.328748	.496483
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-4.193316	.930893	29.851	-4.505	.000	-6.094851	-2.291782
[Assessment2=4]	-3.791487	.908681	26.511	-4.173	.000	-5.657559	-1.925415
[Assessment2=5]	-3.370436	.909711	25.847	-3.705	.001	-5.240916	-1.499957
[Assessment2=6]	-2.710592	.938485	28.766	-2.888	.007	-4.630687	-.790496
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	1.706951	1.316482	29.851	1.297	.205	-.982225	4.396127
[Assessment2=4] * [Group=0]	.641570	1.285070	26.511	.499	.622	-1.997455	3.280594
[Assessment2=5] * [Group=0]	.356357	1.286526	25.847	.277	.784	-2.288900	3.001614
[Assessment2=6] * [Group=0]	.464679	1.327218	28.766	.350	.729	-2.250745	3.180104
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration of circular movements (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment2	(J) Assessment2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	.131	.313	35.406	1.000	-.808	1.069
	Training 2	-.148	.315	43.707	1.000	-1.079	.784
	Training 1	-.862	.355	56.704	.183	-1.898	.174
	Adaptation NDA	-3.340*	.658	29.851	.000	-5.335	-1.345
Training 3	Washout NDA	-.131	.313	35.406	1.000	-1.069	.808
	Training 2	-.278	.281	57.499	1.000	-1.098	.541
	Training 1	-.992*	.325	54.947	.034	-1.942	-.043
	Adaptation NDA	-3.471*	.643	26.511	.000	-5.438	-1.504
Training 2	Washout NDA	.148	.315	43.707	1.000	-.784	1.079
	Training 3	.278	.281	57.499	1.000	-.541	1.098
	Training 1	-.714	.326	40.473	.343	-1.682	.254
	Adaptation NDA	-3.192*	.643	25.847	.000	-5.166	-1.218
Training 1	Washout NDA	.862	.355	56.704	.183	-.174	1.898
	Training 3	.992*	.325	54.947	.034	.043	1.942
	Training 2	.714	.326	40.473	.343	-.254	1.682
	Adaptation NDA	-2.478*	.664	28.766	.008	-4.496	-.461
Adaptation NDA	Washout NDA	3.340*	.658	29.851	.000	1.345	5.335
	Training 3	3.471*	.643	26.511	.000	1.504	5.438
	Training 2	3.192*	.643	25.847	.000	1.218	5.166
	Training 1	2.478*	.664	28.766	.008	.461	4.496

Based on estimated marginal means

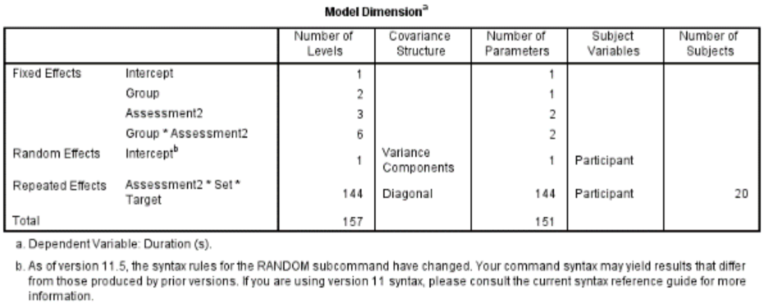
*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration of circular movements (s).

c. Adjustment for multiple comparisons: Bonferroni.

Analysis of the DA

Duration

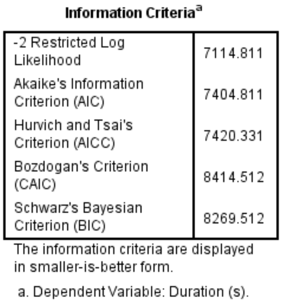


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Duration (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

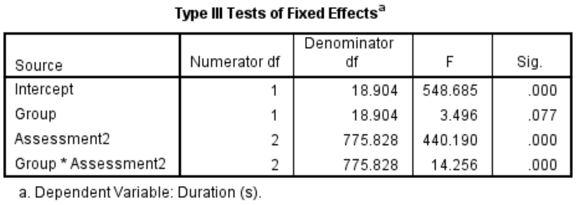


Information Criteria[a]

-2 Restricted Log Likelihood	7114.811
Akaike's Information Criterion (AIC)	7404.811
Hurvich and Tsai's Criterion (AICC)	7420.331
Bozdogan's Criterion (CAIC)	8414.512
Schwarz's Bayesian Criterion (BIC)	8269.512

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration (s).

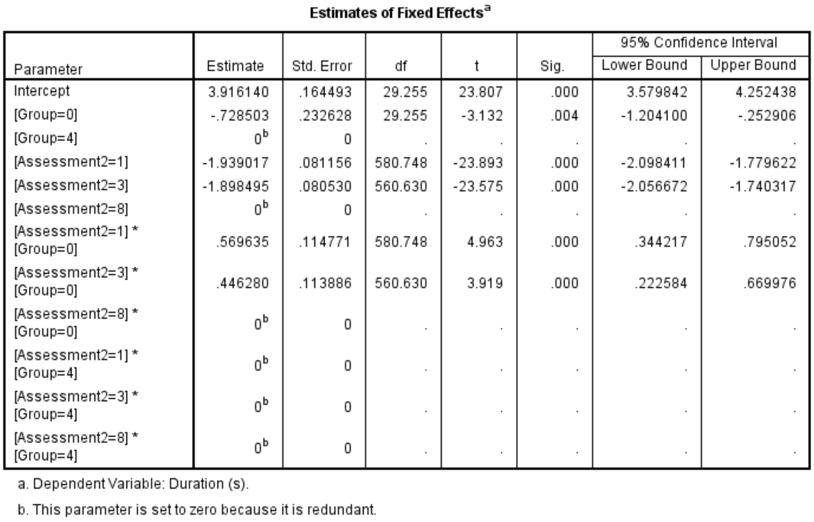


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.904	548.685	.000
Group	1	18.904	3.496	.077
Assessment2	2	775.828	440.190	.000
Group * Assessment2	2	775.828	14.256	.000

a. Dependent Variable: Duration (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

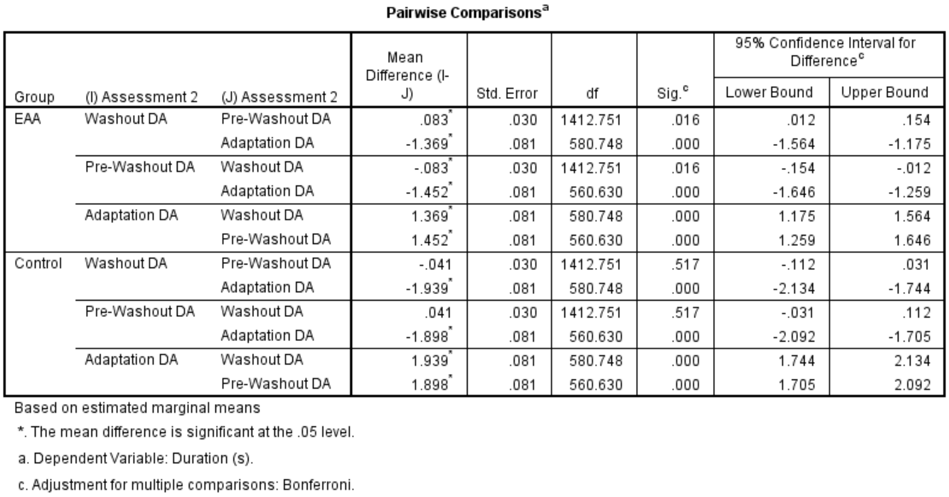


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	3.916140	.164493	29.255	23.807	.000	3.579842	4.252438
[Group=0]	-.728503	.232628	29.255	-3.132	.004	-1.204100	-.252906
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-1.939017	.081156	580.748	-23.893	.000	-2.098411	-1.779622
[Assessment2=3]	-1.898495	.080530	560.630	-23.575	.000	-2.056672	-1.740317
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	.569635	.114771	580.748	4.963	.000	.344217	.795052
[Assessment2=3] * [Group=0]	.446280	.113886	560.630	3.919	.000	.222584	.669976
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout DA	Pre-Washout DA	.083*	.030	1412.751	.016	.012	.154
		Adaptation DA	-1.369*	.081	580.748	.000	-1.564	-1.175
	Pre-Washout DA	Washout DA	-.083*	.030	1412.751	.016	-.154	-.012
		Adaptation DA	-1.452*	.081	560.630	.000	-1.646	-1.259
	Adaptation DA	Washout DA	1.369*	.081	580.748	.000	1.175	1.564
		Pre-Washout DA	1.452*	.081	560.630	.000	1.259	1.646
Control	Washout DA	Pre-Washout DA	-.041	.030	1412.751	.517	-.112	.031
		Adaptation DA	-1.939*	.081	580.748	.000	-2.134	-1.744
	Pre-Washout DA	Washout DA	.041	.030	1412.751	.517	-.031	.112
		Adaptation DA	-1.898*	.081	560.630	.000	-2.092	-1.705
	Adaptation DA	Washout DA	1.939*	.081	580.748	.000	1.744	2.134
		Pre-Washout DA	1.898*	.081	560.630	.000	1.705	2.092

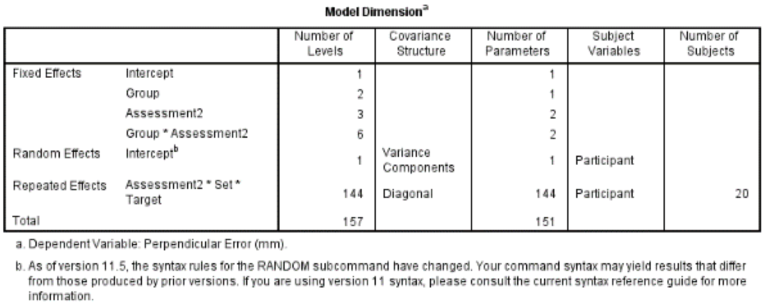
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration (s).

c. Adjustment for multiple comparisons: Bonferroni.

Perpendicular error

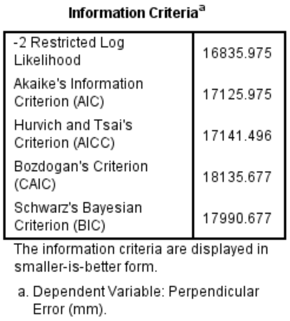


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Perpendicular Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

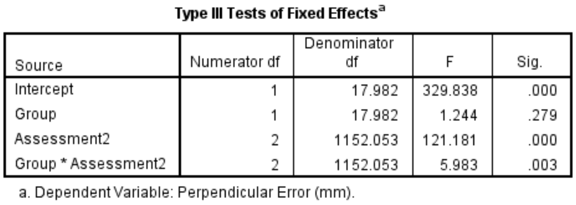


Information Criteria[a]

-2 Restricted Log Likelihood	16835.975
Akaike's Information Criterion (AIC)	17125.975
Hurvich and Tsai's Criterion (AICC)	17141.496
Bozdogan's Criterion (CAIC)	18135.677
Schwarz's Bayesian Criterion (BIC)	17990.677

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Perpendicular Error (mm).

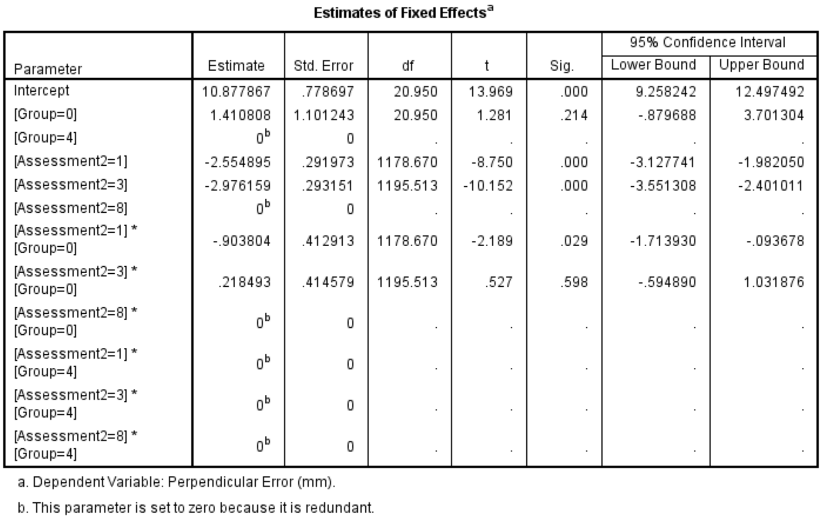


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.982	329.838	.000
Group	1	17.982	1.244	.279
Assessment2	2	1152.053	121.181	.000
Group * Assessment2	2	1152.053	5.983	.003

a. Dependent Variable: Perpendicular Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

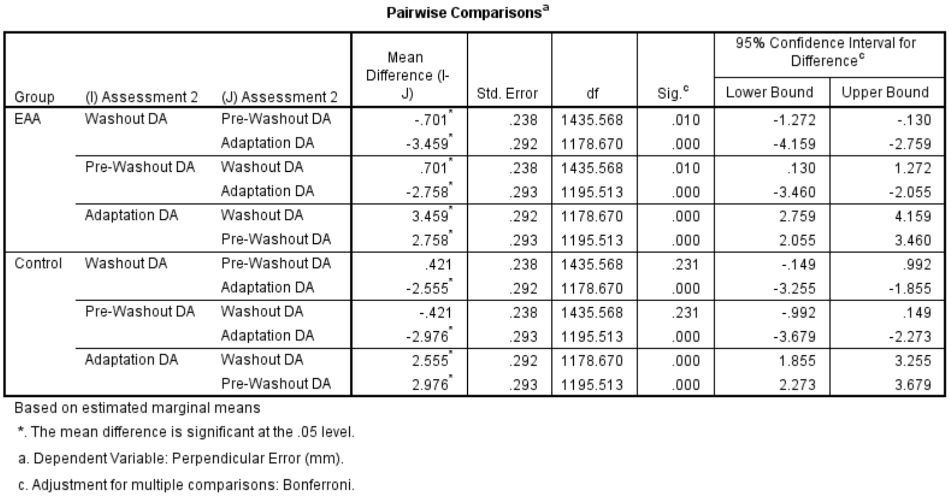


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	10.877867	.778697	20.950	13.969	.000	9.258242	12.497492
[Group=0]	1.410808	1.101243	20.950	1.281	.214	-.879688	3.701304
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-2.554895	.291973	1178.670	-8.750	.000	-3.127741	-1.982050
[Assessment2=3]	-2.976159	.293151	1195.513	-10.152	.000	-3.551308	-2.401011
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	-.903804	.412913	1178.670	-2.189	.029	-1.713930	-.093678
[Assessment2=3] * [Group=0]	.218493	.414579	1195.513	.527	.598	-.594890	1.031876
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Perpendicular Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c] Lower Bound	95% Confidence Interval for Difference[c] Upper Bound
EAA	Washout DA	Pre-Washout DA	-.701*	.238	1435.568	.010	-1.272	-.130
		Adaptation DA	-3.459*	.292	1178.670	.000	-4.159	-2.759
	Pre-Washout DA	Washout DA	.701*	.238	1435.568	.010	.130	1.272
		Adaptation DA	-2.758*	.293	1195.513	.000	-3.460	-2.055
	Adaptation DA	Washout DA	3.459*	.292	1178.670	.000	2.759	4.159
		Pre-Washout DA	2.758*	.293	1195.513	.000	2.055	3.460
Control	Washout DA	Pre-Washout DA	.421	.238	1435.568	.231	-.149	.992
		Adaptation DA	-2.555*	.292	1178.670	.000	-3.255	-1.855
	Pre-Washout DA	Washout DA	-.421	.238	1435.568	.231	-.992	.149
		Adaptation DA	-2.976*	.293	1195.513	.000	-3.679	-2.273
	Adaptation DA	Washout DA	2.555*	.292	1178.670	.000	1.855	3.255
		Pre-Washout DA	2.976*	.293	1195.513	.000	2.273	3.679

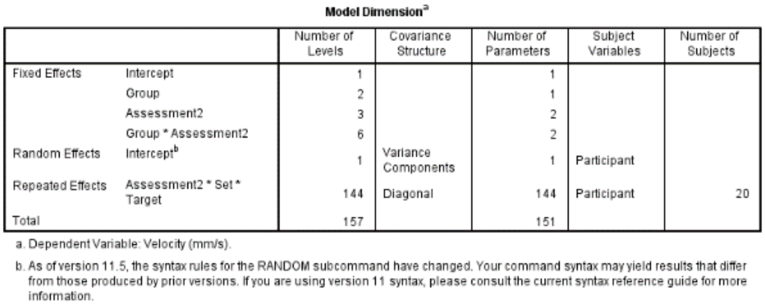
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Perpendicular Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Mean velocity

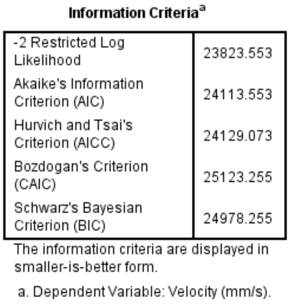


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Velocity (mm/s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

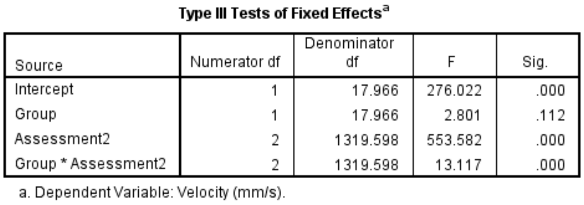


Information Criteria[a]

-2 Restricted Log Likelihood	23823.553
Akaike's Information Criterion (AIC)	24113.553
Hurvich and Tsai's Criterion (AICC)	24129.073
Bozdogan's Criterion (CAIC)	25123.255
Schwarz's Bayesian Criterion (BIC)	24978.255

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Velocity (mm/s).

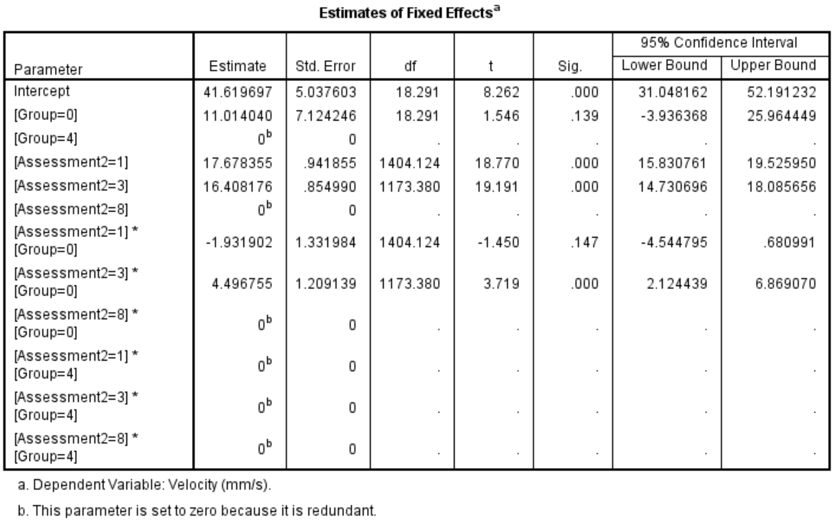


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.966	276.022	.000
Group	1	17.966	2.801	.112
Assessment2	2	1319.598	553.582	.000
Group * Assessment2	2	1319.598	13.117	.000

a. Dependent Variable: Velocity (mm/s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

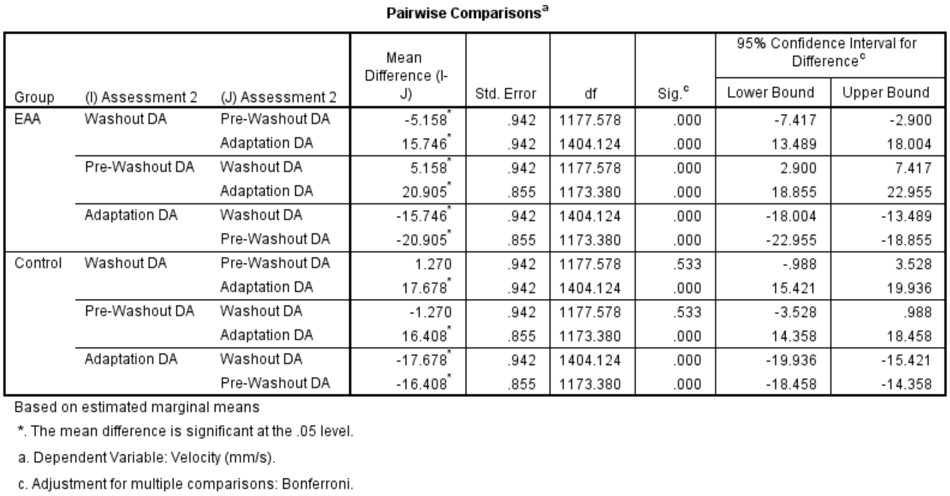


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	41.619697	5.037603	18.291	8.262	.000	31.048162	52.191232
[Group=0]	11.014040	7.124246	18.291	1.546	.139	-3.936368	25.964449
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	17.678355	.941855	1404.124	18.770	.000	15.830761	19.525950
[Assessment2=3]	16.408176	.854990	1173.380	19.191	.000	14.730696	18.085656
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	-1.931902	1.331984	1404.124	-1.450	.147	-4.544795	.680991
[Assessment2=3] * [Group=0]	4.496755	1.209139	1173.380	3.719	.000	2.124439	6.869070
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Velocity (mm/s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout DA	Pre-Washout DA	-5.158*	.942	1177.578	.000	-7.417	-2.900
		Adaptation DA	15.746*	.942	1404.124	.000	13.489	18.004
	Pre-Washout DA	Washout DA	5.158*	.942	1177.578	.000	2.900	7.417
		Adaptation DA	20.905*	.855	1173.380	.000	18.855	22.955
	Adaptation DA	Washout DA	-15.746*	.942	1404.124	.000	-18.004	-13.489
		Pre-Washout DA	-20.905*	.855	1173.380	.000	-22.955	-18.855
Control	Washout DA	Pre-Washout DA	1.270	.942	1177.578	.533	-.988	3.528
		Adaptation DA	17.678*	.942	1404.124	.000	15.421	19.936
	Pre-Washout DA	Washout DA	-1.270	.942	1177.578	.533	-3.528	.988
		Adaptation DA	16.408*	.855	1173.380	.000	14.358	18.458
	Adaptation DA	Washout DA	-17.678*	.942	1404.124	.000	-19.936	-15.421
		Pre-Washout DA	-16.408*	.855	1173.380	.000	-18.458	-14.358

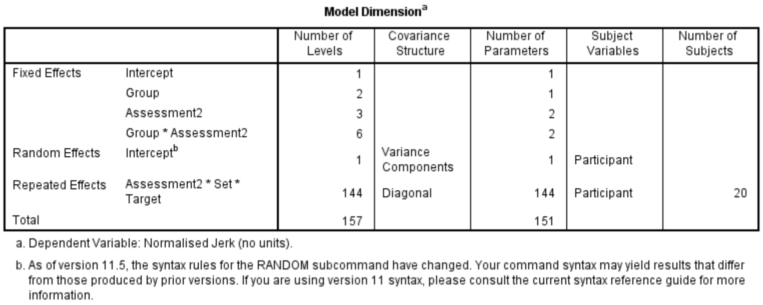
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Velocity (mm/s).

c. Adjustment for multiple comparisons: Bonferroni.

Normalised jerk

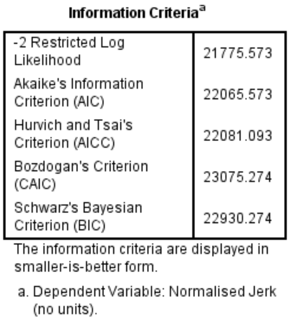


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Normalised Jerk (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

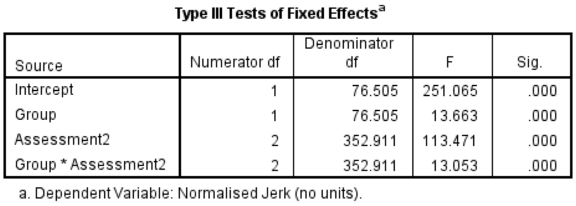


Information Criteria[a]

-2 Restricted Log Likelihood	21775.573
Akaike's Information Criterion (AIC)	22065.573
Hurvich and Tsai's Criterion (AICC)	22081.093
Bozdogan's Criterion (CAIC)	23075.274
Schwarz's Bayesian Criterion (BIC)	22930.274

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Normalised Jerk (no units).

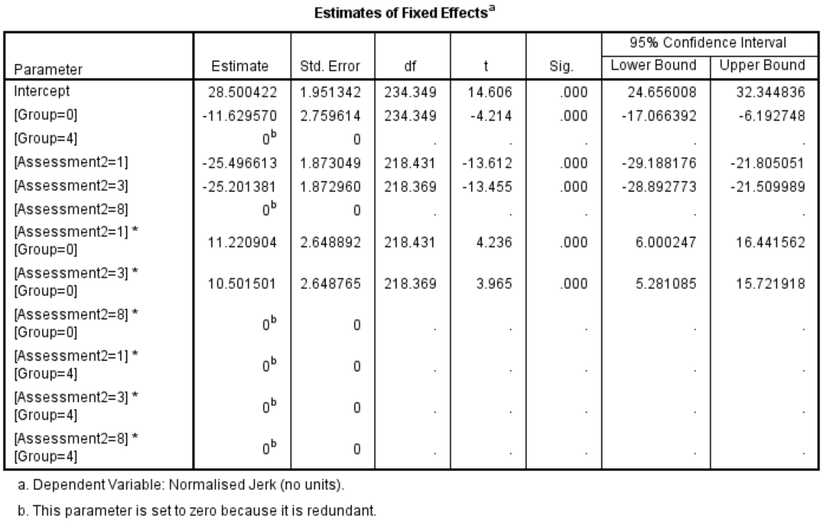


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	76.505	251.065	.000
Group	1	76.505	13.663	.000
Assessment2	2	352.911	113.471	.000
Group * Assessment2	2	352.911	13.053	.000

a. Dependent Variable: Normalised Jerk (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

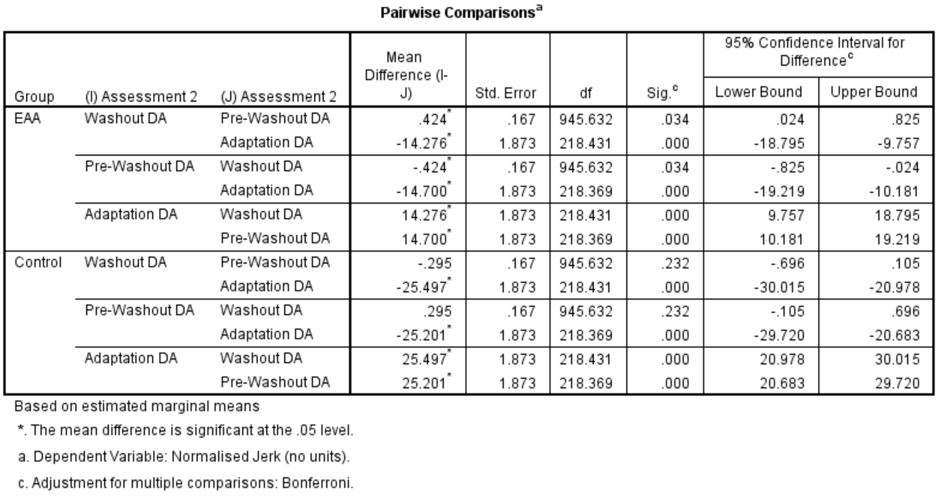


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	28.500422	1.951342	234.349	14.606	.000	24.656008	32.344836
[Group=0]	-11.629570	2.759614	234.349	-4.214	.000	-17.066392	-6.192748
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-25.496613	1.873049	218.431	-13.612	.000	-29.188176	-21.805051
[Assessment2=3]	-25.201381	1.872960	218.369	-13.455	.000	-28.892773	-21.509989
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	11.220904	2.648892	218.431	4.236	.000	6.000247	16.441562
[Assessment2=3] * [Group=0]	10.501501	2.648765	218.369	3.965	.000	5.281085	15.721918
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Normalised Jerk (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout DA	Pre-Washout DA	.424*	.167	945.632	.034	.024	.825
		Adaptation DA	-14.276*	1.873	218.431	.000	-18.795	-9.757
	Pre-Washout DA	Washout DA	-.424*	.167	945.632	.034	-.825	-.024
		Adaptation DA	-14.700*	1.873	218.369	.000	-19.219	-10.181
	Adaptation DA	Washout DA	14.276*	1.873	218.431	.000	9.757	18.795
		Pre-Washout DA	14.700*	1.873	218.369	.000	10.181	19.219
Control	Washout DA	Pre-Washout DA	-.295	.167	945.632	.232	-.696	.105
		Adaptation DA	-25.497*	1.873	218.431	.000	-30.015	-20.978
	Pre-Washout DA	Washout DA	.295	.167	945.632	.232	-.105	.696
		Adaptation DA	-25.201*	1.873	218.369	.000	-29.720	-20.683
	Adaptation DA	Washout DA	25.497*	1.873	218.431	.000	20.978	30.015
		Pre-Washout DA	25.201*	1.873	218.369	.000	20.683	29.720

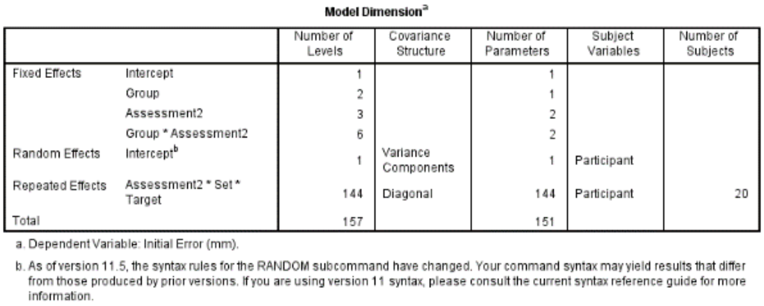
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Normalised Jerk (no units).

c. Adjustment for multiple comparisons: Bonferroni.

Initial error

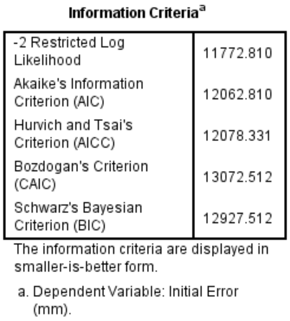


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Initial Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

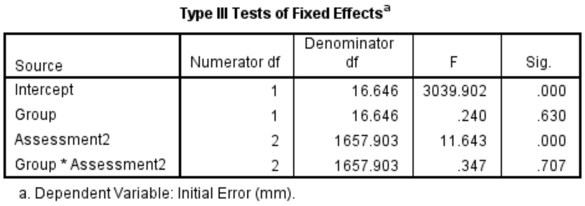


Information Criteria[a]

-2 Restricted Log Likelihood	11772.810
Akaike's Information Criterion (AIC)	12062.810
Hurvich and Tsai's Criterion (AICC)	12078.331
Bozdogan's Criterion (CAIC)	13072.512
Schwarz's Bayesian Criterion (BIC)	12927.512

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Initial Error (mm).

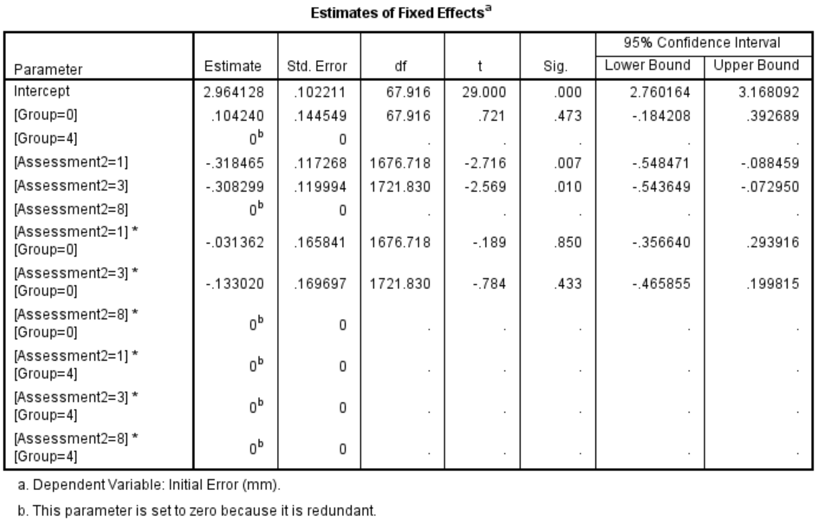


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	16.646	3039.902	.000
Group	1	16.646	.240	.630
Assessment2	2	1657.903	11.643	.000
Group * Assessment2	2	1657.903	.347	.707

a. Dependent Variable: Initial Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

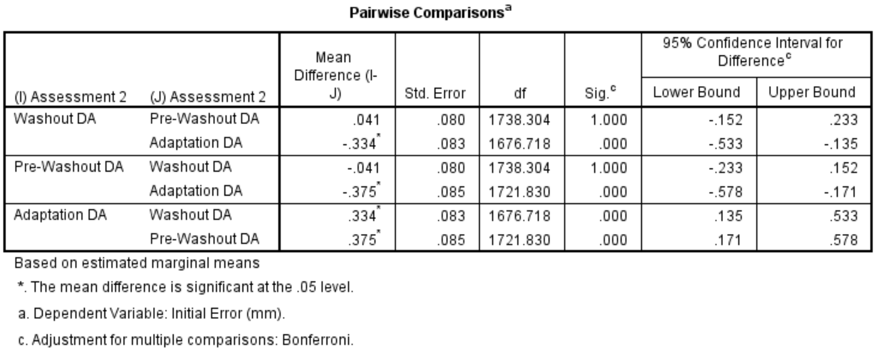


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	2.964128	.102211	67.916	29.000	.000	2.760164	3.168092
[Group=0]	.104240	.144549	67.916	.721	.473	-.184208	.392689
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-.318465	.117268	1676.718	-2.716	.007	-.548471	-.088459
[Assessment2=3]	-.308299	.119994	1721.830	-2.569	.010	-.543649	-.072950
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	-.031362	.165841	1676.718	-.189	.850	-.356640	.293916
[Assessment2=3] * [Group=0]	-.133020	.169697	1721.830	-.784	.433	-.465855	.199815
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Initial Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout DA	Pre-Washout DA	.041	.080	1738.304	1.000	-.152	.233
	Adaptation DA	-.334*	.083	1676.718	.000	-.533	-.135
Pre-Washout DA	Washout DA	-.041	.080	1738.304	1.000	-.233	.152
	Adaptation DA	-.375*	.085	1721.830	.000	-.578	-.171
Adaptation DA	Washout DA	.334*	.083	1676.718	.000	.135	.533
	Pre-Washout DA	.375*	.085	1721.830	.000	.171	.578

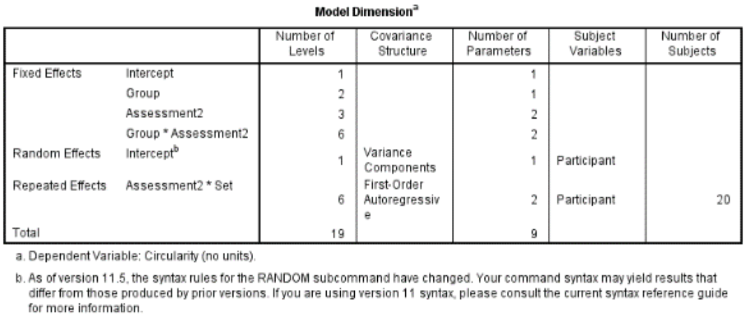
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Initial Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Circularity

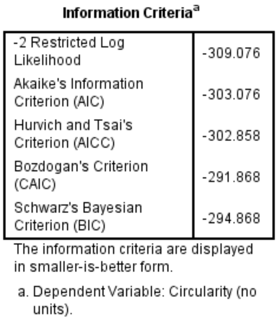


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	6	First-Order Autoregressiv e	2	Participant	20
Total		19		9		

a. Dependent Variable: Circularity (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

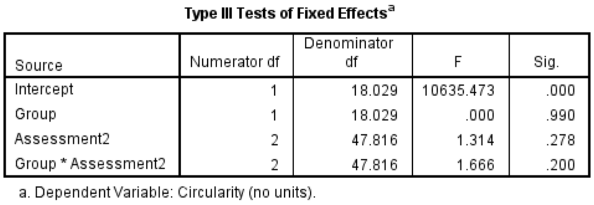


Information Criteria[a]

-2 Restricted Log Likelihood	-309.076
Akaike's Information Criterion (AIC)	-303.076
Hurvich and Tsai's Criterion (AICC)	-302.858
Bozdogan's Criterion (CAIC)	-291.868
Schwarz's Bayesian Criterion (BIC)	-294.868

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Circularity (no units).

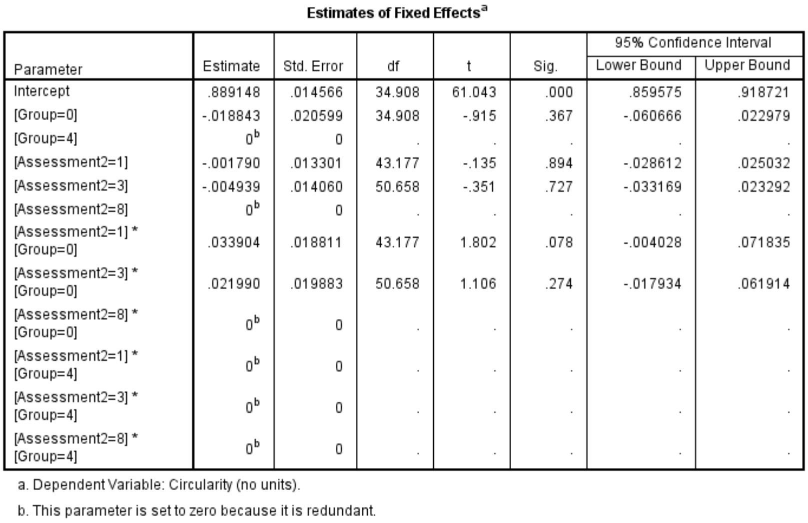


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.029	10635.473	.000
Group	1	18.029	.000	.990
Assessment2	2	47.816	1.314	.278
Group * Assessment2	2	47.816	1.666	.200

a. Dependent Variable: Circularity (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

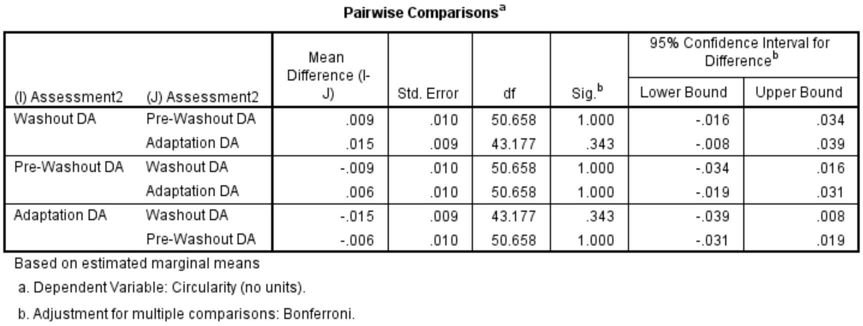


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.889148	.014566	34.908	61.043	.000	.859575	.918721
[Group=0]	-.018843	.020599	34.908	-.915	.367	-.060666	.022979
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-.001790	.013301	43.177	-.135	.894	-.028612	.025032
[Assessment2=3]	-.004939	.014060	50.658	-.351	.727	-.033169	.023292
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	.033904	.018811	43.177	1.802	.078	-.004028	.071835
[Assessment2=3] * [Group=0]	.021990	.019883	50.658	1.106	.274	-.017934	.061914
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Circularity (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

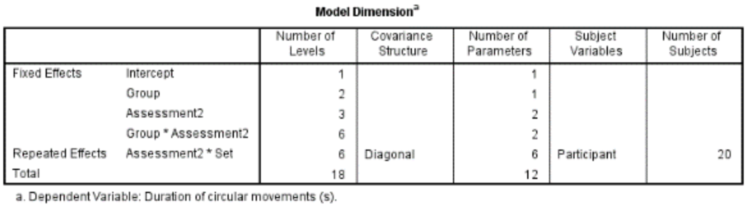
(I) Assessment2	(J) Assessment2	Mean Difference (I-J)	Std. Error	df	Sig.[b]	95% Confidence Interval for Difference[b]	
						Lower Bound	Upper Bound
Washout DA	Pre-Washout DA	.009	.010	50.658	1.000	-.016	.034
	Adaptation DA	.015	.009	43.177	.343	-.008	.039
Pre-Washout DA	Washout DA	-.009	.010	50.658	1.000	-.034	.016
	Adaptation DA	.006	.010	50.658	1.000	-.019	.031
Adaptation DA	Washout DA	-.015	.009	43.177	.343	-.039	.008
	Pre-Washout DA	-.006	.010	50.658	1.000	-.031	.019

Based on estimated marginal means

a. Dependent Variable: Circularity (no units).

b. Adjustment for multiple comparisons: Bonferroni.

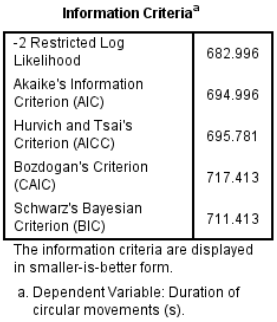
Duration of circular movements



Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Repeated Effects	Assessment2 * Set	6	Diagonal	6	Participant	20
Total		18		12		

a. Dependent Variable: Duration of circular movements (s).

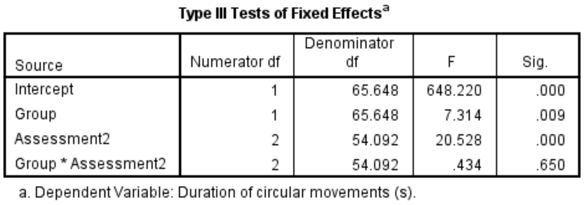


Information Criteria[a]

-2 Restricted Log Likelihood	682.996
Akaike's Information Criterion (AIC)	694.996
Hurvich and Tsai's Criterion (AICC)	695.781
Bozdogan's Criterion (CAIC)	717.413
Schwarz's Bayesian Criterion (BIC)	711.413

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration of circular movements (s).

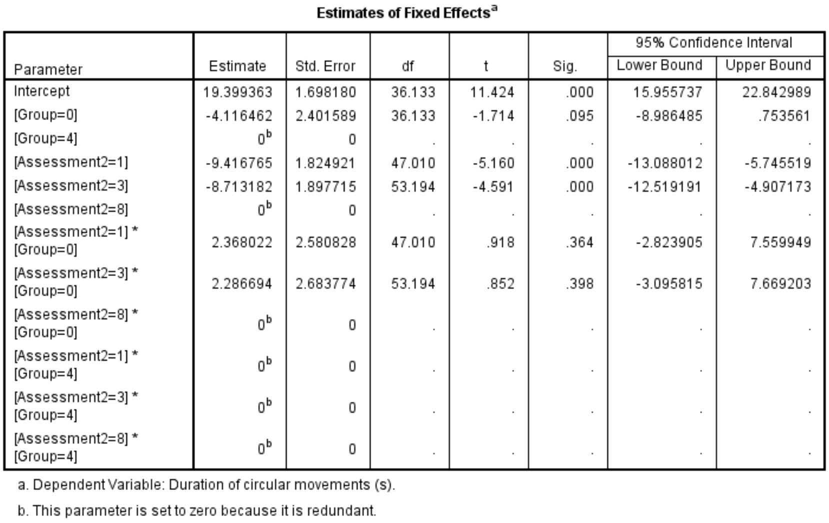


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	65.648	648.220	.000
Group	1	65.648	7.314	.009
Assessment2	2	54.092	20.528	.000
Group * Assessment2	2	54.092	.434	.650

a. Dependent Variable: Duration of circular movements (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

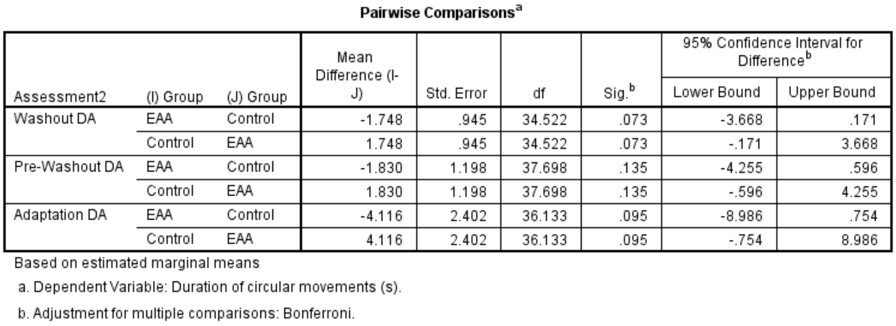


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	19.399363	1.698180	36.133	11.424	.000	15.955737	22.842989
[Group=0]	-4.116462	2.401589	36.133	-1.714	.095	-8.986485	.753561
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-9.416765	1.824921	47.010	-5.160	.000	-13.088012	-5.745519
[Assessment2=3]	-8.713182	1.897715	53.194	-4.591	.000	-12.519191	-4.907173
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	2.368022	2.580828	47.010	.918	.364	-2.823905	7.559949
[Assessment2=3] * [Group=0]	2.286694	2.683774	53.194	.852	.398	-3.095815	7.669203
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration of circular movements (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Assessment2	(I) Group	(J) Group	Mean Difference (I-J)	Std. Error	df	Sig.[b]	95% Confidence Interval for Difference[b] Lower Bound	95% Confidence Interval for Difference[b] Upper Bound
Washout DA	EAA	Control	-1.748	.945	34.522	.073	-3.668	.171
	Control	EAA	1.748	.945	34.522	.073	-.171	3.668
Pre-Washout DA	EAA	Control	-1.830	1.198	37.698	.135	-4.255	.596
	Control	EAA	1.830	1.198	37.698	.135	-.596	4.255
Adaptation DA	EAA	Control	-4.116	2.402	36.133	.095	-8.986	.754
	Control	EAA	4.116	2.402	36.133	.095	-.754	8.986

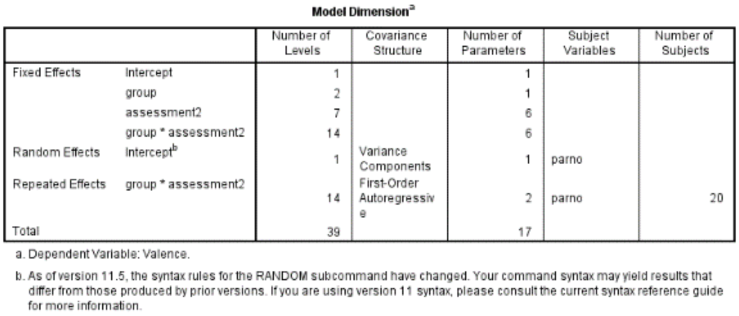
Based on estimated marginal means

a. Dependent Variable: Duration of circular movements (s).

b. Adjustment for multiple comparisons: Bonferroni.

Analysis of the SAM questionnaire

Valence

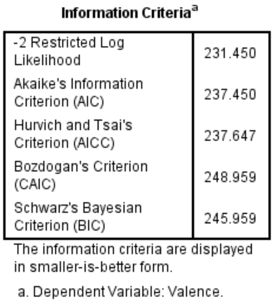


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	2		1		
	assessment2	7		6		
	group * assessment2	14		6		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	14	First-Order Autoregressiv e	2	parno	20
Total		39		17		

a. Dependent Variable: Valence.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

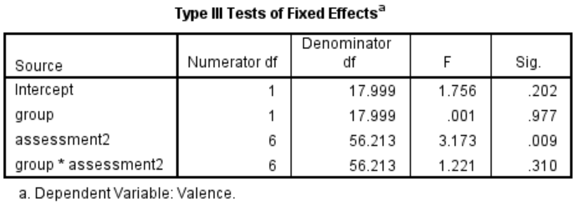


Information Criteria[a]

-2 Restricted Log Likelihood	231.450
Akaike's Information Criterion (AIC)	237.450
Hurvich and Tsai's Criterion (AICC)	237.647
Bozdogan's Criterion (CAIC)	248.959
Schwarz's Bayesian Criterion (BIC)	245.959

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Valence.

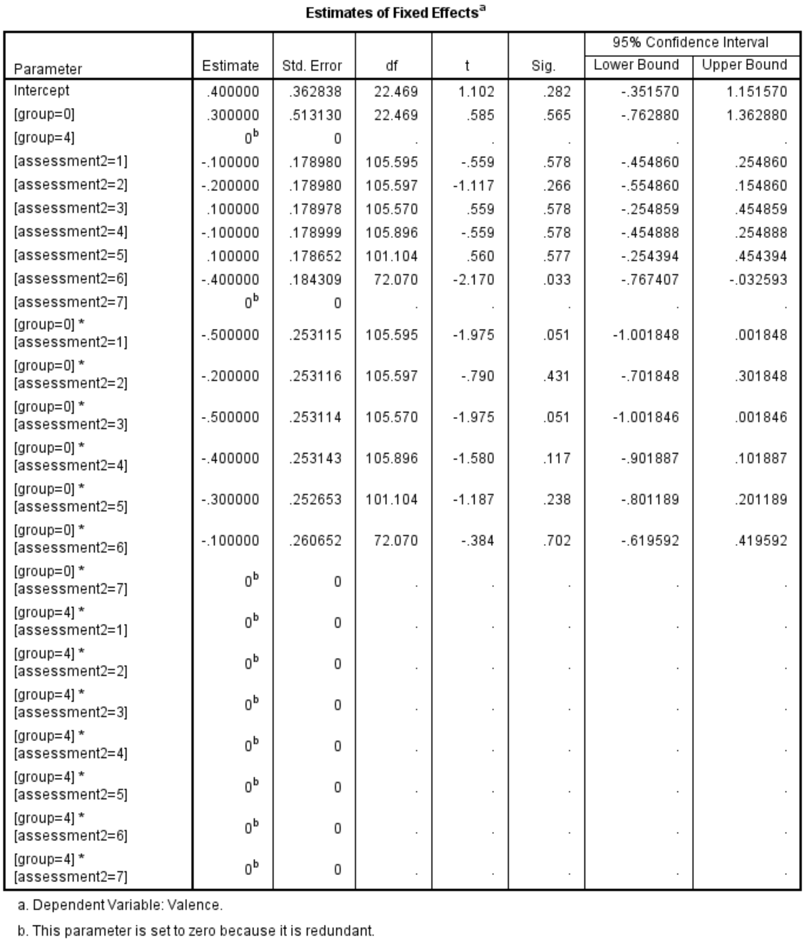


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.999	1.756	.202
group	1	17.999	.001	.977
assessment2	6	56.213	3.173	.009
group * assessment2	6	56.213	1.221	.310

a. Dependent Variable: Valence.

Group 0: EAA	Assessment 8: Adaptation DA
Group 1: AAN	Assessment 7: Adaptation NDA
Group 2: EAP	Assessment 6: Training 1
Group 4: Control	Assessment 5: Training 2
	Assessment 4: Training 3
	Assessment 3: Pre-washout
	Assessment 2: Washout NDA
	Assessment 1: Washout DA



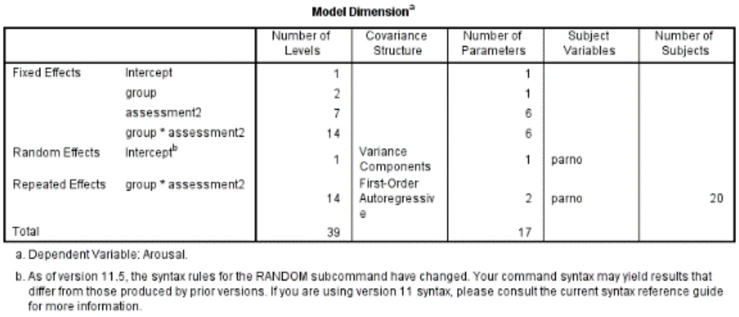
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.400000	.362838	22.469	1.102	.282	-.351570	1.151570
[group=0]	.300000	.513130	22.469	.585	.565	-.762880	1.362880
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	-.100000	.178980	105.595	-.559	.578	-.454860	.254860
[assessment2=2]	-.200000	.178980	105.597	-1.117	.266	-.554860	.154860
[assessment2=3]	.100000	.178978	105.570	.559	.578	-.254859	.454859
[assessment2=4]	-.100000	.178999	105.896	-.559	.578	-.454888	.254888
[assessment2=5]	.100000	.178652	101.104	.560	.577	-.254394	.454394
[assessment2=6]	-.400000	.184309	72.070	-2.170	.033	-.767407	-.032593
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=0] * [assessment2=1]	-.500000	.253115	105.595	-1.975	.051	-1.001848	.001848
[group=0] * [assessment2=2]	-.200000	.253116	105.597	-.790	.431	-.701848	.301848
[group=0] * [assessment2=3]	-.500000	.253114	105.570	-1.975	.051	-1.001846	.001846
[group=0] * [assessment2=4]	-.400000	.253143	105.896	-1.580	.117	-.901887	.101887
[group=0] * [assessment2=5]	-.300000	.252653	101.104	-1.187	.238	-.801189	.201189
[group=0] * [assessment2=6]	-.100000	.260652	72.070	-.384	.702	-.619592	.419592
[group=0] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Valence.

b. This parameter is set to zero because it is redundant.

Arousal

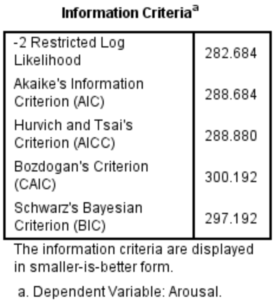


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	2		1		
	assessment2	7		6		
	group * assessment2	14		6		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	14	First-Order Autoregressive	2	parno	20
Total		39		17		

a. Dependent Variable: Arousal.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

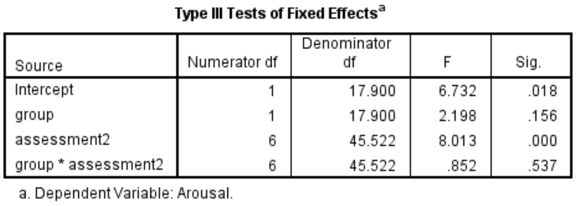


Information Criteria[a]

-2 Restricted Log Likelihood	282.684
Akaike's Information Criterion (AIC)	288.684
Hurvich and Tsai's Criterion (AICC)	288.880
Bozdogan's Criterion (CAIC)	300.192
Schwarz's Bayesian Criterion (BIC)	297.192

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Arousal.

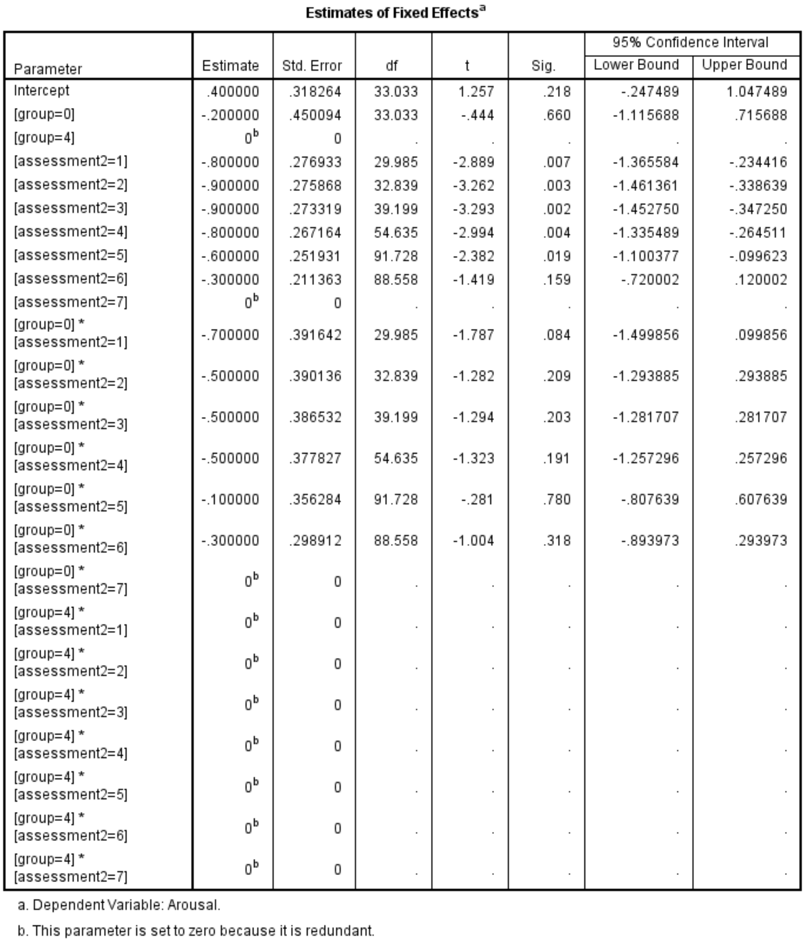


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.900	6.732	.018
group	1	17.900	2.198	.156
assessment2	6	45.522	8.013	.000
group * assessment2	6	45.522	.852	.537

a. Dependent Variable: Arousal.

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



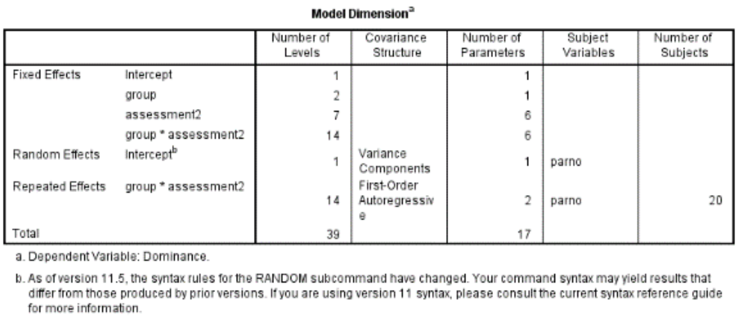
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.400000	.318264	33.033	1.257	.218	-.247489	1.047489
[group=0]	-.200000	.450094	33.033	-.444	.660	-1.115688	.715688
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	-.800000	.276933	29.985	-2.889	.007	-1.365584	-.234416
[assessment2=2]	-.900000	.275868	32.839	-3.262	.003	-1.461361	-.338639
[assessment2=3]	-.900000	.273319	39.199	-3.293	.002	-1.452750	-.347250
[assessment2=4]	-.800000	.267164	54.635	-2.994	.004	-1.335489	-.264511
[assessment2=5]	-.600000	.251931	91.728	-2.382	.019	-1.100377	-.099623
[assessment2=6]	-.300000	.211363	88.558	-1.419	.159	-.720002	.120002
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=0] * [assessment2=1]	-.700000	.391642	29.985	-1.787	.084	-1.499856	.099856
[group=0] * [assessment2=2]	-.500000	.390136	32.839	-1.282	.209	-1.293885	.293885
[group=0] * [assessment2=3]	-.500000	.386532	39.199	-1.294	.203	-1.281707	.281707
[group=0] * [assessment2=4]	-.500000	.377827	54.635	-1.323	.191	-1.257296	.257296
[group=0] * [assessment2=5]	-.100000	.356284	91.728	-.281	.780	-.807639	.607639
[group=0] * [assessment2=6]	-.300000	.298912	88.558	-1.004	.318	-.893973	.293973
[group=0] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Arousal.

b. This parameter is set to zero because it is redundant.

Dominance

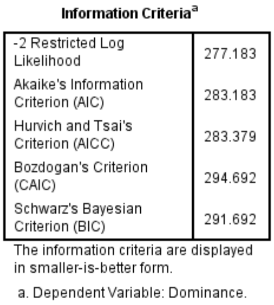


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	2		1		
	assessment2	7		6		
	group * assessment2	14		6		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	14	First-Order Autoregressive	2	parno	20
Total		39		17		

a. Dependent Variable: Dominance.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

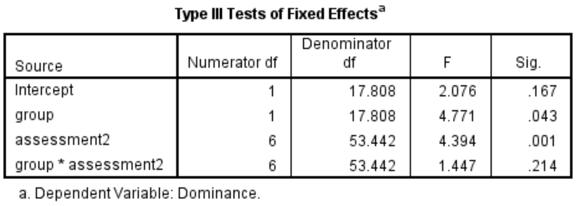


Information Criteria[a]

-2 Restricted Log Likelihood	277.183
Akaike's Information Criterion (AIC)	283.183
Hurvich and Tsai's Criterion (AICC)	283.379
Bozdogan's Criterion (CAIC)	294.692
Schwarz's Bayesian Criterion (BIC)	291.692

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Dominance.

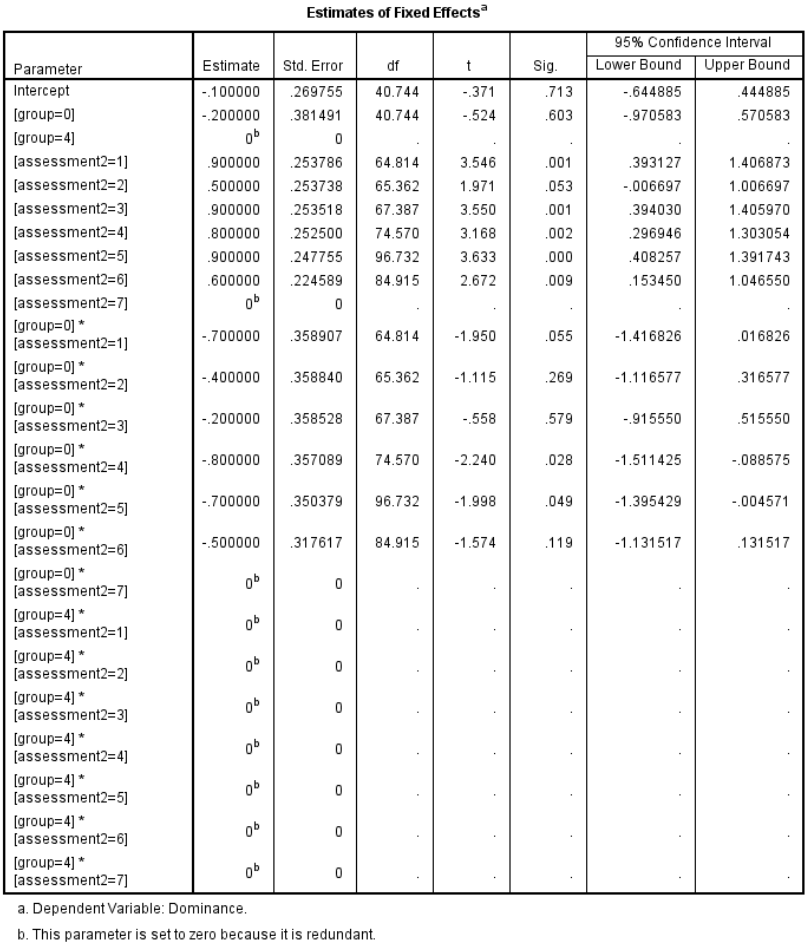


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.808	2.076	.167
group	1	17.808	4.771	.043
assessment2	6	53.442	4.394	.001
group * assessment2	6	53.442	1.447	.214

a. Dependent Variable: Dominance.

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-.100000	.269755	40.744	-.371	.713	-.644885	.444885
[group=0]	-.200000	.381491	40.744	-.524	.603	-.970583	.570583
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	.900000	.253786	64.814	3.546	.001	.393127	1.406873
[assessment2=2]	.500000	.253738	65.362	1.971	.053	-.006697	1.006697
[assessment2=3]	.900000	.253518	67.387	3.550	.001	.394030	1.405970
[assessment2=4]	.800000	.252500	74.570	3.168	.002	.296946	1.303054
[assessment2=5]	.900000	.247755	96.732	3.633	.000	.408257	1.391743
[assessment2=6]	.600000	.224589	84.915	2.672	.009	.153450	1.046550
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=0] * [assessment2=1]	-.700000	.358907	64.814	-1.950	.055	-1.416826	.016826
[group=0] * [assessment2=2]	-.400000	.358840	65.362	-1.115	.269	-1.116577	.316577
[group=0] * [assessment2=3]	-.200000	.358528	67.387	-.558	.579	-.915550	.515550
[group=0] * [assessment2=4]	-.800000	.357089	74.570	-2.240	.028	-1.511425	-.088575
[group=0] * [assessment2=5]	-.700000	.350379	96.732	-1.998	.049	-1.395429	-.004571
[group=0] * [assessment2=6]	-.500000	.317617	84.915	-1.574	.119	-1.131517	.131517
[group=0] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

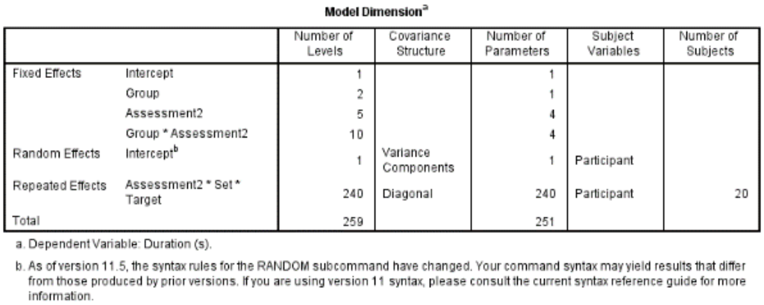
a. Dependent Variable: Dominance.

b. This parameter is set to zero because it is redundant.

Chapter 7: Results of the statistical analysis

Analysis of the NDA

Duration

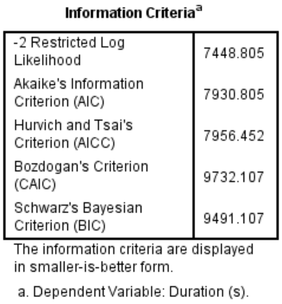


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Duration (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

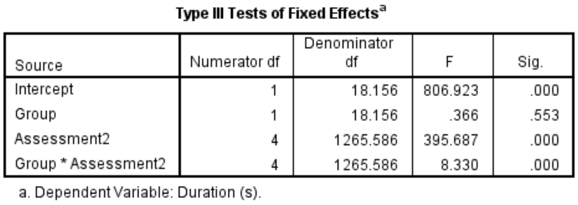


Information Criteria[a]

-2 Restricted Log Likelihood	7448.805
Akaike's Information Criterion (AIC)	7930.805
Hurvich and Tsai's Criterion (AICC)	7956.452
Bozdogan's Criterion (CAIC)	9732.107
Schwarz's Bayesian Criterion (BIC)	9491.107

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration (s).

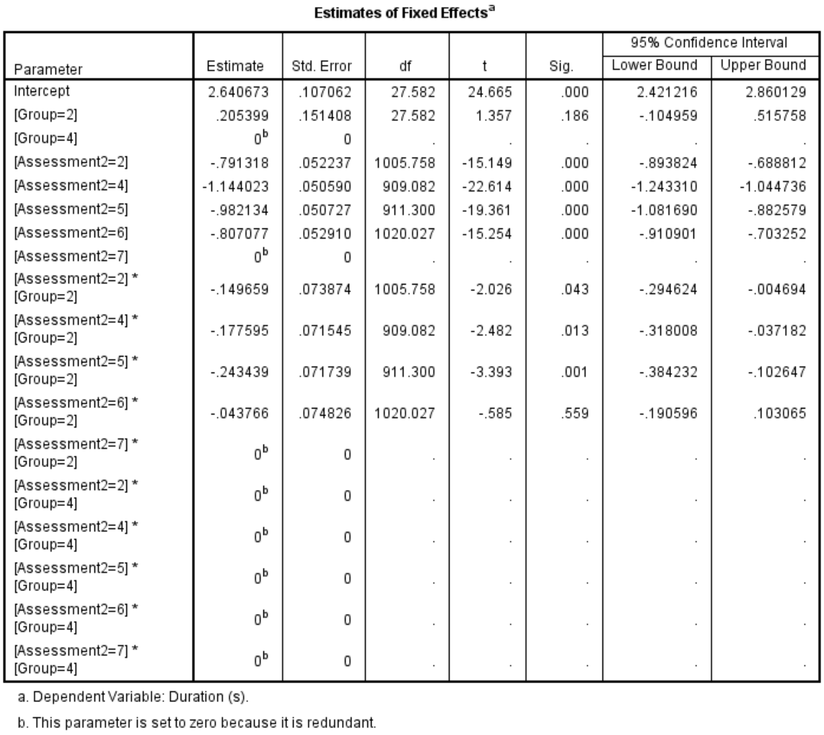


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.156	806.923	.000
Group	1	18.156	.366	.553
Assessment2	4	1265.586	395.687	.000
Group * Assessment2	4	1265.586	8.330	.000

a. Dependent Variable: Duration (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

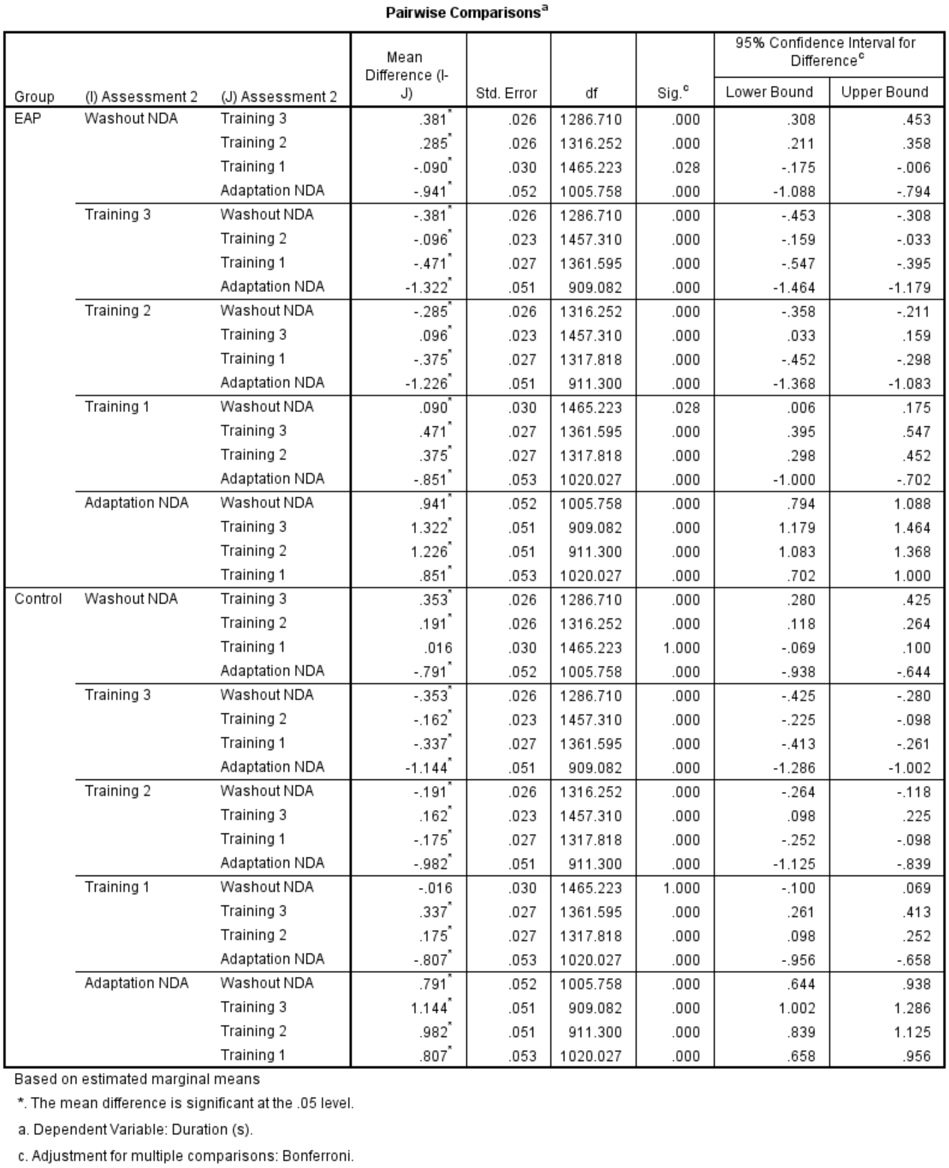


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.640673	.107062	27.582	24.665	.000	2.421216	2.860129
[Group=2]	.205399	.151408	27.582	1.357	.186	-.104959	.515758
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.791318	.052237	1005.758	-15.149	.000	-.893824	-.688812
[Assessment2=4]	-1.144023	.050590	909.082	-22.614	.000	-1.243310	-1.044736
[Assessment2=5]	-.982134	.050727	911.300	-19.361	.000	-1.081690	-.882579
[Assessment2=6]	-.807077	.052910	1020.027	-15.254	.000	-.910901	-.703252
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	-.149659	.073874	1005.758	-2.026	.043	-.294624	-.004694
[Assessment2=4] * [Group=2]	-.177595	.071545	909.082	-2.482	.013	-.318008	-.037182
[Assessment2=5] * [Group=2]	-.243439	.071739	911.300	-3.393	.001	-.384232	-.102647
[Assessment2=6] * [Group=2]	-.043766	.074826	1020.027	-.585	.559	-.190596	.103065
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAP	Washout NDA	Training 3	.381*	.026	1286.710	.000	.308	.453
		Training 2	.285*	.026	1316.252	.000	.211	.358
		Training 1	-.090*	.030	1465.223	.028	-.175	-.006
		Adaptation NDA	-.941*	.052	1005.758	.000	-1.088	-.794
	Training 3	Washout NDA	-.381*	.026	1286.710	.000	-.453	-.308
		Training 2	-.096*	.023	1457.310	.000	-.159	-.033
		Training 1	-.471*	.027	1361.595	.000	-.547	-.395
		Adaptation NDA	-1.322*	.051	909.082	.000	-1.464	-1.179
	Training 2	Washout NDA	-.285*	.026	1316.252	.000	-.358	-.211
		Training 3	.096*	.023	1457.310	.000	.033	.159
		Training 1	-.375*	.027	1317.818	.000	-.452	-.298
		Adaptation NDA	-1.226*	.051	911.300	.000	-1.368	-1.083
	Training 1	Washout NDA	.090*	.030	1465.223	.028	.006	.175
		Training 3	.471*	.027	1361.595	.000	.395	.547
		Training 2	.375*	.027	1317.818	.000	.298	.452
		Adaptation NDA	-.851*	.053	1020.027	.000	-1.000	-.702
	Adaptation NDA	Washout NDA	.941*	.052	1005.758	.000	.794	1.088
		Training 3	1.322*	.051	909.082	.000	1.179	1.464
		Training 2	1.226*	.051	911.300	.000	1.083	1.368
		Training 1	.851*	.053	1020.027	.000	.702	1.000
Control	Washout NDA	Training 3	.353*	.026	1286.710	.000	.280	.425
		Training 2	.191*	.026	1316.252	.000	.118	.264
		Training 1	.016	.030	1465.223	1.000	-.069	.100
		Adaptation NDA	-.791*	.052	1005.758	.000	-.938	-.644
	Training 3	Washout NDA	-.353*	.026	1286.710	.000	-.425	-.280
		Training 2	-.162*	.023	1457.310	.000	-.225	-.098
		Training 1	-.337*	.027	1361.595	.000	-.413	-.261
		Adaptation NDA	-1.144*	.051	909.082	.000	-1.286	-1.002
	Training 2	Washout NDA	-.191*	.026	1316.252	.000	-.264	-.118
		Training 3	.162*	.023	1457.310	.000	.098	.225
		Training 1	-.175*	.027	1317.818	.000	-.252	-.098
		Adaptation NDA	-.982*	.051	911.300	.000	-1.125	-.839
	Training 1	Washout NDA	-.016	.030	1465.223	1.000	-.100	.069
		Training 3	.337*	.027	1361.595	.000	.261	.413
		Training 2	.175*	.027	1317.818	.000	.098	.252
		Adaptation NDA	-.807*	.053	1020.027	.000	-.956	-.658
	Adaptation NDA	Washout NDA	.791*	.052	1005.758	.000	.644	.938
		Training 3	1.144*	.051	909.082	.000	1.002	1.286
		Training 2	.982*	.051	911.300	.000	.839	1.125
		Training 1	.807*	.053	1020.027	.000	.658	.956

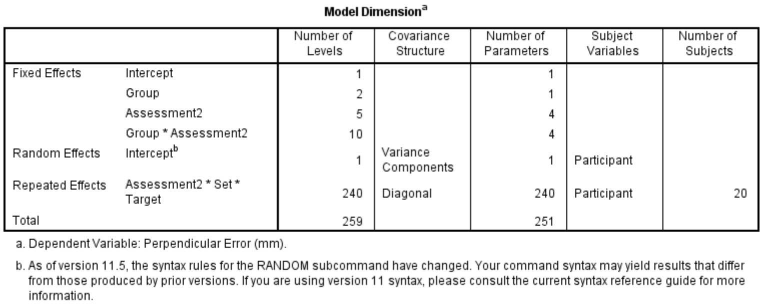
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration (s).

c. Adjustment for multiple comparisons: Bonferroni.

Perpendicular error

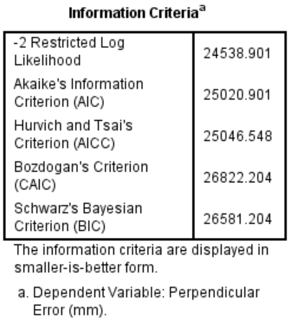


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Perpendicular Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

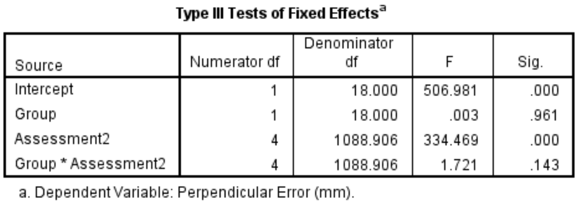


Information Criteria[a]

-2 Restricted Log Likelihood	24538.901
Akaike's Information Criterion (AIC)	25020.901
Hurvich and Tsai's Criterion (AICC)	25046.548
Bozdogan's Criterion (CAIC)	26822.204
Schwarz's Bayesian Criterion (BIC)	26581.204

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Perpendicular Error (mm).



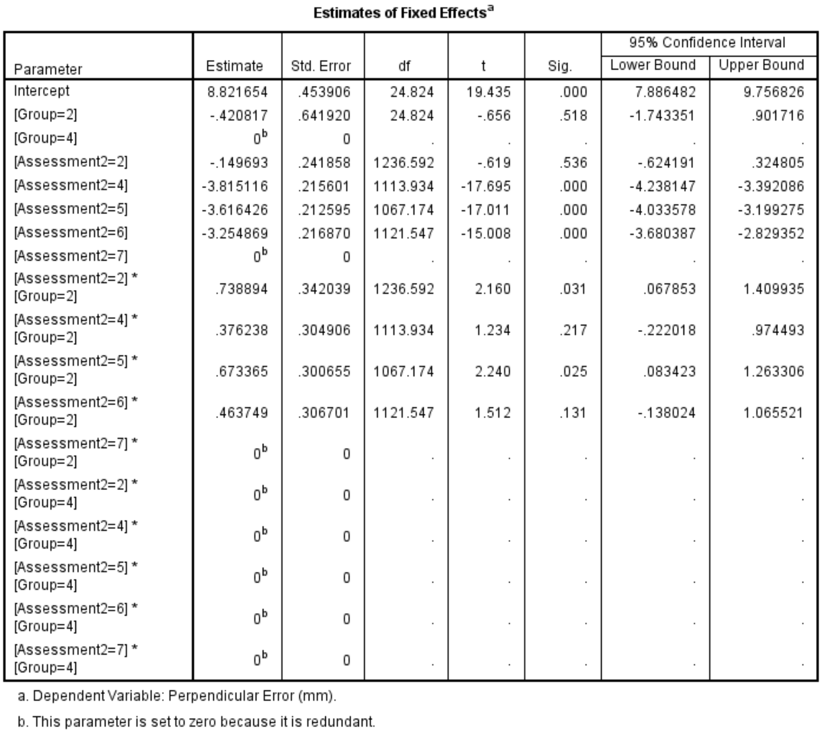
Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.000	506.981	.000
Group	1	18.000	.003	.961
Assessment2	4	1088.906	334.469	.000
Group * Assessment2	4	1088.906	1.721	.143

a. Dependent Variable: Perpendicular Error (mm).

Group 0: EAA
Group 1: AAN
Group 2: EAP
Group 4: Control

Assessment 8: Adaptation DA
Assessment 7: Adaptation NDA
Assessment 6: Training 1
Assessment 5: Training 2
Assessment 4: Training 3
Assessment 3: Pre-washout
Assessment 2: Washout NDA
Assessment 1: Washout DA

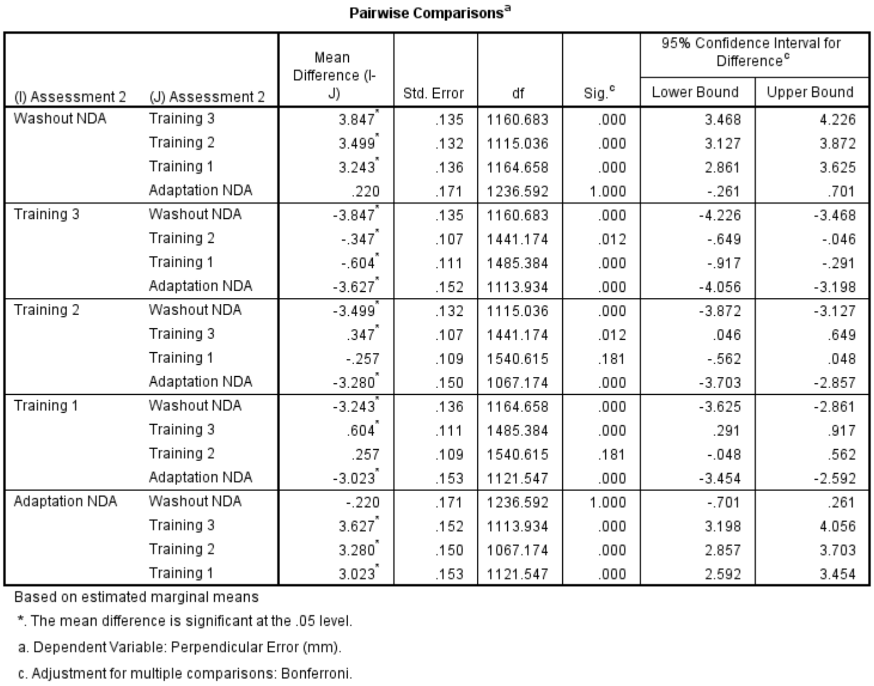


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	8.821654	.453906	24.824	19.435	.000	7.886482	9.756826
[Group=2]	-.420817	.641920	24.824	-.656	.518	-1.743351	.901716
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.149693	.241858	1236.592	-.619	.536	-.624191	.324805
[Assessment2=4]	-3.815116	.215601	1113.934	-17.695	.000	-4.238147	-3.392086
[Assessment2=5]	-3.616426	.212595	1067.174	-17.011	.000	-4.033578	-3.199275
[Assessment2=6]	-3.254869	.216870	1121.547	-15.008	.000	-3.680387	-2.829352
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	.738894	.342039	1236.592	2.160	.031	.067853	1.409935
[Assessment2=4] * [Group=2]	.376238	.304906	1113.934	1.234	.217	-.222018	.974493
[Assessment2=5] * [Group=2]	.673365	.300655	1067.174	2.240	.025	.083423	1.263306
[Assessment2=6] * [Group=2]	.463749	.306701	1121.547	1.512	.131	-.138024	1.065521
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Perpendicular Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	3.847*	.135	1160.683	.000	3.468	4.226
	Training 2	3.499*	.132	1115.036	.000	3.127	3.872
	Training 1	3.243*	.136	1164.658	.000	2.861	3.625
	Adaptation NDA	.220	.171	1236.592	1.000	-.261	.701
Training 3	Washout NDA	-3.847*	.135	1160.683	.000	-4.226	-3.468
	Training 2	-.347*	.107	1441.174	.012	-.649	-.046
	Training 1	-.604*	.111	1485.384	.000	-.917	-.291
	Adaptation NDA	-3.627*	.152	1113.934	.000	-4.056	-3.198
Training 2	Washout NDA	-3.499*	.132	1115.036	.000	-3.872	-3.127
	Training 3	.347*	.107	1441.174	.012	.046	.649
	Training 1	-.257	.109	1540.615	.181	-.562	.048
	Adaptation NDA	-3.280*	.150	1067.174	.000	-3.703	-2.857
Training 1	Washout NDA	-3.243*	.136	1164.658	.000	-3.625	-2.861
	Training 3	.604*	.111	1485.384	.000	.291	.917
	Training 2	.257	.109	1540.615	.181	-.048	.562
	Adaptation NDA	-3.023*	.153	1121.547	.000	-3.454	-2.592
Adaptation NDA	Washout NDA	-.220	.171	1236.592	1.000	-.701	.261
	Training 3	3.627*	.152	1113.934	.000	3.198	4.056
	Training 2	3.280*	.150	1067.174	.000	2.857	3.703
	Training 1	3.023*	.153	1121.547	.000	2.592	3.454

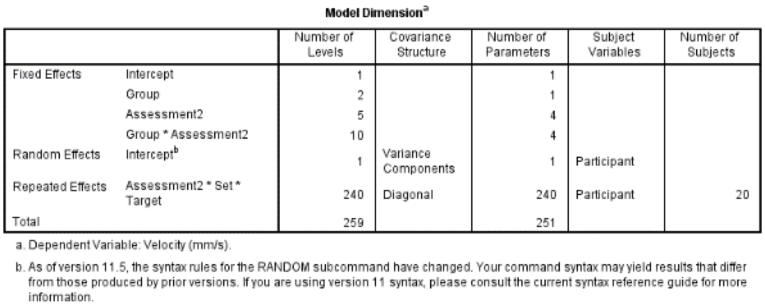
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Perpendicular Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Mean velocity

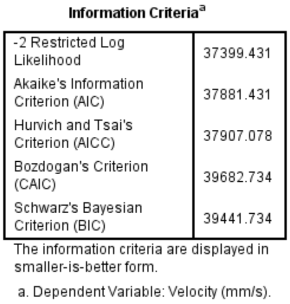


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Velocity (mm/s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

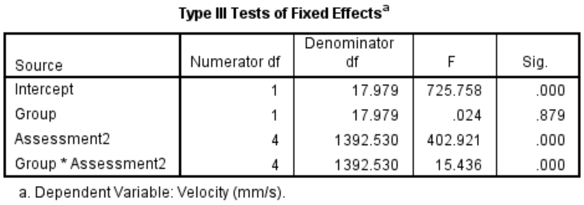


Information Criteria[a]

-2 Restricted Log Likelihood	37399.431
Akaike's Information Criterion (AIC)	37881.431
Hurvich and Tsai's Criterion (AICC)	37907.078
Bozdogan's Criterion (CAIC)	39682.734
Schwarz's Bayesian Criterion (BIC)	39441.734

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Velocity (mm/s).

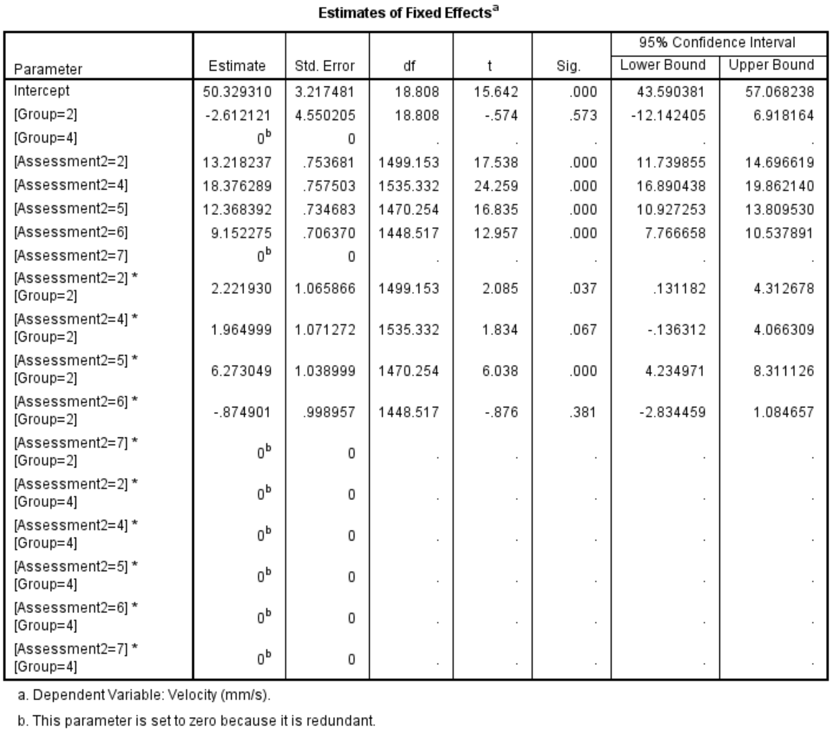


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.979	725.758	.000
Group	1	17.979	.024	.879
Assessment2	4	1392.530	402.921	.000
Group * Assessment2	4	1392.530	15.436	.000

a. Dependent Variable: Velocity (mm/s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

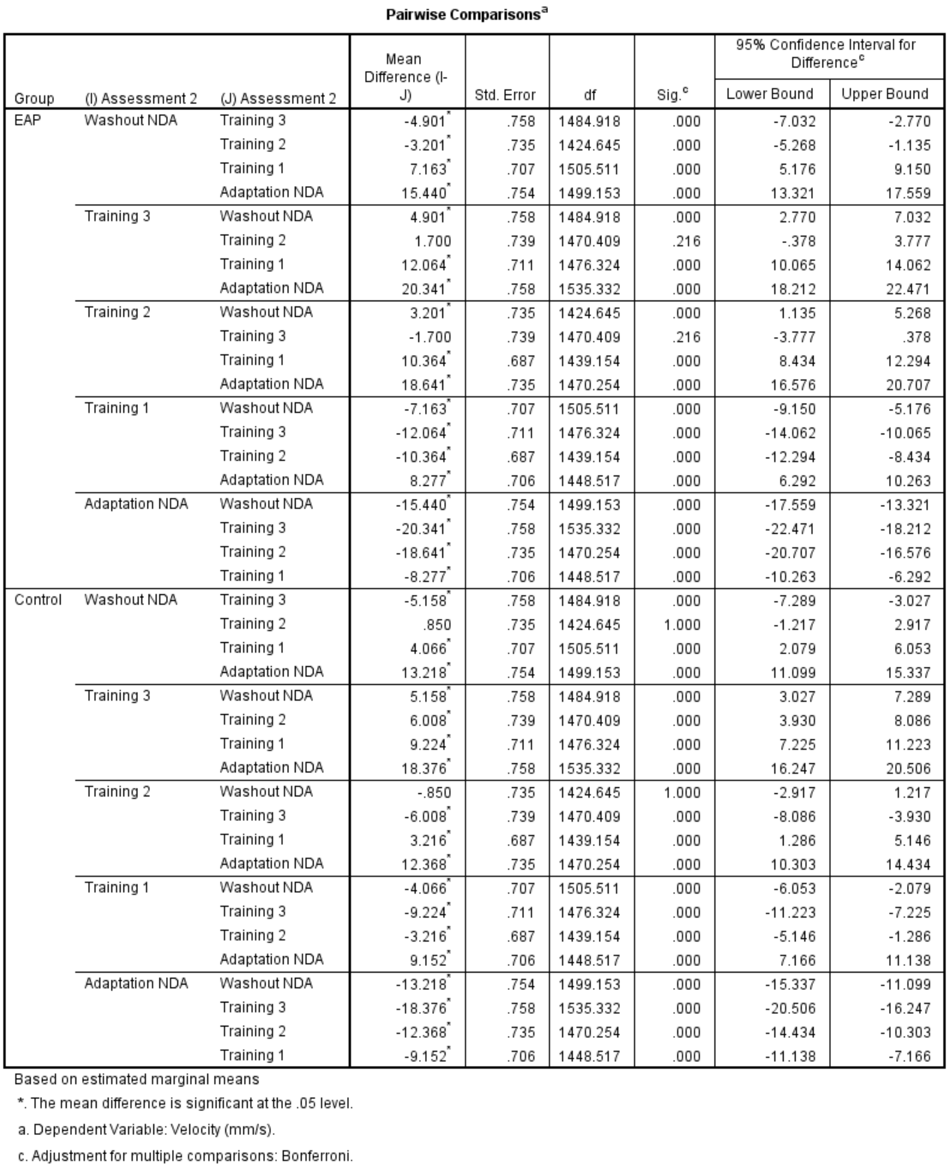


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	50.329310	3.217481	18.808	15.642	.000	43.590381	57.068238
[Group=2]	-2.612121	4.550205	18.808	-.574	.573	-12.142405	6.918164
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	13.218237	.753681	1499.153	17.538	.000	11.739855	14.696619
[Assessment2=4]	18.376289	.757503	1535.332	24.259	.000	16.890438	19.862140
[Assessment2=5]	12.368392	.734683	1470.254	16.835	.000	10.927253	13.809530
[Assessment2=6]	9.152275	.706370	1448.517	12.957	.000	7.766658	10.537891
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	2.221930	1.065866	1499.153	2.085	.037	.131182	4.312678
[Assessment2=4] * [Group=2]	1.964999	1.071272	1535.332	1.834	.067	-.136312	4.066309
[Assessment2=5] * [Group=2]	6.273049	1.038999	1470.254	6.038	.000	4.234971	8.311126
[Assessment2=6] * [Group=2]	-.874901	.998957	1448.517	-.876	.381	-2.834459	1.084657
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Velocity (mm/s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons^{a}

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.^{c}	95% Confidence Interval for Difference^{c}	
							Lower Bound	Upper Bound
EAP	Washout NDA	Training 3	-4.901*	.758	1484.918	.000	-7.032	-2.770
		Training 2	-3.201*	.735	1424.645	.000	-5.268	-1.135
		Training 1	7.163*	.707	1505.511	.000	5.176	9.150
		Adaptation NDA	15.440*	.754	1499.153	.000	13.321	17.559
	Training 3	Washout NDA	4.901*	.758	1484.918	.000	2.770	7.032
		Training 2	1.700	.739	1470.409	.216	-.378	3.777
		Training 1	12.064*	.711	1476.324	.000	10.065	14.062
		Adaptation NDA	20.341*	.758	1535.332	.000	18.212	22.471
	Training 2	Washout NDA	3.201*	.735	1424.645	.000	1.135	5.268
		Training 3	-1.700	.739	1470.409	.216	-3.777	.378
		Training 1	10.364*	.687	1439.154	.000	8.434	12.294
		Adaptation NDA	18.641*	.735	1470.254	.000	16.576	20.707
	Training 1	Washout NDA	-7.163*	.707	1505.511	.000	-9.150	-5.176
		Training 3	-12.064*	.711	1476.324	.000	-14.062	-10.065
		Training 2	-10.364*	.687	1439.154	.000	-12.294	-8.434
		Adaptation NDA	8.277*	.706	1448.517	.000	6.292	10.263
	Adaptation NDA	Washout NDA	-15.440*	.754	1499.153	.000	-17.559	-13.321
		Training 3	-20.341*	.758	1535.332	.000	-22.471	-18.212
		Training 2	-18.641*	.735	1470.254	.000	-20.707	-16.576
		Training 1	-8.277*	.706	1448.517	.000	-10.263	-6.292
Control	Washout NDA	Training 3	-5.158*	.758	1484.918	.000	-7.289	-3.027
		Training 2	.850	.735	1424.645	1.000	-1.217	2.917
		Training 1	4.066*	.707	1505.511	.000	2.079	6.053
		Adaptation NDA	13.218*	.754	1499.153	.000	11.099	15.337
	Training 3	Washout NDA	5.158*	.758	1484.918	.000	3.027	7.289
		Training 2	6.008*	.739	1470.409	.000	3.930	8.086
		Training 1	9.224*	.711	1476.324	.000	7.225	11.223
		Adaptation NDA	18.376*	.758	1535.332	.000	16.247	20.506
	Training 2	Washout NDA	-.850	.735	1424.645	1.000	-2.917	1.217
		Training 3	-6.008*	.739	1470.409	.000	-8.086	-3.930
		Training 1	3.216*	.687	1439.154	.000	1.286	5.146
		Adaptation NDA	12.368*	.735	1470.254	.000	10.303	14.434
	Training 1	Washout NDA	-4.066*	.707	1505.511	.000	-6.053	-2.079
		Training 3	-9.224*	.711	1476.324	.000	-11.223	-7.225
		Training 2	-3.216*	.687	1439.154	.000	-5.146	-1.286
		Adaptation NDA	9.152*	.706	1448.517	.000	7.166	11.138
	Adaptation NDA	Washout NDA	-13.218*	.754	1499.153	.000	-15.337	-11.099
		Training 3	-18.376*	.758	1535.332	.000	-20.506	-16.247
		Training 2	-12.368*	.735	1470.254	.000	-14.434	-10.303
		Training 1	-9.152*	.706	1448.517	.000	-11.138	-7.166

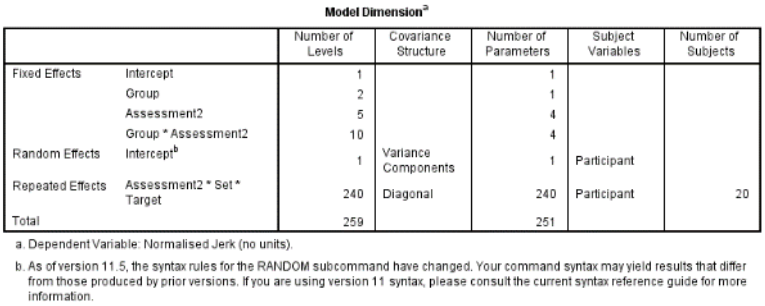
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Velocity (mm/s).

c. Adjustment for multiple comparisons: Bonferroni.

Normalised jerk

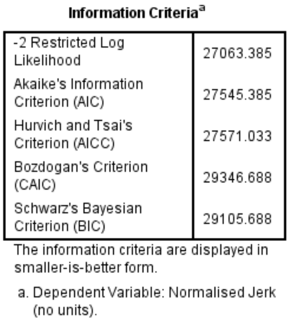


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Normalised Jerk (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

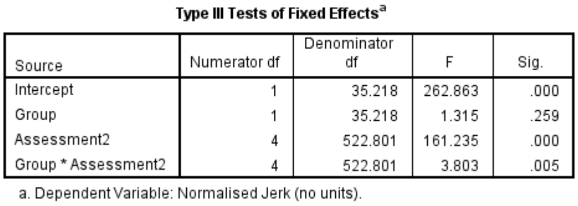


Information Criteria[a]

-2 Restricted Log Likelihood	27063.385
Akaike's Information Criterion (AIC)	27545.385
Hurvich and Tsai's Criterion (AICC)	27571.033
Bozdogan's Criterion (CAIC)	29346.688
Schwarz's Bayesian Criterion (BIC)	29105.688

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Normalised Jerk (no units).

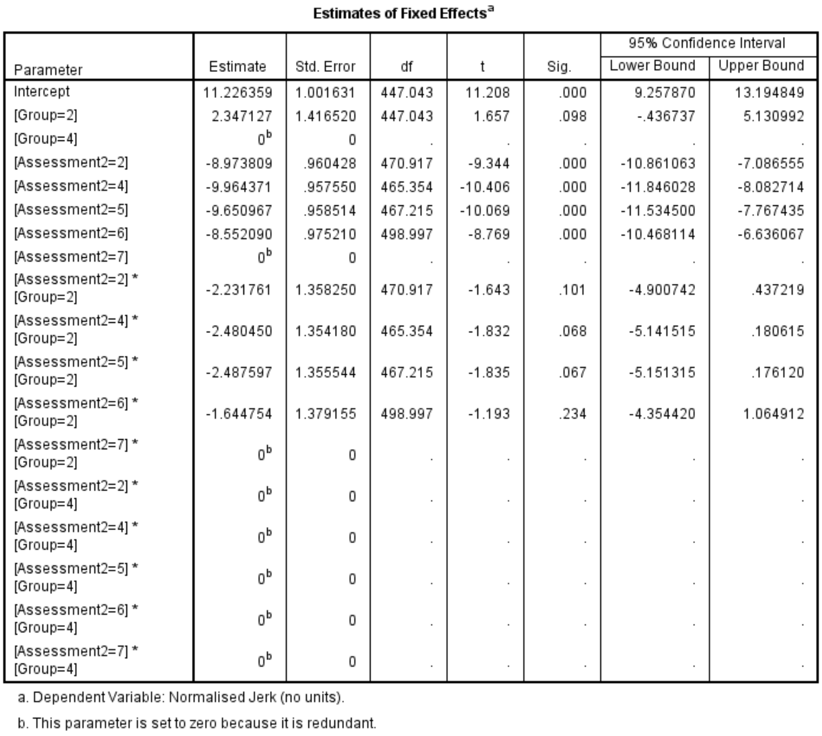


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	35.218	262.863	.000
Group	1	35.218	1.315	.259
Assessment2	4	522.801	161.235	.000
Group * Assessment2	4	522.801	3.803	.005

a. Dependent Variable: Normalised Jerk (no units).

Group 0: EAA	Assessment 8: Adaptation DA
Group 1: AAN	Assessment 7: Adaptation NDA
Group 2: EAP	Assessment 6: Training 1
Group 4: Control	Assessment 5: Training 2
	Assessment 4: Training 3
	Assessment 3: Pre-washout
	Assessment 2: Washout NDA
	Assessment 1: Washout DA

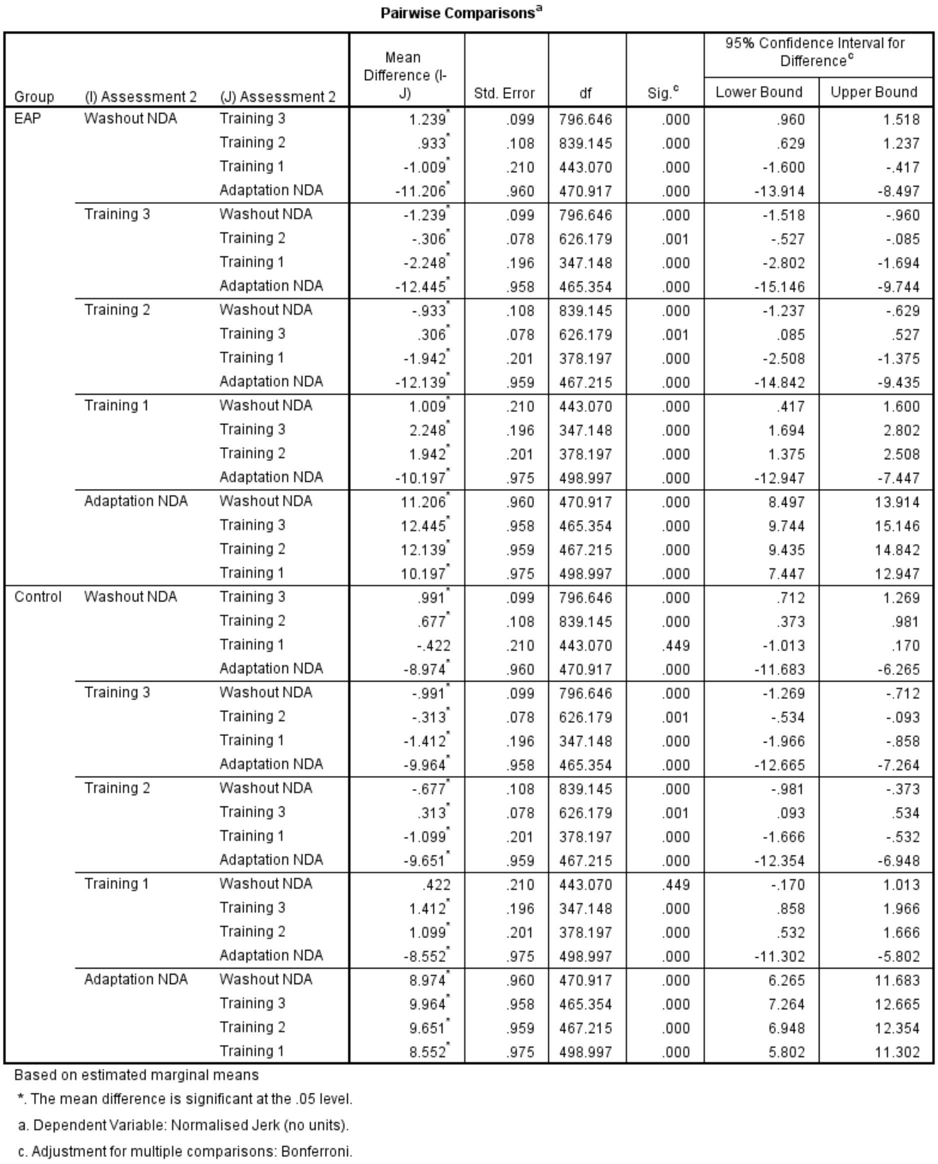


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	11.226359	1.001631	447.043	11.208	.000	9.257870	13.194849
[Group=2]	2.347127	1.416520	447.043	1.657	.098	-.436737	5.130992
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-8.973809	.960428	470.917	-9.344	.000	-10.861063	-7.086555
[Assessment2=4]	-9.964371	.957550	465.354	-10.406	.000	-11.846028	-8.082714
[Assessment2=5]	-9.650967	.958514	467.215	-10.069	.000	-11.534500	-7.767435
[Assessment2=6]	-8.552090	.975210	498.997	-8.769	.000	-10.468114	-6.636067
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	-2.231761	1.358250	470.917	-1.643	.101	-4.900742	.437219
[Assessment2=4] * [Group=2]	-2.480450	1.354180	465.354	-1.832	.068	-5.141515	.180615
[Assessment2=5] * [Group=2]	-2.487597	1.355544	467.215	-1.835	.067	-5.151315	.176120
[Assessment2=6] * [Group=2]	-1.644754	1.379155	498.997	-1.193	.234	-4.354420	1.064912
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Normalised Jerk (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAP	Washout NDA	Training 3	1.239*	.099	796.646	.000	.960	1.518
		Training 2	.933*	.108	839.145	.000	.629	1.237
		Training 1	-1.009*	.210	443.070	.000	-1.600	-.417
		Adaptation NDA	-11.206*	.960	470.917	.000	-13.914	-8.497
	Training 3	Washout NDA	-1.239*	.099	796.646	.000	-1.518	-.960
		Training 2	-.306*	.078	626.179	.001	-.527	-.085
		Training 1	-2.248*	.196	347.148	.000	-2.802	-1.694
		Adaptation NDA	-12.445*	.958	465.354	.000	-15.146	-9.744
	Training 2	Washout NDA	-.933*	.108	839.145	.000	-1.237	-.629
		Training 3	.306*	.078	626.179	.001	.085	.527
		Training 1	-1.942*	.201	378.197	.000	-2.508	-1.375
		Adaptation NDA	-12.139*	.959	467.215	.000	-14.842	-9.435
	Training 1	Washout NDA	1.009*	.210	443.070	.000	.417	1.600
		Training 3	2.248*	.196	347.148	.000	1.694	2.802
		Training 2	1.942*	.201	378.197	.000	1.375	2.508
		Adaptation NDA	-10.197*	.975	498.997	.000	-12.947	-7.447
	Adaptation NDA	Washout NDA	11.206*	.960	470.917	.000	8.497	13.914
		Training 3	12.445*	.958	465.354	.000	9.744	15.146
		Training 2	12.139*	.959	467.215	.000	9.435	14.842
		Training 1	10.197*	.975	498.997	.000	7.447	12.947
Control	Washout NDA	Training 3	.991*	.099	796.646	.000	.712	1.269
		Training 2	.677*	.108	839.145	.000	.373	.981
		Training 1	-.422	.210	443.070	.449	-1.013	.170
		Adaptation NDA	-8.974*	.960	470.917	.000	-11.683	-6.265
	Training 3	Washout NDA	-.991*	.099	796.646	.000	-1.269	-.712
		Training 2	-.313*	.078	626.179	.001	-.534	-.093
		Training 1	-1.412*	.196	347.148	.000	-1.966	-.858
		Adaptation NDA	-9.964*	.958	465.354	.000	-12.665	-7.264
	Training 2	Washout NDA	-.677*	.108	839.145	.000	-.981	-.373
		Training 3	.313*	.078	626.179	.001	.093	.534
		Training 1	-1.099*	.201	378.197	.000	-1.666	-.532
		Adaptation NDA	-9.651*	.959	467.215	.000	-12.354	-6.948
	Training 1	Washout NDA	.422	.210	443.070	.449	-.170	1.013
		Training 3	1.412*	.196	347.148	.000	.858	1.966
		Training 2	1.099*	.201	378.197	.000	.532	1.666
		Adaptation NDA	-8.552*	.975	498.997	.000	-11.302	-5.802
	Adaptation NDA	Washout NDA	8.974*	.960	470.917	.000	6.265	11.683
		Training 3	9.964*	.958	465.354	.000	7.264	12.665
		Training 2	9.651*	.959	467.215	.000	6.948	12.354
		Training 1	8.552*	.975	498.997	.000	5.802	11.302

Based on estimated marginal means

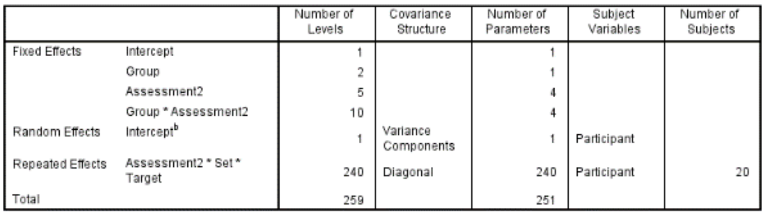
*. The mean difference is significant at the .05 level.

a. Dependent Variable: Normalised Jerk (no units).

c. Adjustment for multiple comparisons: Bonferroni.

Initial error

Model Dimension[a]

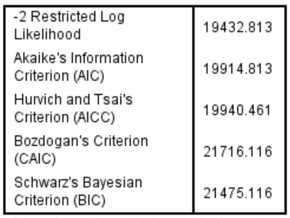


		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	20
Total		259		251		

a. Dependent Variable: Initial Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

Information Criteria[a]

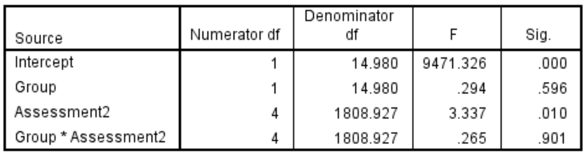


-2 Restricted Log Likelihood	19432.813
Akaike's Information Criterion (AIC)	19914.813
Hurvich and Tsai's Criterion (AICC)	19940.461
Bozdogan's Criterion (CAIC)	21716.116
Schwarz's Bayesian Criterion (BIC)	21475.116

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Initial Error (mm).

Type III Tests of Fixed Effects[a]

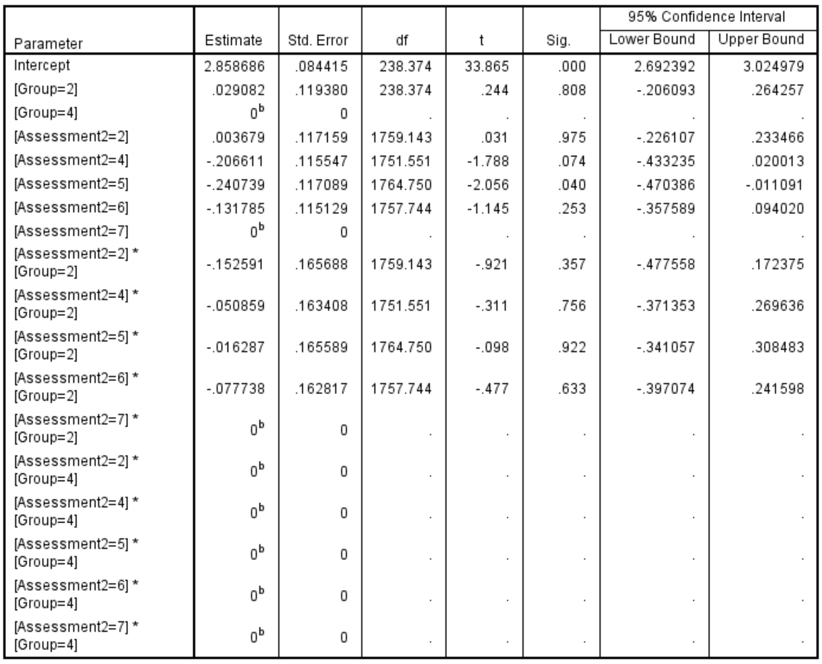


Source	Numerator df	Denominator df	F	Sig.
Intercept	1	14.980	9471.326	.000
Group	1	14.980	.294	.596
Assessment2	4	1808.927	3.337	.010
Group * Assessment2	4	1808.927	.265	.901

a. Dependent Variable: Initial Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

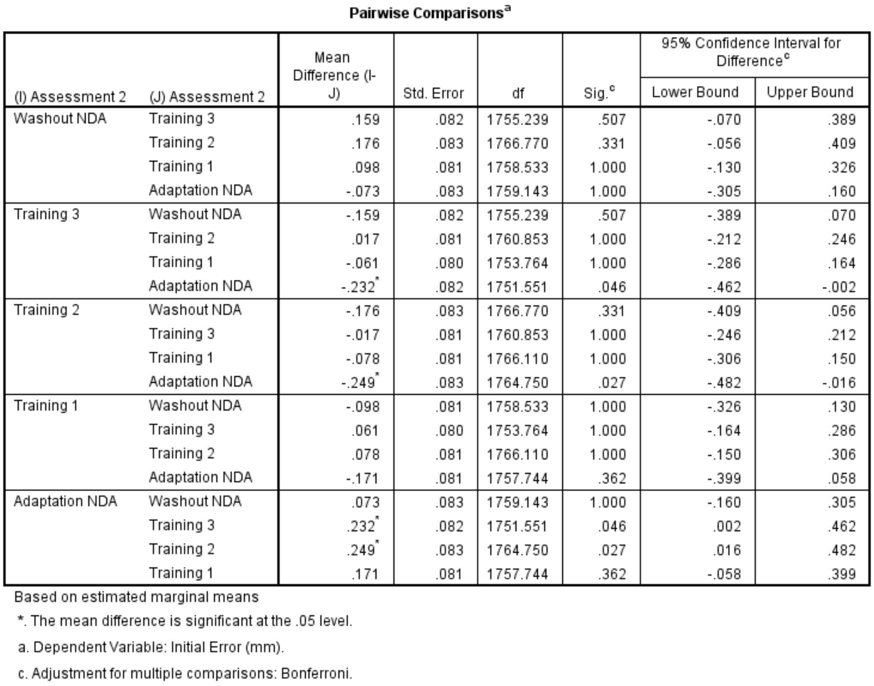
Estimates of Fixed Effects[a]



Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	2.858686	.084415	238.374	33.865	.000	2.692392	3.024979
[Group=2]	.029082	.119380	238.374	.244	.808	-.206093	.264257
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	.003679	.117159	1759.143	.031	.975	-.226107	.233466
[Assessment2=4]	-.206611	.115547	1751.551	-1.788	.074	-.433235	.020013
[Assessment2=5]	-.240739	.117089	1764.750	-2.056	.040	-.470386	-.011091
[Assessment2=6]	-.131785	.115129	1757.744	-1.145	.253	-.357589	.094020
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	-.152591	.165688	1759.143	-.921	.357	-.477558	.172375
[Assessment2=4] * [Group=2]	-.050859	.163408	1751.551	-.311	.756	-.371353	.269636
[Assessment2=5] * [Group=2]	-.016287	.165589	1764.750	-.098	.922	-.341057	.308483
[Assessment2=6] * [Group=2]	-.077738	.162817	1757.744	-.477	.633	-.397074	.241598
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Initial Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	.159	.082	1755.239	.507	-.070	.389
	Training 2	.176	.083	1766.770	.331	-.056	.409
	Training 1	.098	.081	1758.533	1.000	-.130	.326
	Adaptation NDA	-.073	.083	1759.143	1.000	-.305	.160
Training 3	Washout NDA	-.159	.082	1755.239	.507	-.389	.070
	Training 2	.017	.081	1760.853	1.000	-.212	.246
	Training 1	-.061	.080	1753.764	1.000	-.286	.164
	Adaptation NDA	-.232*	.082	1751.551	.046	-.462	-.002
Training 2	Washout NDA	-.176	.083	1766.770	.331	-.409	.056
	Training 3	-.017	.081	1760.853	1.000	-.246	.212
	Training 1	-.078	.081	1766.110	1.000	-.306	.150
	Adaptation NDA	-.249*	.083	1764.750	.027	-.482	-.016
Training 1	Washout NDA	-.098	.081	1758.533	1.000	-.326	.130
	Training 3	.061	.080	1753.764	1.000	-.164	.286
	Training 2	.078	.081	1766.110	1.000	-.150	.306
	Adaptation NDA	-.171	.081	1757.744	.362	-.399	.058
Adaptation NDA	Washout NDA	.073	.083	1759.143	1.000	-.160	.305
	Training 3	.232*	.082	1751.551	.046	.002	.462
	Training 2	.249*	.083	1764.750	.027	.016	.482
	Training 1	.171	.081	1757.744	.362	-.058	.399

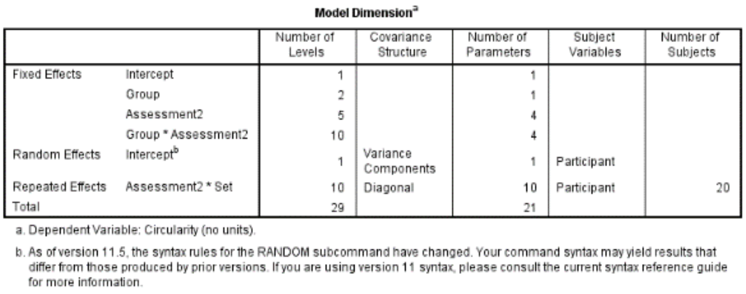
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Initial Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Circularity

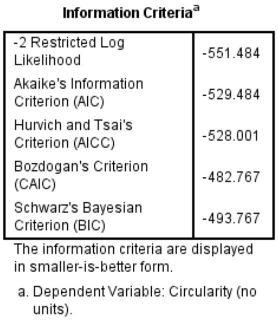


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	10	Diagonal	10	Participant	20
Total		29		21		

a. Dependent Variable: Circularity (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

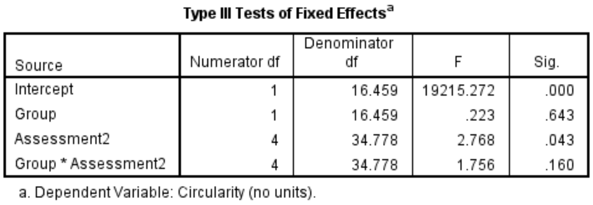


Information Criteria[a]

-2 Restricted Log Likelihood	-551.484
Akaike's Information Criterion (AIC)	-529.484
Hurvich and Tsai's Criterion (AICC)	-528.001
Bozdogan's Criterion (CAIC)	-482.767
Schwarz's Bayesian Criterion (BIC)	-493.767

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Circularity (no units).

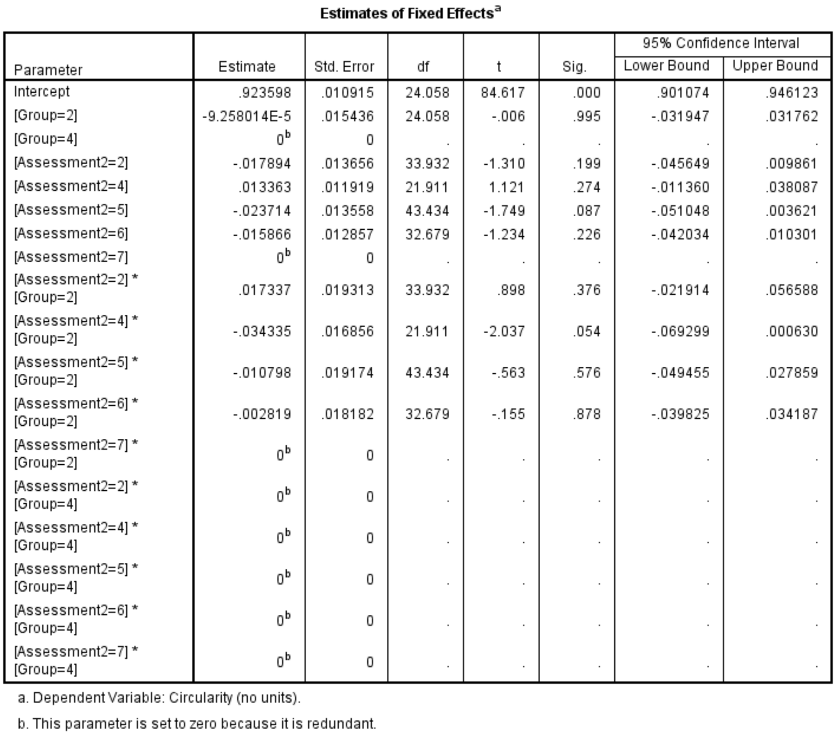


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	16.459	19215.272	.000
Group	1	16.459	.223	.643
Assessment2	4	34.778	2.768	.043
Group * Assessment2	4	34.778	1.756	.160

a. Dependent Variable: Circularity (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



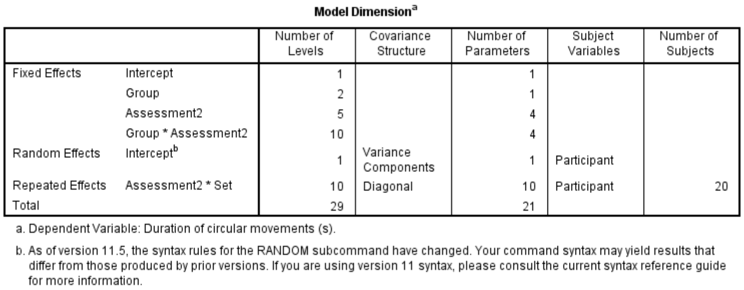
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.923598	.010915	24.058	84.617	.000	.901074	.946123
[Group=2]	-9.258014E-5	.015436	24.058	-.006	.995	-.031947	.031762
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.017894	.013656	33.932	-1.310	.199	-.045649	.009861
[Assessment2=4]	.013363	.011919	21.911	1.121	.274	-.011360	.038087
[Assessment2=5]	-.023714	.013558	43.434	-1.749	.087	-.051048	.003621
[Assessment2=6]	-.015866	.012857	32.679	-1.234	.226	-.042034	.010301
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	.017337	.019313	33.932	.898	.376	-.021914	.056588
[Assessment2=4] * [Group=2]	-.034335	.016856	21.911	-2.037	.054	-.069299	.000630
[Assessment2=5] * [Group=2]	-.010798	.019174	43.434	-.563	.576	-.049455	.027859
[Assessment2=6] * [Group=2]	-.002819	.018182	32.679	-.155	.878	-.039825	.034187
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Circularity (no units).

b. This parameter is set to zero because it is redundant.

Duration of circular movements

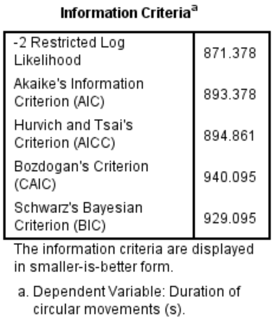


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	5		4		
	Group * Assessment2	10		4		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	10	Diagonal	10	Participant	20
Total		29		21		

a. Dependent Variable: Duration of circular movements (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

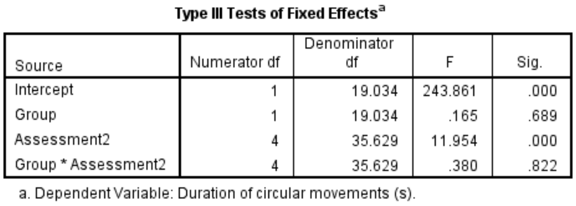


Information Criteria[a]

-2 Restricted Log Likelihood	871.378
Akaike's Information Criterion (AIC)	893.378
Hurvich and Tsai's Criterion (AICC)	894.861
Bozdogan's Criterion (CAIC)	940.095
Schwarz's Bayesian Criterion (BIC)	929.095

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration of circular movements (s).

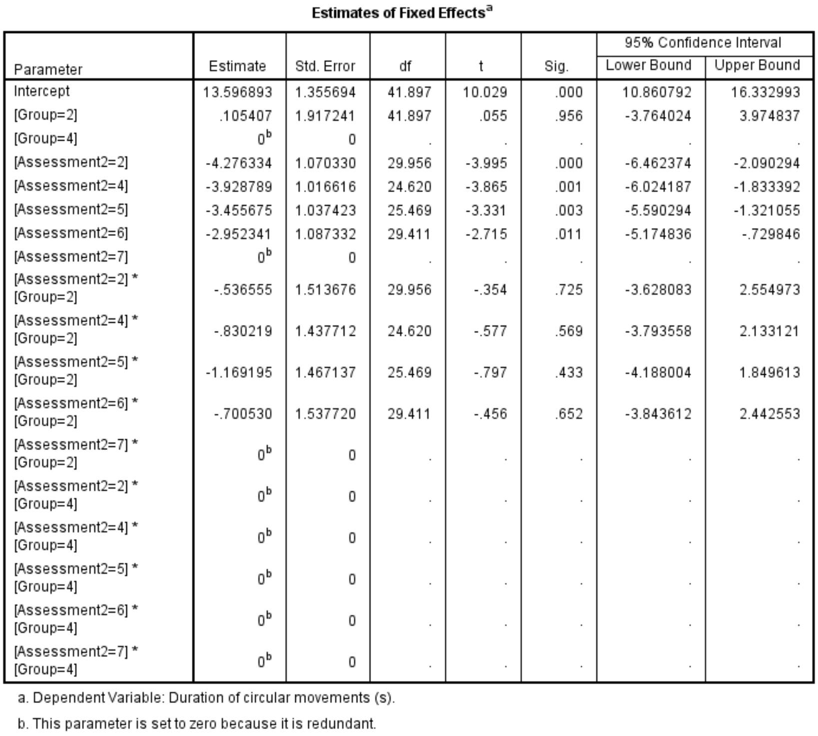


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	19.034	243.861	.000
Group	1	19.034	.165	.689
Assessment2	4	35.629	11.954	.000
Group * Assessment2	4	35.629	.380	.822

a. Dependent Variable: Duration of circular movements (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



Estimates of Fixed Effects[a]

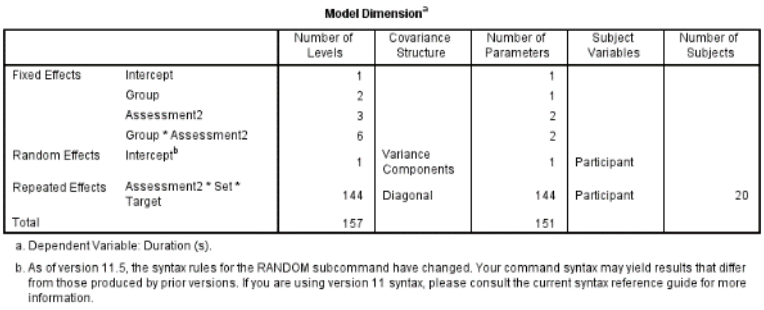
Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	13.596893	1.355694	41.897	10.029	.000	10.860792	16.332993
[Group=2]	.105407	1.917241	41.897	.055	.956	-3.764024	3.974837
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-4.276334	1.070330	29.956	-3.995	.000	-6.462374	-2.090294
[Assessment2=4]	-3.928789	1.016616	24.620	-3.865	.001	-6.024187	-1.833392
[Assessment2=5]	-3.455675	1.037423	25.469	-3.331	.003	-5.590294	-1.321055
[Assessment2=6]	-2.952341	1.087332	29.411	-2.715	.011	-5.174836	-.729846
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	-.536555	1.513676	29.956	-.354	.725	-3.628083	2.554973
[Assessment2=4] * [Group=2]	-.830219	1.437712	24.620	-.577	.569	-3.793558	2.133121
[Assessment2=5] * [Group=2]	-1.169195	1.467137	25.469	-.797	.433	-4.188004	1.849613
[Assessment2=6] * [Group=2]	-.700530	1.537720	29.411	-.456	.652	-3.843612	2.442553
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration of circular movements (s).

b. This parameter is set to zero because it is redundant.

Analysis of the DA

Duration

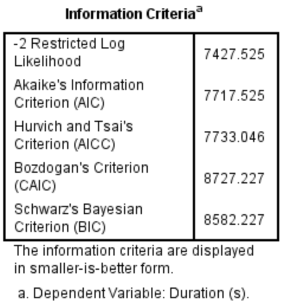


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Duration (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

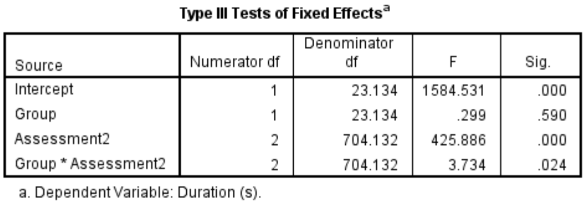


Information Criteria[a]

-2 Restricted Log Likelihood	7427.525
Akaike's Information Criterion (AIC)	7717.525
Hurvich and Tsai's Criterion (AICC)	7733.046
Bozdogan's Criterion (CAIC)	8727.227
Schwarz's Bayesian Criterion (BIC)	8582.227

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration (s).

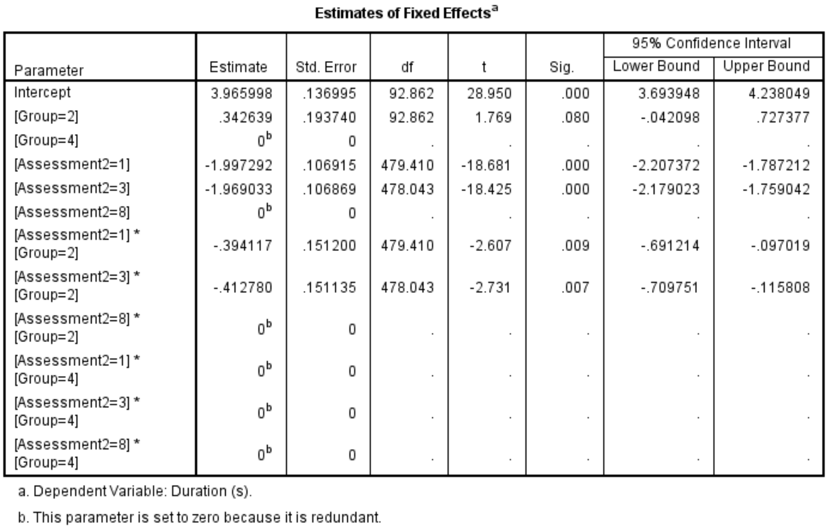


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	23.134	1584.531	.000
Group	1	23.134	.299	.590
Assessment2	2	704.132	425.886	.000
Group * Assessment2	2	704.132	3.734	.024

a. Dependent Variable: Duration (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

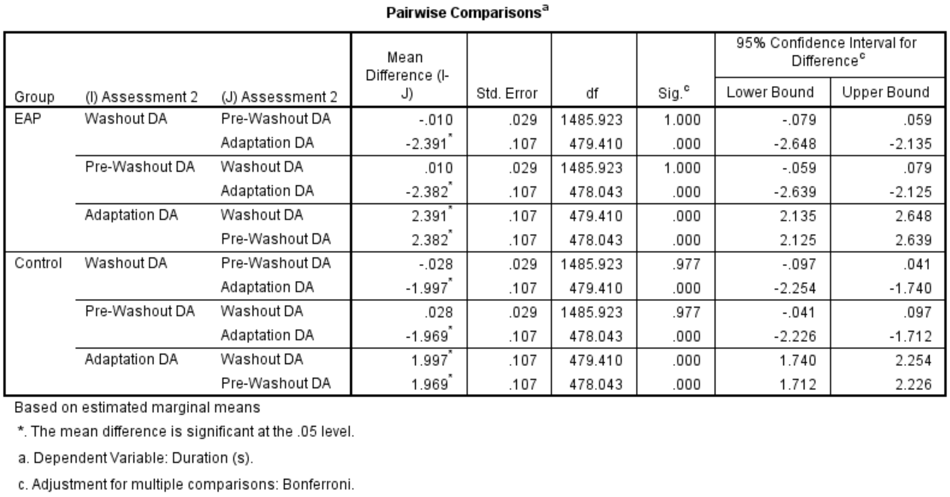


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	3.965998	.136995	92.862	28.950	.000	3.693948	4.238049
[Group=2]	.342639	.193740	92.862	1.769	.080	-.042098	.727377
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-1.997292	.106915	479.410	-18.681	.000	-2.207372	-1.787212
[Assessment2=3]	-1.969033	.106869	478.043	-18.425	.000	-2.179023	-1.759042
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	-.394117	.151200	479.410	-2.607	.009	-.691214	-.097019
[Assessment2=3] * [Group=2]	-.412780	.151135	478.043	-2.731	.007	-.709751	-.115808
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAP	Washout DA	Pre-Washout DA	-.010	.029	1485.923	1.000	-.079	.059
		Adaptation DA	-2.391*	.107	479.410	.000	-2.648	-2.135
	Pre-Washout DA	Washout DA	.010	.029	1485.923	1.000	-.059	.079
		Adaptation DA	-2.382*	.107	478.043	.000	-2.639	-2.125
	Adaptation DA	Washout DA	2.391*	.107	479.410	.000	2.135	2.648
		Pre-Washout DA	2.382*	.107	478.043	.000	2.125	2.639
Control	Washout DA	Pre-Washout DA	-.028	.029	1485.923	.977	-.097	.041
		Adaptation DA	-1.997*	.107	479.410	.000	-2.254	-1.740
	Pre-Washout DA	Washout DA	.028	.029	1485.923	.977	-.041	.097
		Adaptation DA	-1.969*	.107	478.043	.000	-2.226	-1.712
	Adaptation DA	Washout DA	1.997*	.107	479.410	.000	1.740	2.254
		Pre-Washout DA	1.969*	.107	478.043	.000	1.712	2.226

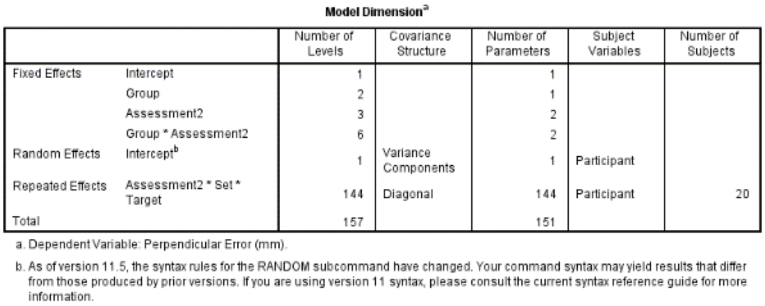
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration (s).

c. Adjustment for multiple comparisons: Bonferroni.

Perpendicular error

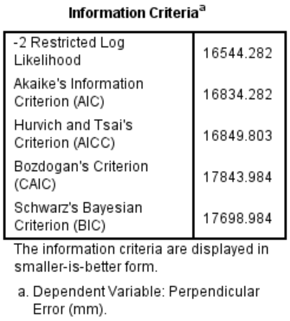


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Perpendicular Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

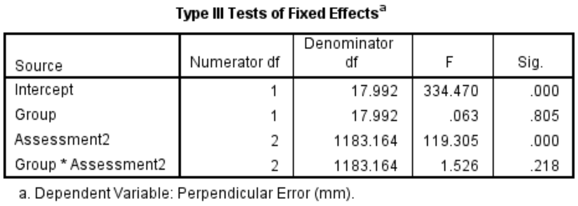


Information Criteria[a]

-2 Restricted Log Likelihood	16544.282
Akaike's Information Criterion (AIC)	16834.282
Hurvich and Tsai's Criterion (AICC)	16849.803
Bozdogan's Criterion (CAIC)	17843.984
Schwarz's Bayesian Criterion (BIC)	17698.984

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Perpendicular Error (mm).

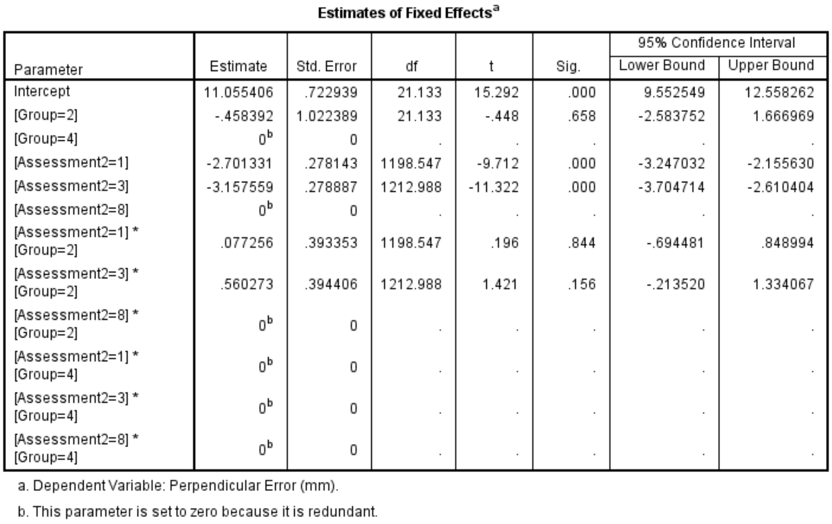


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.992	334.470	.000
Group	1	17.992	.063	.805
Assessment2	2	1183.164	119.305	.000
Group * Assessment2	2	1183.164	1.526	.218

a. Dependent Variable: Perpendicular Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

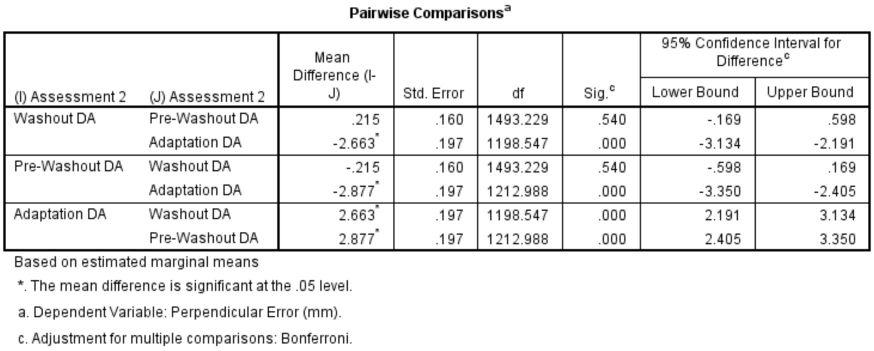


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	11.055406	.722939	21.133	15.292	.000	9.552549	12.558262
[Group=2]	-.458392	1.022389	21.133	-.448	.658	-2.583752	1.666969
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-2.701331	.278143	1198.547	-9.712	.000	-3.247032	-2.155630
[Assessment2=3]	-3.157559	.278887	1212.988	-11.322	.000	-3.704714	-2.610404
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	.077256	.393353	1198.547	.196	.844	-.694481	.848994
[Assessment2=3] * [Group=2]	.560273	.394406	1212.988	1.421	.156	-.213520	1.334067
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Perpendicular Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout DA	Pre-Washout DA	.215	.160	1493.229	.540	-.169	.598
	Adaptation DA	-2.663*	.197	1198.547	.000	-3.134	-2.191
Pre-Washout DA	Washout DA	-.215	.160	1493.229	.540	-.598	.169
	Adaptation DA	-2.877*	.197	1212.988	.000	-3.350	-2.405
Adaptation DA	Washout DA	2.663*	.197	1198.547	.000	2.191	3.134
	Pre-Washout DA	2.877*	.197	1212.988	.000	2.405	3.350

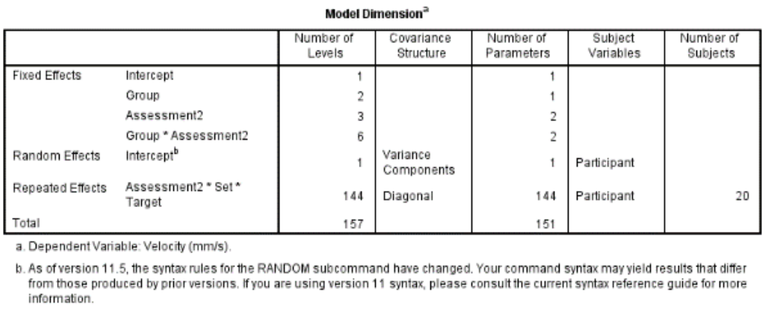
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Perpendicular Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Mean velocity

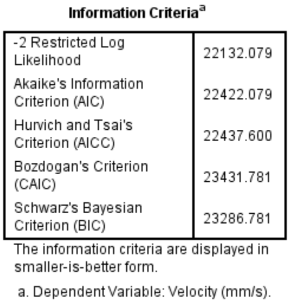


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Velocity (mm/s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

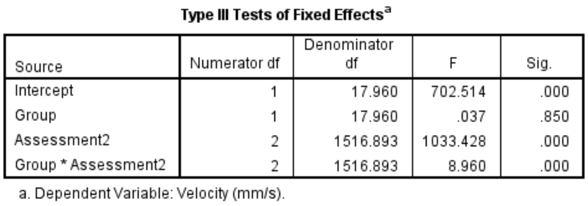


Information Criteria[a]

-2 Restricted Log Likelihood	22132.079
Akaike's Information Criterion (AIC)	22422.079
Hurvich and Tsai's Criterion (AICC)	22437.600
Bozdogan's Criterion (CAIC)	23431.781
Schwarz's Bayesian Criterion (BIC)	23286.781

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Velocity (mm/s).

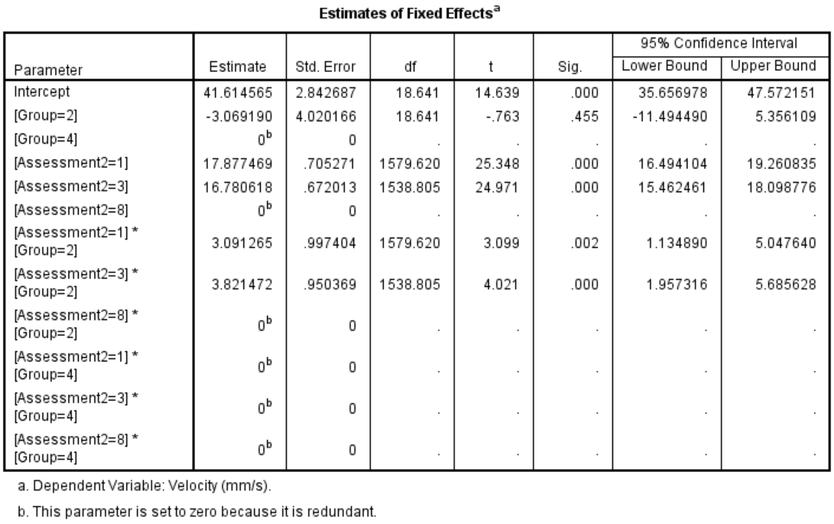


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.960	702.514	.000
Group	1	17.960	.037	.850
Assessment2	2	1516.893	1033.428	.000
Group * Assessment2	2	1516.893	8.960	.000

a. Dependent Variable: Velocity (mm/s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

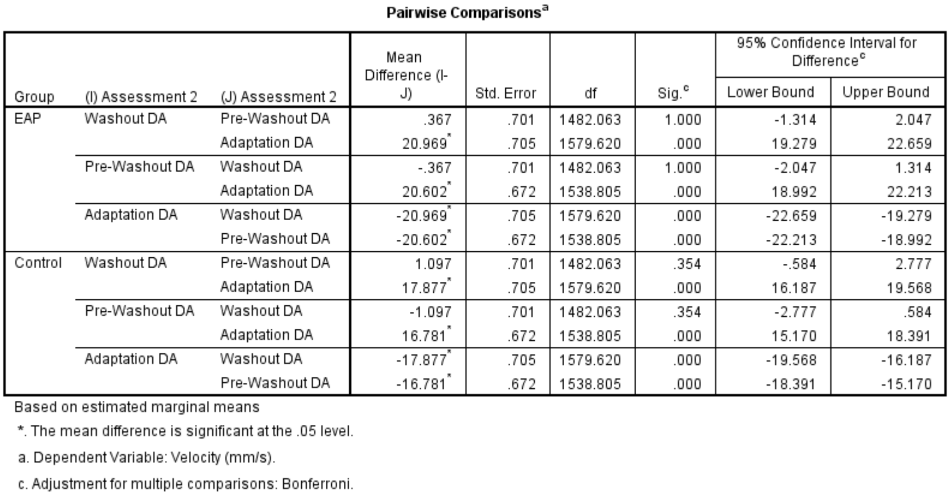


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	41.614565	2.842687	18.641	14.639	.000	35.656978	47.572151
[Group=2]	-3.069190	4.020166	18.641	-.763	.455	-11.494490	5.356109
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	17.877469	.705271	1579.620	25.348	.000	16.494104	19.260835
[Assessment2=3]	16.780618	.672013	1538.805	24.971	.000	15.462461	18.098776
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	3.091265	.997404	1579.620	3.099	.002	1.134890	5.047640
[Assessment2=3] * [Group=2]	3.821472	.950369	1538.805	4.021	.000	1.957316	5.685628
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Velocity (mm/s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAP	Washout DA	Pre-Washout DA	.367	.701	1482.063	1.000	-1.314	2.047
		Adaptation DA	20.969*	.705	1579.620	.000	19.279	22.659
	Pre-Washout DA	Washout DA	-.367	.701	1482.063	1.000	-2.047	1.314
		Adaptation DA	20.602*	.672	1538.805	.000	18.992	22.213
	Adaptation DA	Washout DA	-20.969*	.705	1579.620	.000	-22.659	-19.279
		Pre-Washout DA	-20.602*	.672	1538.805	.000	-22.213	-18.992
Control	Washout DA	Pre-Washout DA	1.097	.701	1482.063	.354	-.584	2.777
		Adaptation DA	17.877*	.705	1579.620	.000	16.187	19.568
	Pre-Washout DA	Washout DA	-1.097	.701	1482.063	.354	-2.777	.584
		Adaptation DA	16.781*	.672	1538.805	.000	15.170	18.391
	Adaptation DA	Washout DA	-17.877*	.705	1579.620	.000	-19.568	-16.187
		Pre-Washout DA	-16.781*	.672	1538.805	.000	-18.391	-15.170

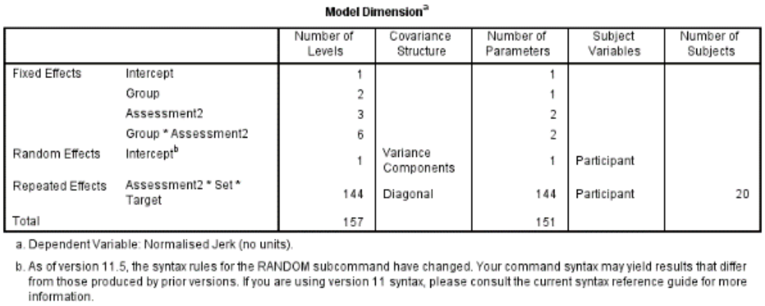
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Velocity (mm/s).

c. Adjustment for multiple comparisons: Bonferroni.

Normalised jerk

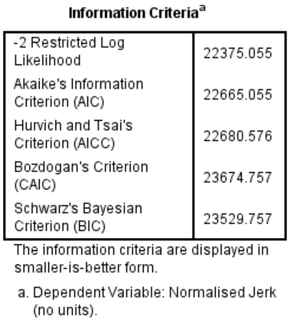


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Normalised Jerk (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

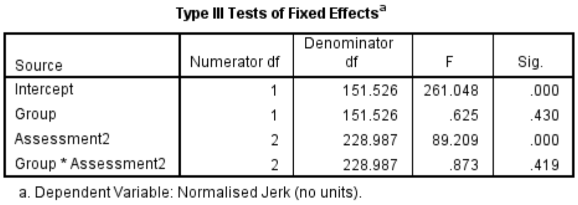


Information Criteria[a]

-2 Restricted Log Likelihood	22375.055
Akaike's Information Criterion (AIC)	22665.055
Hurvich and Tsai's Criterion (AICC)	22680.576
Bozdogan's Criterion (CAIC)	23674.757
Schwarz's Bayesian Criterion (BIC)	23529.757

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Normalised Jerk (no units).

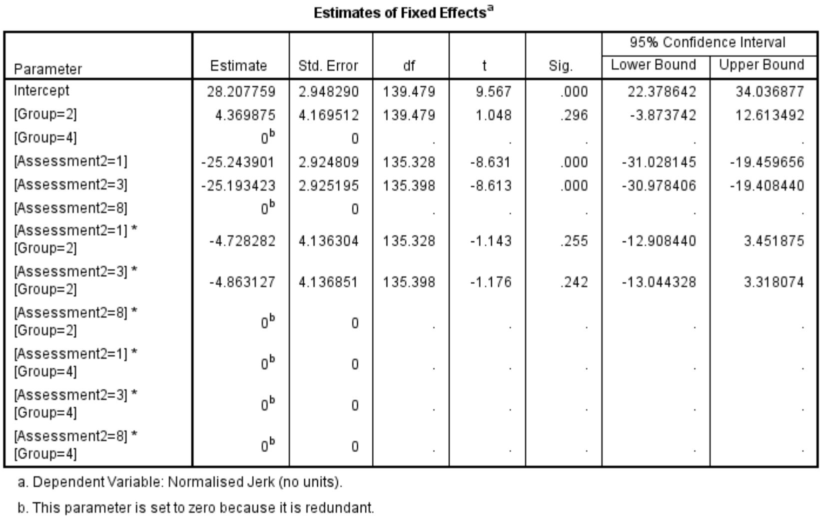


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	151.526	261.048	.000
Group	1	151.526	.625	.430
Assessment2	2	228.987	89.209	.000
Group * Assessment2	2	228.987	.873	.419

a. Dependent Variable: Normalised Jerk (no units).

Group 0: EAA	Assessment 8: Adaptation DA
Group 1: AAN	Assessment 7: Adaptation NDA
Group 2: EAP	Assessment 6: Training 1
Group 4: Control	Assessment 5: Training 2
	Assessment 4: Training 3
	Assessment 3: Pre-washout
	Assessment 2: Washout NDA
	Assessment 1: Washout DA

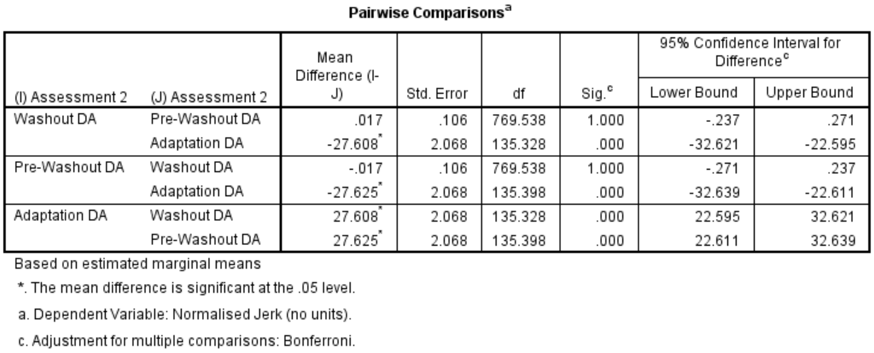


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	28.207759	2.948290	139.479	9.567	.000	22.378642	34.036877
[Group=2]	4.369875	4.169512	139.479	1.048	.296	-3.873742	12.613492
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-25.243901	2.924809	135.328	-8.631	.000	-31.028145	-19.459656
[Assessment2=3]	-25.193423	2.925195	135.398	-8.613	.000	-30.978406	-19.408440
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	-4.728282	4.136304	135.328	-1.143	.255	-12.908440	3.451875
[Assessment2=3] * [Group=2]	-4.863127	4.136851	135.398	-1.176	.242	-13.044328	3.318074
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Normalised Jerk (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout DA	Pre-Washout DA	.017	.106	769.538	1.000	-.237	.271
	Adaptation DA	-27.608*	2.068	135.328	.000	-32.621	-22.595
Pre-Washout DA	Washout DA	-.017	.106	769.538	1.000	-.271	.237
	Adaptation DA	-27.625*	2.068	135.398	.000	-32.639	-22.611
Adaptation DA	Washout DA	27.608*	2.068	135.328	.000	22.595	32.621
	Pre-Washout DA	27.625*	2.068	135.398	.000	22.611	32.639

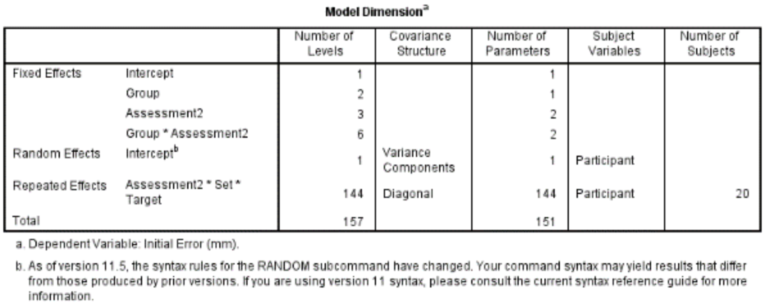
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Normalised Jerk (no units).

c. Adjustment for multiple comparisons: Bonferroni.

Initial error

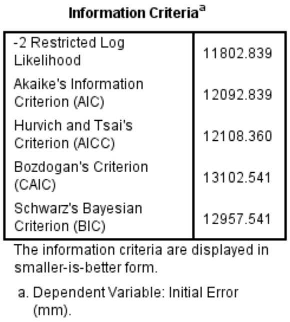


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	20
Total		157		151		

a. Dependent Variable: Initial Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

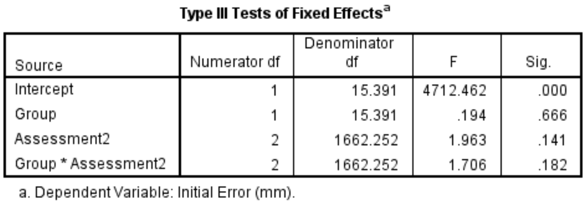


Information Criteria[a]

-2 Restricted Log Likelihood	11802.839
Akaike's Information Criterion (AIC)	12092.839
Hurvich and Tsai's Criterion (AICC)	12108.360
Bozdogan's Criterion (CAIC)	13102.541
Schwarz's Bayesian Criterion (BIC)	12957.541

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Initial Error (mm).

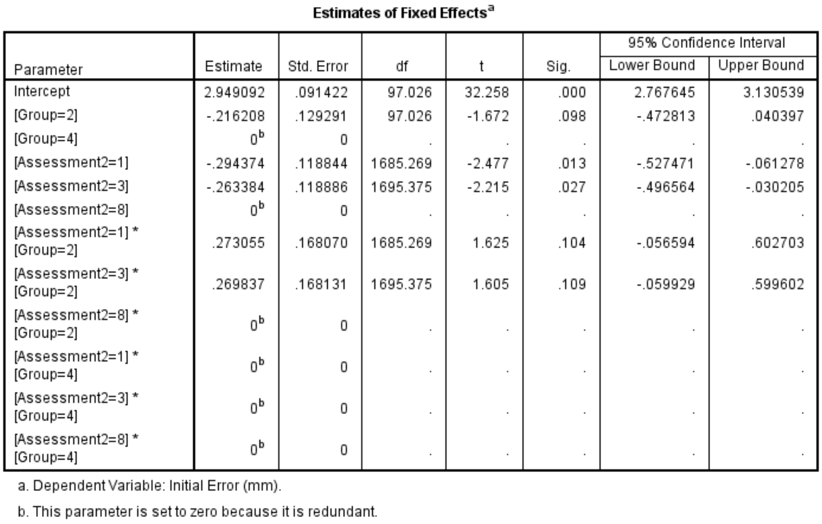


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	15.391	4712.462	.000
Group	1	15.391	.194	.666
Assessment2	2	1662.252	1.963	.141
Group * Assessment2	2	1662.252	1.706	.182

a. Dependent Variable: Initial Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

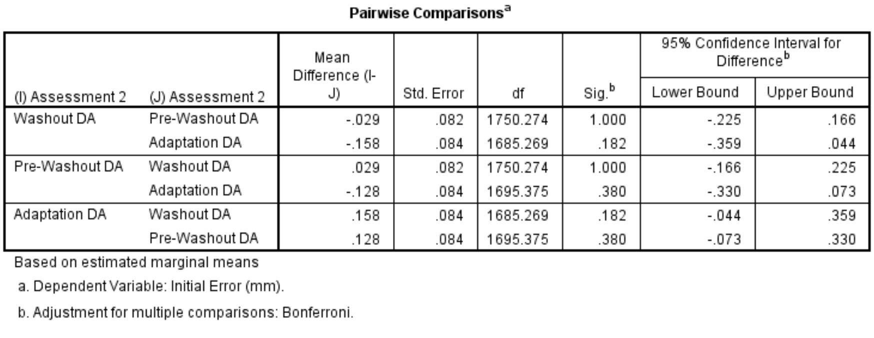


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	2.949092	.091422	97.026	32.258	.000	2.767645	3.130539
[Group=2]	-.216208	.129291	97.026	-1.672	.098	-.472813	.040397
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-.294374	.118844	1685.269	-2.477	.013	-.527471	-.061278
[Assessment2=3]	-.263384	.118886	1695.375	-2.215	.027	-.496564	-.030205
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	.273055	.168070	1685.269	1.625	.104	-.056594	.602703
[Assessment2=3] * [Group=2]	.269837	.168131	1695.375	1.605	.109	-.059929	.599602
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Initial Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

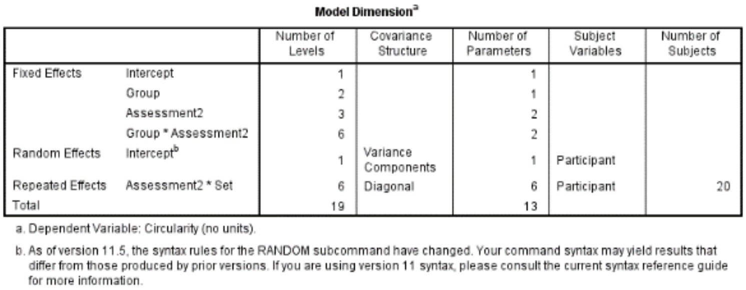
(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[b]	95% Confidence Interval for Difference[b]	
						Lower Bound	Upper Bound
Washout DA	Pre-Washout DA	-.029	.082	1750.274	1.000	-.225	.166
	Adaptation DA	-.158	.084	1685.269	.182	-.359	.044
Pre-Washout DA	Washout DA	.029	.082	1750.274	1.000	-.166	.225
	Adaptation DA	-.128	.084	1695.375	.380	-.330	.073
Adaptation DA	Washout DA	.158	.084	1685.269	.182	-.044	.359
	Pre-Washout DA	.128	.084	1695.375	.380	-.073	.330

Based on estimated marginal means

a. Dependent Variable: Initial Error (mm).

b. Adjustment for multiple comparisons: Bonferroni.

Circularity

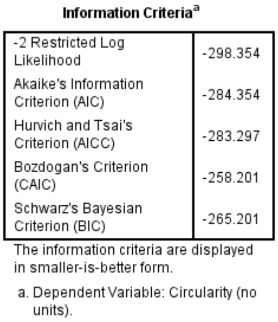


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	6	Diagonal	6	Participant	20
Total		19		13		

a. Dependent Variable: Circularity (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

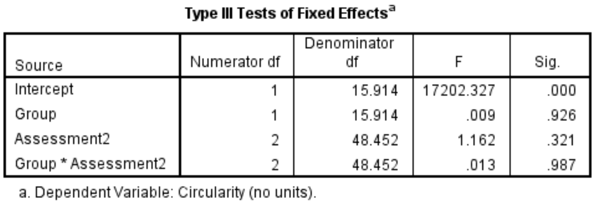


Information Criteria[a]

-2 Restricted Log Likelihood	-298.354
Akaike's Information Criterion (AIC)	-284.354
Hurvich and Tsai's Criterion (AICC)	-283.297
Bozdogan's Criterion (CAIC)	-258.201
Schwarz's Bayesian Criterion (BIC)	-265.201

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Circularity (no units).

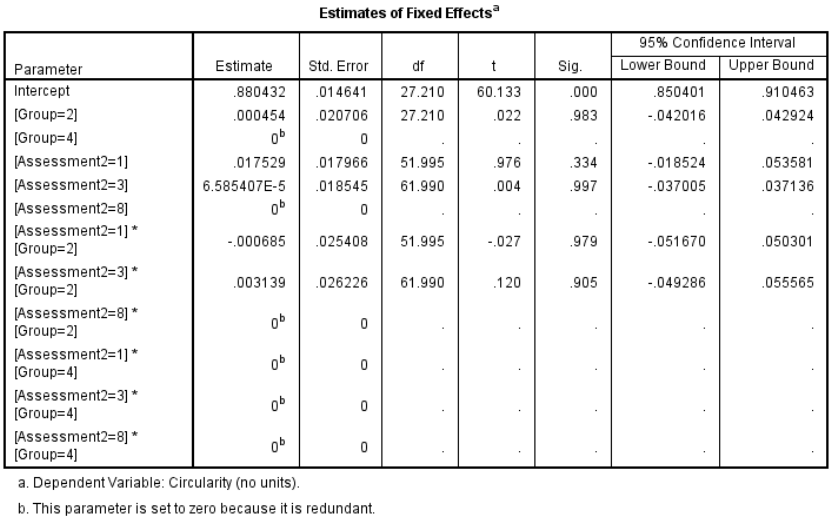


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	15.914	17202.327	.000
Group	1	15.914	.009	.926
Assessment2	2	48.452	1.162	.321
Group * Assessment2	2	48.452	.013	.987

a. Dependent Variable: Circularity (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

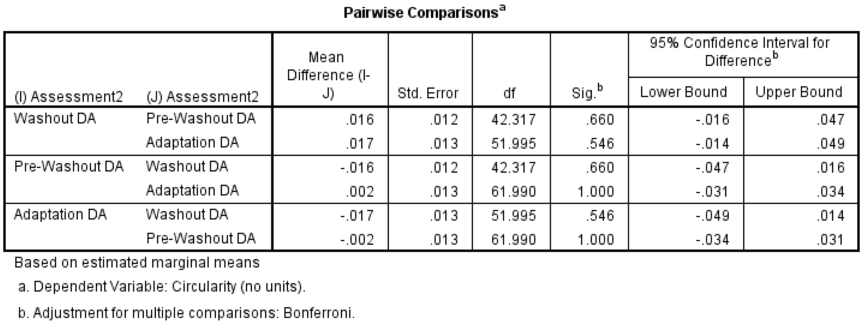


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.880432	.014641	27.210	60.133	.000	.850401	.910463
[Group=2]	.000454	.020706	27.210	.022	.983	-.042016	.042924
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	.017529	.017966	51.995	.976	.334	-.018524	.053581
[Assessment2=3]	6.585407E-5	.018545	61.990	.004	.997	-.037005	.037136
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	-.000685	.025408	51.995	-.027	.979	-.051670	.050301
[Assessment2=3] * [Group=2]	.003139	.026226	61.990	.120	.905	-.049286	.055565
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Circularity (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

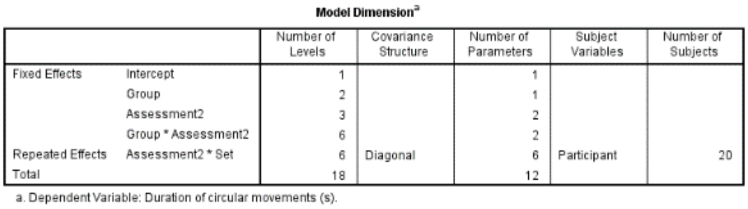
(I) Assessment2	(J) Assessment2	Mean Difference (I-J)	Std. Error	df	Sig.[b]	95% Confidence Interval for Difference[b]	
						Lower Bound	Upper Bound
Washout DA	Pre-Washout DA	.016	.012	42.317	.660	-.016	.047
	Adaptation DA	.017	.013	51.995	.546	-.014	.049
Pre-Washout DA	Washout DA	-.016	.012	42.317	.660	-.047	.016
	Adaptation DA	.002	.013	61.990	1.000	-.031	.034
Adaptation DA	Washout DA	-.017	.013	51.995	.546	-.049	.014
	Pre-Washout DA	-.002	.013	61.990	1.000	-.034	.031

Based on estimated marginal means

a. Dependent Variable: Circularity (no units).

b. Adjustment for multiple comparisons: Bonferroni.

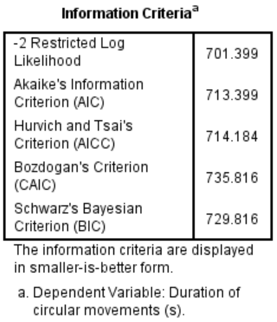
Duration of circular movements



Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	2		1		
	Assessment2	3		2		
	Group * Assessment2	6		2		
Repeated Effects	Assessment2 * Set	6	Diagonal	6	Participant	20
Total		18		12		

a. Dependent Variable: Duration of circular movements (s).

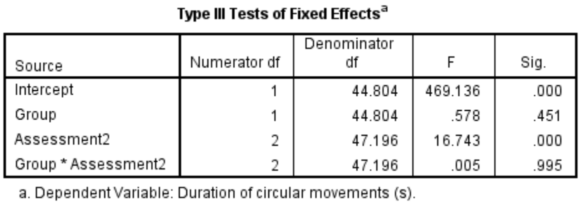


Information Criteria[a]

-2 Restricted Log Likelihood	701.399
Akaike's Information Criterion (AIC)	713.399
Hurvich and Tsai's Criterion (AICC)	714.184
Bozdogan's Criterion (CAIC)	735.816
Schwarz's Bayesian Criterion (BIC)	729.816

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration of circular movements (s).

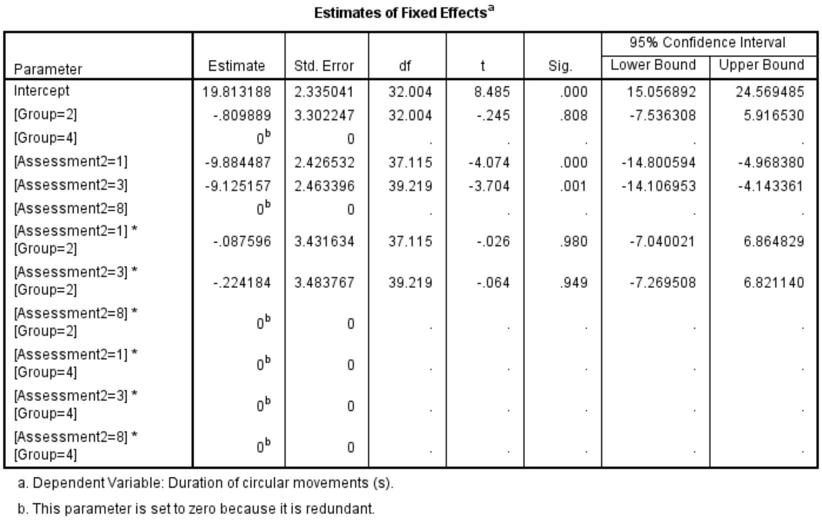


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	44.804	469.136	.000
Group	1	44.804	.578	.451
Assessment2	2	47.196	16.743	.000
Group * Assessment2	2	47.196	.005	.995

a. Dependent Variable: Duration of circular movements (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

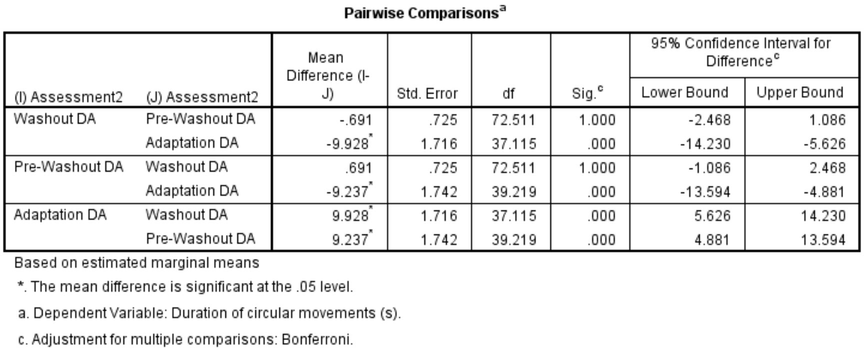


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	19.813188	2.335041	32.004	8.485	.000	15.056892	24.569485
[Group=2]	-.809889	3.302247	32.004	-.245	.808	-7.536308	5.916530
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-9.884487	2.426532	37.115	-4.074	.000	-14.800594	-4.968380
[Assessment2=3]	-9.125157	2.463396	39.219	-3.704	.001	-14.106953	-4.143361
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	-.087596	3.431634	37.115	-.026	.980	-7.040021	6.864829
[Assessment2=3] * [Group=2]	-.224184	3.483767	39.219	-.064	.949	-7.269508	6.821140
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration of circular movements (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment2	(J) Assessment2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout DA	Pre-Washout DA	-.691	.725	72.511	1.000	-2.468	1.086
	Adaptation DA	-9.928*	1.716	37.115	.000	-14.230	-5.626
Pre-Washout DA	Washout DA	.691	.725	72.511	1.000	-1.086	2.468
	Adaptation DA	-9.237*	1.742	39.219	.000	-13.594	-4.881
Adaptation DA	Washout DA	9.928*	1.716	37.115	.000	5.626	14.230
	Pre-Washout DA	9.237*	1.742	39.219	.000	4.881	13.594

Based on estimated marginal means

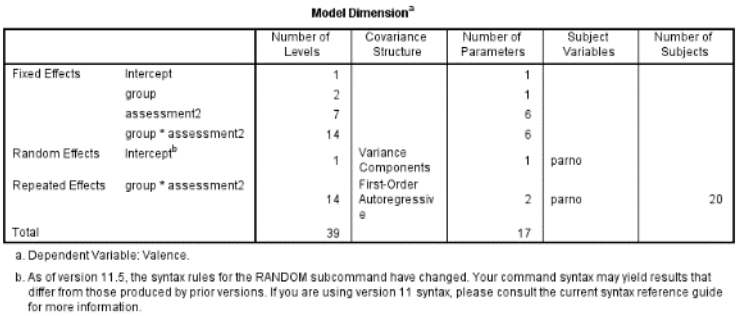
*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration of circular movements (s).

c. Adjustment for multiple comparisons: Bonferroni.

Analysis of the SAM questionnaire

Valence

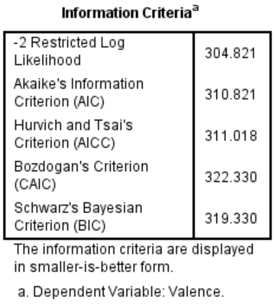


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	2		1		
	assessment2	7		6		
	group * assessment2	14		6		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	14	First-Order Autoregressive	2	parno	20
Total		39		17		

a. Dependent Variable: Valence.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

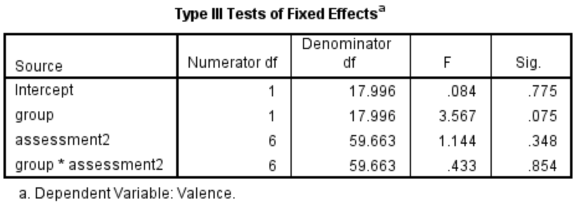


Information Criteria[a]

-2 Restricted Log Likelihood	304.821
Akaike's Information Criterion (AIC)	310.821
Hurvich and Tsai's Criterion (AICC)	311.018
Bozdogan's Criterion (CAIC)	322.330
Schwarz's Bayesian Criterion (BIC)	319.330

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Valence.

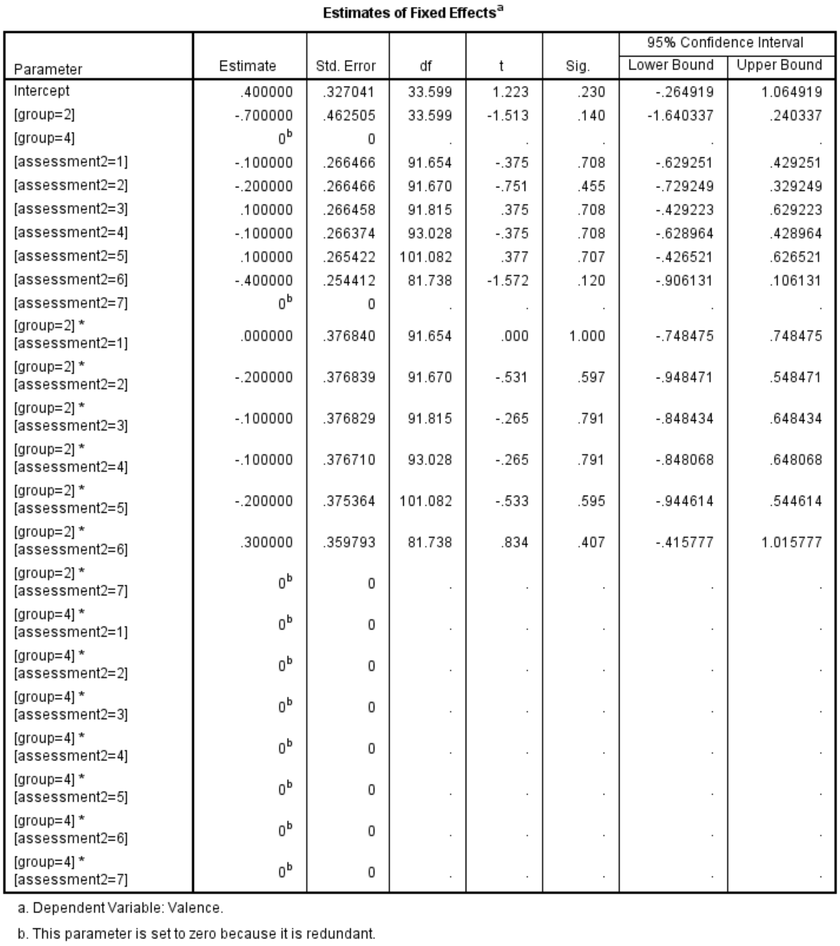


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.996	.084	.775
group	1	17.996	3.567	.075
assessment2	6	59.663	1.144	.348
group * assessment2	6	59.663	.433	.854

a. Dependent Variable: Valence.

Group 0: EAA	Assessment 8: Adaptation DA
Group 1: AAN	Assessment 7: Adaptation NDA
Group 2: EAP	Assessment 6: Training 1
Group 4: Control	Assessment 5: Training 2
	Assessment 4: Training 3
	Assessment 3: Pre-washout
	Assessment 2: Washout NDA
	Assessment 1: Washout DA



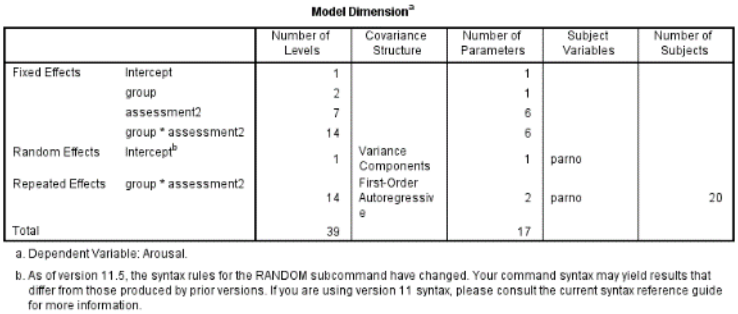
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.400000	.327041	33.599	1.223	.230	-.264919	1.064919
[group=2]	-.700000	.462505	33.599	-1.513	.140	-1.640337	.240337
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	-.100000	.266466	91.654	-.375	.708	-.629251	.429251
[assessment2=2]	-.200000	.266466	91.670	-.751	.455	-.729249	.329249
[assessment2=3]	.100000	.266458	91.815	.375	.708	-.429223	.629223
[assessment2=4]	-.100000	.266374	93.028	-.375	.708	-.628964	.428964
[assessment2=5]	.100000	.265422	101.082	.377	.707	-.426521	.626521
[assessment2=6]	-.400000	.254412	81.738	-1.572	.120	-.906131	.106131
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=2] * [assessment2=1]	.000000	.376840	91.654	.000	1.000	-.748475	.748475
[group=2] * [assessment2=2]	-.200000	.376839	91.670	-.531	.597	-.948471	.548471
[group=2] * [assessment2=3]	-.100000	.376829	91.815	-.265	.791	-.848434	.648434
[group=2] * [assessment2=4]	-.100000	.376710	93.028	-.265	.791	-.848068	.648068
[group=2] * [assessment2=5]	-.200000	.375364	101.082	-.533	.595	-.944614	.544614
[group=2] * [assessment2=6]	.300000	.359793	81.738	.834	.407	-.415777	1.015777
[group=2] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Valence.

b. This parameter is set to zero because it is redundant.

Arousal

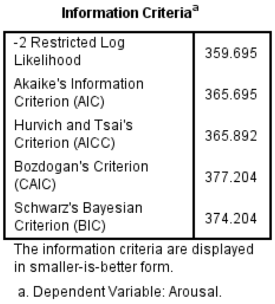


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	2		1		
	assessment2	7		6		
	group * assessment2	14		6		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	14	First-Order Autoregressive	2	parno	20
Total		39		17		

a. Dependent Variable: Arousal.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

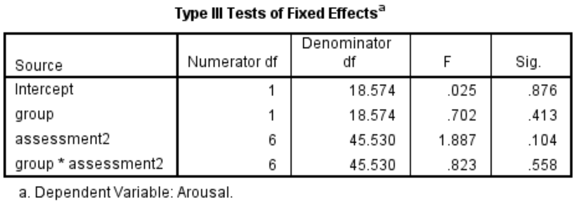


Information Criteria[a]

-2 Restricted Log Likelihood	359.695
Akaike's Information Criterion (AIC)	365.695
Hurvich and Tsai's Criterion (AICC)	365.892
Bozdogan's Criterion (CAIC)	377.204
Schwarz's Bayesian Criterion (BIC)	374.204

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Arousal.

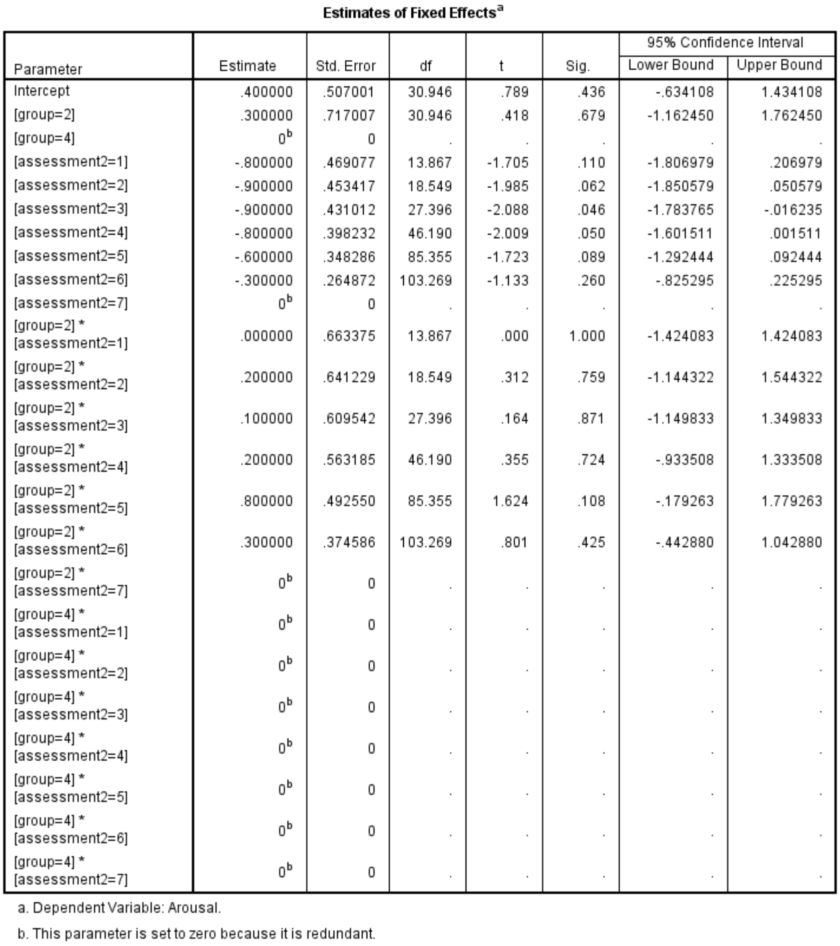


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	18.574	.025	.876
group	1	18.574	.702	.413
assessment2	6	45.530	1.887	.104
group * assessment2	6	45.530	.823	.558

a. Dependent Variable: Arousal.

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



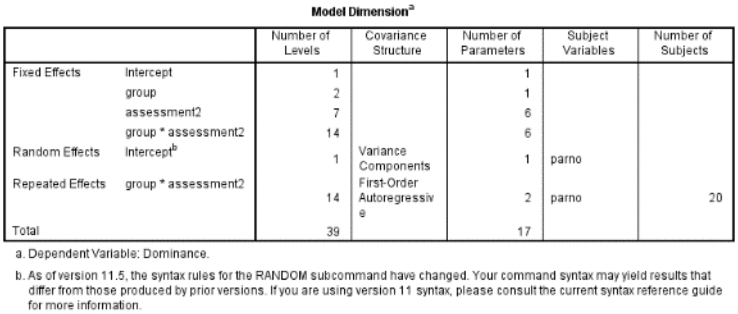
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.400000	.507001	30.946	.789	.436	-.634108	1.434108
[group=2]	.300000	.717007	30.946	.418	.679	-1.162450	1.762450
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	-.800000	.469077	13.867	-1.705	.110	-1.806979	.206979
[assessment2=2]	-.900000	.453417	18.549	-1.985	.062	-1.850579	.050579
[assessment2=3]	-.900000	.431012	27.396	-2.088	.046	-1.783765	-.016235
[assessment2=4]	-.800000	.398232	46.190	-2.009	.050	-1.601511	.001511
[assessment2=5]	-.600000	.348286	85.355	-1.723	.089	-1.292444	.092444
[assessment2=6]	-.300000	.264872	103.269	-1.133	.260	-.825295	.225295
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=2] * [assessment2=1]	.000000	.663375	13.867	.000	1.000	-1.424083	1.424083
[group=2] * [assessment2=2]	.200000	.641229	18.549	.312	.759	-1.144322	1.544322
[group=2] * [assessment2=3]	.100000	.609542	27.396	.164	.871	-1.149833	1.349833
[group=2] * [assessment2=4]	.200000	.563185	46.190	.355	.724	-.933508	1.333508
[group=2] * [assessment2=5]	.800000	.492550	85.355	1.624	.108	-.179263	1.779263
[group=2] * [assessment2=6]	.300000	.374586	103.269	.801	.425	-.442880	1.042880
[group=2] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Arousal.

b. This parameter is set to zero because it is redundant.

Dominance

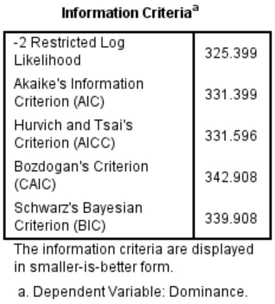


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	2		1		
	assessment2	7		6		
	group * assessment2	14		6		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	14	First-Order Autoregressive	2	parno	20
Total		39		17		

a. Dependent Variable: Dominance.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

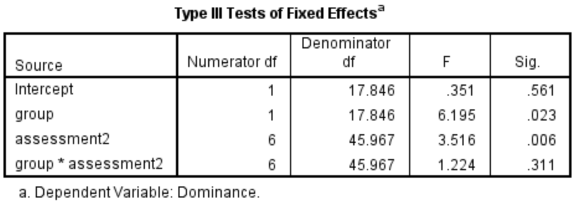


Information Criteria[a]

-2 Restricted Log Likelihood	325.399
Akaike's Information Criterion (AIC)	331.399
Hurvich and Tsai's Criterion (AICC)	331.596
Bozdogan's Criterion (CAIC)	342.908
Schwarz's Bayesian Criterion (BIC)	339.908

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Dominance.



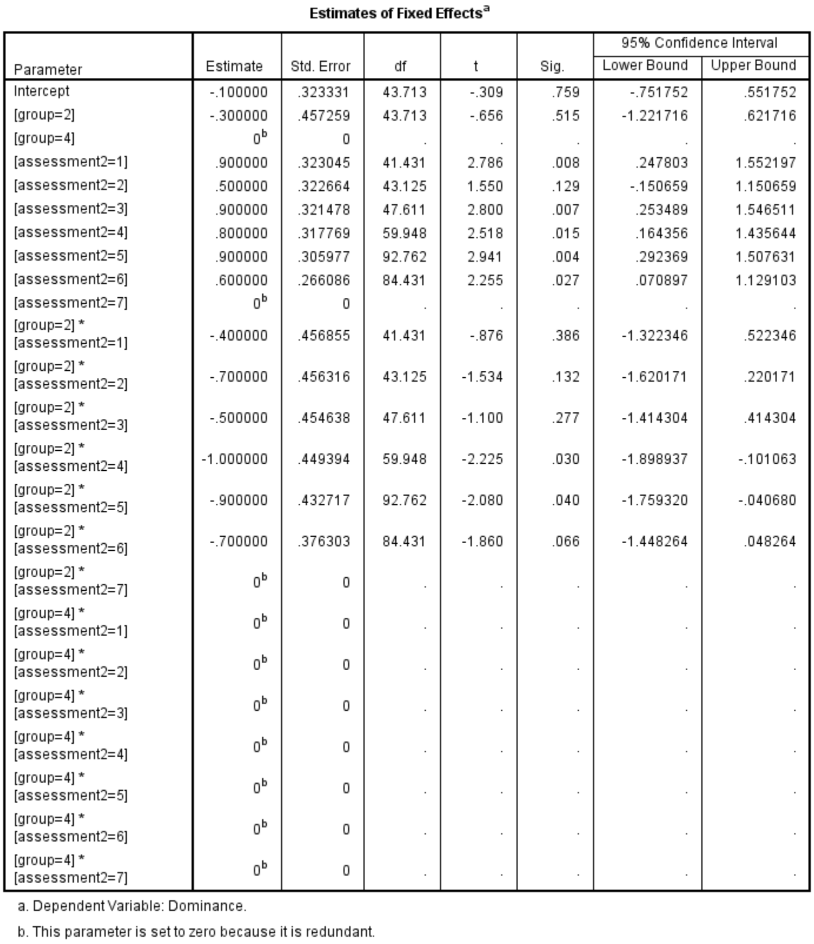
Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	17.846	.351	.561
group	1	17.846	6.195	.023
assessment2	6	45.967	3.516	.006
group * assessment2	6	45.967	1.224	.311

a. Dependent Variable: Dominance.

Group 0: EAA
Group 1: AAN
Group 2: EAP
Group 4: Control

Assessment 8: Adaptation DA
Assessment 7: Adaptation NDA
Assessment 6: Training 1
Assessment 5: Training 2
Assessment 4: Training 3
Assessment 3: Pre-washout
Assessment 2: Washout NDA
Assessment 1: Washout DA



Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-.100000	.323331	43.713	-.309	.759	-.751752	.551752
[group=2]	-.300000	.457259	43.713	-.656	.515	-1.221716	.621716
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	.900000	.323045	41.431	2.786	.008	.247803	1.552197
[assessment2=2]	.500000	.322664	43.125	1.550	.129	-.150659	1.150659
[assessment2=3]	.900000	.321478	47.611	2.800	.007	.253489	1.546511
[assessment2=4]	.800000	.317769	59.948	2.518	.015	.164356	1.435644
[assessment2=5]	.900000	.305977	92.762	2.941	.004	.292369	1.507631
[assessment2=6]	.600000	.266086	84.431	2.255	.027	.070897	1.129103
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=2] * [assessment2=1]	-.400000	.456855	41.431	-.876	.386	-1.322346	.522346
[group=2] * [assessment2=2]	-.700000	.456316	43.125	-1.534	.132	-1.620171	.220171
[group=2] * [assessment2=3]	-.500000	.454638	47.611	-1.100	.277	-1.414304	.414304
[group=2] * [assessment2=4]	-1.000000	.449394	59.948	-2.225	.030	-1.898937	-.101063
[group=2] * [assessment2=5]	-.900000	.432717	92.762	-2.080	.040	-1.759320	-.040680
[group=2] * [assessment2=6]	-.700000	.376303	84.431	-1.860	.066	-1.448264	.048264
[group=2] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

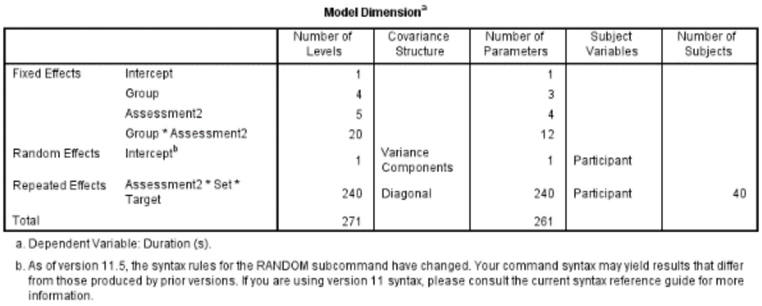
a. Dependent Variable: Dominance.

b. This parameter is set to zero because it is redundant.

Chapter 8: Results of the statistical analysis

Analysis of the NDA

Duration

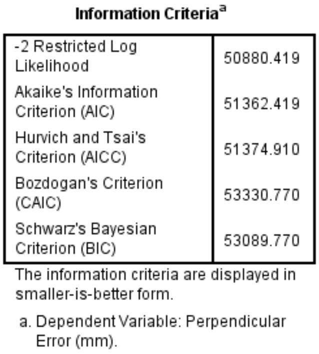


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	5		4		
	Group * Assessment2	20		12		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	40
Total		271		261		

a. Dependent Variable: Duration (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

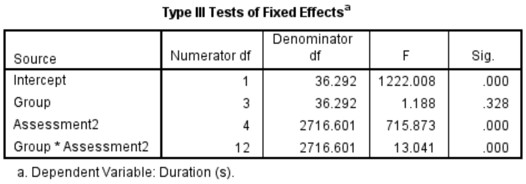


Information Criteria[a]

-2 Restricted Log Likelihood	50880.419
Akaike's Information Criterion (AIC)	51362.419
Hurvich and Tsai's Criterion (AICC)	51374.910
Bozdogan's Criterion (CAIC)	53330.770
Schwarz's Bayesian Criterion (BIC)	53089.770

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Perpendicular Error (mm).

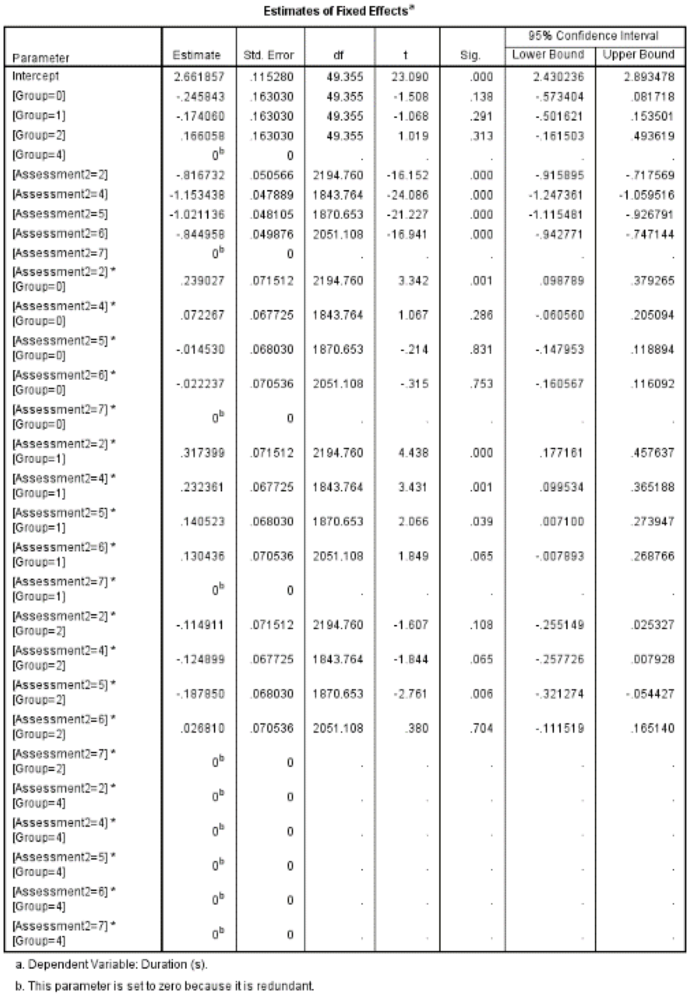


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	36.292	1222.008	.000
Group	3	36.292	1.188	.328
Assessment2	4	2716.601	715.873	.000
Group * Assessment2	12	2716.601	13.041	.000

a. Dependent Variable: Duration (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

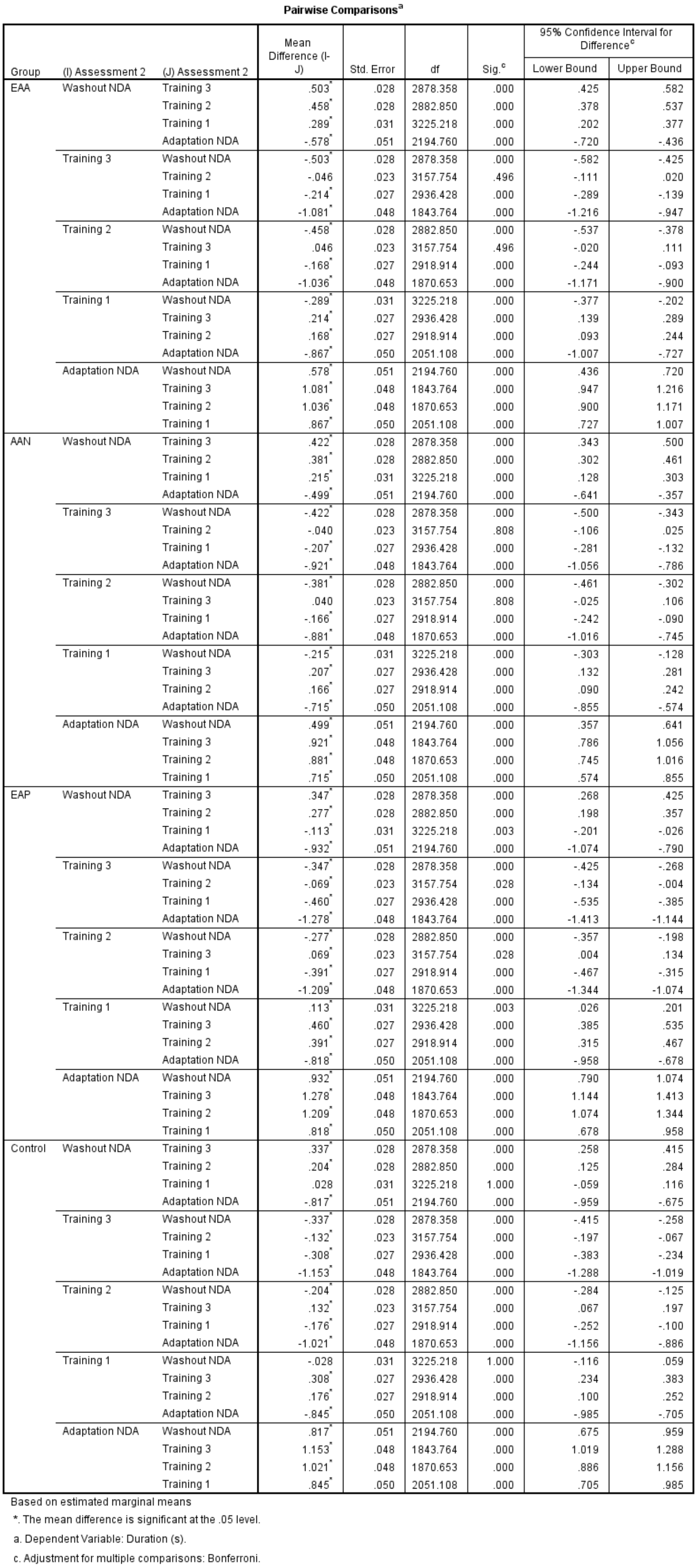


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	2.661857	.115280	49.355	23.090	.000	2.430236	2.893478
[Group=0]	-.245843	.163030	49.355	-1.508	.138	-.573404	.081718
[Group=1]	-.174060	.163030	49.355	-1.068	.291	-.501621	.153501
[Group=2]	.166058	.163030	49.355	1.019	.313	-.161503	.493619
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.816732	.050566	2194.760	-16.152	.000	-.915895	-.717569
[Assessment2=4]	-1.153438	.047889	1843.764	-24.086	.000	-1.247361	-1.059516
[Assessment2=5]	-1.021136	.048105	1870.653	-21.227	.000	-1.115481	-.926791
[Assessment2=6]	-.844958	.049876	2051.108	-16.941	.000	-.942771	-.747144
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	.239027	.071512	2194.760	3.342	.001	.098789	.379265
[Assessment2=4] * [Group=0]	.072267	.067725	1843.764	1.067	.286	-.060560	.205094
[Assessment2=5] * [Group=0]	-.014530	.068030	1870.653	-.214	.831	-.147953	.118894
[Assessment2=6] * [Group=0]	-.022237	.070536	2051.108	-.315	.753	-.160567	.116092
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	.317399	.071512	2194.760	4.438	.000	.177161	.457637
[Assessment2=4] * [Group=1]	.232361	.067725	1843.764	3.431	.001	.099534	.365188
[Assessment2=5] * [Group=1]	.140523	.068030	1870.653	2.066	.039	.007100	.273947
[Assessment2=6] * [Group=1]	.130436	.070536	2051.108	1.849	.065	-.007893	.268766
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	-.114911	.071512	2194.760	-1.607	.108	-.255149	.025327
[Assessment2=4] * [Group=2]	-.124899	.067725	1843.764	-1.844	.065	-.257726	.007928
[Assessment2=5] * [Group=2]	-.187850	.068030	1870.653	-2.761	.006	-.321274	-.054427
[Assessment2=6] * [Group=2]	.026810	.070536	2051.108	.380	.704	-.111519	.165140
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout NDA	Training 3	.503*	.028	2878.358	.000	.425	.582
		Training 2	.458*	.028	2882.850	.000	.378	.537
		Training 1	.289*	.031	3225.218	.000	.202	.377
		Adaptation NDA	-.578*	.051	2194.760	.000	-.720	-.436
	Training 3	Washout NDA	-.503*	.028	2878.358	.000	-.582	-.425
		Training 2	-.046	.023	3157.754	.496	-.111	.020
		Training 1	-.214*	.027	2936.428	.000	-.289	-.139
		Adaptation NDA	-1.081*	.048	1843.764	.000	-1.216	-.947
	Training 2	Washout NDA	-.458*	.028	2882.850	.000	-.537	-.378
		Training 3	.046	.023	3157.754	.496	-.020	.111
		Training 1	-.168*	.027	2918.914	.000	-.244	-.093
		Adaptation NDA	-1.036*	.048	1870.653	.000	-1.171	-.900
	Training 1	Washout NDA	-.289*	.031	3225.218	.000	-.377	-.202
		Training 3	.214*	.027	2936.428	.000	.139	.289
		Training 2	.168*	.027	2918.914	.000	.093	.244
		Adaptation NDA	-.867*	.050	2051.108	.000	-1.007	-.727
	Adaptation NDA	Washout NDA	.578*	.051	2194.760	.000	.436	.720
		Training 3	1.081*	.048	1843.764	.000	.947	1.216
		Training 2	1.036*	.048	1870.653	.000	.900	1.171
		Training 1	.867*	.050	2051.108	.000	.727	1.007
AAN	Washout NDA	Training 3	.422*	.028	2878.358	.000	.343	.500
		Training 2	.381*	.028	2882.850	.000	.302	.461
		Training 1	.215*	.031	3225.218	.000	.128	.303
		Adaptation NDA	-.499*	.051	2194.760	.000	-.641	-.357
	Training 3	Washout NDA	-.422*	.028	2878.358	.000	-.500	-.343
		Training 2	-.040	.023	3157.754	.808	-.106	.025
		Training 1	-.207*	.027	2936.428	.000	-.281	-.132
		Adaptation NDA	-.921*	.048	1843.764	.000	-1.056	-.786
	Training 2	Washout NDA	-.381*	.028	2882.850	.000	-.461	-.302
		Training 3	.040	.023	3157.754	.808	-.025	.106
		Training 1	-.166*	.027	2918.914	.000	-.242	-.090
		Adaptation NDA	-.881*	.048	1870.653	.000	-1.016	-.745
	Training 1	Washout NDA	-.215*	.031	3225.218	.000	-.303	-.128
		Training 3	.207*	.027	2936.428	.000	.132	.281
		Training 2	.166*	.027	2918.914	.000	.090	.242
		Adaptation NDA	-.715*	.050	2051.108	.000	-.855	-.574
	Adaptation NDA	Washout NDA	.499*	.051	2194.760	.000	.357	.641
		Training 3	.921*	.048	1843.764	.000	.786	1.056
		Training 2	.881*	.048	1870.653	.000	.745	1.016
		Training 1	.715*	.050	2051.108	.000	.574	.855
EAP	Washout NDA	Training 3	.347*	.028	2878.358	.000	.268	.425
		Training 2	.277*	.028	2882.850	.000	.198	.357
		Training 1	-.113*	.031	3225.218	.003	-.201	-.026
		Adaptation NDA	-.932*	.051	2194.760	.000	-1.074	-.790
	Training 3	Washout NDA	-.347*	.028	2878.358	.000	-.425	-.268
		Training 2	-.069*	.023	3157.754	.028	-.134	-.004
		Training 1	-.460*	.027	2936.428	.000	-.535	-.385
		Adaptation NDA	-1.278*	.048	1843.764	.000	-1.413	-1.144
	Training 2	Washout NDA	-.277*	.028	2882.850	.000	-.357	-.198
		Training 3	.069*	.023	3157.754	.028	.004	.134
		Training 1	-.391*	.027	2918.914	.000	-.467	-.315
		Adaptation NDA	-1.209*	.048	1870.653	.000	-1.344	-1.074
	Training 1	Washout NDA	.113*	.031	3225.218	.003	.026	.201
		Training 3	.460*	.027	2936.428	.000	.385	.535
		Training 2	.391*	.027	2918.914	.000	.315	.467
		Adaptation NDA	-.818*	.050	2051.108	.000	-.958	-.678
	Adaptation NDA	Washout NDA	.932*	.051	2194.760	.000	.790	1.074
		Training 3	1.278*	.048	1843.764	.000	1.144	1.413
		Training 2	1.209*	.048	1870.653	.000	1.074	1.344
		Training 1	.818*	.050	2051.108	.000	.678	.958
Control	Washout NDA	Training 3	.337*	.028	2878.358	.000	.258	.415
		Training 2	.204*	.028	2882.850	.000	.125	.284
		Training 1	.028	.031	3225.218	1.000	-.059	.116
		Adaptation NDA	-.817*	.051	2194.760	.000	-.959	-.675
	Training 3	Washout NDA	-.337*	.028	2878.358	.000	-.415	-.258
		Training 2	-.132*	.023	3157.754	.000	-.197	-.067
		Training 1	-.308*	.027	2936.428	.000	-.383	-.234
		Adaptation NDA	-1.153*	.048	1843.764	.000	-1.288	-1.019
	Training 2	Washout NDA	-.204*	.028	2882.850	.000	-.284	-.125
		Training 3	.132*	.023	3157.754	.000	.067	.197
		Training 1	-.176*	.027	2918.914	.000	-.252	-.100
		Adaptation NDA	-1.021*	.048	1870.653	.000	-1.156	-.886
	Training 1	Washout NDA	-.028	.031	3225.218	1.000	-.116	.059
		Training 3	.308*	.027	2936.428	.000	.234	.383
		Training 2	.176*	.027	2918.914	.000	.100	.252
		Adaptation NDA	-.845*	.050	2051.108	.000	-.985	-.705
	Adaptation NDA	Washout NDA	.817*	.051	2194.760	.000	.675	.959
		Training 3	1.153*	.048	1843.764	.000	1.019	1.288
		Training 2	1.021*	.048	1870.653	.000	.886	1.156
		Training 1	.845*	.050	2051.108	.000	.705	.985

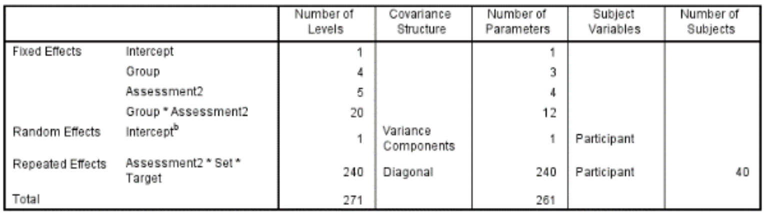
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration (s).

c. Adjustment for multiple comparisons: Bonferroni.

Perpendicular error

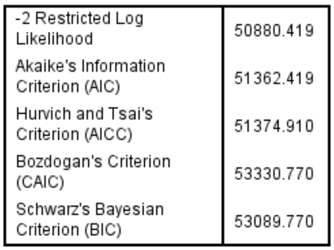


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	5		4		
	Group * Assessment2	20		12		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	40
Total		271		261		

a. Dependent Variable: Perpendicular Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

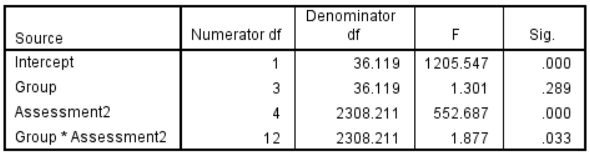


Information Criteria[a]

-2 Restricted Log Likelihood	50880.419
Akaike's Information Criterion (AIC)	51362.419
Hurvich and Tsai's Criterion (AICC)	51374.910
Bozdogan's Criterion (CAIC)	53330.770
Schwarz's Bayesian Criterion (BIC)	53089.770

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Perpendicular Error (mm).

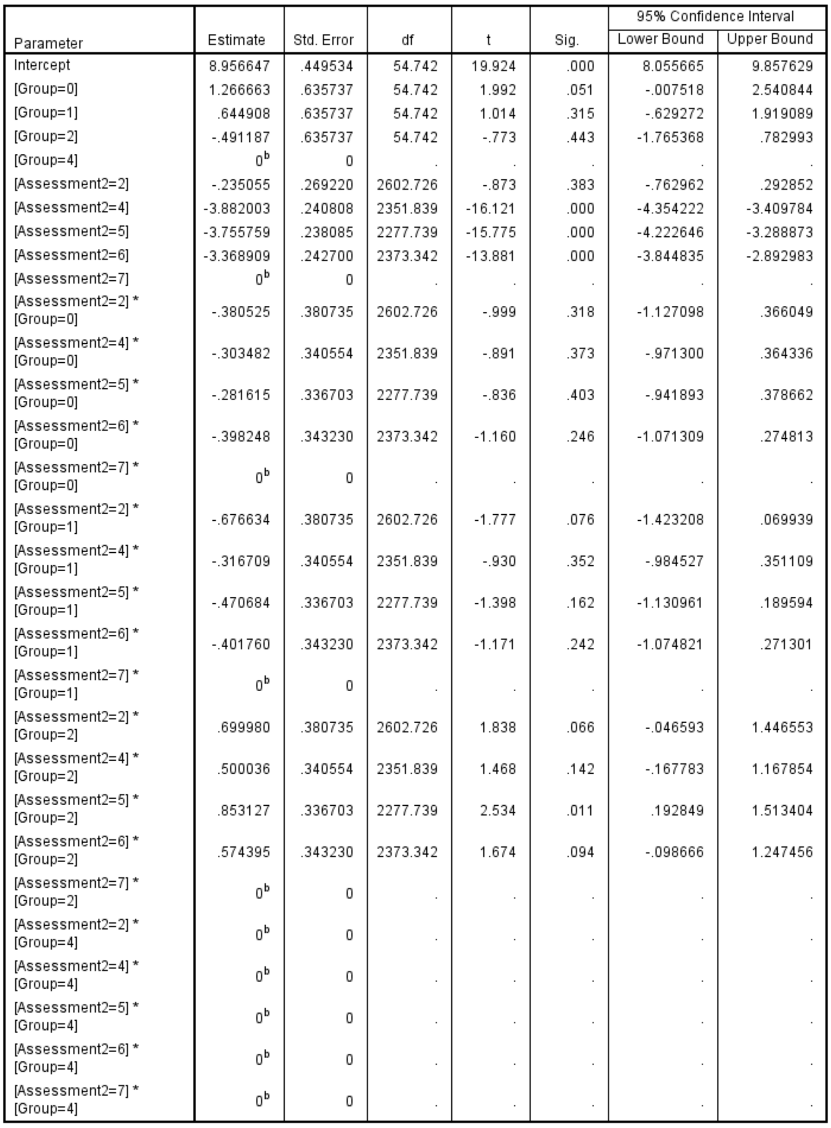


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	36.119	1205.547	.000
Group	3	36.119	1.301	.289
Assessment2	4	2308.211	552.687	.000
Group * Assessment2	12	2308.211	1.877	.033

a. Dependent Variable: Perpendicular Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

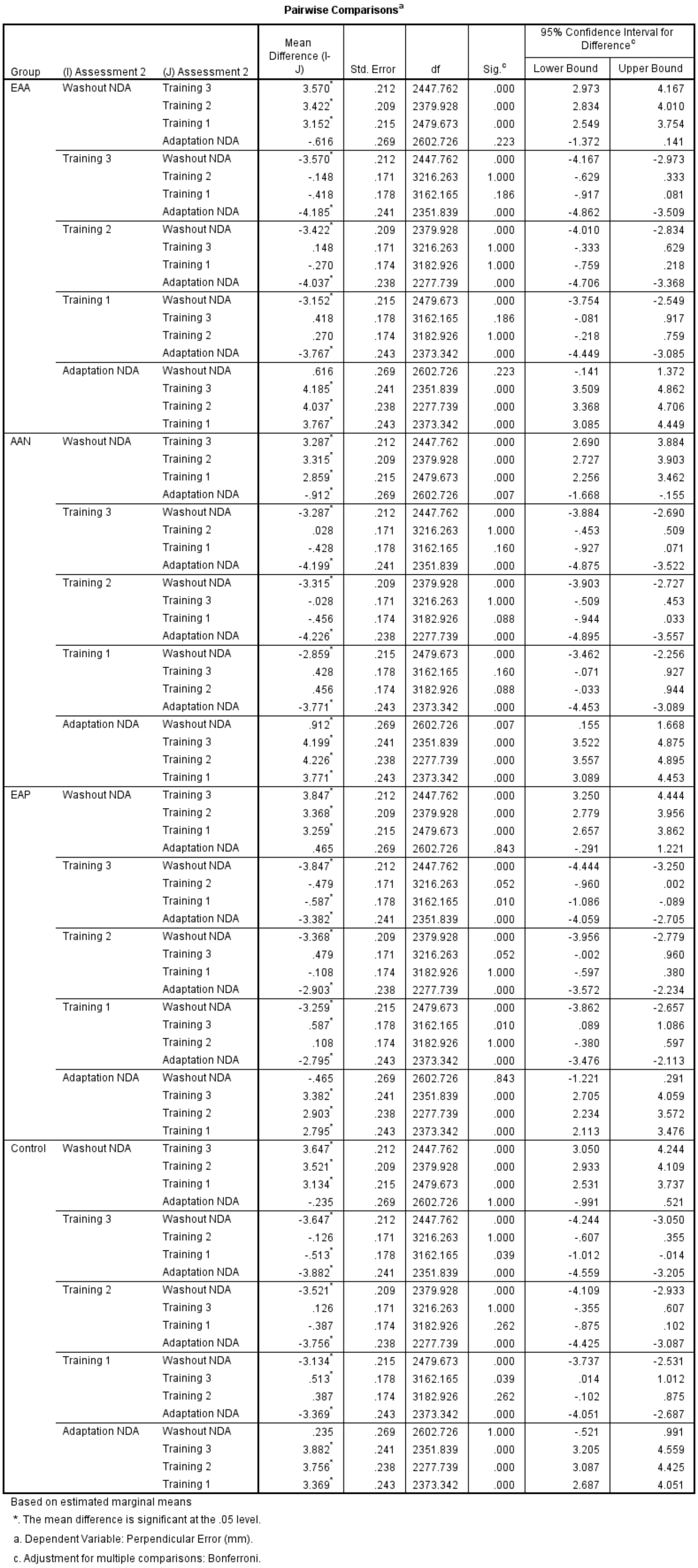


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	8.956647	.449534	54.742	19.924	.000	8.055665	9.857629
[Group=0]	1.266663	.635737	54.742	1.992	.051	-.007518	2.540844
[Group=1]	.644908	.635737	54.742	1.014	.315	-.629272	1.919089
[Group=2]	-.491187	.635737	54.742	-.773	.443	-1.765368	.782993
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.235055	.269220	2602.726	-.873	.383	-.762962	.292852
[Assessment2=4]	-3.882003	.240808	2351.839	-16.121	.000	-4.354222	-3.409784
[Assessment2=5]	-3.755759	.238085	2277.739	-15.775	.000	-4.222646	-3.288873
[Assessment2=6]	-3.368909	.242700	2373.342	-13.881	.000	-3.844835	-2.892983
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	-.380525	.380735	2602.726	-.999	.318	-1.127098	.366049
[Assessment2=4] * [Group=0]	-.303482	.340554	2351.839	-.891	.373	-.971300	.364336
[Assessment2=5] * [Group=0]	-.281615	.336703	2277.739	-.836	.403	-.941893	.378662
[Assessment2=6] * [Group=0]	-.398248	.343230	2373.342	-1.160	.246	-1.071309	.274813
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	-.676634	.380735	2602.726	-1.777	.076	-1.423208	.069939
[Assessment2=4] * [Group=1]	-.316709	.340554	2351.839	-.930	.352	-.984527	.351109
[Assessment2=5] * [Group=1]	-.470684	.336703	2277.739	-1.398	.162	-1.130961	.189594
[Assessment2=6] * [Group=1]	-.401760	.343230	2373.342	-1.171	.242	-1.074821	.271301
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	.699980	.380735	2602.726	1.838	.066	-.046593	1.446553
[Assessment2=4] * [Group=2]	.500036	.340554	2351.839	1.468	.142	-.167783	1.167854
[Assessment2=5] * [Group=2]	.853127	.336703	2277.739	2.534	.011	.192849	1.513404
[Assessment2=6] * [Group=2]	.574395	.343230	2373.342	1.674	.094	-.098666	1.247456
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Perpendicular Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout NDA	Training 3	3.570*	.212	2447.762	.000	2.973	4.167
		Training 2	3.422*	.209	2379.928	.000	2.834	4.010
		Training 1	3.152*	.215	2479.673	.000	2.549	3.754
		Adaptation NDA	-.616	.269	2602.726	.223	-1.372	.141
	Training 3	Washout NDA	-3.570*	.212	2447.762	.000	-4.167	-2.973
		Training 2	-.148	.171	3216.263	1.000	-.629	.333
		Training 1	-.418	.178	3162.165	.186	-.917	.081
		Adaptation NDA	-4.185*	.241	2351.839	.000	-4.862	-3.509
	Training 2	Washout NDA	-3.422*	.209	2379.928	.000	-4.010	-2.834
		Training 3	.148	.171	3216.263	1.000	-.333	.629
		Training 1	-.270	.174	3182.926	1.000	-.759	.218
		Adaptation NDA	-4.037*	.238	2277.739	.000	-4.706	-3.368
	Training 1	Washout NDA	-3.152*	.215	2479.673	.000	-3.754	-2.549
		Training 3	.418	.178	3162.165	.186	-.081	.917
		Training 2	.270	.174	3182.926	1.000	-.218	.759
		Adaptation NDA	-3.767*	.243	2373.342	.000	-4.449	-3.085
	Adaptation NDA	Washout NDA	.616	.269	2602.726	.223	-.141	1.372
		Training 3	4.185*	.241	2351.839	.000	3.509	4.862
		Training 2	4.037*	.238	2277.739	.000	3.368	4.706
		Training 1	3.767*	.243	2373.342	.000	3.085	4.449
AAN	Washout NDA	Training 3	3.287*	.212	2447.762	.000	2.690	3.884
		Training 2	3.315*	.209	2379.928	.000	2.727	3.903
		Training 1	2.859*	.215	2479.673	.000	2.256	3.462
		Adaptation NDA	-.912*	.269	2602.726	.007	-1.668	-.155
	Training 3	Washout NDA	-3.287*	.212	2447.762	.000	-3.884	-2.690
		Training 2	.028	.171	3216.263	1.000	-.453	.509
		Training 1	-.428	.178	3162.165	.160	-.927	.071
		Adaptation NDA	-4.199*	.241	2351.839	.000	-4.875	-3.522
	Training 2	Washout NDA	-3.315*	.209	2379.928	.000	-3.903	-2.727
		Training 3	-.028	.171	3216.263	1.000	-.509	.453
		Training 1	-.456	.174	3182.926	.088	-.944	.033
		Adaptation NDA	-4.226*	.238	2277.739	.000	-4.895	-3.557
	Training 1	Washout NDA	-2.859*	.215	2479.673	.000	-3.462	-2.256
		Training 3	.428	.178	3162.165	.160	-.071	.927
		Training 2	.456	.174	3182.926	.088	-.033	.944
		Adaptation NDA	-3.771*	.243	2373.342	.000	-4.453	-3.089
	Adaptation NDA	Washout NDA	.912*	.269	2602.726	.007	.155	1.668
		Training 3	4.199*	.241	2351.839	.000	3.522	4.875
		Training 2	4.226*	.238	2277.739	.000	3.557	4.895
		Training 1	3.771*	.243	2373.342	.000	3.089	4.453
EAP	Washout NDA	Training 3	3.847*	.212	2447.762	.000	3.250	4.444
		Training 2	3.368*	.209	2379.928	.000	2.779	3.956
		Training 1	3.259*	.215	2479.673	.000	2.657	3.862
		Adaptation NDA	.465	.269	2602.726	.843	-.291	1.221
	Training 3	Washout NDA	-3.847*	.212	2447.762	.000	-4.444	-3.250
		Training 2	-.479	.171	3216.263	.052	-.960	.002
		Training 1	-.587*	.178	3162.165	.010	-1.086	-.089
		Adaptation NDA	-3.382*	.241	2351.839	.000	-4.059	-2.705
	Training 2	Washout NDA	-3.368*	.209	2379.928	.000	-3.956	-2.779
		Training 3	.479	.171	3216.263	.052	-.002	.960
		Training 1	-.108	.174	3182.926	1.000	-.597	.380
		Adaptation NDA	-2.903*	.238	2277.739	.000	-3.572	-2.234
	Training 1	Washout NDA	-3.259*	.215	2479.673	.000	-3.862	-2.657
		Training 3	.587*	.178	3162.165	.010	.089	1.086
		Training 2	.108	.174	3182.926	1.000	-.380	.597
		Adaptation NDA	-2.795*	.243	2373.342	.000	-3.476	-2.113
	Adaptation NDA	Washout NDA	-.465	.269	2602.726	.843	-1.221	.291
		Training 3	3.382*	.241	2351.839	.000	2.705	4.059
		Training 2	2.903*	.238	2277.739	.000	2.234	3.572
		Training 1	2.795*	.243	2373.342	.000	2.113	3.476
Control	Washout NDA	Training 3	3.647*	.212	2447.762	.000	3.050	4.244
		Training 2	3.521*	.209	2379.928	.000	2.933	4.109
		Training 1	3.134*	.215	2479.673	.000	2.531	3.737
		Adaptation NDA	-.235	.269	2602.726	1.000	-.991	.521
	Training 3	Washout NDA	-3.647*	.212	2447.762	.000	-4.244	-3.050
		Training 2	-.126	.171	3216.263	1.000	-.607	.355
		Training 1	-.513*	.178	3162.165	.039	-1.012	-.014
		Adaptation NDA	-3.882*	.241	2351.839	.000	-4.559	-3.205
	Training 2	Washout NDA	-3.521*	.209	2379.928	.000	-4.109	-2.933
		Training 3	.126	.171	3216.263	1.000	-.355	.607
		Training 1	-.387	.174	3182.926	.262	-.875	.102
		Adaptation NDA	-3.756*	.238	2277.739	.000	-4.425	-3.087
	Training 1	Washout NDA	-3.134*	.215	2479.673	.000	-3.737	-2.531
		Training 3	.513*	.178	3162.165	.039	.014	1.012
		Training 2	.387	.174	3182.926	.262	-.102	.875
		Adaptation NDA	-3.369*	.243	2373.342	.000	-4.051	-2.687
	Adaptation NDA	Washout NDA	.235	.269	2602.726	1.000	-.521	.991
		Training 3	3.882*	.241	2351.839	.000	3.205	4.559
		Training 2	3.756*	.238	2277.739	.000	3.087	4.425
		Training 1	3.369*	.243	2373.342	.000	2.687	4.051

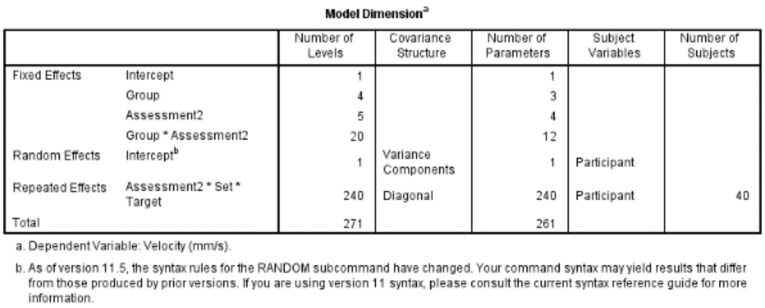
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Perpendicular Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Mean Velocity

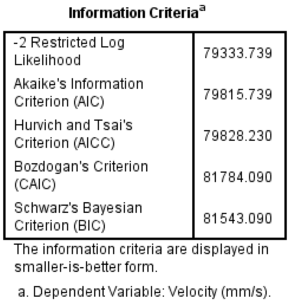


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	5		4		
	Group * Assessment2	20		12		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	40
Total		271		261		

a. Dependent Variable: Velocity (mm/s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

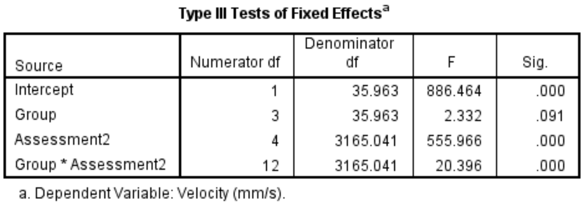


Information Criteria[a]

-2 Restricted Log Likelihood	79333.739
Akaike's Information Criterion (AIC)	79815.739
Hurvich and Tsai's Criterion (AICC)	79828.230
Bozdogan's Criterion (CAIC)	81784.090
Schwarz's Bayesian Criterion (BIC)	81543.090

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Velocity (mm/s).

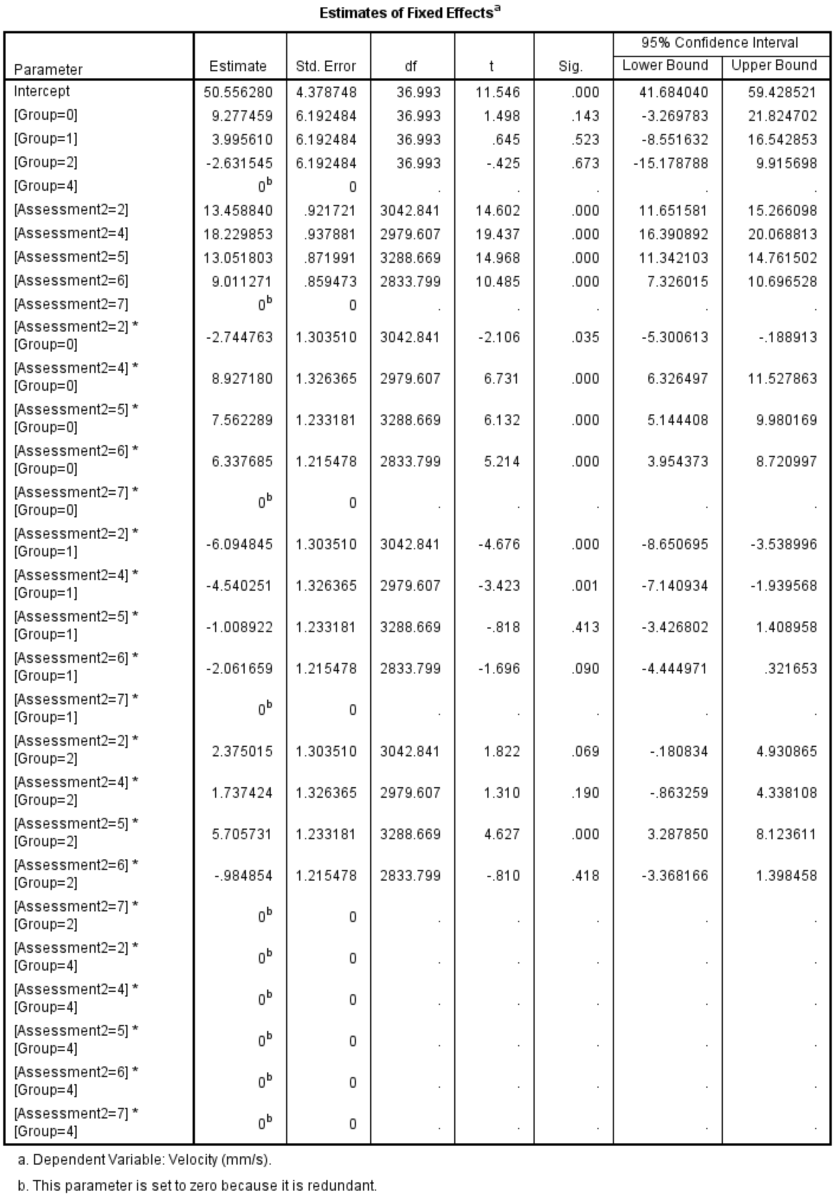


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	35.963	886.464	.000
Group	3	35.963	2.332	.091
Assessment2	4	3165.041	555.966	.000
Group * Assessment2	12	3165.041	20.396	.000

a. Dependent Variable: Velocity (mm/s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



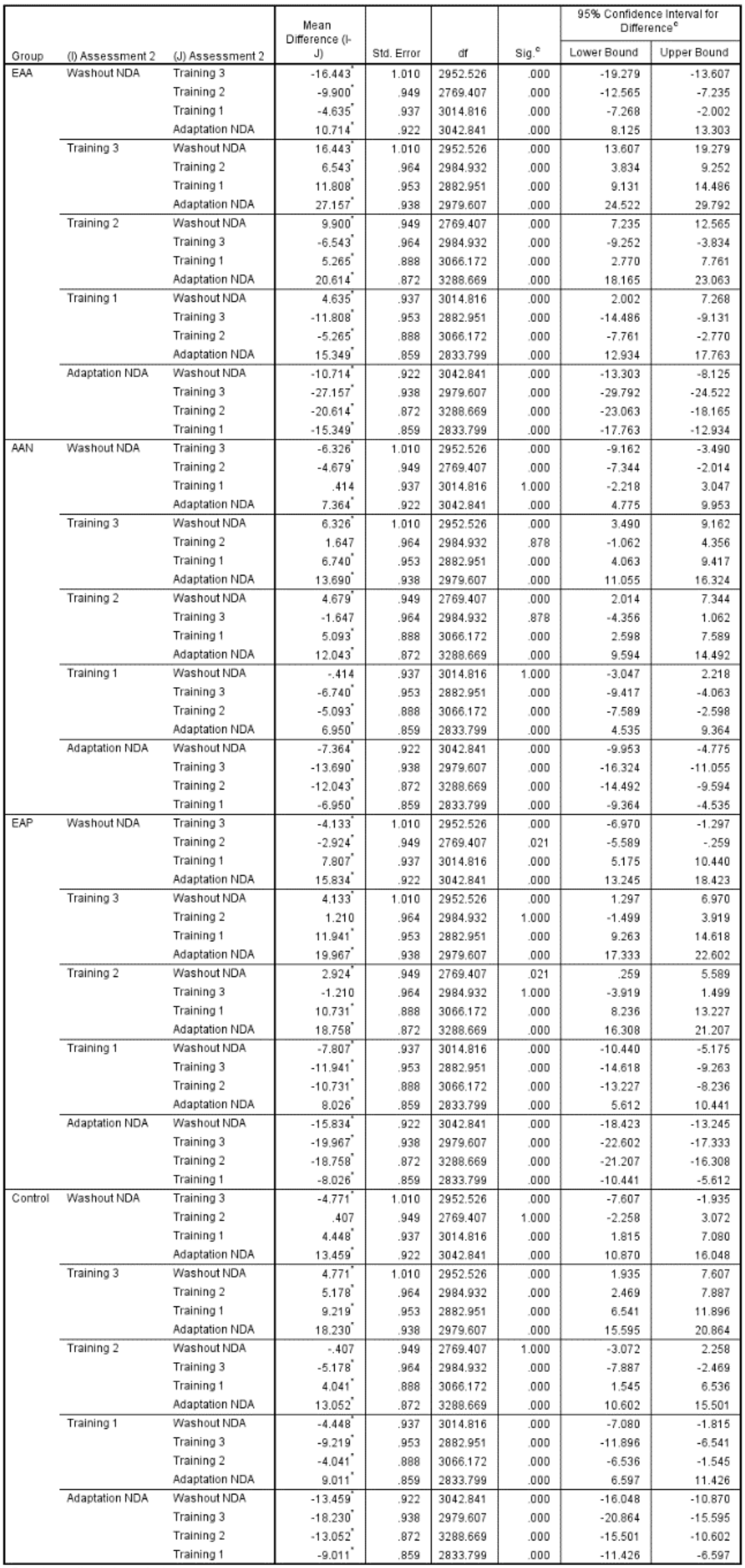
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	50.556280	4.378748	36.993	11.546	.000	41.684040	59.428521
[Group=0]	9.277459	6.192484	36.993	1.498	.143	-3.269783	21.824702
[Group=1]	3.995610	6.192484	36.993	.645	.523	-8.551632	16.542853
[Group=2]	-2.631545	6.192484	36.993	-.425	.673	-15.178788	9.915698
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	13.458840	.921721	3042.841	14.602	.000	11.651581	15.266098
[Assessment2=4]	18.229853	.937881	2979.607	19.437	.000	16.390892	20.068813
[Assessment2=5]	13.051803	.871991	3288.669	14.968	.000	11.342103	14.761502
[Assessment2=6]	9.011271	.859473	2833.799	10.485	.000	7.326015	10.696528
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	-2.744763	1.303510	3042.841	-2.106	.035	-5.300613	-.188913
[Assessment2=4] * [Group=0]	8.927180	1.326365	2979.607	6.731	.000	6.326497	11.527863
[Assessment2=5] * [Group=0]	7.562289	1.233181	3288.669	6.132	.000	5.144408	9.980169
[Assessment2=6] * [Group=0]	6.337685	1.215478	2833.799	5.214	.000	3.954373	8.720997
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	-6.094845	1.303510	3042.841	-4.676	.000	-8.650695	-3.538996
[Assessment2=4] * [Group=1]	-4.540251	1.326365	2979.607	-3.423	.001	-7.140934	-1.939568
[Assessment2=5] * [Group=1]	-1.008922	1.233181	3288.669	-.818	.413	-3.426802	1.408958
[Assessment2=6] * [Group=1]	-2.061659	1.215478	2833.799	-1.696	.090	-4.444971	.321653
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	2.375015	1.303510	3042.841	1.822	.069	-.180834	4.930865
[Assessment2=4] * [Group=2]	1.737424	1.326365	2979.607	1.310	.190	-.863259	4.338108
[Assessment2=5] * [Group=2]	5.705731	1.233181	3288.669	4.627	.000	3.287850	8.123611
[Assessment2=6] * [Group=2]	-.984854	1.215478	2833.799	-.810	.418	-3.368166	1.398458
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Velocity (mm/s).

b. This parameter is set to zero because it is redundant.

Pairwise Comparisons[a]



Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout NDA	Training 3	-16.443*	1.010	2952.526	.000	-19.279	-13.607
		Training 2	-9.900*	.949	2769.407	.000	-12.565	-7.235
		Training 1	-4.635*	.937	3014.816	.000	-7.268	-2.002
		Adaptation NDA	10.714*	.922	3042.841	.000	8.125	13.303
	Training 3	Washout NDA	16.443*	1.010	2952.526	.000	13.607	19.279
		Training 2	6.543*	.964	2984.932	.000	3.834	9.252
		Training 1	11.808*	.953	2882.951	.000	9.131	14.486
		Adaptation NDA	27.157*	.938	2979.607	.000	24.522	29.792
	Training 2	Washout NDA	9.900*	.949	2769.407	.000	7.235	12.565
		Training 3	-6.543*	.964	2984.932	.000	-9.252	-3.834
		Training 1	5.265*	.888	3066.172	.000	2.770	7.761
		Adaptation NDA	20.614*	.872	3288.669	.000	18.165	23.063
	Training 1	Washout NDA	4.635*	.937	3014.816	.000	2.002	7.268
		Training 3	-11.808*	.953	2882.951	.000	-14.486	-9.131
		Training 2	-5.265*	.888	3066.172	.000	-7.761	-2.770
		Adaptation NDA	15.349*	.859	2833.799	.000	12.934	17.763
	Adaptation NDA	Washout NDA	-10.714*	.922	3042.841	.000	-13.303	-8.125
		Training 3	-27.157*	.938	2979.607	.000	-29.792	-24.522
		Training 2	-20.614*	.872	3288.669	.000	-23.063	-18.165
		Training 1	-15.349*	.859	2833.799	.000	-17.763	-12.934
AAN	Washout NDA	Training 3	-6.326*	1.010	2952.526	.000	-9.162	-3.490
		Training 2	-4.679*	.949	2769.407	.000	-7.344	-2.014
		Training 1	.414	.937	3014.816	1.000	-2.218	3.047
		Adaptation NDA	7.364*	.922	3042.841	.000	4.775	9.953
	Training 3	Washout NDA	6.326*	1.010	2952.526	.000	3.490	9.162
		Training 2	1.647	.964	2984.932	.878	-1.062	4.356
		Training 1	6.740*	.953	2882.951	.000	4.063	9.417
		Adaptation NDA	13.690*	.938	2979.607	.000	11.055	16.324
	Training 2	Washout NDA	4.679*	.949	2769.407	.000	2.014	7.344
		Training 3	-1.647	.964	2984.932	.878	-4.356	1.062
		Training 1	5.093*	.888	3066.172	.000	2.598	7.589
		Adaptation NDA	12.043*	.872	3288.669	.000	9.594	14.492
	Training 1	Washout NDA	-.414	.937	3014.816	1.000	-3.047	2.218
		Training 3	-6.740*	.953	2882.951	.000	-9.417	-4.063
		Training 2	-5.093*	.888	3066.172	.000	-7.589	-2.598
		Adaptation NDA	6.950*	.859	2833.799	.000	4.535	9.364
	Adaptation NDA	Washout NDA	-7.364*	.922	3042.841	.000	-9.953	-4.775
		Training 3	-13.690*	.938	2979.607	.000	-16.324	-11.055
		Training 2	-12.043*	.872	3288.669	.000	-14.492	-9.594
		Training 1	-6.950*	.859	2833.799	.000	-9.364	-4.535
EAP	Washout NDA	Training 3	-4.133*	1.010	2952.526	.000	-6.970	-1.297
		Training 2	-2.924*	.949	2769.407	.021	-5.589	-.259
		Training 1	7.807*	.937	3014.816	.000	5.175	10.440
		Adaptation NDA	15.834*	.922	3042.841	.000	13.245	18.423
	Training 3	Washout NDA	4.133*	1.010	2952.526	.000	1.297	6.970
		Training 2	1.210	.964	2984.932	1.000	-1.499	3.919
		Training 1	11.941*	.953	2882.951	.000	9.263	14.618
		Adaptation NDA	19.967*	.938	2979.607	.000	17.333	22.602
	Training 2	Washout NDA	2.924*	.949	2769.407	.021	.259	5.589
		Training 3	-1.210	.964	2984.932	1.000	-3.919	1.499
		Training 1	10.731*	.888	3066.172	.000	8.236	13.227
		Adaptation NDA	18.758*	.872	3288.669	.000	16.308	21.207
	Training 1	Washout NDA	-7.807*	.937	3014.816	.000	-10.440	-5.175
		Training 3	-11.941*	.953	2882.951	.000	-14.618	-9.263
		Training 2	-10.731*	.888	3066.172	.000	-13.227	-8.236
		Adaptation NDA	8.026*	.859	2833.799	.000	5.612	10.441
	Adaptation NDA	Washout NDA	-15.834*	.922	3042.841	.000	-18.423	-13.245
		Training 3	-19.967*	.938	2979.607	.000	-22.602	-17.333
		Training 2	-18.758*	.872	3288.669	.000	-21.207	-16.308
		Training 1	-8.026*	.859	2833.799	.000	-10.441	-5.612
Control	Washout NDA	Training 3	-4.771*	1.010	2952.526	.000	-7.607	-1.935
		Training 2	.407	.949	2769.407	1.000	-2.258	3.072
		Training 1	4.448*	.937	3014.816	.000	1.815	7.080
		Adaptation NDA	13.459*	.922	3042.841	.000	10.870	16.048
	Training 3	Washout NDA	4.771*	1.010	2952.526	.000	1.935	7.607
		Training 2	5.178*	.964	2984.932	.000	2.469	7.887
		Training 1	9.219*	.953	2882.951	.000	6.541	11.896
		Adaptation NDA	18.230*	.938	2979.607	.000	15.595	20.864
	Training 2	Washout NDA	-.407	.949	2769.407	1.000	-3.072	2.258
		Training 3	-5.178*	.964	2984.932	.000	-7.887	-2.469
		Training 1	4.041*	.888	3066.172	.000	1.545	6.536
		Adaptation NDA	13.052*	.872	3288.669	.000	10.602	15.501
	Training 1	Washout NDA	-4.448*	.937	3014.816	.000	-7.080	-1.815
		Training 3	-9.219*	.953	2882.951	.000	-11.896	-6.541
		Training 2	-4.041*	.888	3066.172	.000	-6.536	-1.545
		Adaptation NDA	9.011*	.859	2833.799	.000	6.597	11.426
	Adaptation NDA	Washout NDA	-13.459*	.922	3042.841	.000	-16.048	-10.870
		Training 3	-18.230*	.938	2979.607	.000	-20.864	-15.595
		Training 2	-13.052*	.872	3288.669	.000	-15.501	-10.602
		Training 1	-9.011*	.859	2833.799	.000	-11.426	-6.597

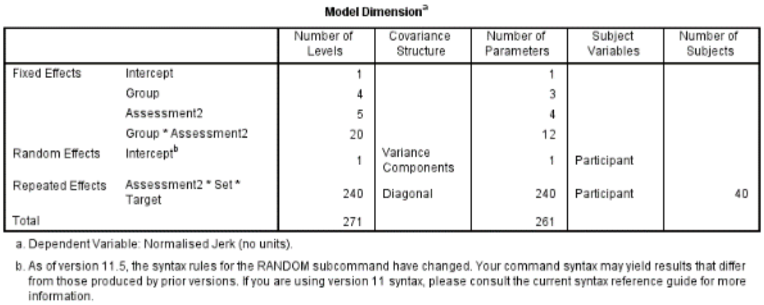
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Velocity (mm/s).

c. Adjustment for multiple comparisons: Bonferroni.

Normalised jerk

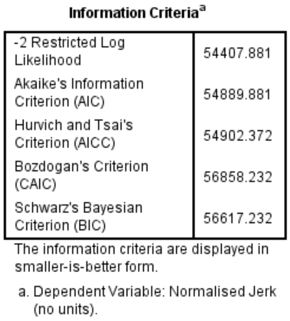


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	5		4		
	Group * Assessment2	20		12		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	40
Total		271		261		

a. Dependent Variable: Normalised Jerk (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

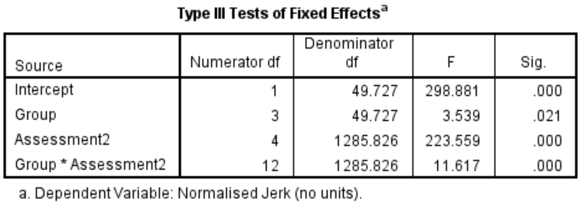


Information Criteria[a]

-2 Restricted Log Likelihood	54407.881
Akaike's Information Criterion (AIC)	54889.881
Hurvich and Tsai's Criterion (AICC)	54902.372
Bozdogan's Criterion (CAIC)	56858.232
Schwarz's Bayesian Criterion (BIC)	56617.232

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Normalised Jerk (no units).

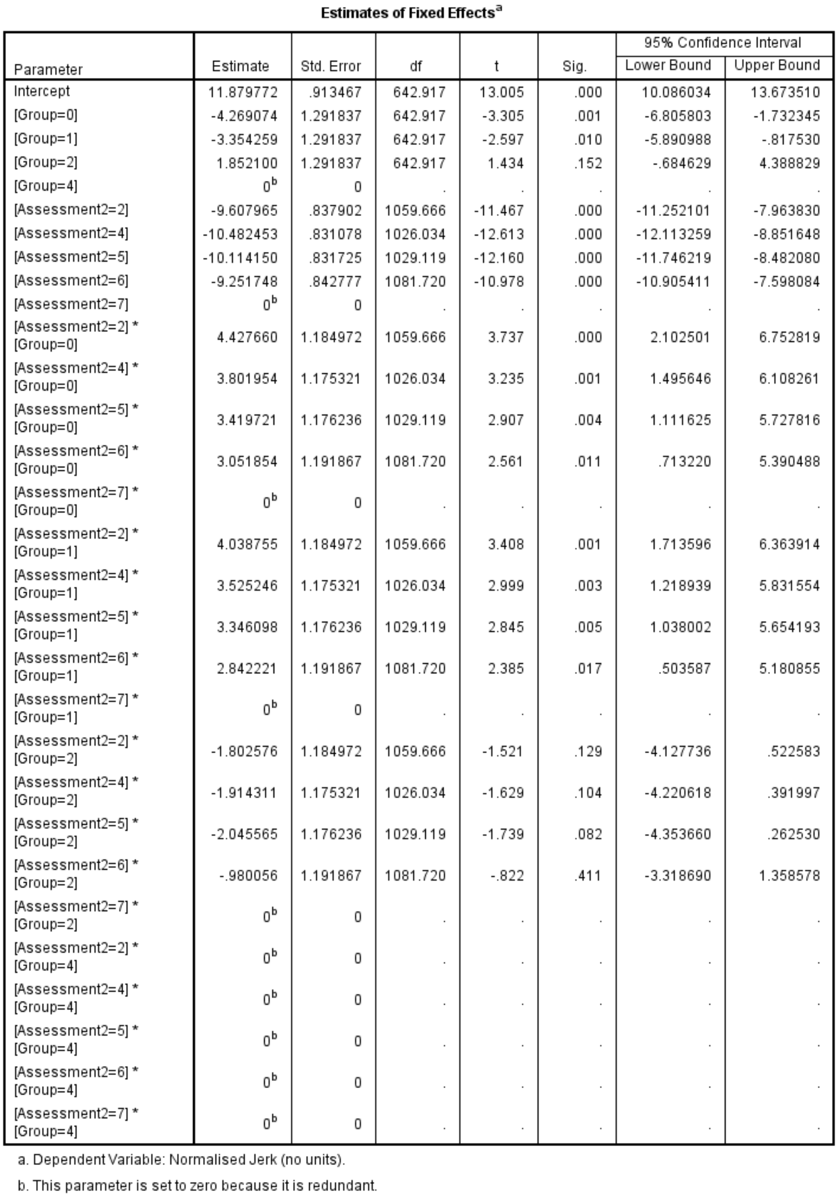


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	49.727	298.881	.000
Group	3	49.727	3.539	.021
Assessment2	4	1285.826	223.559	.000
Group * Assessment2	12	1285.826	11.617	.000

a. Dependent Variable: Normalised Jerk (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

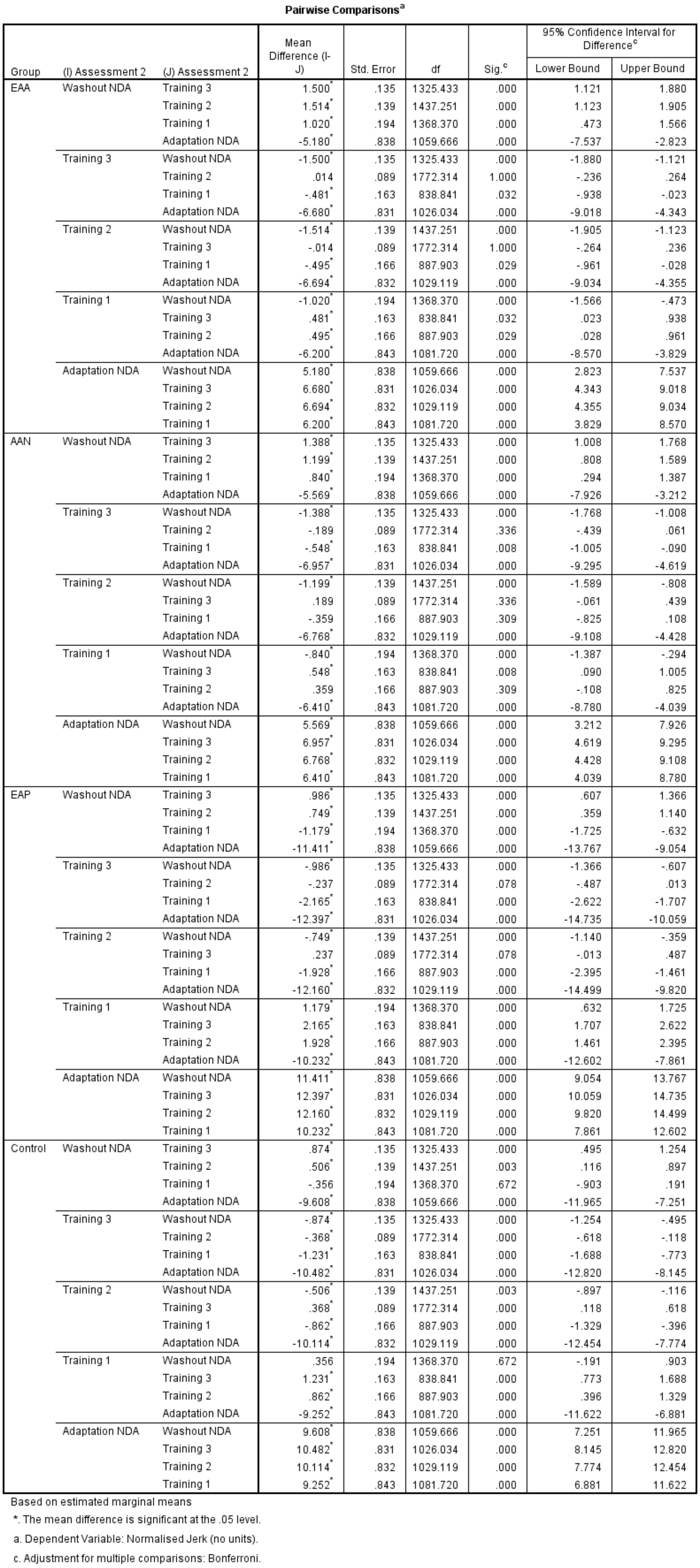


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	11.879772	.913467	642.917	13.005	.000	10.086034	13.673510
[Group=0]	-4.269074	1.291837	642.917	-3.305	.001	-6.805803	-1.732345
[Group=1]	-3.354259	1.291837	642.917	-2.597	.010	-5.890988	-.817530
[Group=2]	1.852100	1.291837	642.917	1.434	.152	-.684629	4.388829
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-9.607965	.837902	1059.666	-11.467	.000	-11.252101	-7.963830
[Assessment2=4]	-10.482453	.831078	1026.034	-12.613	.000	-12.113259	-8.851648
[Assessment2=5]	-10.114150	.831725	1029.119	-12.160	.000	-11.746219	-8.482080
[Assessment2=6]	-9.251748	.842777	1081.720	-10.978	.000	-10.905411	-7.598084
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	4.427660	1.184972	1059.666	3.737	.000	2.102501	6.752819
[Assessment2=4] * [Group=0]	3.801954	1.175321	1026.034	3.235	.001	1.495646	6.108261
[Assessment2=5] * [Group=0]	3.419721	1.176236	1029.119	2.907	.004	1.111625	5.727816
[Assessment2=6] * [Group=0]	3.051854	1.191867	1081.720	2.561	.011	.713220	5.390488
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	4.038755	1.184972	1059.666	3.408	.001	1.713596	6.363914
[Assessment2=4] * [Group=1]	3.525246	1.175321	1026.034	2.999	.003	1.218939	5.831554
[Assessment2=5] * [Group=1]	3.346098	1.176236	1029.119	2.845	.005	1.038002	5.654193
[Assessment2=6] * [Group=1]	2.842221	1.191867	1081.720	2.385	.017	.503587	5.180855
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	-1.802576	1.184972	1059.666	-1.521	.129	-4.127736	.522583
[Assessment2=4] * [Group=2]	-1.914311	1.175321	1026.034	-1.629	.104	-4.220618	.391997
[Assessment2=5] * [Group=2]	-2.045565	1.176236	1029.119	-1.739	.082	-4.353660	.262530
[Assessment2=6] * [Group=2]	-.980056	1.191867	1081.720	-.822	.411	-3.318690	1.358578
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Normalised Jerk (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout NDA	Training 3	1.500*	.135	1325.433	.000	1.121	1.880
		Training 2	1.514*	.139	1437.251	.000	1.123	1.905
		Training 1	1.020*	.194	1368.370	.000	.473	1.566
		Adaptation NDA	-5.180*	.838	1059.666	.000	-7.537	-2.823
	Training 3	Washout NDA	-1.500*	.135	1325.433	.000	-1.880	-1.121
		Training 2	.014	.089	1772.314	1.000	-.236	.264
		Training 1	-.481*	.163	838.841	.032	-.938	-.023
		Adaptation NDA	-6.680*	.831	1026.034	.000	-9.018	-4.343
	Training 2	Washout NDA	-1.514*	.139	1437.251	.000	-1.905	-1.123
		Training 3	-.014	.089	1772.314	1.000	-.264	.236
		Training 1	-.495*	.166	887.903	.029	-.961	-.028
		Adaptation NDA	-6.694*	.832	1029.119	.000	-9.034	-4.355
	Training 1	Washout NDA	-1.020*	.194	1368.370	.000	-1.566	-.473
		Training 3	.481*	.163	838.841	.032	.023	.938
		Training 2	.495*	.166	887.903	.029	.028	.961
		Adaptation NDA	-6.200*	.843	1081.720	.000	-8.570	-3.829
	Adaptation NDA	Washout NDA	5.180*	.838	1059.666	.000	2.823	7.537
		Training 3	6.680*	.831	1026.034	.000	4.343	9.018
		Training 2	6.694*	.832	1029.119	.000	4.355	9.034
		Training 1	6.200*	.843	1081.720	.000	3.829	8.570
AAN	Washout NDA	Training 3	1.388*	.135	1325.433	.000	1.008	1.768
		Training 2	1.199*	.139	1437.251	.000	.808	1.589
		Training 1	.840*	.194	1368.370	.000	.294	1.387
		Adaptation NDA	-5.569*	.838	1059.666	.000	-7.926	-3.212
	Training 3	Washout NDA	-1.388*	.135	1325.433	.000	-1.768	-1.008
		Training 2	-.189	.089	1772.314	.336	-.439	.061
		Training 1	-.548*	.163	838.841	.008	-1.005	-.090
		Adaptation NDA	-6.957*	.831	1026.034	.000	-9.295	-4.619
	Training 2	Washout NDA	-1.199*	.139	1437.251	.000	-1.589	-.808
		Training 3	.189	.089	1772.314	.336	-.061	.439
		Training 1	-.359	.166	887.903	.309	-.825	.108
		Adaptation NDA	-6.768*	.832	1029.119	.000	-9.108	-4.428
	Training 1	Washout NDA	-.840*	.194	1368.370	.000	-1.387	-.294
		Training 3	.548*	.163	838.841	.008	.090	1.005
		Training 2	.359	.166	887.903	.309	-.108	.825
		Adaptation NDA	-6.410*	.843	1081.720	.000	-8.780	-4.039
	Adaptation NDA	Washout NDA	5.569*	.838	1059.666	.000	3.212	7.926
		Training 3	6.957*	.831	1026.034	.000	4.619	9.295
		Training 2	6.768*	.832	1029.119	.000	4.428	9.108
		Training 1	6.410*	.843	1081.720	.000	4.039	8.780
EAP	Washout NDA	Training 3	.986*	.135	1325.433	.000	.607	1.366
		Training 2	.749*	.139	1437.251	.000	.359	1.140
		Training 1	-1.179*	.194	1368.370	.000	-1.725	-.632
		Adaptation NDA	-11.411*	.838	1059.666	.000	-13.767	-9.054
	Training 3	Washout NDA	-.986*	.135	1325.433	.000	-1.366	-.607
		Training 2	-.237	.089	1772.314	.078	-.487	.013
		Training 1	-2.165*	.163	838.841	.000	-2.622	-1.707
		Adaptation NDA	-12.397*	.831	1026.034	.000	-14.735	-10.059
	Training 2	Washout NDA	-.749*	.139	1437.251	.000	-1.140	-.359
		Training 3	.237	.089	1772.314	.078	-.013	.487
		Training 1	-1.928*	.166	887.903	.000	-2.395	-1.461
		Adaptation NDA	-12.160*	.832	1029.119	.000	-14.499	-9.820
	Training 1	Washout NDA	1.179*	.194	1368.370	.000	.632	1.725
		Training 3	2.165*	.163	838.841	.000	1.707	2.622
		Training 2	1.928*	.166	887.903	.000	1.461	2.395
		Adaptation NDA	-10.232*	.843	1081.720	.000	-12.602	-7.861
	Adaptation NDA	Washout NDA	11.411*	.838	1059.666	.000	9.054	13.767
		Training 3	12.397*	.831	1026.034	.000	10.059	14.735
		Training 2	12.160*	.832	1029.119	.000	9.820	14.499
		Training 1	10.232*	.843	1081.720	.000	7.861	12.602
Control	Washout NDA	Training 3	.874*	.135	1325.433	.000	.495	1.254
		Training 2	.506*	.139	1437.251	.003	.116	.897
		Training 1	-.356	.194	1368.370	.672	-.903	.191
		Adaptation NDA	-9.608*	.838	1059.666	.000	-11.965	-7.251
	Training 3	Washout NDA	-.874*	.135	1325.433	.000	-1.254	-.495
		Training 2	-.368*	.089	1772.314	.000	-.618	-.118
		Training 1	-1.231*	.163	838.841	.000	-1.688	-.773
		Adaptation NDA	-10.482*	.831	1026.034	.000	-12.820	-8.145
	Training 2	Washout NDA	-.506*	.139	1437.251	.003	-.897	-.116
		Training 3	.368*	.089	1772.314	.000	.118	.618
		Training 1	-.862*	.166	887.903	.000	-1.329	-.396
		Adaptation NDA	-10.114*	.832	1029.119	.000	-12.454	-7.774
	Training 1	Washout NDA	.356	.194	1368.370	.672	-.191	.903
		Training 3	1.231*	.163	838.841	.000	.773	1.688
		Training 2	.862*	.166	887.903	.000	.396	1.329
		Adaptation NDA	-9.252*	.843	1081.720	.000	-11.622	-6.881
	Adaptation NDA	Washout NDA	9.608*	.838	1059.666	.000	7.251	11.965
		Training 3	10.482*	.831	1026.034	.000	8.145	12.820
		Training 2	10.114*	.832	1029.119	.000	7.774	12.454
		Training 1	9.252*	.843	1081.720	.000	6.881	11.622

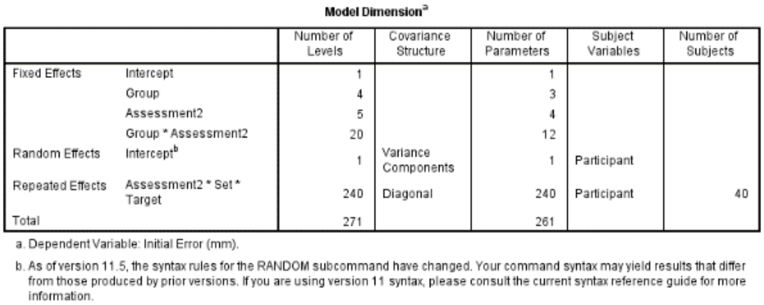
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Normalised Jerk (no units).

c. Adjustment for multiple comparisons: Bonferroni.

Initial error

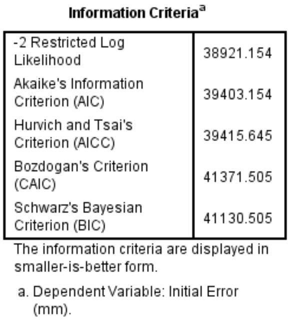


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	5		4		
	Group * Assessment2	20		12		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	240	Diagonal	240	Participant	40
Total		271		261		

a. Dependent Variable: Initial Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

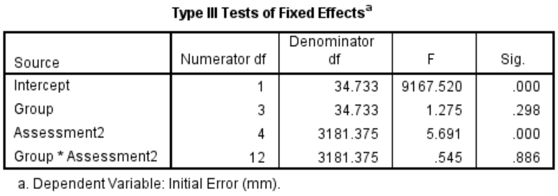


Information Criteria[a]

-2 Restricted Log Likelihood	38921.154
Akaike's Information Criterion (AIC)	39403.154
Hurvich and Tsai's Criterion (AICC)	39415.645
Bozdogan's Criterion (CAIC)	41371.505
Schwarz's Bayesian Criterion (BIC)	41130.505

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Initial Error (mm).

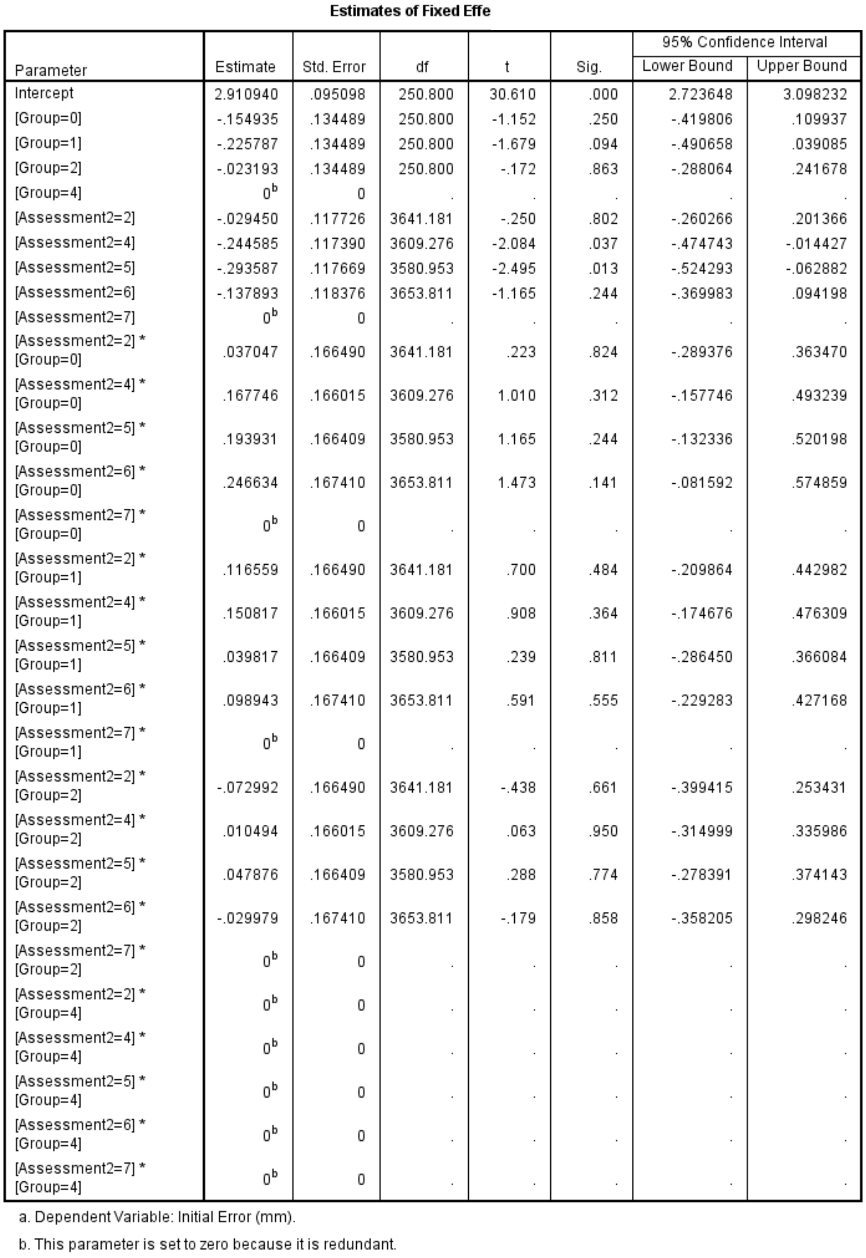


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	34.733	9167.520	.000
Group	3	34.733	1.275	.298
Assessment2	4	3181.375	5.691	.000
Group * Assessment2	12	3181.375	.545	.886

a. Dependent Variable: Initial Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

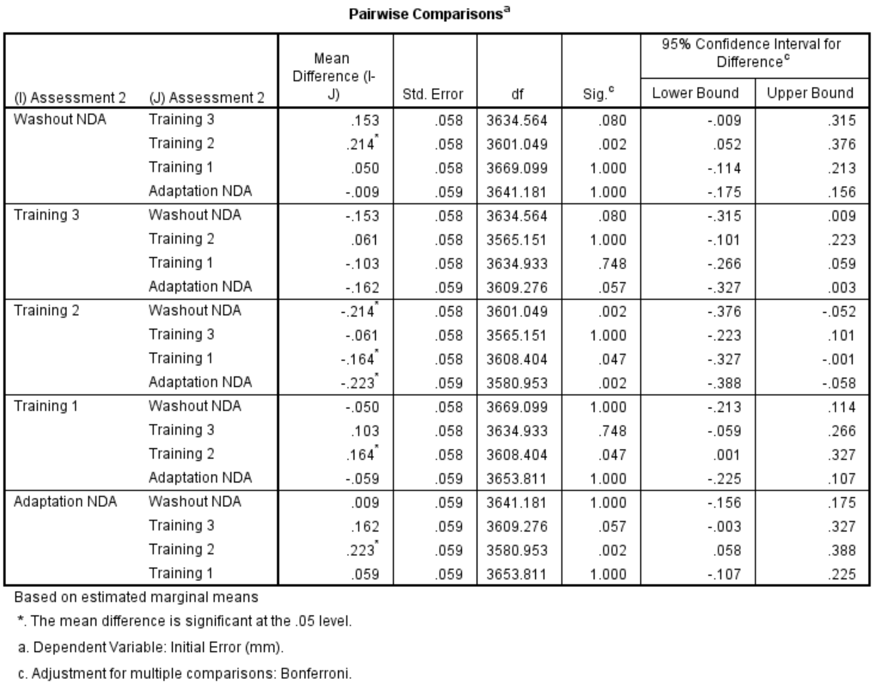


Estimates of Fixed Effe

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	2.910940	.095098	250.800	30.610	.000	2.723648	3.098232
[Group=0]	-.154935	.134489	250.800	-1.152	.250	-.419806	.109937
[Group=1]	-.225787	.134489	250.800	-1.679	.094	-.490658	.039085
[Group=2]	-.023193	.134489	250.800	-.172	.863	-.288064	.241678
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.029450	.117726	3641.181	-.250	.802	-.260266	.201366
[Assessment2=4]	-.244585	.117390	3609.276	-2.084	.037	-.474743	-.014427
[Assessment2=5]	-.293587	.117669	3580.953	-2.495	.013	-.524293	-.062882
[Assessment2=6]	-.137893	.118376	3653.811	-1.165	.244	-.369983	.094198
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	.037047	.166490	3641.181	.223	.824	-.289376	.363470
[Assessment2=4] * [Group=0]	.167746	.166015	3609.276	1.010	.312	-.157746	.493239
[Assessment2=5] * [Group=0]	.193931	.166409	3580.953	1.165	.244	-.132336	.520198
[Assessment2=6] * [Group=0]	.246634	.167410	3653.811	1.473	.141	-.081592	.574859
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	.116559	.166490	3641.181	.700	.484	-.209864	.442982
[Assessment2=4] * [Group=1]	.150817	.166015	3609.276	.908	.364	-.174676	.476309
[Assessment2=5] * [Group=1]	.039817	.166409	3580.953	.239	.811	-.286450	.366084
[Assessment2=6] * [Group=1]	.098943	.167410	3653.811	.591	.555	-.229283	.427168
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	-.072992	.166490	3641.181	-.438	.661	-.399415	.253431
[Assessment2=4] * [Group=2]	.010494	.166015	3609.276	.063	.950	-.314999	.335986
[Assessment2=5] * [Group=2]	.047876	.166409	3580.953	.288	.774	-.278391	.374143
[Assessment2=6] * [Group=2]	-.029979	.167410	3653.811	-.179	.858	-.358205	.298246
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Initial Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout NDA	Training 3	.153	.058	3634.564	.080	-.009	.315
	Training 2	.214*	.058	3601.049	.002	.052	.376
	Training 1	.050	.058	3669.099	1.000	-.114	.213
	Adaptation NDA	-.009	.059	3641.181	1.000	-.175	.156
Training 3	Washout NDA	-.153	.058	3634.564	.080	-.315	.009
	Training 2	.061	.058	3565.151	1.000	-.101	.223
	Training 1	-.103	.058	3634.933	.748	-.266	.059
	Adaptation NDA	-.162	.059	3609.276	.057	-.327	.003
Training 2	Washout NDA	-.214*	.058	3601.049	.002	-.376	-.052
	Training 3	-.061	.058	3565.151	1.000	-.223	.101
	Training 1	-.164*	.058	3608.404	.047	-.327	-.001
	Adaptation NDA	-.223*	.059	3580.953	.002	-.388	-.058
Training 1	Washout NDA	-.050	.058	3669.099	1.000	-.213	.114
	Training 3	.103	.058	3634.933	.748	-.059	.266
	Training 2	.164*	.058	3608.404	.047	.001	.327
	Adaptation NDA	-.059	.059	3653.811	1.000	-.225	.107
Adaptation NDA	Washout NDA	.009	.059	3641.181	1.000	-.156	.175
	Training 3	.162	.059	3609.276	.057	-.003	.327
	Training 2	.223*	.059	3580.953	.002	.058	.388
	Training 1	.059	.059	3653.811	1.000	-.107	.225

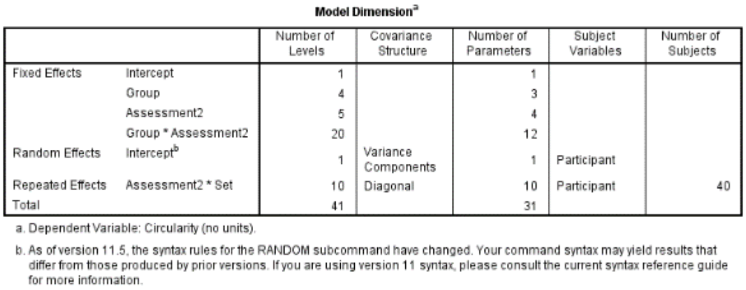
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Initial Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Circularity

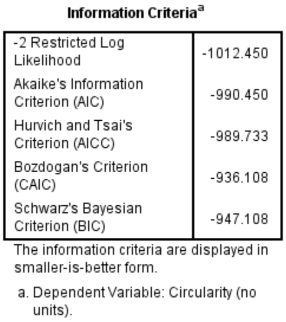


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	5		4		
	Group * Assessment2	20		12		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	10	Diagonal	10	Participant	40
Total		41		31		

a. Dependent Variable: Circularity (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

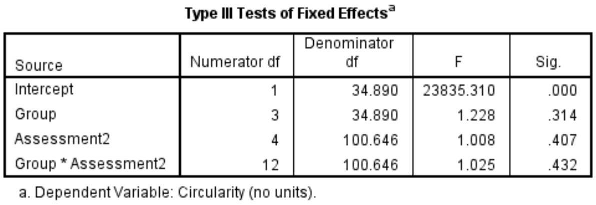


Information Criteria[a]

-2 Restricted Log Likelihood	-1012.450
Akaike's Information Criterion (AIC)	-990.450
Hurvich and Tsai's Criterion (AICC)	-989.733
Bozdogan's Criterion (CAIC)	-936.108
Schwarz's Bayesian Criterion (BIC)	-947.108

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Circularity (no units).

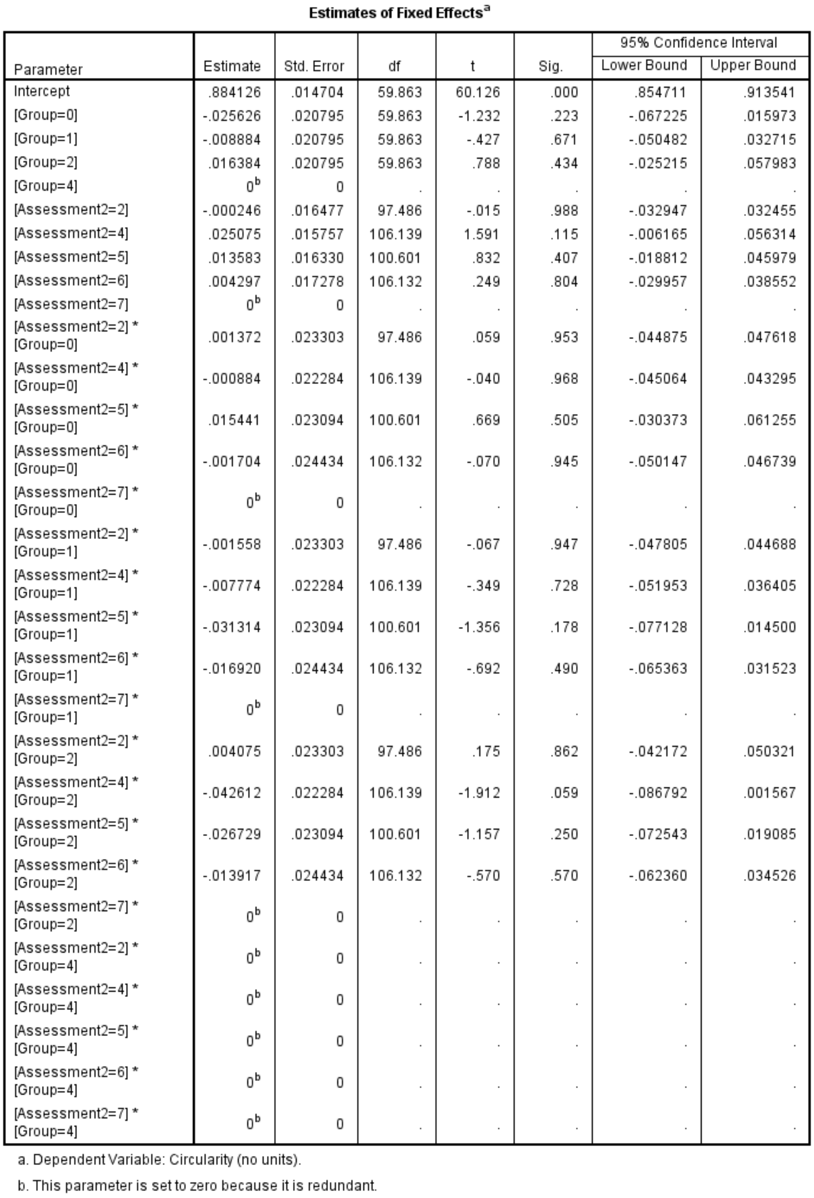


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	34.890	23835.310	.000
Group	3	34.890	1.228	.314
Assessment2	4	100.646	1.008	.407
Group * Assessment2	12	100.646	1.025	.432

a. Dependent Variable: Circularity (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



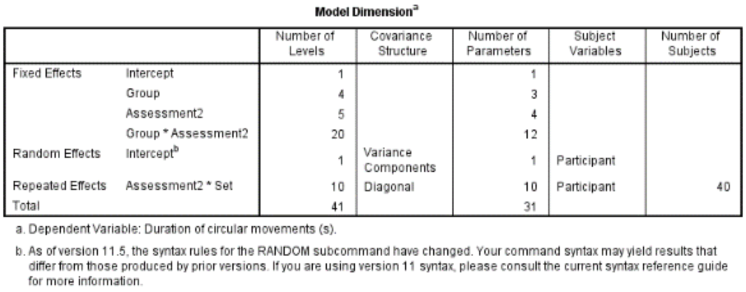
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	.884126	.014704	59.863	60.126	.000	.854711	.913541
[Group=0]	-.025626	.020795	59.863	-1.232	.223	-.067225	.015973
[Group=1]	-.008884	.020795	59.863	-.427	.671	-.050482	.032715
[Group=2]	.016384	.020795	59.863	.788	.434	-.025215	.057983
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-.000246	.016477	97.486	-.015	.988	-.032947	.032455
[Assessment2=4]	.025075	.015757	106.139	1.591	.115	-.006165	.056314
[Assessment2=5]	.013583	.016330	100.601	.832	.407	-.018812	.045979
[Assessment2=6]	.004297	.017278	106.132	.249	.804	-.029957	.038552
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	.001372	.023303	97.486	.059	.953	-.044875	.047618
[Assessment2=4] * [Group=0]	-.000884	.022284	106.139	-.040	.968	-.045064	.043295
[Assessment2=5] * [Group=0]	.015441	.023094	100.601	.669	.505	-.030373	.061255
[Assessment2=6] * [Group=0]	-.001704	.024434	106.132	-.070	.945	-.050147	.046739
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	-.001558	.023303	97.486	-.067	.947	-.047805	.044688
[Assessment2=4] * [Group=1]	-.007774	.022284	106.139	-.349	.728	-.051953	.036405
[Assessment2=5] * [Group=1]	-.031314	.023094	100.601	-1.356	.178	-.077128	.014500
[Assessment2=6] * [Group=1]	-.016920	.024434	106.132	-.692	.490	-.065363	.031523
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	.004075	.023303	97.486	.175	.862	-.042172	.050321
[Assessment2=4] * [Group=2]	-.042612	.022284	106.139	-1.912	.059	-.086792	.001567
[Assessment2=5] * [Group=2]	-.026729	.023094	100.601	-1.157	.250	-.072543	.019085
[Assessment2=6] * [Group=2]	-.013917	.024434	106.132	-.570	.570	-.062360	.034526
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Circularity (no units).

b. This parameter is set to zero because it is redundant.

Duration of circular movements

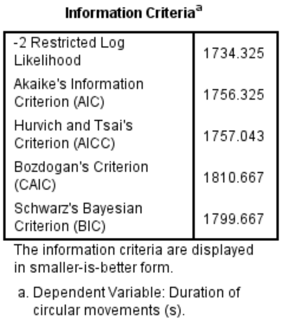


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	5		4		
	Group * Assessment2	20		12		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	10	Diagonal	10	Participant	40
Total		41		31		

a. Dependent Variable: Duration of circular movements (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

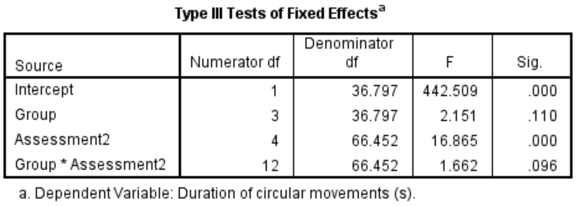


Information Criteria[a]

-2 Restricted Log Likelihood	1734.325
Akaike's Information Criterion (AIC)	1756.325
Hurvich and Tsai's Criterion (AICC)	1757.043
Bozdogan's Criterion (CAIC)	1810.667
Schwarz's Bayesian Criterion (BIC)	1799.667

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration of circular movements (s).

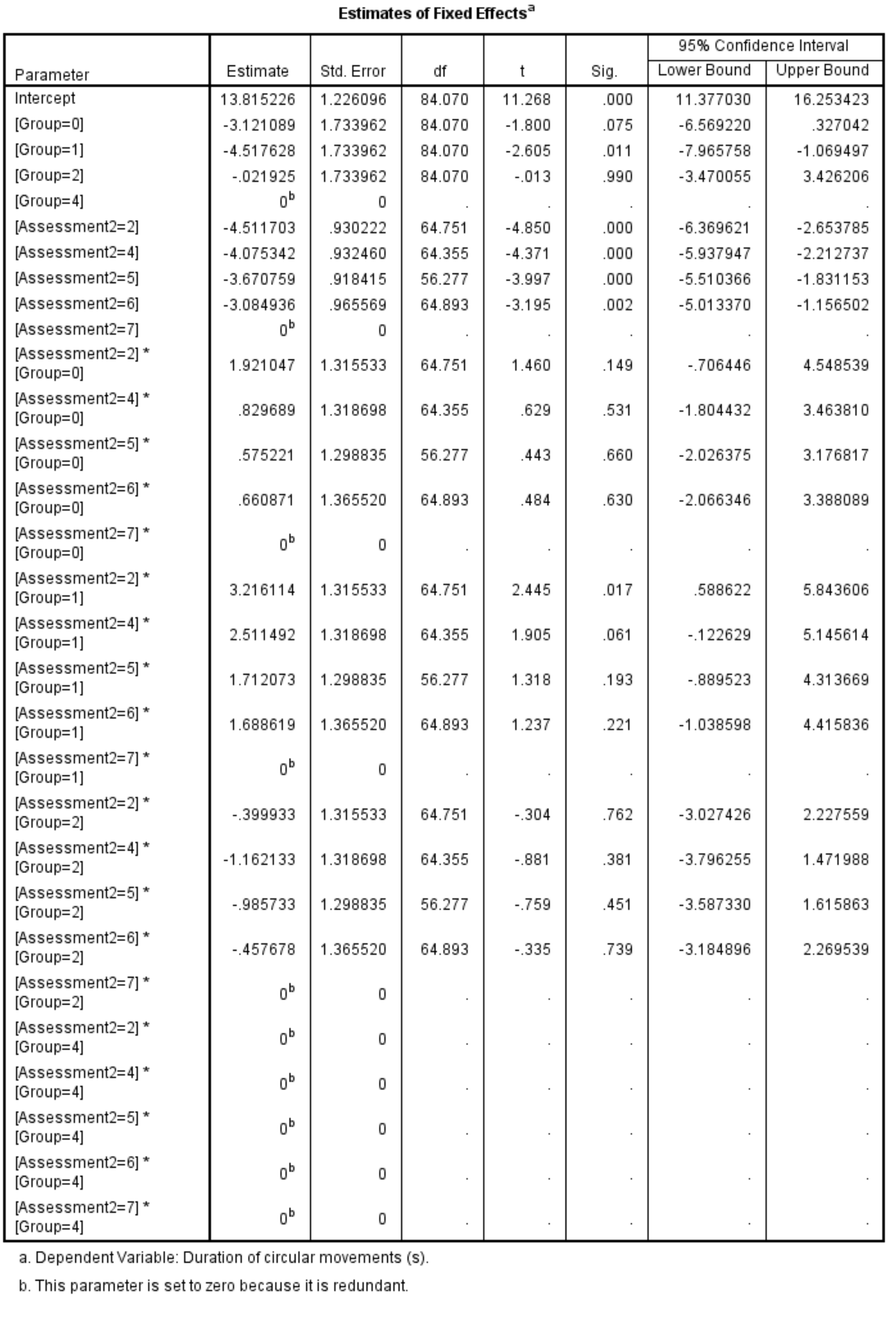


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	36.797	442.509	.000
Group	3	36.797	2.151	.110
Assessment2	4	66.452	16.865	.000
Group * Assessment2	12	66.452	1.662	.096

a. Dependent Variable: Duration of circular movements (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

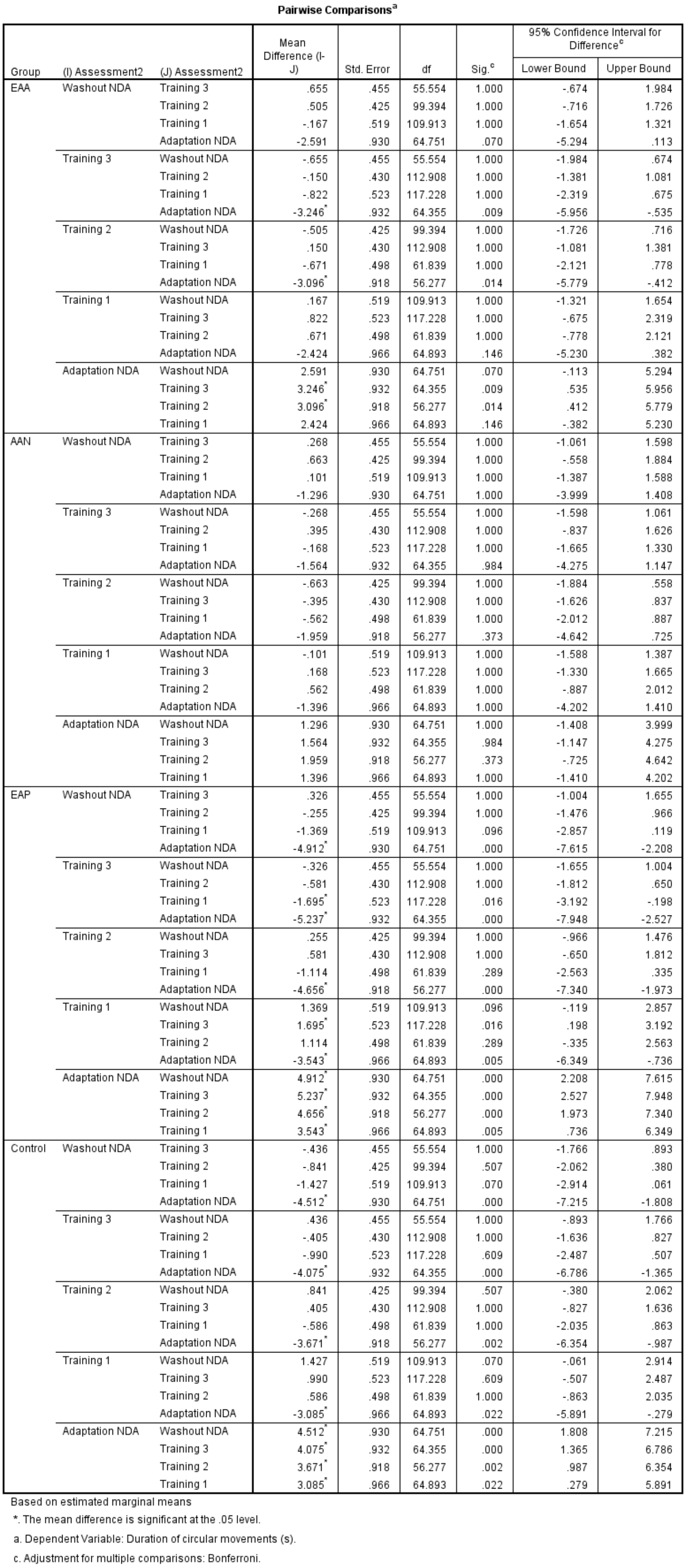


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	13.815226	1.226096	84.070	11.268	.000	11.377030	16.253423
[Group=0]	-3.121089	1.733962	84.070	-1.800	.075	-6.569220	.327042
[Group=1]	-4.517628	1.733962	84.070	-2.605	.011	-7.965758	-1.069497
[Group=2]	-.021925	1.733962	84.070	-.013	.990	-3.470055	3.426206
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=2]	-4.511703	.930222	64.751	-4.850	.000	-6.369621	-2.653785
[Assessment2=4]	-4.075342	.932460	64.355	-4.371	.000	-5.937947	-2.212737
[Assessment2=5]	-3.670759	.918415	56.277	-3.997	.000	-5.510366	-1.831153
[Assessment2=6]	-3.084936	.965569	64.893	-3.195	.002	-5.013370	-1.156502
[Assessment2=7]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=0]	1.921047	1.315533	64.751	1.460	.149	-.706446	4.548539
[Assessment2=4] * [Group=0]	.829689	1.318698	64.355	.629	.531	-1.804432	3.463810
[Assessment2=5] * [Group=0]	.575221	1.298835	56.277	.443	.660	-2.026375	3.176817
[Assessment2=6] * [Group=0]	.660871	1.365520	64.893	.484	.630	-2.066346	3.388089
[Assessment2=7] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=1]	3.216114	1.315533	64.751	2.445	.017	.588622	5.843606
[Assessment2=4] * [Group=1]	2.511492	1.318698	64.355	1.905	.061	-.122629	5.145614
[Assessment2=5] * [Group=1]	1.712073	1.298835	56.277	1.318	.193	-.889523	4.313669
[Assessment2=6] * [Group=1]	1.688619	1.365520	64.893	1.237	.221	-1.038598	4.415836
[Assessment2=7] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=2]	-.399933	1.315533	64.751	-.304	.762	-3.027426	2.227559
[Assessment2=4] * [Group=2]	-1.162133	1.318698	64.355	-.881	.381	-3.796255	1.471988
[Assessment2=5] * [Group=2]	-.985733	1.298835	56.277	-.759	.451	-3.587330	1.615863
[Assessment2=6] * [Group=2]	-.457678	1.365520	64.893	-.335	.739	-3.184896	2.269539
[Assessment2=7] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=2] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=4] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=5] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=6] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=7] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration of circular movements (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons^a

Group	(I) Assessment2	(J) Assessment2	Mean Difference (I-J)	Std. Error	df	Sig.^{c}	95% Confidence Interval for Difference^c	
							Lower Bound	Upper Bound
EAA	Washout NDA	Training 3	.655	.455	55.554	1.000	-.674	1.984
		Training 2	.505	.425	99.394	1.000	-.716	1.726
		Training 1	-.167	.519	109.913	1.000	-1.654	1.321
		Adaptation NDA	-2.591	.930	64.751	.070	-5.294	.113
	Training 3	Washout NDA	-.655	.455	55.554	1.000	-1.984	.674
		Training 2	-.150	.430	112.908	1.000	-1.381	1.081
		Training 1	-.822	.523	117.228	1.000	-2.319	.675
		Adaptation NDA	-3.246*	.932	64.355	.009	-5.956	-.535
	Training 2	Washout NDA	-.505	.425	99.394	1.000	-1.726	.716
		Training 3	.150	.430	112.908	1.000	-1.081	1.381
		Training 1	-.671	.498	61.839	1.000	-2.121	.778
		Adaptation NDA	-3.096*	.918	56.277	.014	-5.779	-.412
	Training 1	Washout NDA	.167	.519	109.913	1.000	-1.321	1.654
		Training 3	.822	.523	117.228	1.000	-.675	2.319
		Training 2	.671	.498	61.839	1.000	-.778	2.121
		Adaptation NDA	-2.424	.966	64.893	.146	-5.230	.382
	Adaptation NDA	Washout NDA	2.591	.930	64.751	.070	-.113	5.294
		Training 3	3.246*	.932	64.355	.009	.535	5.956
		Training 2	3.096*	.918	56.277	.014	.412	5.779
		Training 1	2.424	.966	64.893	.146	-.382	5.230
AAN	Washout NDA	Training 3	.268	.455	55.554	1.000	-1.061	1.598
		Training 2	.663	.425	99.394	1.000	-.558	1.884
		Training 1	.101	.519	109.913	1.000	-1.387	1.588
		Adaptation NDA	-1.296	.930	64.751	1.000	-3.999	1.408
	Training 3	Washout NDA	-.268	.455	55.554	1.000	-1.598	1.061
		Training 2	.395	.430	112.908	1.000	-.837	1.626
		Training 1	-.168	.523	117.228	1.000	-1.665	1.330
		Adaptation NDA	-1.564	.932	64.355	.984	-4.275	1.147
	Training 2	Washout NDA	-.663	.425	99.394	1.000	-1.884	.558
		Training 3	-.395	.430	112.908	1.000	-1.626	.837
		Training 1	-.562	.498	61.839	1.000	-2.012	.887
		Adaptation NDA	-1.959	.918	56.277	.373	-4.642	.725
	Training 1	Washout NDA	-.101	.519	109.913	1.000	-1.588	1.387
		Training 3	.168	.523	117.228	1.000	-1.330	1.665
		Training 2	.562	.498	61.839	1.000	-.887	2.012
		Adaptation NDA	-1.396	.966	64.893	1.000	-4.202	1.410
	Adaptation NDA	Washout NDA	1.296	.930	64.751	1.000	-1.408	3.999
		Training 3	1.564	.932	64.355	.984	-1.147	4.275
		Training 2	1.959	.918	56.277	.373	-.725	4.642
		Training 1	1.396	.966	64.893	1.000	-1.410	4.202
EAP	Washout NDA	Training 3	.326	.455	55.554	1.000	-1.004	1.655
		Training 2	-.255	.425	99.394	1.000	-1.476	.966
		Training 1	-1.369	.519	109.913	.096	-2.857	.119
		Adaptation NDA	-4.912*	.930	64.751	.000	-7.615	-2.208
	Training 3	Washout NDA	-.326	.455	55.554	1.000	-1.655	1.004
		Training 2	-.581	.430	112.908	1.000	-1.812	.650
		Training 1	-1.695*	.523	117.228	.016	-3.192	-.198
		Adaptation NDA	-5.237*	.932	64.355	.000	-7.948	-2.527
	Training 2	Washout NDA	.255	.425	99.394	1.000	-.966	1.476
		Training 3	.581	.430	112.908	1.000	-.650	1.812
		Training 1	-1.114	.498	61.839	.289	-2.563	.335
		Adaptation NDA	-4.656*	.918	56.277	.000	-7.340	-1.973
	Training 1	Washout NDA	1.369	.519	109.913	.096	-.119	2.857
		Training 3	1.695*	.523	117.228	.016	.198	3.192
		Training 2	1.114	.498	61.839	.289	-.335	2.563
		Adaptation NDA	-3.543*	.966	64.893	.005	-6.349	-.736
	Adaptation NDA	Washout NDA	4.912*	.930	64.751	.000	2.208	7.615
		Training 3	5.237*	.932	64.355	.000	2.527	7.948
		Training 2	4.656*	.918	56.277	.000	1.973	7.340
		Training 1	3.543*	.966	64.893	.005	.736	6.349
Control	Washout NDA	Training 3	-.436	.455	55.554	1.000	-1.766	.893
		Training 2	-.841	.425	99.394	.507	-2.062	.380
		Training 1	-1.427	.519	109.913	.070	-2.914	.061
		Adaptation NDA	-4.512*	.930	64.751	.000	-7.215	-1.808
	Training 3	Washout NDA	.436	.455	55.554	1.000	-.893	1.766
		Training 2	-.405	.430	112.908	1.000	-1.636	.827
		Training 1	-.990	.523	117.228	.609	-2.487	.507
		Adaptation NDA	-4.075*	.932	64.355	.000	-6.786	-1.365
	Training 2	Washout NDA	.841	.425	99.394	.507	-.380	2.062
		Training 3	.405	.430	112.908	1.000	-.827	1.636
		Training 1	-.586	.498	61.839	1.000	-2.035	.863
		Adaptation NDA	-3.671*	.918	56.277	.002	-6.354	-.987
	Training 1	Washout NDA	1.427	.519	109.913	.070	-.061	2.914
		Training 3	.990	.523	117.228	.609	-.507	2.487
		Training 2	.586	.498	61.839	1.000	-.863	2.035
		Adaptation NDA	-3.085*	.966	64.893	.022	-5.891	-.279
	Adaptation NDA	Washout NDA	4.512*	.930	64.751	.000	1.808	7.215
		Training 3	4.075*	.932	64.355	.000	1.365	6.786
		Training 2	3.671*	.918	56.277	.002	.987	6.354
		Training 1	3.085*	.966	64.893	.022	.279	5.891

Based on estimated marginal means

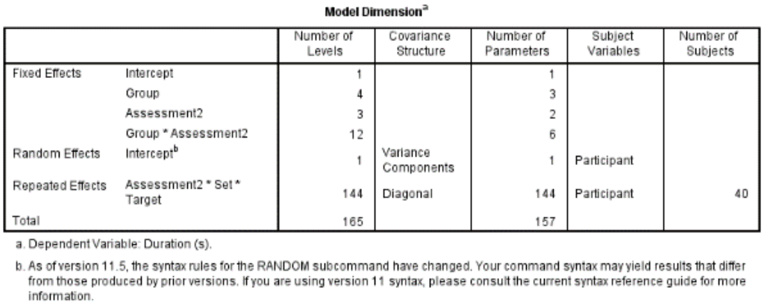
*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration of circular movements (s).

c. Adjustment for multiple comparisons: Bonferroni.

Analysis of the DA

Duration

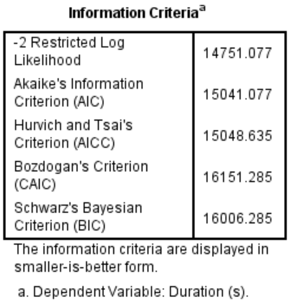


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	3		2		
	Group * Assessment2	12		6		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	40
Total		165		157		

a. Dependent Variable: Duration (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

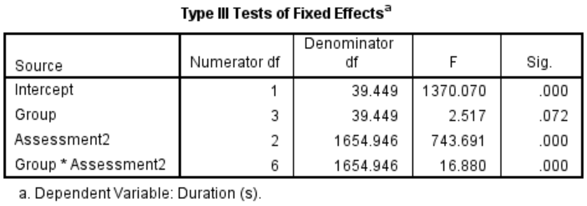


Information Criteria[a]

-2 Restricted Log Likelihood	14751.077
Akaike's Information Criterion (AIC)	15041.077
Hurvich and Tsai's Criterion (AICC)	15048.635
Bozdogan's Criterion (CAIC)	16151.285
Schwarz's Bayesian Criterion (BIC)	16006.285

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration (s).

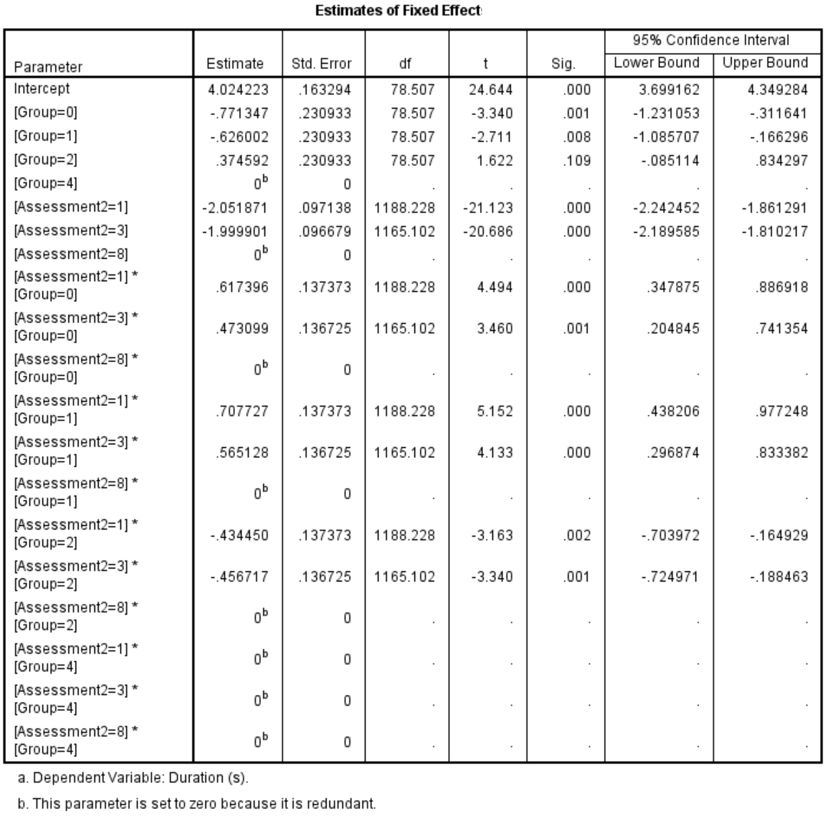


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	39.449	1370.070	.000
Group	3	39.449	2.517	.072
Assessment2	2	1654.946	743.691	.000
Group * Assessment2	6	1654.946	16.880	.000

a. Dependent Variable: Duration (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

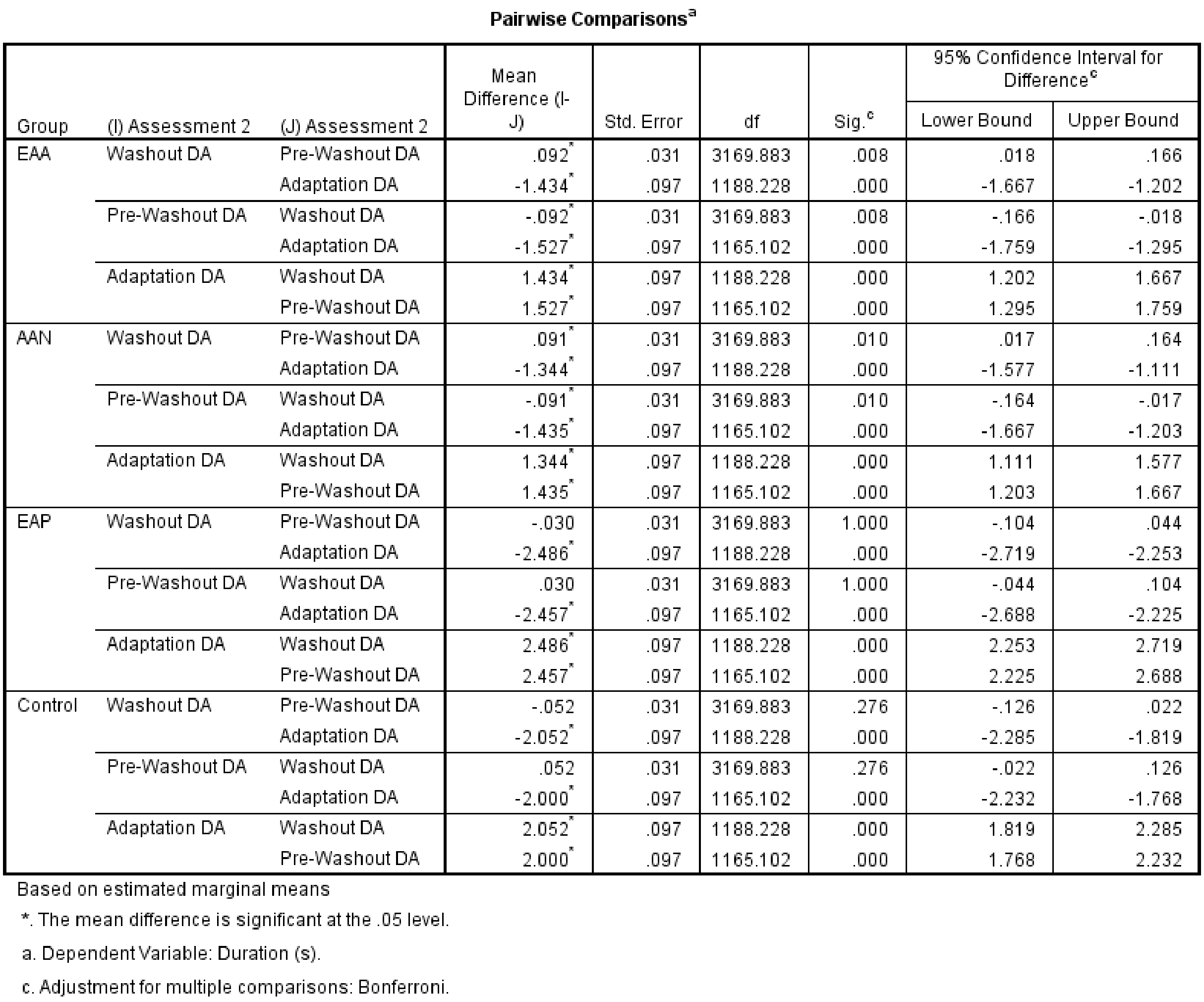


Estimates of Fixed Effect

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	4.024223	.163294	78.507	24.644	.000	3.699162	4.349284
[Group=0]	-.771347	.230933	78.507	-3.340	.001	-1.231053	-.311641
[Group=1]	-.626002	.230933	78.507	-2.711	.008	-1.085707	-.166296
[Group=2]	.374592	.230933	78.507	1.622	.109	-.085114	.834297
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-2.051871	.097138	1188.228	-21.123	.000	-2.242452	-1.861291
[Assessment2=3]	-1.999901	.096679	1165.102	-20.686	.000	-2.189585	-1.810217
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	.617396	.137373	1188.228	4.494	.000	.347875	.886918
[Assessment2=3] * [Group=0]	.473099	.136725	1165.102	3.460	.001	.204845	.741354
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	.707727	.137373	1188.228	5.152	.000	.438206	.977248
[Assessment2=3] * [Group=1]	.565128	.136725	1165.102	4.133	.000	.296874	.833382
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	-.434450	.137373	1188.228	-3.163	.002	-.703972	-.164929
[Assessment2=3] * [Group=2]	-.456717	.136725	1165.102	-3.340	.001	-.724971	-.188463
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration (s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout DA	Pre-Washout DA	.092*	.031	3169.883	.008	.018	.166
		Adaptation DA	-1.434*	.097	1188.228	.000	-1.667	-1.202
	Pre-Washout DA	Washout DA	-.092*	.031	3169.883	.008	-.166	-.018
		Adaptation DA	-1.527*	.097	1165.102	.000	-1.759	-1.295
	Adaptation DA	Washout DA	1.434*	.097	1188.228	.000	1.202	1.667
		Pre-Washout DA	1.527*	.097	1165.102	.000	1.295	1.759
AAN	Washout DA	Pre-Washout DA	.091*	.031	3169.883	.010	.017	.164
		Adaptation DA	-1.344*	.097	1188.228	.000	-1.577	-1.111
	Pre-Washout DA	Washout DA	-.091*	.031	3169.883	.010	-.164	-.017
		Adaptation DA	-1.435*	.097	1165.102	.000	-1.667	-1.203
	Adaptation DA	Washout DA	1.344*	.097	1188.228	.000	1.111	1.577
		Pre-Washout DA	1.435*	.097	1165.102	.000	1.203	1.667
EAP	Washout DA	Pre-Washout DA	-.030	.031	3169.883	1.000	-.104	.044
		Adaptation DA	-2.486*	.097	1188.228	.000	-2.719	-2.253
	Pre-Washout DA	Washout DA	.030	.031	3169.883	1.000	-.044	.104
		Adaptation DA	-2.457*	.097	1165.102	.000	-2.688	-2.225
	Adaptation DA	Washout DA	2.486*	.097	1188.228	.000	2.253	2.719
		Pre-Washout DA	2.457*	.097	1165.102	.000	2.225	2.688
Control	Washout DA	Pre-Washout DA	-.052	.031	3169.883	.276	-.126	.022
		Adaptation DA	-2.052*	.097	1188.228	.000	-2.285	-1.819
	Pre-Washout DA	Washout DA	.052	.031	3169.883	.276	-.022	.126
		Adaptation DA	-2.000*	.097	1165.102	.000	-2.232	-1.768
	Adaptation DA	Washout DA	2.052*	.097	1188.228	.000	1.819	2.285
		Pre-Washout DA	2.000*	.097	1165.102	.000	1.768	2.232

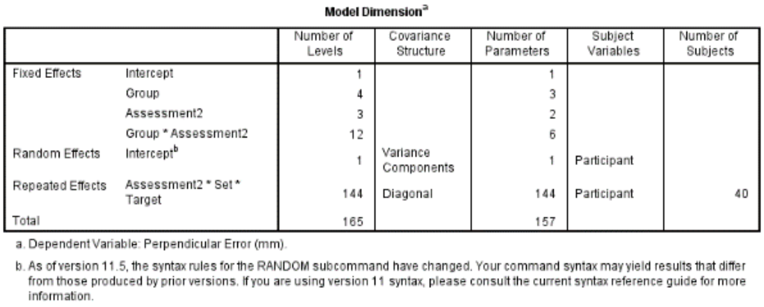
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Duration (s).

c. Adjustment for multiple comparisons: Bonferroni.

Perpendicular error

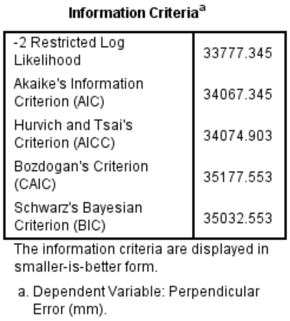


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	3		2		
	Group * Assessment2	12		6		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	40
Total		165		157		

a. Dependent Variable: Perpendicular Error (mm).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

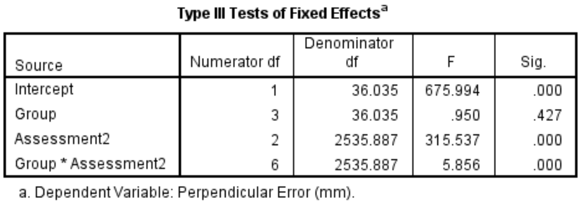


Information Criteria[a]

-2 Restricted Log Likelihood	33777.345
Akaike's Information Criterion (AIC)	34067.345
Hurvich and Tsai's Criterion (AICC)	34074.903
Bozdogan's Criterion (CAIC)	35177.553
Schwarz's Bayesian Criterion (BIC)	35032.553

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Perpendicular Error (mm).

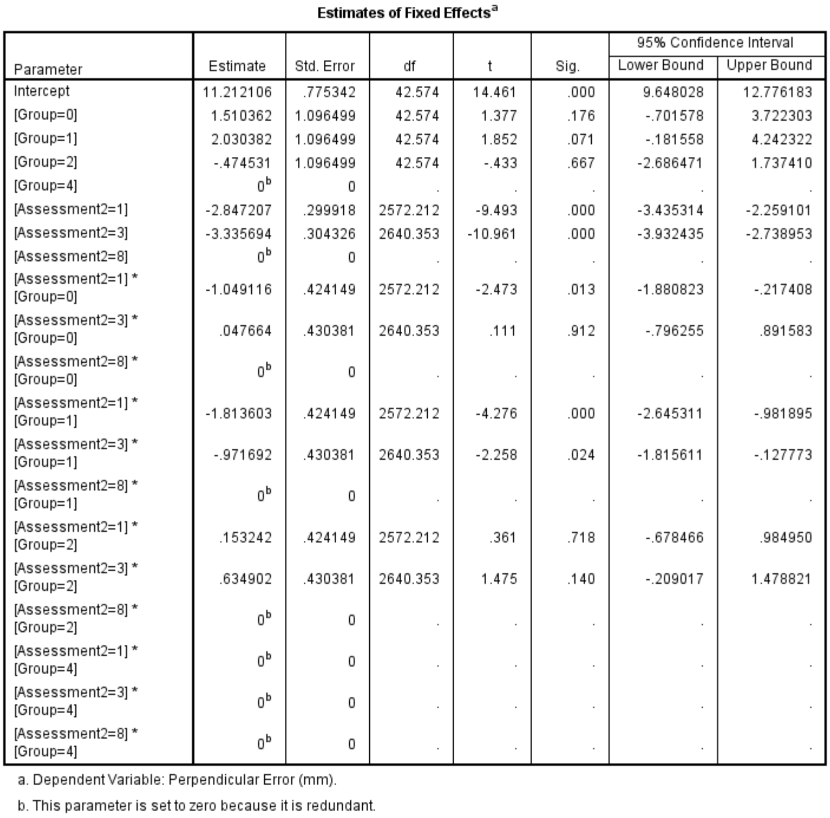


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	36.035	675.994	.000
Group	3	36.035	.950	.427
Assessment2	2	2535.887	315.537	.000
Group * Assessment2	6	2535.887	5.856	.000

a. Dependent Variable: Perpendicular Error (mm).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

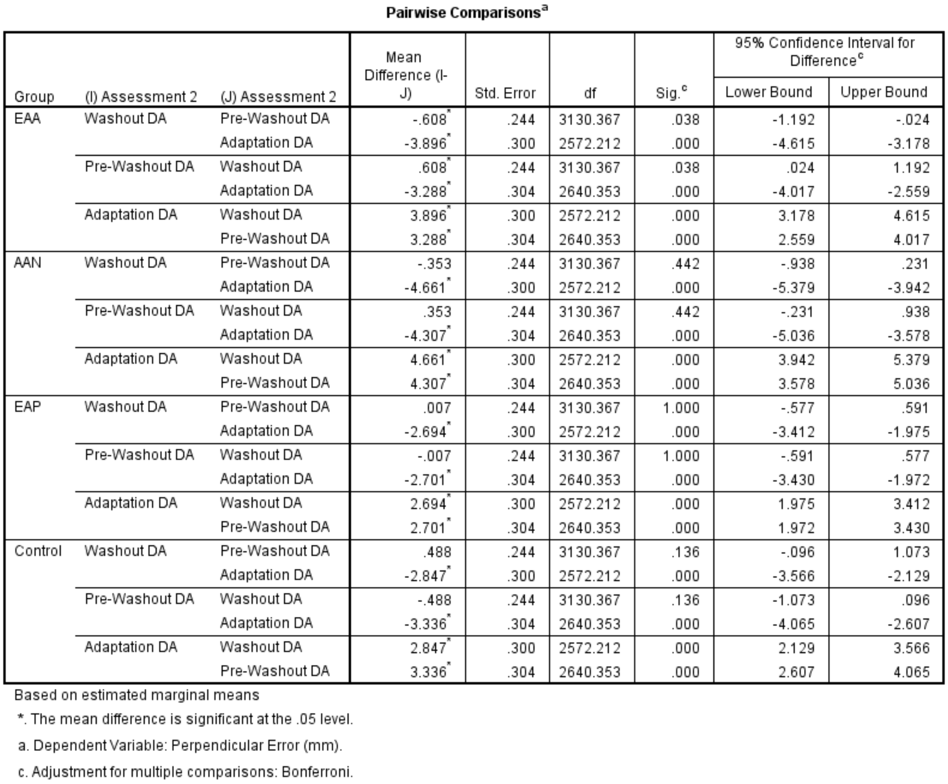


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	11.212106	.775342	42.574	14.461	.000	9.648028	12.776183
[Group=0]	1.510362	1.096499	42.574	1.377	.176	-.701578	3.722303
[Group=1]	2.030382	1.096499	42.574	1.852	.071	-.181558	4.242322
[Group=2]	-.474531	1.096499	42.574	-.433	.667	-2.686471	1.737410
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-2.847207	.299918	2572.212	-9.493	.000	-3.435314	-2.259101
[Assessment2=3]	-3.335694	.304326	2640.353	-10.961	.000	-3.932435	-2.738953
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	-1.049116	.424149	2572.212	-2.473	.013	-1.880823	-.217408
[Assessment2=3] * [Group=0]	.047664	.430381	2640.353	.111	.912	-.796255	.891583
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	-1.813603	.424149	2572.212	-4.276	.000	-2.645311	-.981895
[Assessment2=3] * [Group=1]	-.971692	.430381	2640.353	-2.258	.024	-1.815611	-.127773
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	.153242	.424149	2572.212	.361	.718	-.678466	.984950
[Assessment2=3] * [Group=2]	.634902	.430381	2640.353	1.475	.140	-.209017	1.478821
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Perpendicular Error (mm).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout DA	Pre-Washout DA	-.608*	.244	3130.367	.038	-1.192	-.024
		Adaptation DA	-3.896*	.300	2572.212	.000	-4.615	-3.178
	Pre-Washout DA	Washout DA	.608*	.244	3130.367	.038	.024	1.192
		Adaptation DA	-3.288*	.304	2640.353	.000	-4.017	-2.559
	Adaptation DA	Washout DA	3.896*	.300	2572.212	.000	3.178	4.615
		Pre-Washout DA	3.288*	.304	2640.353	.000	2.559	4.017
AAN	Washout DA	Pre-Washout DA	-.353	.244	3130.367	.442	-.938	.231
		Adaptation DA	-4.661*	.300	2572.212	.000	-5.379	-3.942
	Pre-Washout DA	Washout DA	.353	.244	3130.367	.442	-.231	.938
		Adaptation DA	-4.307*	.304	2640.353	.000	-5.036	-3.578
	Adaptation DA	Washout DA	4.661*	.300	2572.212	.000	3.942	5.379
		Pre-Washout DA	4.307*	.304	2640.353	.000	3.578	5.036
EAP	Washout DA	Pre-Washout DA	.007	.244	3130.367	1.000	-.577	.591
		Adaptation DA	-2.694*	.300	2572.212	.000	-3.412	-1.975
	Pre-Washout DA	Washout DA	-.007	.244	3130.367	1.000	-.591	.577
		Adaptation DA	-2.701*	.304	2640.353	.000	-3.430	-1.972
	Adaptation DA	Washout DA	2.694*	.300	2572.212	.000	1.975	3.412
		Pre-Washout DA	2.701*	.304	2640.353	.000	1.972	3.430
Control	Washout DA	Pre-Washout DA	.488	.244	3130.367	.136	-.096	1.073
		Adaptation DA	-2.847*	.300	2572.212	.000	-3.566	-2.129
	Pre-Washout DA	Washout DA	-.488	.244	3130.367	.136	-1.073	.096
		Adaptation DA	-3.336*	.304	2640.353	.000	-4.065	-2.607
	Adaptation DA	Washout DA	2.847*	.300	2572.212	.000	2.129	3.566
		Pre-Washout DA	3.336*	.304	2640.353	.000	2.607	4.065

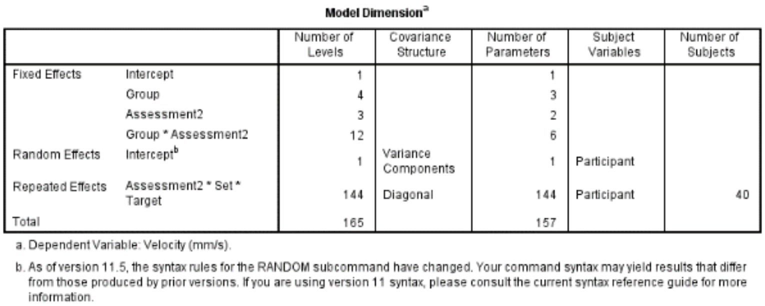
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Perpendicular Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Mean Velocity

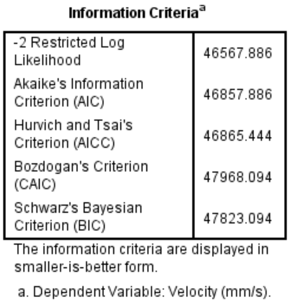


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	3		2		
	Group * Assessment2	12		6		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	40
Total		165		157		

a. Dependent Variable: Velocity (mm/s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

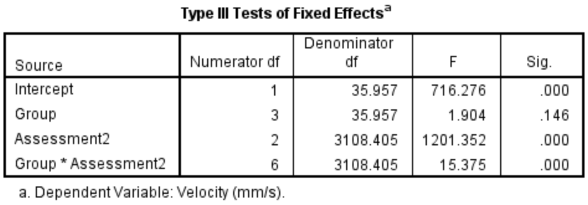


Information Criteria[a]

-2 Restricted Log Likelihood	46567.886
Akaike's Information Criterion (AIC)	46857.886
Hurvich and Tsai's Criterion (AICC)	46865.444
Bozdogan's Criterion (CAIC)	47968.094
Schwarz's Bayesian Criterion (BIC)	47823.094

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Velocity (mm/s).

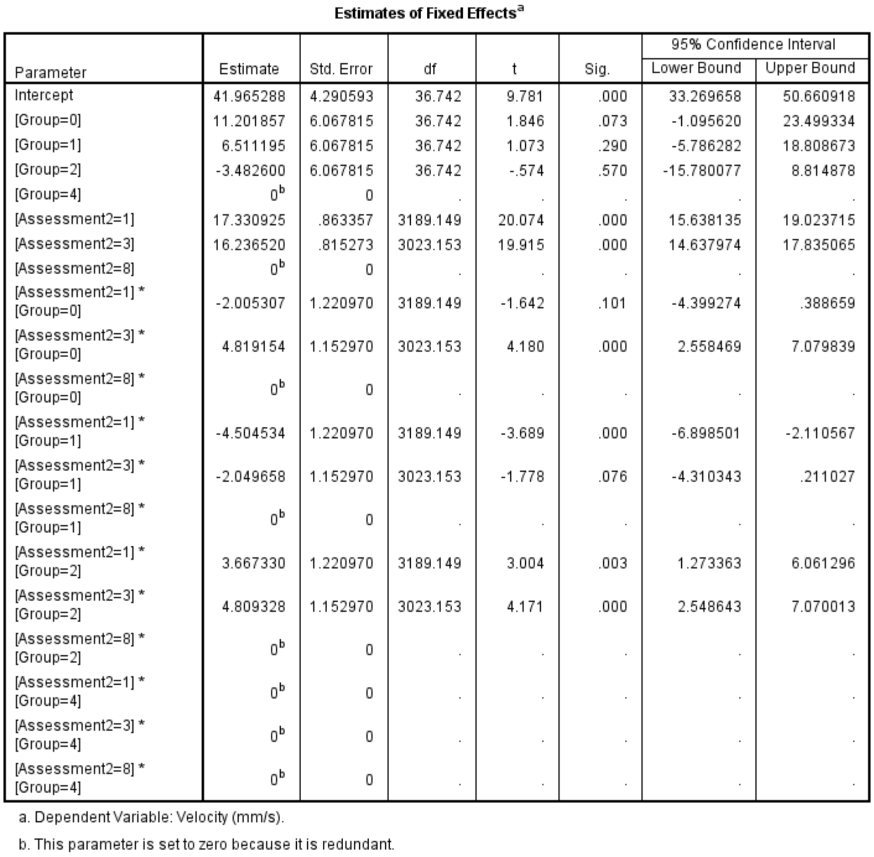


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	35.957	716.276	.000
Group	3	35.957	1.904	.146
Assessment2	2	3108.405	1201.352	.000
Group * Assessment2	6	3108.405	15.375	.000

a. Dependent Variable: Velocity (mm/s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

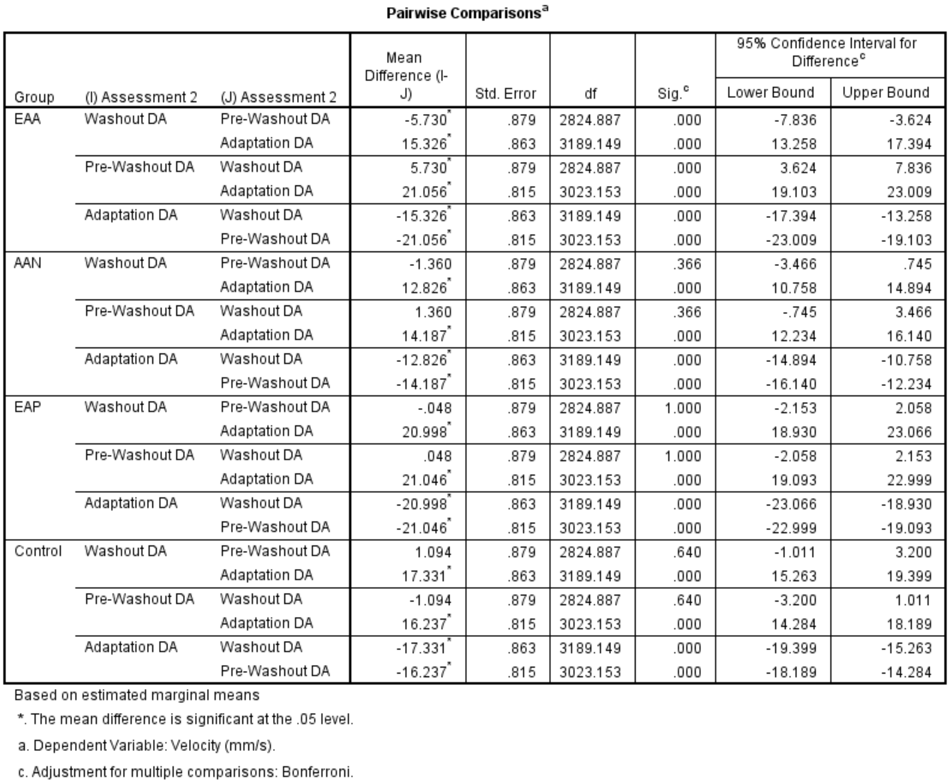


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Intercept	41.965288	4.290593	36.742	9.781	.000	33.269658	50.660918
[Group=0]	11.201857	6.067815	36.742	1.846	.073	-1.095620	23.499334
[Group=1]	6.511195	6.067815	36.742	1.073	.290	-5.786282	18.808673
[Group=2]	-3.482600	6.067815	36.742	-.574	.570	-15.780077	8.814878
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	17.330925	.863357	3189.149	20.074	.000	15.638135	19.023715
[Assessment2=3]	16.236520	.815273	3023.153	19.915	.000	14.637974	17.835065
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	-2.005307	1.220970	3189.149	-1.642	.101	-4.399274	.388659
[Assessment2=3] * [Group=0]	4.819154	1.152970	3023.153	4.180	.000	2.558469	7.079839
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	-4.504534	1.220970	3189.149	-3.689	.000	-6.898501	-2.110567
[Assessment2=3] * [Group=1]	-2.049658	1.152970	3023.153	-1.778	.076	-4.310343	.211027
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	3.667330	1.220970	3189.149	3.004	.003	1.273363	6.061296
[Assessment2=3] * [Group=2]	4.809328	1.152970	3023.153	4.171	.000	2.548643	7.070013
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Velocity (mm/s).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons^a

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.^{c}	95% Confidence Interval for Difference^c	
							Lower Bound	Upper Bound
EAA	Washout DA	Pre-Washout DA	-5.730*	.879	2824.887	.000	-7.836	-3.624
		Adaptation DA	15.326*	.863	3189.149	.000	13.258	17.394
	Pre-Washout DA	Washout DA	5.730*	.879	2824.887	.000	3.624	7.836
		Adaptation DA	21.056*	.815	3023.153	.000	19.103	23.009
	Adaptation DA	Washout DA	-15.326*	.863	3189.149	.000	-17.394	-13.258
		Pre-Washout DA	-21.056*	.815	3023.153	.000	-23.009	-19.103
AAN	Washout DA	Pre-Washout DA	-1.360	.879	2824.887	.366	-3.466	.745
		Adaptation DA	12.826*	.863	3189.149	.000	10.758	14.894
	Pre-Washout DA	Washout DA	1.360	.879	2824.887	.366	-.745	3.466
		Adaptation DA	14.187*	.815	3023.153	.000	12.234	16.140
	Adaptation DA	Washout DA	-12.826*	.863	3189.149	.000	-14.894	-10.758
		Pre-Washout DA	-14.187*	.815	3023.153	.000	-16.140	-12.234
EAP	Washout DA	Pre-Washout DA	-.048	.879	2824.887	1.000	-2.153	2.058
		Adaptation DA	20.998*	.863	3189.149	.000	18.930	23.066
	Pre-Washout DA	Washout DA	.048	.879	2824.887	1.000	-2.058	2.153
		Adaptation DA	21.046*	.815	3023.153	.000	19.093	22.999
	Adaptation DA	Washout DA	-20.998*	.863	3189.149	.000	-23.066	-18.930
		Pre-Washout DA	-21.046*	.815	3023.153	.000	-22.999	-19.093
Control	Washout DA	Pre-Washout DA	1.094	.879	2824.887	.640	-1.011	3.200
		Adaptation DA	17.331*	.863	3189.149	.000	15.263	19.399
	Pre-Washout DA	Washout DA	-1.094	.879	2824.887	.640	-3.200	1.011
		Adaptation DA	16.237*	.815	3023.153	.000	14.284	18.189
	Adaptation DA	Washout DA	-17.331*	.863	3189.149	.000	-19.399	-15.263
		Pre-Washout DA	-16.237*	.815	3023.153	.000	-18.189	-14.284

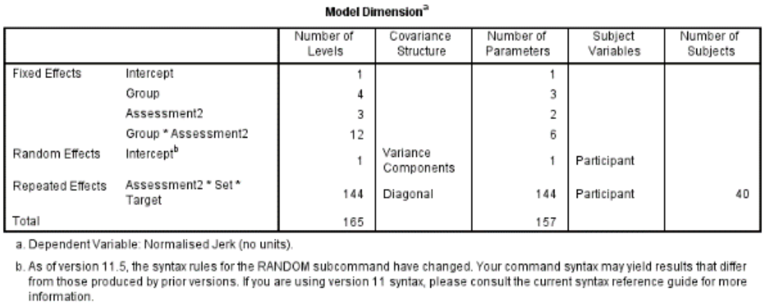
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Velocity (mm/s).

c. Adjustment for multiple comparisons: Bonferroni.

Normalised jerk

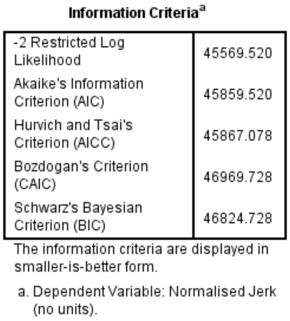


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	3		2		
	Group * Assessment2	12		6		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	40
Total		165		157		

a. Dependent Variable: Normalised Jerk (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

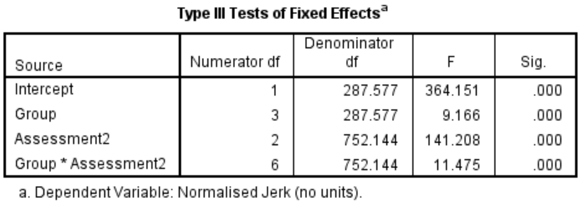


Information Criteria[a]

-2 Restricted Log Likelihood	45569.520
Akaike's Information Criterion (AIC)	45859.520
Hurvich and Tsai's Criterion (AICC)	45867.078
Bozdogan's Criterion (CAIC)	46969.728
Schwarz's Bayesian Criterion (BIC)	46824.728

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Normalised Jerk (no units).

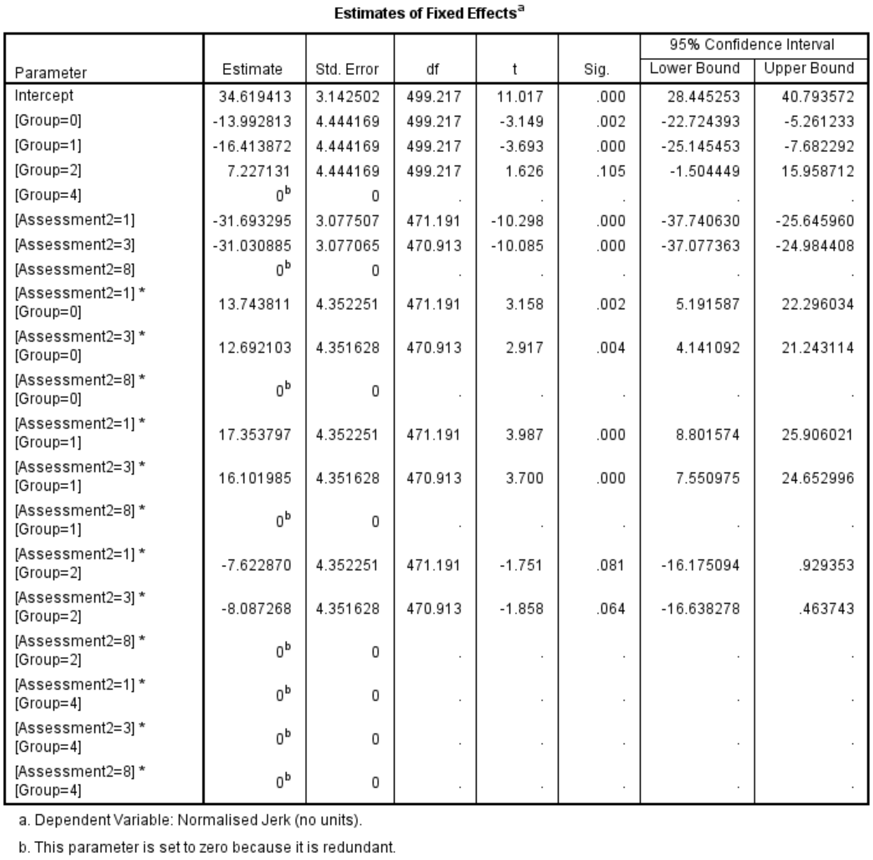


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	287.577	364.151	.000
Group	3	287.577	9.166	.000
Assessment2	2	752.144	141.208	.000
Group * Assessment2	6	752.144	11.475	.000

a. Dependent Variable: Normalised Jerk (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA

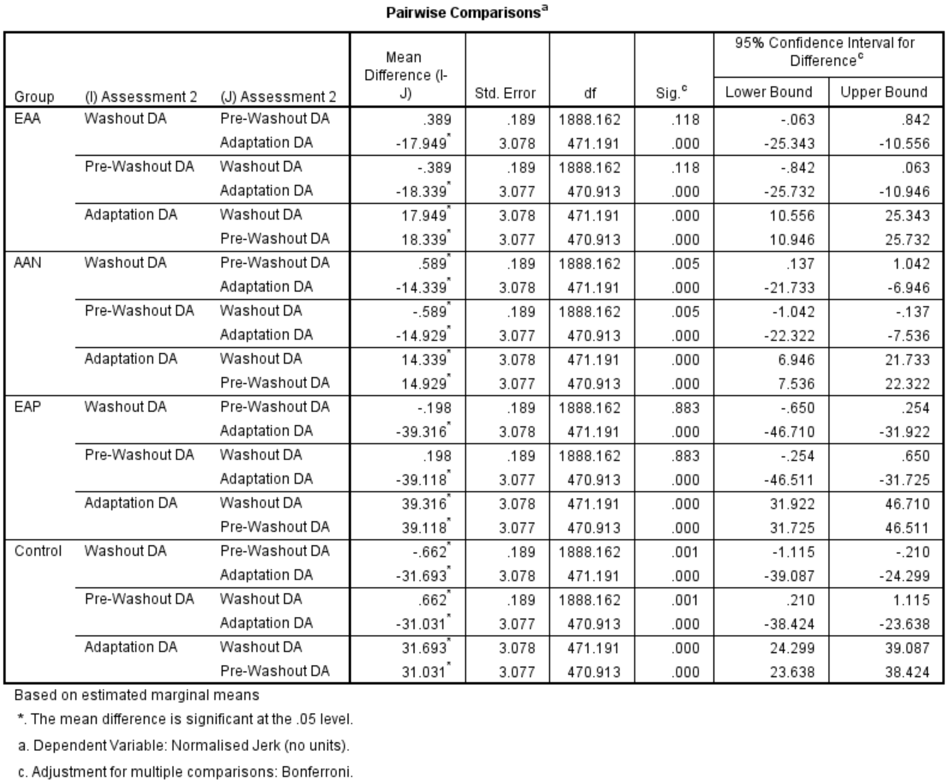


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	34.619413	3.142502	499.217	11.017	.000	28.445253	40.793572
[Group=0]	-13.992813	4.444169	499.217	-3.149	.002	-22.724393	-5.261233
[Group=1]	-16.413872	4.444169	499.217	-3.693	.000	-25.145453	-7.682292
[Group=2]	7.227131	4.444169	499.217	1.626	.105	-1.504449	15.958712
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-31.693295	3.077507	471.191	-10.298	.000	-37.740630	-25.645960
[Assessment2=3]	-31.030885	3.077065	470.913	-10.085	.000	-37.077363	-24.984408
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	13.743811	4.352251	471.191	3.158	.002	5.191587	22.296034
[Assessment2=3] * [Group=0]	12.692103	4.351628	470.913	2.917	.004	4.141092	21.243114
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	17.353797	4.352251	471.191	3.987	.000	8.801574	25.906021
[Assessment2=3] * [Group=1]	16.101985	4.351628	470.913	3.700	.000	7.550975	24.652996
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	-7.622870	4.352251	471.191	-1.751	.081	-16.175094	.929353
[Assessment2=3] * [Group=2]	-8.087268	4.351628	470.913	-1.858	.064	-16.638278	.463743
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Normalised Jerk (no units).

b. This parameter is set to zero because it is redundant.



Pairwise Comparisons[a]

Group	(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
							Lower Bound	Upper Bound
EAA	Washout DA	Pre-Washout DA	.389	.189	1888.162	.118	-.063	.842
		Adaptation DA	-17.949*	3.078	471.191	.000	-25.343	-10.556
	Pre-Washout DA	Washout DA	-.389	.189	1888.162	.118	-.842	.063
		Adaptation DA	-18.339*	3.077	470.913	.000	-25.732	-10.946
	Adaptation DA	Washout DA	17.949*	3.078	471.191	.000	10.556	25.343
		Pre-Washout DA	18.339*	3.077	470.913	.000	10.946	25.732
AAN	Washout DA	Pre-Washout DA	.589*	.189	1888.162	.005	.137	1.042
		Adaptation DA	-14.339*	3.078	471.191	.000	-21.733	-6.946
	Pre-Washout DA	Washout DA	-.589*	.189	1888.162	.005	-1.042	-.137
		Adaptation DA	-14.929*	3.077	470.913	.000	-22.322	-7.536
	Adaptation DA	Washout DA	14.339*	3.078	471.191	.000	6.946	21.733
		Pre-Washout DA	14.929*	3.077	470.913	.000	7.536	22.322
EAP	Washout DA	Pre-Washout DA	-.198	.189	1888.162	.883	-.650	.254
		Adaptation DA	-39.316*	3.078	471.191	.000	-46.710	-31.922
	Pre-Washout DA	Washout DA	.198	.189	1888.162	.883	-.254	.650
		Adaptation DA	-39.118*	3.077	470.913	.000	-46.511	-31.725
	Adaptation DA	Washout DA	39.316*	3.078	471.191	.000	31.922	46.710
		Pre-Washout DA	39.118*	3.077	470.913	.000	31.725	46.511
Control	Washout DA	Pre-Washout DA	-.662*	.189	1888.162	.001	-1.115	-.210
		Adaptation DA	-31.693*	3.078	471.191	.000	-39.087	-24.299
	Pre-Washout DA	Washout DA	.662*	.189	1888.162	.001	.210	1.115
		Adaptation DA	-31.031*	3.077	470.913	.000	-38.424	-23.638
	Adaptation DA	Washout DA	31.693*	3.078	471.191	.000	24.299	39.087
		Pre-Washout DA	31.031*	3.077	470.913	.000	23.638	38.424

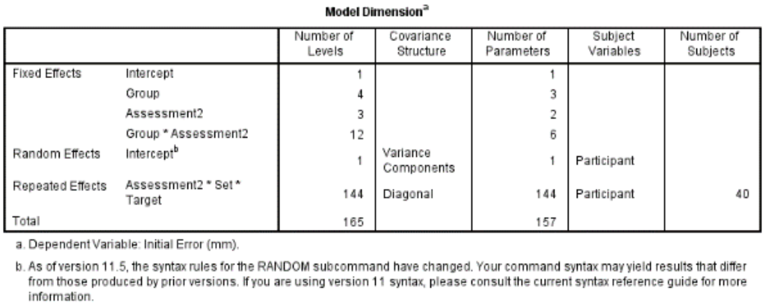
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Normalised Jerk (no units).

c. Adjustment for multiple comparisons: Bonferroni.

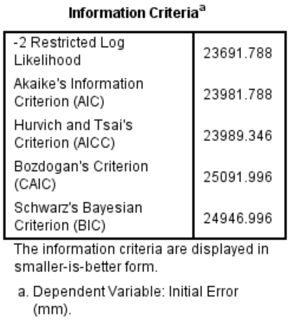
Initial error


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	3		2		
	Group * Assessment2	12		6		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set * Target	144	Diagonal	144	Participant	40
Total		165		157		

a. Dependent Variable: Initial Error (mm).

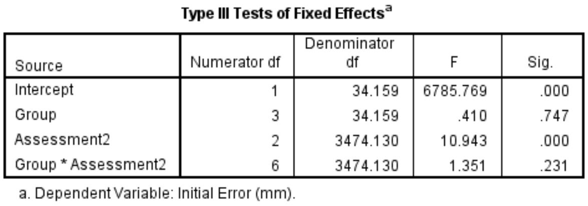
b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.


Information Criteria[a]

-2 Restricted Log Likelihood	23691.788
Akaike's Information Criterion (AIC)	23981.788
Hurvich and Tsai's Criterion (AICC)	23989.346
Bozdogan's Criterion (CAIC)	25091.996
Schwarz's Bayesian Criterion (BIC)	24946.996

The information criteria are displayed in smaller-is-better form.

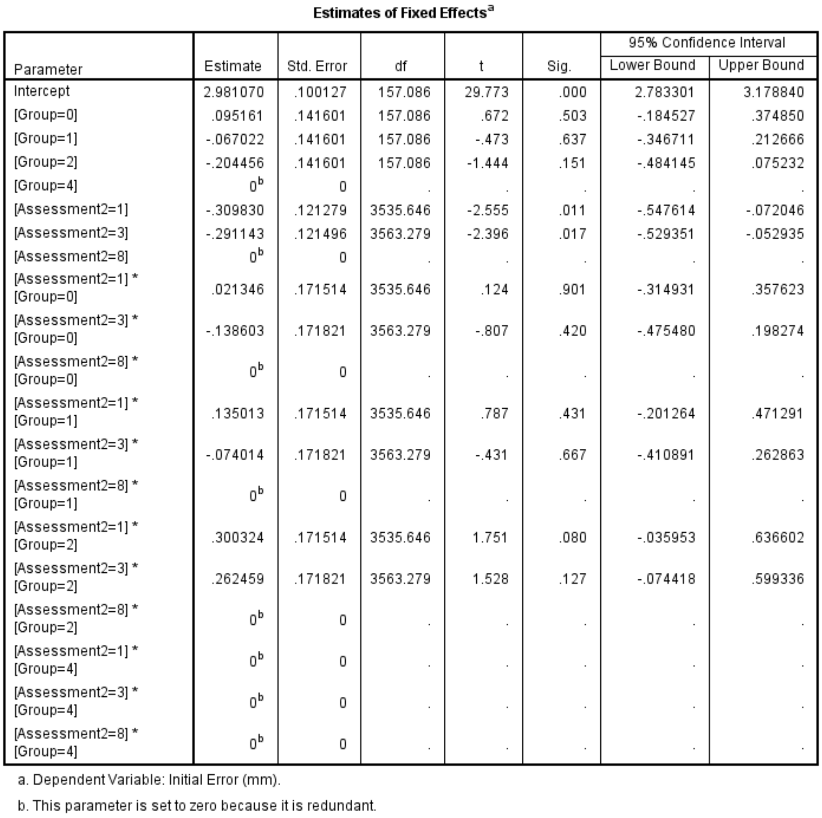
a. Dependent Variable: Initial Error (mm).


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	34.159	6785.769	.000
Group	3	34.159	.410	.747
Assessment2	2	3474.130	10.943	.000
Group * Assessment2	6	3474.130	1.351	.231

a. Dependent Variable: Initial Error (mm).

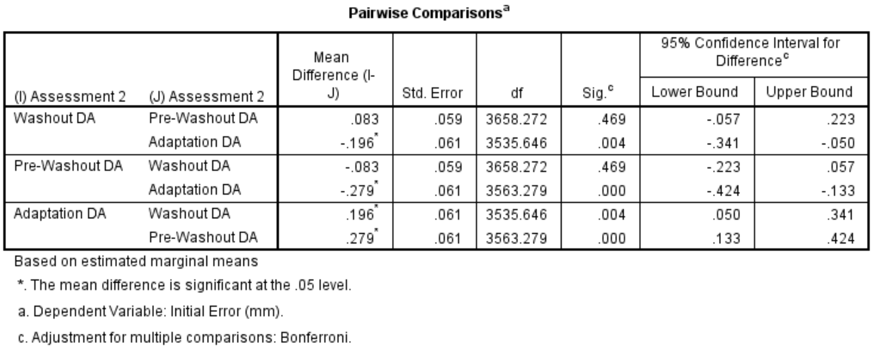
Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA


Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	2.981070	.100127	157.086	29.773	.000	2.783301	3.178840
[Group=0]	.095161	.141601	157.086	.672	.503	-.184527	.374850
[Group=1]	-.067022	.141601	157.086	-.473	.637	-.346711	.212666
[Group=2]	-.204456	.141601	157.086	-1.444	.151	-.484145	.075232
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-.309830	.121279	3535.646	-2.555	.011	-.547614	-.072046
[Assessment2=3]	-.291143	.121496	3563.279	-2.396	.017	-.529351	-.052935
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	.021346	.171514	3535.646	.124	.901	-.314931	.357623
[Assessment2=3] * [Group=0]	-.138603	.171821	3563.279	-.807	.420	-.475480	.198274
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	.135013	.171514	3535.646	.787	.431	-.201264	.471291
[Assessment2=3] * [Group=1]	-.074014	.171821	3563.279	-.431	.667	-.410891	.262863
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	.300324	.171514	3535.646	1.751	.080	-.035953	.636602
[Assessment2=3] * [Group=2]	.262459	.171821	3563.279	1.528	.127	-.074418	.599336
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Initial Error (mm).

b. This parameter is set to zero because it is redundant.


Pairwise Comparisons[a]

(I) Assessment 2	(J) Assessment 2	Mean Difference (I-J)	Std. Error	df	Sig.[c]	95% Confidence Interval for Difference[c]	
						Lower Bound	Upper Bound
Washout DA	Pre-Washout DA	.083	.059	3658.272	.469	-.057	.223
	Adaptation DA	-.196*	.061	3535.646	.004	-.341	-.050
Pre-Washout DA	Washout DA	-.083	.059	3658.272	.469	-.223	.057
	Adaptation DA	-.279*	.061	3563.279	.000	-.424	-.133
Adaptation DA	Washout DA	.196*	.061	3535.646	.004	.050	.341
	Pre-Washout DA	.279*	.061	3563.279	.000	.133	.424

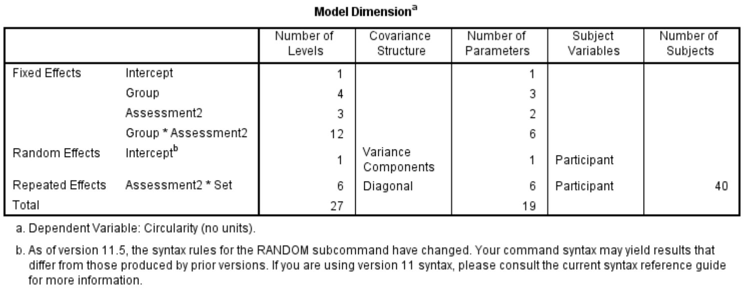
Based on estimated marginal means

*. The mean difference is significant at the .05 level.

a. Dependent Variable: Initial Error (mm).

c. Adjustment for multiple comparisons: Bonferroni.

Circularity

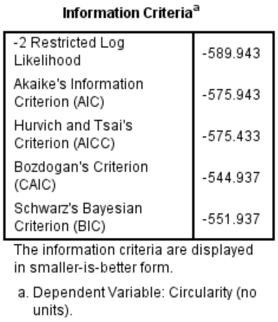


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	3		2		
	Group * Assessment2	12		6		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	6	Diagonal	6	Participant	40
Total		27		19		

a. Dependent Variable: Circularity (no units).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

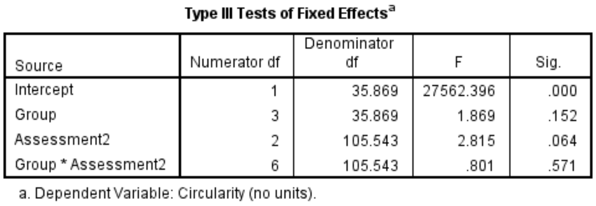


Information Criteria[a]

-2 Restricted Log Likelihood	-589.943
Akaike's Information Criterion (AIC)	-575.943
Hurvich and Tsai's Criterion (AICC)	-575.433
Bozdogan's Criterion (CAIC)	-544.937
Schwarz's Bayesian Criterion (BIC)	-551.937

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Circularity (no units).

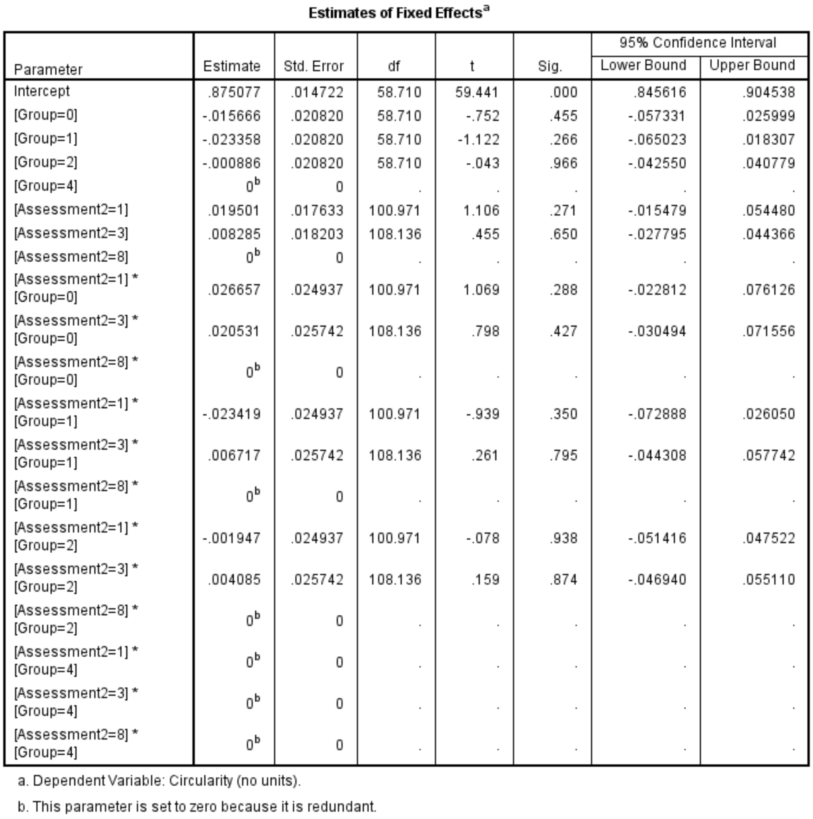


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	35.869	27562.396	.000
Group	3	35.869	1.869	.152
Assessment2	2	105.543	2.815	.064
Group * Assessment2	6	105.543	.801	.571

a. Dependent Variable: Circularity (no units).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



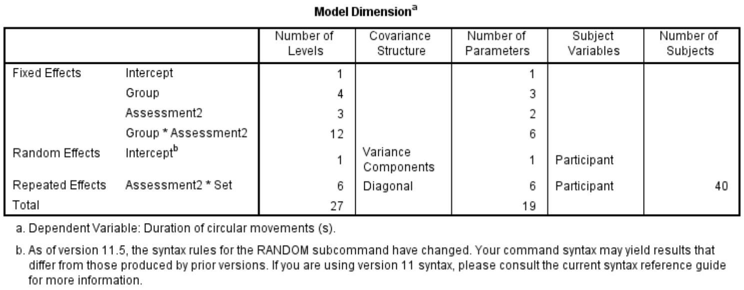
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.875077	.014722	58.710	59.441	.000	.845616	.904538
[Group=0]	-.015666	.020820	58.710	-.752	.455	-.057331	.025999
[Group=1]	-.023358	.020820	58.710	-1.122	.266	-.065023	.018307
[Group=2]	-.000886	.020820	58.710	-.043	.966	-.042550	.040779
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	.019501	.017633	100.971	1.106	.271	-.015479	.054480
[Assessment2=3]	.008285	.018203	108.136	.455	.650	-.027795	.044366
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	.026657	.024937	100.971	1.069	.288	-.022812	.076126
[Assessment2=3] * [Group=0]	.020531	.025742	108.136	.798	.427	-.030494	.071556
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	-.023419	.024937	100.971	-.939	.350	-.072888	.026050
[Assessment2=3] * [Group=1]	.006717	.025742	108.136	.261	.795	-.044308	.057742
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	-.001947	.024937	100.971	-.078	.938	-.051416	.047522
[Assessment2=3] * [Group=2]	.004085	.025742	108.136	.159	.874	-.046940	.055110
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Circularity (no units).

b. This parameter is set to zero because it is redundant.

Duration of circular movements

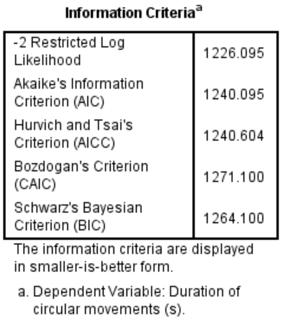


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	Group	4		3		
	Assessment2	3		2		
	Group * Assessment2	12		6		
Random Effects	Intercept[b]	1	Variance Components	1	Participant	
Repeated Effects	Assessment2 * Set	6	Diagonal	6	Participant	40
Total		27		19		

a. Dependent Variable: Duration of circular movements (s).

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

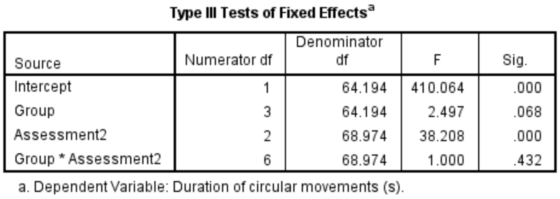


Information Criteria[a]

-2 Restricted Log Likelihood	1226.095
Akaike's Information Criterion (AIC)	1240.095
Hurvich and Tsai's Criterion (AICC)	1240.604
Bozdogan's Criterion (CAIC)	1271.100
Schwarz's Bayesian Criterion (BIC)	1264.100

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Duration of circular movements (s).

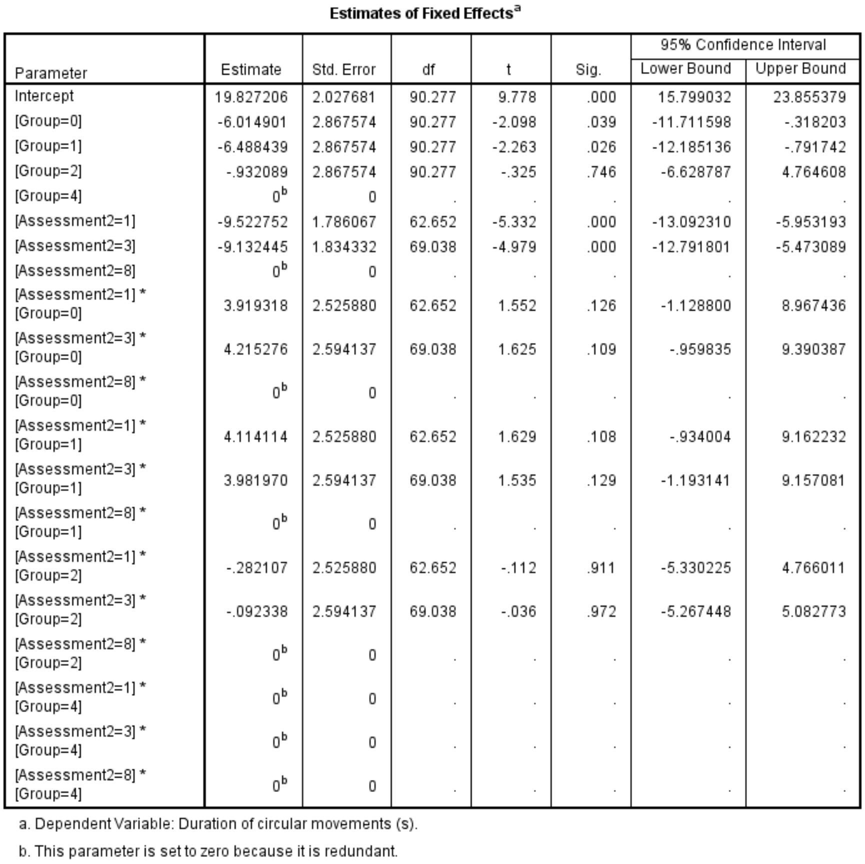


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	64.194	410.064	.000
Group	3	64.194	2.497	.068
Assessment2	2	68.974	38.208	.000
Group * Assessment2	6	68.974	1.000	.432

a. Dependent Variable: Duration of circular movements (s).

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



Estimates of Fixed Effects[a]

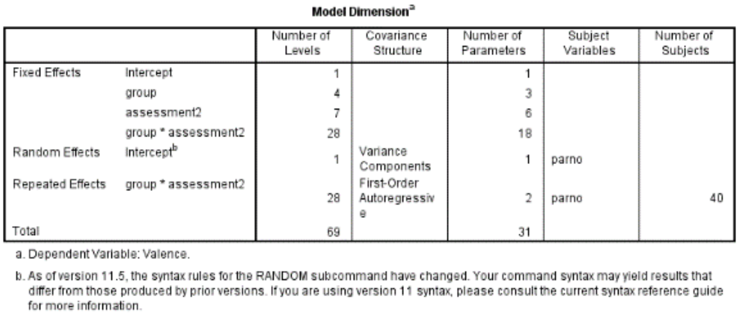
Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	19.827206	2.027681	90.277	9.778	.000	15.799032	23.855379
[Group=0]	-6.014901	2.867574	90.277	-2.098	.039	-11.711598	-.318203
[Group=1]	-6.488439	2.867574	90.277	-2.263	.026	-12.185136	-.791742
[Group=2]	-.932089	2.867574	90.277	-.325	.746	-6.628787	4.764608
[Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=1]	-9.522752	1.786067	62.652	-5.332	.000	-13.092310	-5.953193
[Assessment2=3]	-9.132445	1.834332	69.038	-4.979	.000	-12.791801	-5.473089
[Assessment2=8]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=0]	3.919318	2.525880	62.652	1.552	.126	-1.128800	8.967436
[Assessment2=3] * [Group=0]	4.215276	2.594137	69.038	1.625	.109	-.959835	9.390387
[Assessment2=8] * [Group=0]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=1]	4.114114	2.525880	62.652	1.629	.108	-.934004	9.162232
[Assessment2=3] * [Group=1]	3.981970	2.594137	69.038	1.535	.129	-1.193141	9.157081
[Assessment2=8] * [Group=1]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=2]	-.282107	2.525880	62.652	-.112	.911	-5.330225	4.766011
[Assessment2=3] * [Group=2]	-.092338	2.594137	69.038	-.036	.972	-5.267448	5.082773
[Assessment2=8] * [Group=2]	0[b]	0	.	.	.	.	.
[Assessment2=1] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=3] * [Group=4]	0[b]	0	.	.	.	.	.
[Assessment2=8] * [Group=4]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Duration of circular movements (s).

b. This parameter is set to zero because it is redundant.

Analysis of the SAM questionnaire

Valence

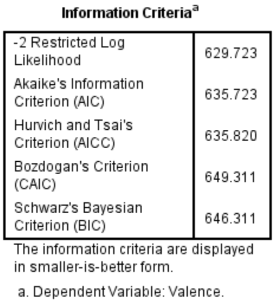


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	4		3		
	assessment2	7		6		
	group * assessment2	28		18		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	28	First-Order Autoregressive	2	parno	40
Total		69		31		

a. Dependent Variable: Valence.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

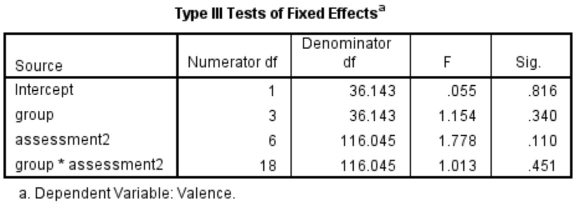


Information Criteria[a]

-2 Restricted Log Likelihood	629.723
Akaike's Information Criterion (AIC)	635.723
Hurvich and Tsai's Criterion (AICC)	635.820
Bozdogan's Criterion (CAIC)	649.311
Schwarz's Bayesian Criterion (BIC)	646.311

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Valence.

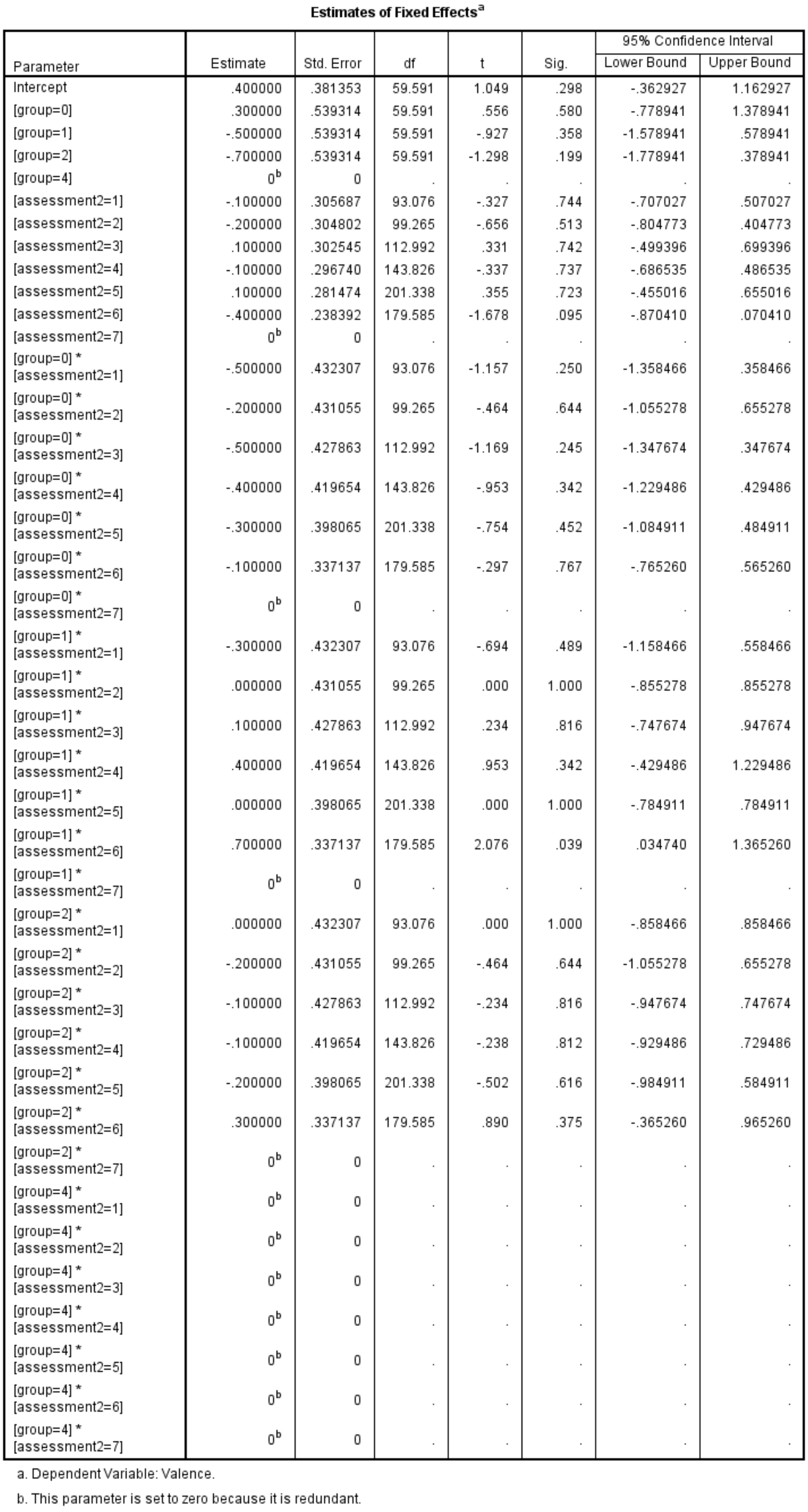


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	36.143	.055	.816
group	3	36.143	1.154	.340
assessment2	6	116.045	1.778	.110
group * assessment2	18	116.045	1.013	.451

a. Dependent Variable: Valence.

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



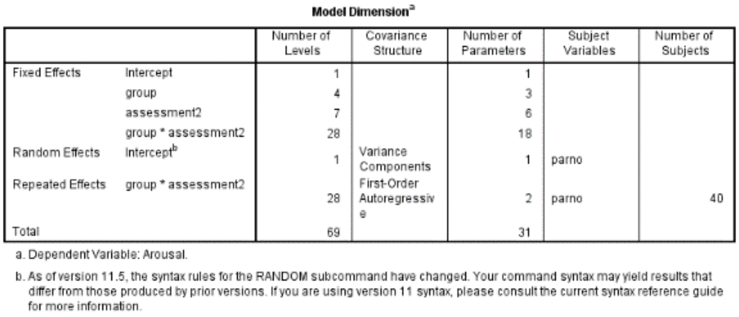
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.400000	.381353	59.591	1.049	.298	-.362927	1.162927
[group=0]	.300000	.539314	59.591	.556	.580	-.778941	1.378941
[group=1]	-.500000	.539314	59.591	-.927	.358	-1.578941	.578941
[group=2]	-.700000	.539314	59.591	-1.298	.199	-1.778941	.378941
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	-.100000	.305687	93.076	-.327	.744	-.707027	.507027
[assessment2=2]	-.200000	.304802	99.265	-.656	.513	-.804773	.404773
[assessment2=3]	.100000	.302545	112.992	.331	.742	-.499396	.699396
[assessment2=4]	-.100000	.296740	143.826	-.337	.737	-.686535	.486535
[assessment2=5]	.100000	.281474	201.338	.355	.723	-.455016	.655016
[assessment2=6]	-.400000	.238392	179.585	-1.678	.095	-.870410	.070410
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=0] * [assessment2=1]	-.500000	.432307	93.076	-1.157	.250	-1.358466	.358466
[group=0] * [assessment2=2]	-.200000	.431055	99.265	-.464	.644	-1.055278	.655278
[group=0] * [assessment2=3]	-.500000	.427863	112.992	-1.169	.245	-1.347674	.347674
[group=0] * [assessment2=4]	-.400000	.419654	143.826	-.953	.342	-1.229486	.429486
[group=0] * [assessment2=5]	-.300000	.398065	201.338	-.754	.452	-1.084911	.484911
[group=0] * [assessment2=6]	-.100000	.337137	179.585	-.297	.767	-.765260	.565260
[group=0] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=1] * [assessment2=1]	-.300000	.432307	93.076	-.694	.489	-1.158466	.558466
[group=1] * [assessment2=2]	.000000	.431055	99.265	.000	1.000	-.855278	.855278
[group=1] * [assessment2=3]	.100000	.427863	112.992	.234	.816	-.747674	.947674
[group=1] * [assessment2=4]	.400000	.419654	143.826	.953	.342	-.429486	1.229486
[group=1] * [assessment2=5]	.000000	.398065	201.338	.000	1.000	-.784911	.784911
[group=1] * [assessment2=6]	.700000	.337137	179.585	2.076	.039	.034740	1.365260
[group=1] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=2] * [assessment2=1]	.000000	.432307	93.076	.000	1.000	-.858466	.858466
[group=2] * [assessment2=2]	-.200000	.431055	99.265	-.464	.644	-1.055278	.655278
[group=2] * [assessment2=3]	-.100000	.427863	112.992	-.234	.816	-.947674	.747674
[group=2] * [assessment2=4]	-.100000	.419654	143.826	-.238	.812	-.929486	.729486
[group=2] * [assessment2=5]	-.200000	.398065	201.338	-.502	.616	-.984911	.584911
[group=2] * [assessment2=6]	.300000	.337137	179.585	.890	.375	-.365260	.965260
[group=2] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Valence.

b. This parameter is set to zero because it is redundant.

Arousal

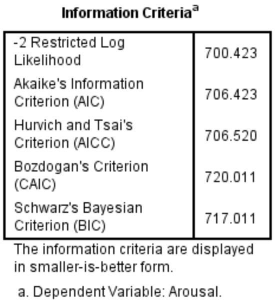


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	4		3		
	assessment2	7		6		
	group * assessment2	28		18		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	28	First-Order Autoregressive	2	parno	40
Total		69		31		

a. Dependent Variable: Arousal.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

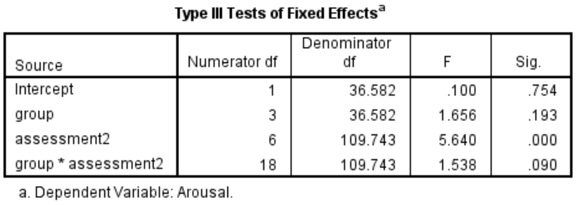


Information Criteria[a]

-2 Restricted Log Likelihood	700.423
Akaike's Information Criterion (AIC)	706.423
Hurvich and Tsai's Criterion (AICC)	706.520
Bozdogan's Criterion (CAIC)	720.011
Schwarz's Bayesian Criterion (BIC)	717.011

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Arousal.

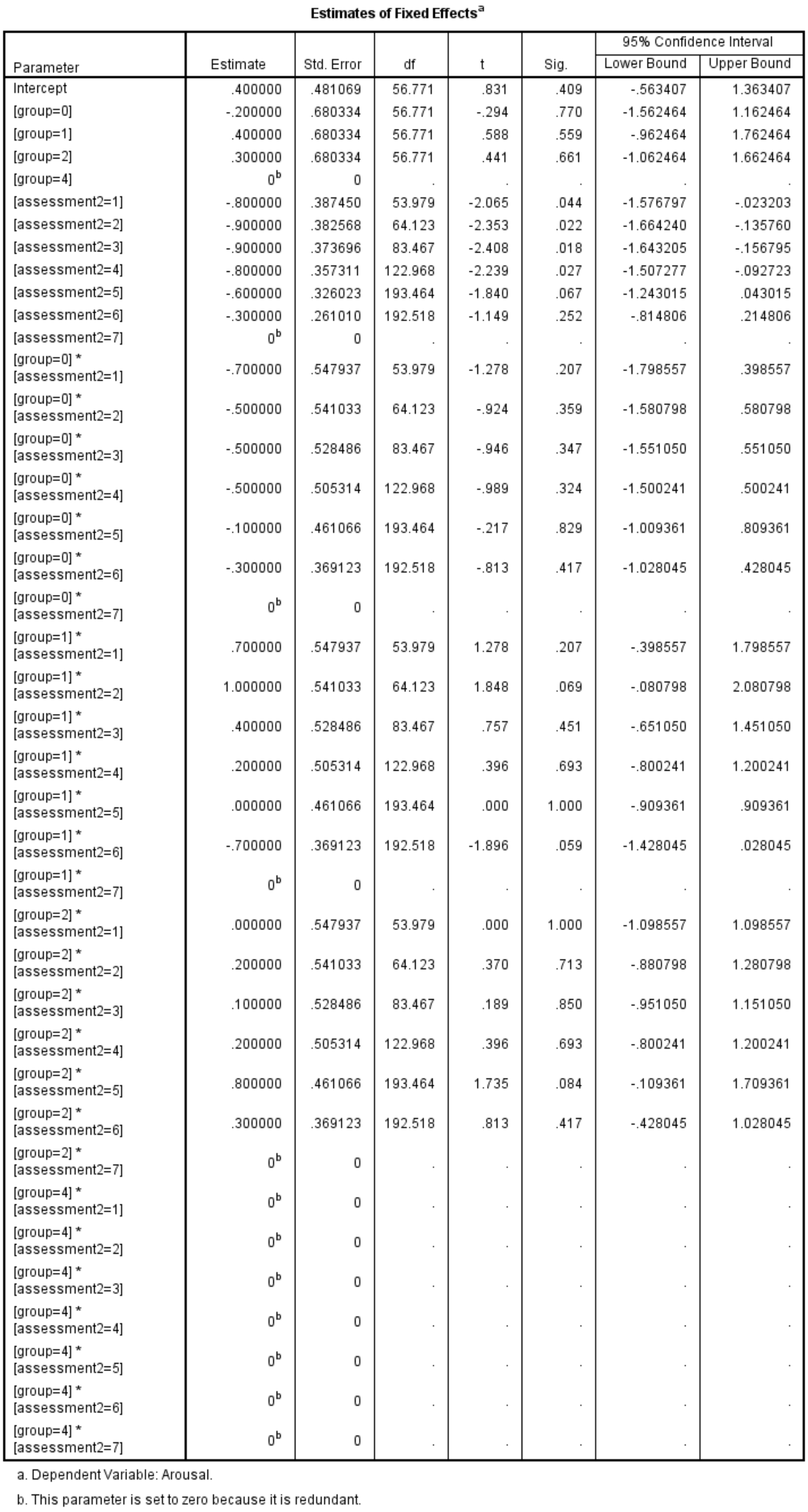


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	36.582	.100	.754
group	3	36.582	1.656	.193
assessment2	6	109.743	5.640	.000
group * assessment2	18	109.743	1.538	.090

a. Dependent Variable: Arousal.

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



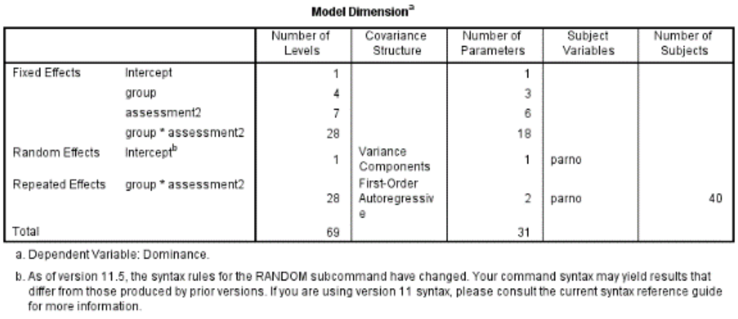
Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	.400000	.481069	56.771	.831	.409	-.563407	1.363407
[group=0]	-.200000	.680334	56.771	-.294	.770	-1.562464	1.162464
[group=1]	.400000	.680334	56.771	.588	.559	-.962464	1.762464
[group=2]	.300000	.680334	56.771	.441	.661	-1.062464	1.662464
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	-.800000	.387450	53.979	-2.065	.044	-1.576797	-.023203
[assessment2=2]	-.900000	.382568	64.123	-2.353	.022	-1.664240	-.135760
[assessment2=3]	-.900000	.373696	83.467	-2.408	.018	-1.643205	-.156795
[assessment2=4]	-.800000	.357311	122.968	-2.239	.027	-1.507277	-.092723
[assessment2=5]	-.600000	.326023	193.464	-1.840	.067	-1.243015	.043015
[assessment2=6]	-.300000	.261010	192.518	-1.149	.252	-.814806	.214806
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=0] * [assessment2=1]	-.700000	.547937	53.979	-1.278	.207	-1.798557	.398557
[group=0] * [assessment2=2]	-.500000	.541033	64.123	-.924	.359	-1.580798	.580798
[group=0] * [assessment2=3]	-.500000	.528486	83.467	-.946	.347	-1.551050	.551050
[group=0] * [assessment2=4]	-.500000	.505314	122.968	-.989	.324	-1.500241	.500241
[group=0] * [assessment2=5]	-.100000	.461066	193.464	-.217	.829	-1.009361	.809361
[group=0] * [assessment2=6]	-.300000	.369123	192.518	-.813	.417	-1.028045	.428045
[group=0] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=1] * [assessment2=1]	.700000	.547937	53.979	1.278	.207	-.398557	1.798557
[group=1] * [assessment2=2]	1.000000	.541033	64.123	1.848	.069	-.080798	2.080798
[group=1] * [assessment2=3]	.400000	.528486	83.467	.757	.451	-.651050	1.451050
[group=1] * [assessment2=4]	.200000	.505314	122.968	.396	.693	-.800241	1.200241
[group=1] * [assessment2=5]	.000000	.461066	193.464	.000	1.000	-.909361	.909361
[group=1] * [assessment2=6]	-.700000	.369123	192.518	-1.896	.059	-1.428045	.028045
[group=1] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=2] * [assessment2=1]	.000000	.547937	53.979	.000	1.000	-1.098557	1.098557
[group=2] * [assessment2=2]	.200000	.541033	64.123	.370	.713	-.880798	1.280798
[group=2] * [assessment2=3]	.100000	.528486	83.467	.189	.850	-.951050	1.151050
[group=2] * [assessment2=4]	.200000	.505314	122.968	.396	.693	-.800241	1.200241
[group=2] * [assessment2=5]	.800000	.461066	193.464	1.735	.084	-.109361	1.709361
[group=2] * [assessment2=6]	.300000	.369123	192.518	.813	.417	-.428045	1.028045
[group=2] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Arousal.

b. This parameter is set to zero because it is redundant.

Dominance

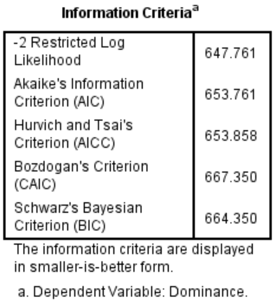


Model Dimension[a]

		Number of Levels	Covariance Structure	Number of Parameters	Subject Variables	Number of Subjects
Fixed Effects	Intercept	1		1		
	group	4		3		
	assessment2	7		6		
	group * assessment2	28		18		
Random Effects	Intercept[b]	1	Variance Components	1	parno	
Repeated Effects	group * assessment2	28	First-Order Autoregressive	2	parno	40
Total		69		31		

a. Dependent Variable: Dominance.

b. As of version 11.5, the syntax rules for the RANDOM subcommand have changed. Your command syntax may yield results that differ from those produced by prior versions. If you are using version 11 syntax, please consult the current syntax reference guide for more information.

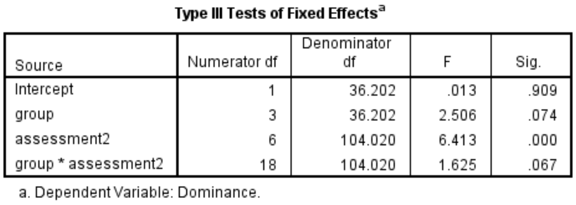


Information Criteria[a]

-2 Restricted Log Likelihood	647.761
Akaike's Information Criterion (AIC)	653.761
Hurvich and Tsai's Criterion (AICC)	653.858
Bozdogan's Criterion (CAIC)	667.350
Schwarz's Bayesian Criterion (BIC)	664.350

The information criteria are displayed in smaller-is-better form.

a. Dependent Variable: Dominance.

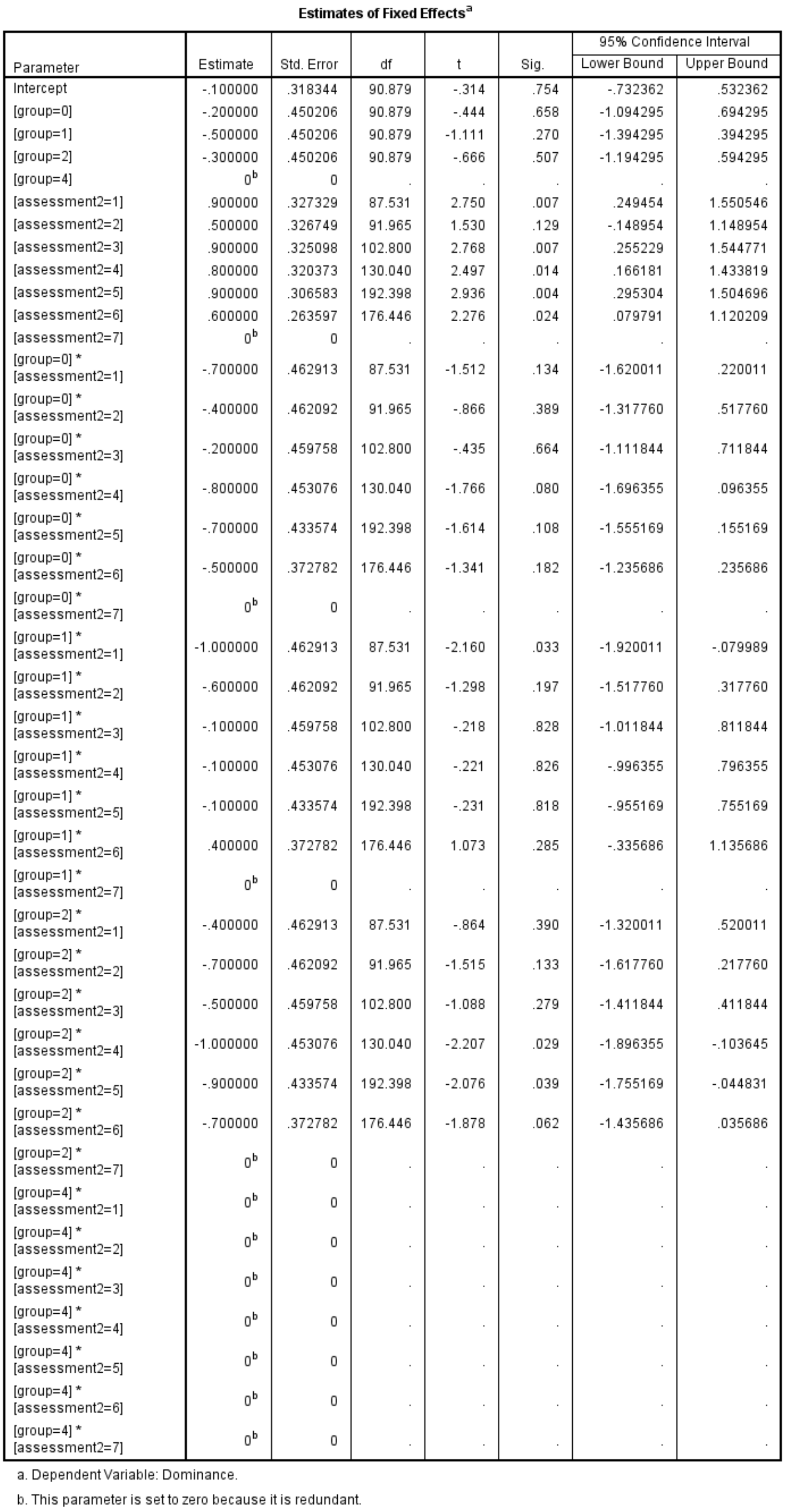


Type III Tests of Fixed Effects[a]

Source	Numerator df	Denominator df	F	Sig.
Intercept	1	36.202	.013	.909
group	3	36.202	2.506	.074
assessment2	6	104.020	6.413	.000
group * assessment2	18	104.020	1.625	.067

a. Dependent Variable: Dominance.

Group 0: EAA Group 1: AAN Group 2: EAP Group 4: Control	Assessment 8: Adaptation DA Assessment 7: Adaptation NDA Assessment 6: Training 1 Assessment 5: Training 2 Assessment 4: Training 3 Assessment 3: Pre-washout Assessment 2: Washout NDA Assessment 1: Washout DA



Estimates of Fixed Effects[a]

Parameter	Estimate	Std. Error	df	t	Sig.	95% Confidence Interval	
						Lower Bound	Upper Bound
Intercept	-.100000	.318344	90.879	-.314	.754	-.732362	.532362
[group=0]	-.200000	.450206	90.879	-.444	.658	-1.094295	.694295
[group=1]	-.500000	.450206	90.879	-1.111	.270	-1.394295	.394295
[group=2]	-.300000	.450206	90.879	-.666	.507	-1.194295	.594295
[group=4]	0[b]	0	.	.	.	.	.
[assessment2=1]	.900000	.327329	87.531	2.750	.007	.249454	1.550546
[assessment2=2]	.500000	.326749	91.965	1.530	.129	-.148954	1.148954
[assessment2=3]	.900000	.325098	102.800	2.768	.007	.255229	1.544771
[assessment2=4]	.800000	.320373	130.040	2.497	.014	.166181	1.433819
[assessment2=5]	.900000	.306583	192.398	2.936	.004	.295304	1.504696
[assessment2=6]	.600000	.263597	176.446	2.276	.024	.079791	1.120209
[assessment2=7]	0[b]	0	.	.	.	.	.
[group=0] * [assessment2=1]	-.700000	.462913	87.531	-1.512	.134	-1.620011	.220011
[group=0] * [assessment2=2]	-.400000	.462092	91.965	-.866	.389	-1.317760	.517760
[group=0] * [assessment2=3]	-.200000	.459758	102.800	-.435	.664	-1.111844	.711844
[group=0] * [assessment2=4]	-.800000	.453076	130.040	-1.766	.080	-1.696355	.096355
[group=0] * [assessment2=5]	-.700000	.433574	192.398	-1.614	.108	-1.555169	.155169
[group=0] * [assessment2=6]	-.500000	.372782	176.446	-1.341	.182	-1.235686	.235686
[group=0] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=1] * [assessment2=1]	-1.000000	.462913	87.531	-2.160	.033	-1.920011	-.079989
[group=1] * [assessment2=2]	-.600000	.462092	91.965	-1.298	.197	-1.517760	.317760
[group=1] * [assessment2=3]	-.100000	.459758	102.800	-.218	.828	-1.011844	.811844
[group=1] * [assessment2=4]	-.100000	.453076	130.040	-.221	.826	-.996355	.796355
[group=1] * [assessment2=5]	-.100000	.433574	192.398	-.231	.818	-.955169	.755169
[group=1] * [assessment2=6]	.400000	.372782	176.446	1.073	.285	-.335686	1.135686
[group=1] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=2] * [assessment2=1]	-.400000	.462913	87.531	-.864	.390	-1.320011	.520011
[group=2] * [assessment2=2]	-.700000	.462092	91.965	-1.515	.133	-1.617760	.217760
[group=2] * [assessment2=3]	-.500000	.459758	102.800	-1.088	.279	-1.411844	.411844
[group=2] * [assessment2=4]	-1.000000	.453076	130.040	-2.207	.029	-1.896355	-.103645
[group=2] * [assessment2=5]	-.900000	.433574	192.398	-2.076	.039	-1.755169	-.044831
[group=2] * [assessment2=6]	-.700000	.372782	176.446	-1.878	.062	-1.435686	.035686
[group=2] * [assessment2=7]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=1]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=2]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=3]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=4]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=5]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=6]	0[b]	0	.	.	.	.	.
[group=4] * [assessment2=7]	0[b]	0	.	.	.	.	.

a. Dependent Variable: Dominance.

b. This parameter is set to zero because it is redundant.