Motor Imagery During Action Observation in Virtual Reality: The Impact of Watching Myself Performing at a Level I Have Not Yet Achieved

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Abstract

Feedforward modeling, the creation of one's own behaviour that is potentially achievable in the future, can support motor performance and learning. While this has been shown for sequences of motor actions, it remains to be tested whether feedforward modelling is beneficial for single complex motor actions. Using an immersive, state-of-the-art, low-latency Cave Automatic Virtual Environment (CAVE), we compared motor imagery during action observation (AOMI) of oneself performing at one's current skill level against AOMI of oneself performing at an achievable future skill level. We performed 3D scans and created a ready-to-animate virtual human of each participant. During acquisition, participants observed an avatar of themselves performing either one of their own previously executed squats (Me-Novice) or observed an avatar of themselves performing a skilled squat (Me-Skilled), whilst simultaneously imagining the feelings and sensations associated with movement execution. Findings revealed an advantage for the Me-Skilled group as compared to the Me-Novice group in motor performance and cognitive representation structure, while self-efficacy improved in both groups. In comparison to watching and imagining oneself performing at the current novice skill level, watching and imagining oneself performing at a more advanced skill level prevented from making errors in motor performance and led to perceptual-cognitive scaffolding as shown by functional changes in underlying representations. Simultaneous imagery whilst observing future states of action may therefore help to establish cognitive prerequisites that enable better motor performance. To this end, virtual reality is a promising tool to create learning environments that exceed an individual's current performance level.

Keywords: motor learning, observational learning, feedforward modeling, mental practice, self-efficacy, cognitive representation, SDA-M

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Watching someone else perform a motor action, either via a live demonstration or video, can be a powerful tool to improve performance and promote motor learning. Action observation (AO) is a well-established method to enrich the coaching of motor actions and speed up the learning process (for reviews, see McCullagh et al., 2012; Ste-Marie et al., 2012, 2020). Research has shown that watching someone else perform a movement affects motor performance variables such as outcome accuracy (Hayes et al., 2008) and coordination patterns (Horn et al., 2007) as well as psychological variables such as self-efficacy (Feltz et al., 1979; for reviews, see Feltz et al., 2008; Short & Ross-Stewart, 2008). Similarly, using motor imagery (MI) to rehearse a motor action in one's mind without actually executing it (Jeannerod, 1995; Munzert & Zentgraf, 2009) can improve motor performance and promote motor learning across a variety of tasks and variables (for meta-analyses, see Simonsmeier et al., 2020; Toth et al., 2020), and contributes to improved self-efficacy (MacKenzie & Howe, 1997; Sohoo et al., 2004). A recent suggestion is that the combination of action observation and motor imagery (AOMI), whereby individuals observe an action while simultaneously imagining the feelings associated with executing that same action, may be even more effective than AO or MI alone for improving motor performance and promoting motor learning across a range of tasks (Eaves et al., 2016; Vogt et al., 2013). For instance, AOMI was found to be more effective in improving hamstring force compared to MI alone (Scott et al., 2018), and dart throwing accuracy compared to MI or AO alone (Romano-Smith et al., 2018). Whilst AOMI is increasingly seen as being more effective for improving performance (McNeill et al., 2020), the impact of AOMI on self-efficacy is not yet known.

From a neurophysiological point of view (for reviews, see Eaves, Riach, Holmes, & Wright, 2016; Frank et al., 2020), AOMI is associated with greater activity in motor-related brain areas (e.g., Nedelko et al., 2012; Taube et al., 2015), increased event-related desynchronization in motor related frequency bands (e.g., Berends et al., 2013; Eaves, Behmer, & Vogt, 2016) and is associated with greater facilitation of corticospinal excitability (e.g., Sakamoto et al., 2009; Wright et al., 2014). From a cognitive point of view, AOMI has been shown to help structure underlying perceptual-cognitive representations of complex action (Kim et al., in press), with AO and MI possibly playing different roles in this process (Kim et al., 2017). While the provision of visual information through AO may influence cognitive representation features such as the sequencing and timing aspects of the movement, MI may help structure components relating to the sensory consequences of action via simulation of quasi-sensations (Frank et al., 2020; Kim et al., 2017; Wright et al., 2018). Despite the growing body of AOMI research, however, the factors that moderate the effect of this technique on performance and learning are not well understood.

Observational learning research has revealed that the type of model shown can moderate the effect on motor performance and learning (Andrieux & Proteau, 2013, 2014; Pollock & Lee, 1992; for reviews, see McCullagh et al., 2012; Anderson & Campbell, 2015; Law et al., 2017). Two of the most important model characteristics are the similarity between the model and the observer (Bandura, 1986, 1997), such as the model's skill level and the self vs. other distinction. While AO related research on model type is vast, research looking at model type during AOMI remains scarce to date. Addressing this particular gap, McNeill and colleagues were the first to compare self vs. other models during AOMI of the golf putt in skilled golfers (McNeill et al., 2021). From their findings, watching the self was different to watching an expert golfer in terms of putting kinematics, but not in terms of putting outcome. Specifically, club path kinematics during the swing were more accurate for those watching themselves compared to those watching another person. The authors suggested AOMI may help skilled performers to detect and correct errors, which in turn leads to changes in kinematics but not in outcome performance. Although the differences found might be attributed as well to the differences in skill levels of the models used, their findings might indicate a potential beneficial effect for watching and imagining the self compared to another person.

Self-as-a-model interventions can be distinguished according to whether they represent a 'review' or a 'preview' version of the self, ranging from the replay of current or best performances of the self (review) to edited videos of performances observers have not yet achieved (preview), namely a feedforward preview of the self (Dowrick, 2012a, 2012b; Law et al., 2017). The concept of feedforward self-modelling extends from Dowrick (1976, 1999, 2012a, 2012b) who argued that learning from an action becomes possible when an individual models her/himself performing a behaviour that has not occurred previously, but for which the necessary components are already in their motor repertoire. In this sense, feedforward modeling relates to the artificial creation of one's own behaviour that is potentially achievable in the future, instead of a replication of another person's behaviour at a level beyond one's own capabilities. Feedforward modeling (Clark & Ste-Marie, 2007; Starek & McCullagh, 1999; Ste-Marie et al., 2011) can be an effective method that seems particularly promising in the realm of motor learning, as it links the current self to a potential future version of the self.

In the sport domain, research on feedforward modeling has thus far focused on action sequences such as swimming (Clark & Ste-Marie, 2007), trampoline routines (Ste-Marie et al., 2011), and gymnastics bar routines (Rymal & Ste-Marie, 2017). To show the athlete's performances at a level they have not yet achieved, researchers typically use video editing techniques to combine elements and create successful movement sequences. Editing video footage to present a sequence of one's best performances, despite the athlete never having performed the entire sequence successfully, has produced promising results. For instance, Clark and Ste-Marie (2007) found that watching an edited sequence of best performances of the swimming stroke resulted in better performances in 6- to 10-year-old children compared to watching their current performances of the swimming stroke. In a study where 7- to 13-year-old children were tasked with learning two five-skill trampoline routines, Ste-Marie and colleagues (2011) found that feedforward modeling, which included footage combining the best performance of each individual trampoline skill to create a five-skill routine, enhanced motor skill acquisition compared to verbal instructions. Self-efficacy increased over time independent of group in both studies, although self-efficacy tended to be higher after learning in the feedforward modeling groups in one of the two studies (Clark & Ste-Marie, 2007). While these feedforward modeling findings seem promising for sport, no systematic evidence exists to date comparing feedforward modeling to self-review in a single complex motor action.

In sum, while previous studies used video footage to show a successful series of motor actions that one has not yet consistently performed successfully, the impact of watching oneself performing a single full body motor action at a skill level that one has not yet achieved remains to be tested. To our knowledge, only one study compared AOMI of oneself rotating a ball and varying levels of difficulty (Aoyama et al., 2020). Participants either watched a hand and imagined themselves rotating at their current speed, a slightly faster speed or a significantly faster speed. Findings showed that participants learning rates were best during AOMI of a slightly faster speed, indicating that AOMI of a future self, performing at moderate difficulty levels may promote better learning. To date, however, none of the studies from the two fields of self-modeling or AOMI has examined self-as-a-model variations during AOMI interventions of full body motor actions. While research indicates that AOMI promotes motor learning, possibly through the improved structuring of cognitive representations, AOMI of a future self may help to create a functional representation of a new skill based on one’s existing repertoire. This may in turn result in better performance and learning compared to AOMI of the current self. Since virtual reality allows for systematic and gradual manipulations in the AO component of the AOMI experience, it is now possible to vary the model's expertise while holding the model's appearance constant.

The purpose of the present study was to investigate the impact of feedforward AOMI and to compare this to self-review AOMI in novices practicing a complex motor action. Specifically, we sought to examine the impact of watching whilst simultaneously imagining oneself performing a body weight squat at an advanced skill level (Me-Skilled), compared to watching and imagining oneself performing at one's current skill level (Me-Novice). We used virtual reality to manipulate the model's performance while keeping the model's appearance (i.e., self) constant. This allowed us to explore the effects of an avatar of oneself that either performed at one's current skill level or at an advanced skill level. To assess learning, we measured motor performance, cognitive representation, and self-efficacy of the body weight squat prior to and after an acquisition phase as well as after a retention interval on the next day. We predicted that both types of AOMI would lead to improvements in motor performance, cognitive representation, and self-efficacy over time, with the greatest improvements for the Me-Skilled group.

Methods

Participants

Twenty-six university students (mean age = 22.81, *SD* = 3.15; 17 female) participated in the experiment. We determined the number of participants by way of an *a priori* power analysis using G*Power (Franz Faul, Kiel University, Kiel, Germany; F tests/analysis of variance: repeated measures, within-between interaction for a Type I error probability of 0.05, a Type II error probability of 0.80 [Cohen, 1992], and an effect size of f = 0.30). We chose a small effect size based on most related works (Chye et al., in preparation; Clark et al., 2007, McNeill et al., 2021). None of the participants had any prior experience in executing the squat on a regular basis or in squat-related coaching. We assigned participants randomly to one of two conditions: self-appearance/ current novice performance (Me-Novice; n = 13; mean age = 22.15, SD = 2.61; 9 female) or self-appearance/ future skilled performance level (Me-Skilled; n = 13; mean age = 23.46, SD = 3.58; 8 female). Mean imagery ability according to the MIQ-R (Hall & Martin, 1997) was 42.77 (SD = 6.25) for the Me-Novice group and 44.00 (SD = 5.55) for the Me-Skilled group. Participants received 24 Euro (8 Euro/ hour) for participating in the study. We conducted the study in accordance with local ethical guidelines and conformed to the declaration of Helsinki.

Design

A pre-, post-, retention-test design was used, with avatar appearance held constant across conditions (i.e., self-as-a-model), model skill level (i.e., novice vs. skilled) as a between-participants factor, and time (i.e., pre, post, retention) as a within-participants factor (see Figure 1; for more details, see Procedures). Hence, participants in each condition watched an avatar of themselves performing the squat, but the avatar's performance differed in skill level. Specifically, participants in the Me-Novice group watched themselves performing a novice squat as recorded during pre-test. Thus, participants watched themselves performing at their current level of expertise. Participants in the Me-Skilled group watched themselves performing a skilled squat. This was done by animating their own avatar using pre-recorded movements of a skilled individual. Thus, participants watched themselves performing at a level that was above their current level of expertise.

Apparatus

Cave automated virtual environment

We conducted the study in an immersive, closed-loop virtual reality environment. The 2-sided, L-shaped Cave Automated Virtual Environment (CAVE) was equipped with two walls sized 3m x 2.3 m (front and floor wall), and a resolution of 2100 x 1600 pixel. The virtual reality was realized by way of four projectors, two projecting onto the front wall and two onto the floor from the back, and run by a single computer (2 Intel Xeon CPU E5-2609 @2.4GHz, 16GB Ram, 2 Nvidia Quadro P6000 GPUs). INFITEC filters allowed for passive stereoscopic vision. The scene was rendered by using a self-developed, single-computer multi pipe approach for rendering the two images for left/ right eye for each projection wall in the CAVE at approx. 95 fps, resulting in a low latency of approx. 60 ms (cf. Waltemate et al., 2015). Inside the CAVE, the participant's movements were tracked using an optical motion tracking system (OptiTrack, Corvallis, Oregon, U. S. A.; for details on the system's architecture, see de Kok et al., 2017; Waltemate et al., 2015).

Scanning

We used two dedicated 3D scanners (see Figure 2). The body scanner was equipped with 40 digital single-lens reflex (DSLR) cameras, while the face scanner featured eight DSLR cameras. The actual scans were performed by simultaneously taking 40 photos of the participants' body and eight photos of the participants' face. The resulting images were processed with a commercial photogrammetry software (Agisoft Photoscan, St. Petersburg, Russia), resulting in two 3D point clouds of the participant. To convert these data into ready to animate scans, which allows the mapping of motion tracking data to these scans, we further processed the data by fitting a generic template model to the point clouds and computing a color texture from the photos taken for the fitted model (for details of template fitting, see Achenbach et al., 2017). Specifically, the template model was a surface mesh of a human body and featured an embedded skeleton for animating the mesh. By closely fitting the template model to the data, we reused the skeleton for the fitted model. The 3D characters resulting from this procedure were of high geometry and texture detail, with the final model closely resembling the participant's appearance (body, face, clothes etc.). This 3D character could then be readily animated using motion tracking data, as done in our virtual environment. The whole process of scanning and processing the data took about ten minutes and involved minimal manual effort (for more details on the scanning and fitting procedures, see Achenbach et al., 2017).

Virtual coaching environment

We used a gym setting as a virtual coaching environment. The gym was equipped with a virtual mirror, displaying participant's actions. Moreover, an avatar standing in front of the virtual mirror (45° rotated) demonstrated the target action (for more details, see Procedure section).

Task and Measures

Motor task

The experimental task was a body weight squat. From a functional perspective (cf. Göhner, 1992, 1999; Hossner et al., 2015), the squat is a self-paced, full-body movement that consists of distinct movement phases: after setting up (i.e., preparation), the athlete moves downward by flexing hips and knees until they reach their lowest point (i.e., main phase), before extending the knee and hip joints to move upwards, returning to their start position (i.e., attenuation). We considered the bodyweight squat to be suitable for coaching in VR, and AOMI in particular, because technique and movement quality are key factors during execution of a squat. While novices can execute the action as a whole, they do differ from more skilled individuals in their technique, and typically show erroneous performance with room left for improvement. Finally, we chose the squat as a self-paced action of relatively low speed as it can be executed while staying in the same place, and as such it is suitable to be executed in a CAVE.

Motor performance

We recorded participants' squats by way of a motion capture system (OptiTrack, Corvallis, Oregon). Specifically, we tracked the execution of the squat using ten Prime 13W cameras, with a sampling frequency of 240 Hz and a spatial resolution of 1280 x 1024 pixels. We collected data from 41 markers placed around the relevant joints for tracking whole body movements (standard set by OptiTrack). To quantify the participants' performance, we analysed three variables: participants' overall performance, error patterns and kinematics at the deepest point of the squat (see Data Analysis).

Cognitive representation structure

To measure participants' cognitive representations of the squat stored in their memory, we used structural dimensional analysis of mental representation (SDA-M). This method provides psychometric data on the structuring and dimensioning of cognitive representations of complex actions in long-term memory (for more details, see Schack, 2012). The method proceeds in several steps: Participants perform a split procedure on a suitably predetermined set of basic action concepts (BACs) (for details, see Procedure section). Based on the distance scaling between BACs as obtained from the split procedure, a hierarchical cluster analysis is used to outline the structure. An analysis of invariance allows comparison of structures within- as well as between-groups (for details, see Schack, 2012 and Data Analysis section). From this, it is possible to determine relationships between BACs and their groupings respectively, as an indicator for how one's cognitive representation is structured in long-term memory.

For the specific purpose of the present experiment, a pre-determined set of BACs of the squat was used, with each of the BACs pertaining to one of each movement phases (adopted from Hülsmann et al., 2019): (1) shoulder-width stance, (2) toes slightly rotated outwards, (3) upright posture, (4) bend legs, (5) push bottom backward, (6) keep upright posture, (7) knees remain behind toes, (8) knees remain in same axis as feet and hip joints, (9) heels remain on the ground, (10) knee angle 100°, (11) push hips forward, and (12) extend legs. Each of the BACs of the squat can be designated to one movement phase: Setting up (BAC 1-3), going-down (BAC 4-10), going-up (BAC 11-12). In addition, the set consisted of four additional error pattern concepts (EPC 13-16). The EPCs relate to the main phase of the movement, the moving down phase of the squat: (12) knees move forward, (13) knees move inward, (14) heels leave the ground, (15) upper back is round (for details on the set of BACs and EPCs, see Table 1).

Specifically, the splitting task operates as follows: One concept of the squat is shown on the screen for the next 15 decisions (i.e., the anchor concept), while the rest of the concepts (n = 15) are displayed one after another in randomized order. Participants decide on a yes/no basis whether the two presented BACs (here: verbal labels) relate to one another during movement execution (of the squat) or not. As soon decisions have been recorded for the anchor concept and all 15 other concepts, another BAC takes the anchor position and the procedure continues. The split procedure lasted approximately 20 minutes and was complete when participants had compared each concept to the remaining concepts (16 x 15 = 240 decisions).

Self-efficacy

Four questions, one on the overall performance of the squat and three relating to different details of the squat, served to measure self-efficacy based on Bandura's (2006 guidelines for efficacy measurement. Specifically, we asked participants how confident they were to execute the squat properly, to reach the proper depth of the squat, to distribute their weight appropriately, and to coordinate their arms and legs accurately during the squat. Participants rated each of the questions on a scale from 0 to 100 percent in steps of ten (i.e., 0, 10, 20 etc.).

Imagery ability

We measured visual and kinesthetic imagery ability using the Revised version of the Movement Imagery Questionnaire (MIQ-R; Hall & Martin, 1997). Participants performed, imagined and rated the ease with which they could generate their imagery experience for several movements on 7-point Likert scales ranging from 1, *hard to image,* to 7, *easy to image*.

Virtual reality experience

To check for simulator sickness, we administered the simulator sickness questionnaire in the beginning of the study as well as after the intervention (Kennedy et al. 1993). This served to exclude participants who may be susceptible to sickness in VR environments in general and those who experiences sickness during acquisition phase. To learn more about the participants' VR experience, we asked questions on sense of agency, body ownership, perceived latency, plausibility, and two control questions (see Table 2). Questions were answered on 7-point Likert scales, ranging from -3 to 3 (3 indicating maximum agreement and -3 indicating maximum disagreement).

Imagery and observation experience

In addition to the measures described above, we administered an 8-item post-experimental questionnaire as a manipulation check to measure whether participants had followed the AOMI instructions. We asked participants how easy/difficult it was for them to observe the scene, to imagine the scene and to imagine the feeling of the movement during observation (all rated on 7-point Likert scales: 1 = *very difficult*, 7 = *very easy*). Furthermore, participants rated the clarity and vividness of their imagery as well as the feeling during their imagery (both: 1 = *very difficult*, 7 = *very easy*), and the frequency of using an external perspective as well as an internal perspective (1 = *never*, 7 = *always*). Finally, participants were asked if they had been motivated during imagery (1 = *not at all true*, 7 = *very much true*).

Procedure

Pre-test

On the first day, participants signed informed consent forms, provided demographic information and filled out the questionnaires on simulator sickness. To create a virtual version of each participant, we scanned participants in our scanning laboratory. While the experimenter further processed the data, participants completed the MIQ-R. Participants then completed the split procedure on a computer as part of the SDA-M to assess initial cognitive representation structure for the squat. Participants then put on the motion capture suit. The experimenter placed 41 retro-reflective markers on pre-defined anatomical landmarks. To assess initial self-efficacy levels, participants reported on the four self-efficacy questions regarding the squat. Next, participants entered the CAVE wearing 3D glasses. Participants were asked to attentively observe a virtual character performing two repetitions of a skilled squat. To assess initial squat performance, participants were asked to perform the squats as similarly as possible to the recordings shown in the skilled model they had previously seen with respect to speed, posture and depth. Participants then performed two blocks of five single squats. The virtual mirror was disabled during test phases so that participants did not receive any augmented feedback on their performances during testing.

Acquisition phase

During each of the six acquisition blocks, participants first simultaneously watched and imagined ten repetitions of the squat without movement execution (i.e., 10 x AOMI) and then executed five squats (i.e., 5 x EXE). We repeated each block six times (Block 1: AOMI, EXE; Block 2: AOMI, EXE; …), resulting in 60 AOMI and 30 EXE trials overall.[1]

During AOMI, participants saw an avatar of themselves performing a body weight squat (i.e., Me-Novice or Me-Skilled) in front of the virtual mirror in real-time from an angle of 45° (see Figure 1A and 1B). This view combined the front and side view to best serve motor performance and learning of novice learners (characteristics chosen according to the Applied Model for the Use of Observation (AMUO); Ste-Marie et al., 2012). We asked participants to try and observe the squats as attentively as possible whilst simultaneously imagining the feelings that they would experience when executing a squat themselves. We repeated this instruction before the first, third and fifth blocks. During EXE, they saw themselves (i.e., their own avatar) performing in the virtual mirror in real-time like in a real mirror, but 45° rotated (see Figure 1A). To this end, we used participants' movements captured via Optitrack to animate their avatar, and to display it in a virtual mirror on the walls in the CAVE. This process

[1] We chose the number of blocks and trials per block during acquisition based on existing AOMI and VR related research (e.g., Clark et al., 2007; Eaves et al., 2011; Hülsmann et al., 2019).

was delivered ‘live’ at approx. 95 fps with a latency of around 60 ms. Thus, the only difference to a real mirror was a 45° rotation which we applied to the avatar in the virtual mirror.

Post-test

After the acquisition phase, participants again responded to the four squat related questions to assess their self-efficacy levels again. To assess the resulting performance of their squats, participants again performed two blocks of five squats each (for details, see pre-test). Finally, participants filled out questionnaires relating to simulator sickness and their experience in the virtual environment (cf. Table 2). The procedure on the first day, including the pre-test, acquisition phase and post-test, lasted approximately two hours.

Retention-test

The next day, we assessed the participants’ final level of self-efficacy, motor performance and representation structure of the squat (for details, see pre-test). The retention-test lasted approximately one hour.

Data Analysis

Imagery ability

To control for imagery ability, we conducted three separate independent t-tests on overall, visual, and kinesthetic imagery ability.

Imagery and observation experience

As a manipulation check, we conducted independent samples t-tests for each question on participants’ AOMI experience to control for potential group differences that may have arisen from more general, AOMI related differences.

Virtual reality experience

To check for simulator sickness, we calculated each participant’s median prior to and after the virtual reality experience. For the questionnaire on participants’ virtual reality experiences (cf. Table 2), we used independent samples t-tests for each item to test whether participants' responses significantly differed between the two groups.

Motor performance

To quantify the participants' performance, we analysed three variables: participants' overall performance, error patterns and kinematics at the deepest point of the squat.

Overall performance. As an overall measure of movement quality, we calculated deviations from participants' initial performance as shown during pre-test (i.e., deviations from their sixth squat performed) as well as deviations from the skilled performance (i.e., the skilled performance shown during acquisition) for each time of measurement. We used dynamic time warping (DTW) as a method to link frames of participants' performances to frames of either their pre-test performance or the skilled performance. From this procedure, it is possible to determine spatial as well as temporal deviations accumulated over the whole movement (for details and formulas, see supplemental material from Hülsmann et al., 2019).

Error patterns. To detect errors in participants' performances of the body weight squat and their changes over time, we classified three error patterns during squat performances at each time of measurement. We used both data-driven classifiers as well as manually constructed ad-hoc classifiers to detect three error patterns, that is 'wrong dynamics', 'incorrect weight distribution' and 'too deep' (adopted from Hülsmann et al., 2018).

Kinematics. To further validate whether changes in movement quality were functional, we focused on the center of mass at the deepest point during the squat movement for each time of measurement. This served to reveal changes in depth (y-axis; up/ down) as well as in weight distribution (x-axis; back/ forth) over time (for details and formulas, see supplemental material from Hülsmann et al., 2019). Both moving the center of mass backwards during the movement as well as reversing at a point higher than 90° of knee angle are indicators of a proper squat technique and in this sense skilled performance.

To track changes over time across groups, we ran separate 2 (group: Me-Novice, Me-Skilled) x 4 (time of measurement: pre, intervention, post, retention) mixed measures ANOVAs.

Cognitive representation

Drawing on the Euclidean distance scaling between BACs as obtained by the split procedure, cluster analyses were performed (α = .05; d_{crit} = 3.41) to outline the structure of cognitive representations. Mean group tree diagrams were computed for each group and each time of measurement (for more details, see Schack, 2012).

An analysis of invariance within- and between-groups served to compare different cluster solutions, and thus to track the change in cognitive representation structures. According to Schack (2012), two cluster solutions are variant, that is significantly different, for $\lambda < .68$, while two cluster solutions are invariant for $\lambda \geq .68$. In addition, the similarity between representation structures and a reference structure reflecting well the different movement phases (i.e., preparation phase [BAC 1 2 3]; main phase [BAC 4 5 6 7 8 9 10 11 12]; error patterns [BAC 13 14 15 16]) was examined. The Adjusted Rand Index (ARI; Rand, 1971; Santos & Embrechts, 2009) served as an indicator of similarity between mean group tree diagrams and the reference tree diagram. Indices between "-1" (cluster solutions are different) and "1" (cluster solutions are the same) mark the degree of similarity.

Self-efficacy

To track changes over time across groups, we ran separate 2 (group: Me-Novice, Me-Skilled) x 3 (time of measurement: pre, post, retention) mixed measures ANOVAs on participants' ratings for overall self-efficacy as well as for the three subscales.

Results

Imagery ability

Overall, participants reported acceptable visual imagery ability ($M = 22.65$, $SD = 2.58$.; 5.66 per item) as well as acceptable kinesthetic imagery ability ($M = 20.73$, $SD = 4.31$.; 5.18 per item). On average, imagining the motor actions was *easy to see* and *somewhat easy to feel* for participants. In addition, independent t-tests on imagery ability revealed no difference between groups, neither for overall imagery ability, $t(24) = -.531$, $p = .600$, nor for visual imagery ability, $t(24) = -.224$, $p = .825$, or kinesthetic imagery ability, $t(24) = -.583$, $p = .565$. This indicates that imagery ability was similar for each of the two groups.

Imagery and observation experience

Participants reported that they engaged with the AOMI as instructed. They found it *somewhat easy* (Me-Novice) or *neither easy nor difficult* (Me-Skilled) to observe the squats attentively whilst imagining themselves performing the squat focusing on the feel of the movement (for details, see Table 2). Independent t-tests revealed that the two groups did not differ in any of the questions relating to participants' AOMI experience (all ps $\geq .116$).

Virtual reality experience

Regarding their interaction with the virtual environment, participants did not indicate any simulator sickness, neither in general nor directly after the intervention phase (both $Mdn = 0$). Furthermore, the two groups did not differ in any of the items relating to their virtual reality experience (all ps $\geq .154$). This indicated that both groups had experienced similar sense of agency, ownership, perceived latency, and plausibility toward their avatars (for details, see Table 3).

Motor performance

Overall performance. In comparison to the participants' own performance at baseline, a 2 x 4 repeated measures ANOVA revealed a significant main effect of time for spatial deviation, $F(3,72) = 4.803$, $p = .004$, $\eta_p^2 = .167$. The interaction effect, $F(3,72) = .631$, $p = .598$, $\eta_p^2 = .026$, and the main effect of group, $F(1,24) = .239$, $p = .629$, $\eta_p^2 = .010$, were not significant. Furthermore, analyses revealed a significant main effect of time for temporal deviation, $F(3,72) = 11.810$, $p < .001$ $\eta_p^2 = .330$. The interaction effect, $F(3,72) = .870$, $p = .461$, $\eta_p^2 = .035$, and the main effect of group, $F(1,24) = .634$, $p = .434$, $\eta_p^2 = .026$, were not significant. Post hoc comparisons showed that both the spatial and temporal deviation increased across acquisition, post-test and retention-test, as compared to the pre-test (all ps < 0.05), indicating that participants' performance differed from their initial performance.

In comparison to the skilled performance of the model, analyses on the participants' spatial error revealed neither a significant main effect of time, $F(3,72) = 2.587$, $p = .060$, $\eta_p^2 = .097$, nor a significant group x time interaction effect, $F(3,72) = .809$, $p = .493$, $\eta_p^2 = .033$. The main effect of group was also not significant, $F(1,24) = .067$, $p = .798$, $\eta_p^2 = .003$. Similarly, for temporal error, the main effect of time, $F(3,72) = .625$, $p = .601$, $\eta_p^2 = .025$, the group x time interaction, $F(3,72) = .323$, $p = .809$, $\eta_p^2 = .013$, and the main effect of group, $F(1,24) = 1.277$, $p = .270$, $\eta_p^2 = .051$, were not significant.

Error patterns. For the EP 'Incorrect weight distribution', a 2 x 4 repeated measures ANOVA revealed no significant main effect of time, $F(3,72) = 1.576$, $p = .203$, $\eta_p^2 = .062$, nor a group x time interaction, $F(3,72) = .571$, $p = .493$, $\eta_p^2 = .023$. The main effect of group was also not significant, $F(1,24) = .617$, $p = .440$, $\eta_p^2 = .025$. For the EP 'Too deep', the group x time interaction effect was significant, $F(3,72) = 5.323$, $p = .002$, $\eta_p^2 = .82$. Post hoc comparisons revealed an increase in error for the Me-Novice group for acquisition phase and post-test compared to pre-test (all ps < .05). Both the main effect of time, $F(3,72) = .365$, $p = .778$, $\eta_p^2 = .015$ and the main effect of group, $F(1,24) = 1.391$, $p = .250$, $\eta_p^2 = .055$, were not significant. For the EP 'Wrong movement dynamics', analyses showed no main effect of time, $F(3,72) = 1.881$, $p = .140$, $\eta_p^2 = .073$, or group x time interaction, $F(3,72) = .658$, $p = .580$, $\eta_p^2 = .027$. The main effect of group was not significant either, $F(1,24) = 1.688$, $p = .206$, $\eta_p^2 = .066$.

Kinematics. To further validate whether changes in motor performance were functional, we conducted two separate 2 x 4 mixed measures ANOVAs on the two directions of the center of mass (com) at the deepest point of the movement (i.e., up/ down: depth; back/ forth: weight distribution). Results revealed a significant effect for depth, but not for weight distribution at the deepest point. For depth, we found a significant group x time interaction effect, $F(3,72) = 7.717$, $p < .001$, $\eta_p^2 = .243$. Post hoc comparisons revealed changes in the Me-Novice group for acquisition, post-test and retention-test compared to pre-test (all ps < 0.05), with squats becoming deeper over time. Both the main effect of time, $F(3,72) = 1.289$, $p = .285$, $\eta_p^2 = .051$ and the main effect of group were not significant, $F(1,24) = 2.259$, $p = .146$, $\eta_p^2 = .086$. For weight distribution at the deepest point, we found no significant main effect of time, $F(3,72) = .328$, $p = .805$, $\eta_p^2 = .013$, or group x time interaction effect, $F(3,72) = 2.039$, $p = .116$, $\eta_p^2 = .078$. The main effect of group was not significant either, $F(1,24) = .004$, $p = .952$, $\eta_p^2 = .000$.

To summarize, while overall squat performance changed such that it became different from participants' initial performances, overall squat performance did not change towards that of the skilled performance. Furthermore, the error pattern 'Too deep' increased in the Me-Novice group over time, with the magnitude of all other EPs remaining stable over time in the two groups. Kinematics at the deepest point of the squat revealed that the Me-Novice group performed deeper squats after acquisition phase, post-test and the retention interval compared to pre-test.

Cognitive representation

Mean group tree diagrams are displayed in Figure 3. For each tree diagram, the numbers on the x-axis relate to one particular BAC (for the list of BACs, see Table 1). The numbers on the y-axis display Euclidean distances. The lower the Euclidean distance between BACs, the closer the BACs are. The horizontal dotted line marks the critical value d_{crit} for a given α-level

(d_{crit} = *3.41;* α = .05): links between BACs above this line are considered not related, links between BACs below this line result in groupings or clustering of BACs, as highlighted by the horizontal grey lines on the bottom.

The Me-Novice group's tree diagrams at pre-test was comprised of one cluster holding four BACs ([1 3 6 8]) pertaining to two different phases (i.e., preparation phase [BAC 1 and 3] and main phase [BAC 6 and 8] of the squat). At retention-test, this cluster was comprised of three BACs ([1 3 8]), two relating to the preparation phase and one to the main phase of the squat. The Me-Skilled group's tree diagram at pre-test revealed two clusters ([1 3 6 8]; [4 10]), one comprised of four BACs of two different phases (i.e., preparation phase [BAC 1 and 3] and main phase [BAC 6 and 8] of the squat) and one comprised of two BACs of the main phase [BAC 4 and 10]. Similarly, two clusters were evident at retention-test ([3 6 8 12]; [4 10]). However, while one cluster was the same at retention-test (that of the main phase: [BAC 4 and 10]), the mixed cluster had changed and finally involved three BACs of the main phase and one BAC of the preparation phase ([BAC 3 and BAC 6, 8 and 12]). This means that the number of BACs of the preparation phase decreased in this particular cluster, while the number of BACs of the main phase had increased.

Analysis of invariance revealed that the representation structure of the Me-Novice group remained invariant (i.e., the same: λ = .93) from pre- to retention-test, while the structure of the Me-Skilled group was variant from pre- to retention-test (i.e., had changed over time: λ = .65). Specifically, representation structures in the Me-Skilled group became more similar to the reference structure over time (ARI_{pre} = 0.02, $ARI_{retention}$ = 0.06), while this was not the case for the Me-Novice group (ARI_{pre} = -0.01, $ARI_{retention}$ = -0.01).

Self-efficacy

For overall self-efficacy, a 2 x 3 mixed measures ANOVA revealed neither a main effect of time, $F(2,48) = 1.041$, $p = .361$, $\eta_p^2 = .042$, nor a group x time interaction effect, $F(2,48)$ =

.107, p = .899, η_p^2 =.004. The main effect of group was also not significant, $F(1,24)$ = .740, p = .398, η_p^2 =.03. For the subscale depth, we found a main effect of time, $F(2,48)$ = 3.537, p = .037, η_p^2 = .128. The interaction effect, $F(2,48)$ = .524, p = .596, η_p^2 = .021, and the main effect of group, $F(1,24)$ = .455, p = .507, η_p^2 = .019, were not significant. For the subscale weight distribution, the mixed measures ANOVA revealed a main effect of time, $F(2,48)$ = 9.880, p = .000, η_p^2 = .292. The interaction effect, $F(2,48)$ = .093, p = .911, η_p^2 = .004, and the main effect of group, $F(1,24)$ = .110, p = .743, η_p^2 = .005, were not significant. For the subscale movement dynamics, we found a main effect of time, $F(2,48)$ = 4.647, p = .014, η_p^2 = .162. The interaction effect, $F(2,48)$ = .623, p = .541, η_p^2 = .025, and the main effect of group, $F(1,24)$ = .885, p = .356, η_p^2 = .036, were not significant. Post hoc comparisons showed that self-efficacy related to weight distribution increased from pre-test to post-test and from pre-test to retention-test (all ps < 0.05) across groups, and self-efficacy related to depth and movement dynamics increased from pre- to retention-test (all ps < 0.05).

Discussion

In this study we investigated the impact of feedforward modeling of a complex motor action on motor performance, cognitive representation, and self-efficacy using a pre-post-retention-test design. To this end, we used virtual reality to differentiate the model's appearance and the model's performance level. This allowed to contrast model performance level (i.e., novice vs. skilled) whilst controlling the familiarity of the model (i.e., myself). Novices watched an avatar of themselves and simultaneously imagined themselves (AOMI) performing a body weight squat either at an advanced skill level (Me-Skilled) or at their current skill level (Me-Novice). We predicted that both types of AOMI would lead to improvements in motor performance, cognitive representation, and self-efficacy, and expected greater improvements in the Me-Skilled group compared to the Me-Novice group. Overall, results were partly in line with our hypotheses. Motor performance of the squat changed compared to participants' initial performances in both groups, with participants in the Me-Novice group showing more erroneous performance after the intervention. Moreover, cognitive representations in the Me-Skilled group became more functional. Finally, self-efficacy relating to selected specific aspects of the squat increased in both groups.

Regarding motor performance of the squat, overall movement quality changed over the course of the study for both groups. In line with studies showing that AOMI practice can affect movement quality (e.g., Marusic et al., 2018; Romano-Smith et al., 2019) and motor performance (e.g., Kim et al., in press; Marshall et al., 2020; Marusic et al., 2018; Robin et al., 2019; Romano-Smith et al., 2018), movement quality in both groups deviated from participants' initial performances temporally and spatially after the intervention, as well as after one day of retention. Our results thus confirm findings from prior research showing that AOMI has the potential to change behavior, which is important not only for different sports contexts (e.g., Robin et al., 2019), but also for (re-)learning contexts such as rehabilitation (e.g., Marusic et al., 2018).

Contrary to our hypotheses, however, none of the groups revealed any changes in overall movement quality towards that of the skilled performance. First, the Me-Novice group performed increasingly erroneous (i.e., too deep) squats, as confirmed by both classifiers and kinematics. Although this result was not expected given the potential positive effects of self-modeling (for a review, see McCullagh et al., 2012), it has been shown that modeling one's own performance and related weaknesses for novices can have detrimental effects (Bradley, 1993 in McCullagh et al., 2012) and so may explain the increased error in our sample. It may be that modeling the current level of performance provided a sub-optimal visual representation of the movement that, combined with lack of information about how the movement should be done to allow for error detection/correction, was not sufficient to promote performance benefits.

Second, although AOMI of a skilled performance led to changes in overall quality of the movement compared to participants' initial performances, it did not lead to improvements toward that skilled performance in the present study. Skilled models have previously proven beneficial (Martens et al., 1976), although not necessarily more beneficial compared to learning models (McCullagh & Caird, 1990; Pollock & Lee, 1992). Along these lines, one potential explanation why performance did not (yet) develop toward the skilled performance may be that the skilled performance used for the present study did not match an appropriate level of difficultly. Watching and imagining a future self, performing at moderate difficulty levels (Aoyama et al., 2020), i.e., just one step beyond their own repertoire, may have better promoted novices' learning. Another reason might be that changes in the quality of a movement over the course of learning reflect complex problem solving and therefore are highly individual, relating to the individual's biological, motor and cognitive prerequisites (Bernstein, 1967, 1971, 1996). Changes in overall squat performance, as observed in the present study, may reflect learning at an early cognitive stage (in line with functional changes in cognitive representation in the Me-Skilled group, see below) that is not (yet) reflected as a functional change at the behavioral level. Future studies with longer interventions, allowing novices to practice over the course of multiple days or weeks may provide more insights into learning as it transfers from cognitive to behavioral changes.

While motor performance did not develop towards that of a skilled performance, cognitive representation structures became more functional in the Me-Skilled group after feedforward AOMI, as revealed by an increase of similarity of the mean group tree diagram compared to a reference structure. This corroborates findings from studies showing that AO and AOMI of a skilled performer leads to functional changes in one's cognitive action representation (Frank et al., 2018; Kim et al., 2020; Kim et al., in press), and extends the findings by showing that novices' cognitive representations reveal functional changes after watching and imagining oneself being the skilled performer. Moreover, previous research indicates that changes in cognitive representation structure after MI and/ or AO training precede performance changes, and come into effect only after task execution (Frank et al., 2014; Frank et al., 2016; Frank et al., 2018). It may therefore be that learning has occurred on the cognitive levels in the present study (cognitive stage: Fitts & Posner, 1967), and may transfer to sensorimotor levels of action organization after longer term practice (i.e., perceptual-cognitive scaffolding; Schack et al., 2016). Contrary to our hypotheses, however, self-review AOMI did not result in functional changes in memory over time. One potential explanation might be that watching and imagining one's own novice performance corresponds exactly to one's own current cognitive representation, and thus does not provide useful information to aid the development of the representation beyond the current level.

Finally, self-efficacy increased in both groups for all items related to specific aspects of the squat indicating that AOMI practice can improve self-efficacy in performers. In contrast to our hypotheses, feedforward AOMI did not lead to higher self-efficacy compared to self-review AOMI in the present study. This might be attributed to the fact that we did not inform participants in the Me-Skilled group explicitly that they were watching the technique of a skilled other. Consequently, these participants may have assumed that they were watching their own current performance standard, given that the self-related visual characteristics of the avatar. In contrast, in previous modeling and feedforward modeling studies that show beneficial effects of watching skilled performance (for reviews, see Feltz et al., 2008; Ste-Marie et al., 2011, 2020) participants are usually aware of the fact that they watch a skilled performer. Independent of group, this may have led participants to think that they saw their own performance leading to similar changes in their beliefs.

A potential limitation of the present study was that we did not include action observation or motor imagery control groups. From the design of the present study, it is not possible to draw any conclusions about the impact of MI, or whether the combination of AOMI is better than AO alone. While the focus of the study lay on the impact of feedforward modeling during AOMI, it would be interesting to learn about whether feedforward AOMI has additive effects compared to AO or MI alone in future studies. Moreover, the relative short length of the study and relatively few practice trials during acquisition phase may have resulted in the lack of clear differences between the groups and a clear development in direction of the skilled performance. Larger differences would probably emerge over a greater length of practice. Another possible reason for the small effect between groups could be that the number of squat repetitions may have caused physical fatigue which in turn may have led to decreased imagery accuracy in both groups (Di Rienzo et al., 2012). Future studies, therefore, should consider utilizing more practice sessions over several days or weeks during the acquisition phase, and control for physical fatigue. Although we consider the squat a complex task with many degrees of freedom that must be coordinated during the movement, it is self-paced and relatively slow and simple. While feedforward AOMI might not come into effect in simpler sports tasks, it may be more effective for more complex tasks of higher speeds or with larger ranges of motion. Feedforward AOMI across tasks and across different dimensions of complexity should therefore be examined in future studies. Finally, watching an avatar of themselves was a novel experience for most of the participants and may consequently promote emotional responses that in turn influence participants' actions. It may be worthwhile to measure and control for emotional aspects in future studies when watching a realistic, personalized avatar representing the self during learning and coaching interactions in VR (Latoschik et al., 2017; Ratan, 2012; Waltemate et al., 2018).

In sum, the present study partly confirmed our idea that feedforward AOMI, that is watching and imagining oneself performing at an advanced skill level, can be beneficial. Findings revealed that feedforward AOMI maintained motor performance but improved cognitive representation structure. Self-efficacy improved after both feedforward and self-review AOMI. In comparison to watching and imagining oneself performing at the current novice skill level, watching and imagining oneself performing at a more advanced skill level prevented from making errors and led to functional changes in underlying representations. This improved cognitive representation structure may be indicative of perceptual-cognitive scaffolding during motor learning (Frank et al., 2014; Frank et al., 2020; Schack et al., 2016) that might be beneficial in promoting longer term performance changes. Simultaneous imagery whilst observing future states of action may therefore help to establish cognitive prerequisites that enable better motor performance.

This is the first study to show AOMI feedforward modeling effects using VR. It opens up a promising line of future research and offers a variety of practical applications. First, watching a potential future self may be a valuable tool for learning and coaching in a variety of contexts such as sports, rehabilitation, or physical education. As such, VR is a welcome addition to traditional forms of training as it offers ways to tailor training to the individual (e.g., in terms of appearance, skill level etc.). Second, now that it becomes possible to watch oneself performing at different levels one has not yet achieved, learning together with a future self may enrich coaching not only in terms of behavioural outcomes, but as well with regards to the learner’s motivation and emotion. To experience a future self may not only promote learning, but also motivate athletes, patients or students to invest in their practice and to develop towards an achievable future. Third, watching and imagining oneself performing at an advanced level may prove particularly valuable in children, as it provides better access to imagery training via action observation (Frank et al., 2020; Scott et al., 2020) whilst focusing on a potential future self (Dowrick & Raeburn, 1995; Hitchkock et al., 2004). Finally, and from a more general perspective on VR in sports and sport psychology (Frank, 2020; Neumann et al., 2018), VR can be used as well as an alternative when physical training is not possible due to fatigue or during rehabilitation from injury. As it becomes more affordable, VR becomes more and more accessible to practitioners and will hopefully become a standard tool in applied sport psychology one day.

To conclude, the present study advances the field of feedforward modeling research towards feedforward AOMI, while future work is needed to further explore the potential impact of feedforward AOMI across tasks, skill levels and age. Given the opportunities that VR offers, it has become possible to disentangle the model's appearance and the model's performance, and to display avatars that are both similar to the learner's appearance as well as to the well-coordinated motor actions of skilled performers. Feedforward AOMI therefore paves one promising way to tailor interventions according to the individual's characteristics and prospects, particularly in heterogeneous settings such as physical education (Frank et al., 2021). To this end, virtual reality is a promising tool to create potentially fruitful learning environments which meet individual needs during coaching and support individuals in achieving their goals.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author, CF, upon reasonable request.

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Figure captions

Figure 1. A Design of the study and procedure. The experiment consisted of a pre-test (10 x EXE of the squat), an acquisition phase during which participants executed the squat and imagined whilst observing the squat (6 blocks of 10 x AOMI followed by 5 x EXE) as well as a post-test (10 x EXE) and a retention-test (10 x EXE). B During AOMI blocks of the acquisition phase, participants watched an avatar of themselves and imagined themselves performing squats, either their own squat (Me-Novice group) or a squat of a skilled athlete (Me-Skilled group).

Figure 2. 3D scanning of participants with (a) a body scanner and (b) a face scanner.

Figure 3. Mean group tree diagrams of the squat for the Me-Skilled group from pre-test (a) to retention-test (b) and for the Me-Novice group from pre-test (c) to retention-test (d). For each tree diagram, the numbers on the *x*-axis relate to one particular BAC (for the list of BACs, see Table 1). The numbers on the *y*-axis display Euclidean distances. The lower the Euclidean distance between BACs, the closer the BACs are. The horizontal dotted line marks the critical value d_{crit} for a given α-level (d_{crit} = 3.41; α = .05). Horizontal grey lines on the bottom mark clusters.

Table 1

Basic action concepts (BACs) of the squat

N°	**Basic action concept (BAC)**	**Phase/ Errors**
1	Schulterbreiter Stand [Shoulder-width stance]	Preparation: Setting-up
2	Fußspitzen leicht nach außen gedreht [Toes slightly rotated outwards]	
3	Aufrechte Haltung [Upright posture]	
4	Beine beugen [Bend legs]	Main phase: Going-down
5	Gesäß nach hinten schieben [Push bottom backward]	
6	Aufrechte Haltung beibehalten [Keep upright posture]	
7	Knie bleiben hinter den Fußspitzen [Knees remain behind toes]	
8	Knie bleiben in einer Achse mit Fuß- und Hüftgelenken [Knees remain in same axis as feet and hip joints]	
9	Fersen bleiben am Boden [Heels remain on the ground]	
10	Kniewinkel 100° [Knee angle 100°]	
11	Hüfte vorschieben [Push hips forward]	Attenuation phase: Going-up
12	Beine stricken [Extend legs]	
13	Knie nach vorn schieben [Push knees forward]	Error patterns
14	Knie zeigen nach innen [Knees point inwards]	
15	Fersen vom Boden abheben [Heels leave the ground]	
16	Oberen Rücken rund machen [Bend upper back]	

Table 2

Descriptives of participants' imagery and observation experience per group and item.

	AOMI Experience	
	Me-Novice	Me-Skilled
	n = 13	*n* = 13
Q1. Ease of observation	5.46 ± 1.05	5.38 ± 0.87
Q2. Ease of imagery	4.46 ± 1.27	4.69 ± 0.95
Q3. Ease of kinesthetic imagery during observation	4.54 ± 0.78	3.92 ± 1.12
Q4. Motivation	5.54 ± 1.61	5.85 ± 0.80
Q5. Use of external imagery perspective	4.77 ± 1.30	5.23 ± 1.01
Q6. Use of internal imagery perspective	5.15 ± 1.21	4.85 ± 1.95
Q7. Ease of visual imagery	5.08 ± 1.38	5.00 ± 1.35
Q8. Ease of kinesthetic imagery	4.38 ± 1.66	4.08 ± 1.12

Note: Means and standard deviations of items investigating participants' experience of watching and imagining themselves in the two groups. The 7-point Likert scales ranged from 1 to 7, from *very easy* to *very difficult* (Q1, Q2, Q3, Q7, Q8), from *strongly agree* to *strongly disagree* (Q4) and from *always* to *never* (Q5, Q6).

Table 3

Descriptives of participants' virtual reality experience per group and item.

	Virtual Reality Experience	
	Me-Novice	Me-Skilled
	n = 13	*n* = 13
Agency. The avatar's movements were caused by mine.	1.92 ± 1.24	1.00 ± 1.76
Ownership. I felt like the avatar was my own body.	0.33 ± 2.23	0.75 ±1.91
Latency. The avatar moved as soon as I moved.	1.67 ± 0.89	1.50 ± 2.11
Plausibility. The movement of the avatar seemed plausible.	1.00 ± 1.71	1.42 ± 1.31
Control 1. I felt as if I had more than one body.	-2.25 ± 1.06	-1.75 ± 1.06
Control 2. I felt as if the virtual avatar would move to me.	-1.50 ± 1.31	-2.08 ± 1.24

Note: Means and standard deviations of items investigating participants' experience toward the virtual character in the two groups. The scale ranged from −3 to + 3 (+3 indicated maximum agreement).

Table 4

Descriptives of participants' motor performance.

	Motor performance							
	Me-Novice (n = 13)				Me-Skilled (n = 13)			
	Pre	Intervention	Post	Retention	Pre	Intervention	Post	Retention
Overall movement quality								
Deviation from initial performance								
Spatial error	.02 ± .01	.08 ± .13	.13 ± .23	.11 ± .06	.02 ± .02	.05 ± .03	.15 ± .24	.19 ± .23
Temporal error	2.29 ±.50	2.17 ± .33	2.32 ± .63	2.29 ± .74	1.99 ± .44	2.06 ± .35	2.18 ± .54	2.11 ± .57
Deviation from skilled performance								
Spatial error	.23 ± .07	.28 ± .17	.32 ± .20	.26 ± .09	.22 ± .06	.21 ± .05	.32 ± .21	.31 ± .19
Temporal error	1.75 ±.40	2.09 ± .41	2.18 ± .45	2.31 ± .53	1.78 ± .48	2.37 ± .65	2.40 ± .53	2.31 ± .81
Error patterns								
Wrong dynamics	-1.96 ± 2.28	-1.23 ± 2.26	-1.16 ± 2.10	-1.93 ± 2.56	-.37 ± 1.77	-.56 ± 1.63	-.30 ± 2.58	-1.19 ± 2.43
Incorrect weight distribution	-.36 ± 2.30	.51 ± 1.36	.42 ± 1.42	2.41 ± 6.47	.66 ± 1.36	.13 ± 2.32	4.79 ± 17.78	4.59 ± 13.17
Too deep	23.92 ± 19.61	33.61 ± 22.24	35.39 ± 23.54	34.33 ± 24.06	28.17 ± 21.78	20.71 ± 16.08	19.58 ± 16.45	23.45 ± 22.12
Kinematics at deepest point of the squat								
Depth	.75 ± .07	.71 ± .07	.71 ± .08	.71 ± .08	.74 ± .06	.77 ± .06	.77 ± .06	.76 ± .06
Weight distribution	.03 ±.12	.02 ± .12	.02 ± .10	.04 ± .11	.04 ± .11	.03 ± .12	.04 ± .11	.00 ± .12

Note: Means and standard deviations of the different motor performance variables per group and test phase.