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1 Running head: Feedforward AOMI in VR

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

4 Cornelia Frank^a, Felix Hülsmann^b, Thomas Waltemate^b, David J. Wright^c, Daniel Eaves^d,
5 Adam Bruton^e, Mario Botsch^f, Thomas Schack^g

6 ^a Sports and Movement Research Group, Department of Sports and Movement Science,
7 School of Educational and Cultural Studies, Osnabrück University, Osnabrück, Germany

8 ^b Computer Graphics and Geometry Processing Group, Faculty of Technology, Bielefeld
9 University, Bielefeld, Germany

10 ^c Research Centre for Health, Psychology and Communities, Department of Psychology,
11 Manchester Metropolitan University, Manchester, United Kingdom

12 ^d School of Health and Life Sciences, Teesside University, Middlesbrough, United Kingdom

13 ^e Sport and Exercise Science Research Centre, Department of Life Sciences, University of
14 Roehampton, London, United Kingdom

15 ^f Computer Graphics Group, TU Dortmund University, Dortmund, Germany

16 ^g Neurocognition and Action - Biomechanics Research Group, Faculty of Psychology and
17 Sports Science, Bielefeld University, Bielefeld, Germany

18

19 Author's address:

20 Please send correspondence to Cornelia Frank, Sports and Movement Research Group,
21 Jahnstraße 75, 49080 Osnabrück, Germany

22 E-Mail: cornelia.frank@uni-osnabrueck.de

23 Voice: 0049 541 969 4547

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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

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

50 Watching someone else perform a motor action, either via a live demonstration or
51 video, can be a powerful tool to improve performance and promote motor learning. Action
52 observation (AO) is a well-established method to enrich the coaching of motor actions and
53 speed up the learning process (for reviews, see McCullagh et al., 2012; Ste-Marie et al., 2012,
54 2020). Research has shown that watching someone else perform a movement affects motor
55 performance variables such as outcome accuracy (Hayes et al., 2008) and coordination
56 patterns (Horn et al., 2007) as well as psychological variables such as self-efficacy (Feltz et
57 al., 1979; for reviews, see Feltz et al., 2008; Short & Ross-Stewart, 2008). Similarly, using
58 motor imagery (MI) to rehearse a motor action in one's mind without actually executing it
59 (Jeannerod, 1995; Munzert & Zentgraf, 2009) can improve motor performance and promote
60 motor learning across a variety of tasks and variables (for meta-analyses, see Simonsmeier et
61 al., 2020; Toth et al., 2020), and contributes to improved self-efficacy (MacKenzie & Howe,
62 1997; Sohoo et al., 2004). A recent suggestion is that the combination of action observation
63 and motor imagery (AOMI), whereby individuals observe an action while simultaneously
64 imagining the feelings associated with executing that same action, may be even more
65 effective than AO or MI alone for improving motor performance and promoting motor
66 learning across a range of tasks (Eaves et al., 2016; Vogt et al., 2013). For instance, AOMI
67 was found to be more effective in improving hamstring force compared to MI alone (Scott et
68 al., 2018), and dart throwing accuracy compared to MI or AO alone (Romano-Smith et al.,
69 2018). Whilst AOMI is increasingly seen as being more effective for improving performance
70 (McNeill et al., 2020), the impact of AOMI on self-efficacy is not yet known.

71 From a neurophysiological point of view (for reviews, see Eaves, Riach, Holmes, &
72 Wright, 2016; Frank et al., 2020), AOMI is associated with greater activity in motor-related

73 brain areas (e.g., Nedelko et al., 2012; Taube et al., 2015), increased event-related desynchro-
74 nization in motor related frequency bands (e.g., Berends et al., 2013; Eaves, Behmer, & Vogt,
75 2016) and is associated with greater facilitation of corticospinal excitability (e.g., Sakamoto et
76 al., 2009; Wright et al., 2014). From a cognitive point of view, AOMI has been shown to help
77 structure underlying perceptual-cognitive representations of complex action (Kim et al., in
78 press), with AO and MI possibly playing different roles in this process (Kim et al., 2017). While
79 the provision of visual information through AO may influence cognitive representation features
80 such as the sequencing and timing aspects of the movement, MI may help structure components
81 relating to the sensory consequences of action via simulation of quasi-sensations (Frank et al.,
82 2020; Kim et al., 2017; Wright et al., 2018). Despite the growing body of AOMI research, how-
83 ever, the factors that moderate the effect of this technique on performance and learning are not
84 well understood.

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

98 kinematics but not in outcome performance. Although the differences found might be
99 attributed as well to the differences in skill levels of the models used, their findings might
100 indicate a potential beneficial effect for watching and imagining the self compared to another
101 person.

102 Self-as-a-model interventions can be distinguished according to whether they represent
103 a ‘review’ or a ‘preview’ version of the self, ranging from the replay of current or best
104 performances of the self (review) to edited videos of performances observers have not yet
105 achieved (preview), namely a feedforward preview of the self (Dowrick, 2012a, 2012b; Law et
106 al., 2017). The concept of feedforward self-modelling extends from Dowrick (1976, 1999,
107 2012a, 2012b) who argued that learning from an action becomes possible when an individual
108 models her/himself performing a behaviour that has not occurred previously, but for which the
109 necessary components are already in their motor repertoire. In this sense, feedforward modeling
110 relates to the artificial creation of one’s own behaviour that is potentially achievable in the
111 future, instead of a replication of another person’s behaviour at a level beyond one’s own
112 capabilities. Feedforward modeling (Clark & Ste-Marie, 2007; Starek & McCullagh, 1999; Ste-
113 Marie et al., 2011) can be an effective method that seems particularly promising in the realm of
114 motor learning, as it links the current self to a potential future version of the self.

115 In the sport domain, research on feedforward modeling has thus far focused on action
116 sequences such as swimming (Clark & Ste-Marie, 2007), trampoline routines (Ste-Marie et al.,
117 2011), and gymnastics bar routines (Rymal & Ste-Marie, 2017). To show the athlete’s
118 performances at a level they have not yet achieved, researchers typically use video editing
119 techniques to combine elements and create successful movement sequences. Editing video
120 footage to present a sequence of one’s best performances, despite the athlete never having
121 performed the entire sequence successfully, has produced promising results. For instance, Clark
122 and Ste-Marie (2007) found that watching an edited sequence of best performances of the

123 swimming stroke resulted in better performances in 6- to 10-year-old children compared to
124 watching their current performances of the swimming stroke. In a study where 7- to 13-year-
125 old children were tasked with learning two five-skill trampoline routines, Ste-Marie and
126 colleagues (2011) found that feedforward modeling, which included footage combining the best
127 performance of each individual trampoline skill to create a five-skill routine, enhanced motor
128 skill acquisition compared to verbal instructions. Self-efficacy increased over time independent
129 of group in both studies, although self-efficacy tended to be higher after learning in the
130 feedforward modeling groups in one of the two studies (Clark & Ste-Marie, 2007). While these
131 feedforward modeling findings seem promising for sport, no systematic evidence exists to date
132 comparing feedforward modeling to self-review in a single complex motor action.

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

148 of the AOMI experience, it is now possible to vary the model's expertise while holding the
149 model's appearance constant.

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

163 **Methods**

164 **Participants**

165 Twenty-six university students (mean age = 22.81, $SD = 3.15$; 17 female) participated
166 in the experiment. We determined the number of participants by way of an *a priori* power
167 analysis using G*Power (Franz Faul, Kiel University, Kiel, Germany; F tests/analysis of
168 variance: repeated measures, within-between interaction for a Type I error probability of 0.05,
169 a Type II error probability of 0.80 [Cohen, 1992], and an effect size of $f = 0.30$). We chose a
170 small effect size based on most related works (Chye et al., in preparation; Clark et al., 2007,
171 McNeill et al., 2021). None of the participants had any prior experience in executing the squat
172 on a regular basis or in squat-related coaching. We assigned participants randomly to one of

173 two conditions: self-appearance/ current novice performance (Me-Novice; $n = 13$; mean age =
174 22.15, $SD = 2.61$; 9 female) or self-appearance/ future skilled performance level (Me-Skilled;
175 $n = 13$; mean age = 23.46, $SD = 3.58$; 8 female). Mean imagery ability according to the MIQ-
176 R (Hall & Martin, 1997) was 42.77 ($SD = 6.25$) for the Me-Novice group and 44.00 ($SD = 5.55$)
177 for the Me-Skilled group. Participants received 24 Euro (8 Euro/ hour) for participating in the
178 study. We conducted the study in accordance with local ethical guidelines and conformed to
179 the declaration of Helsinki.

180 **Design**

181 A pre-, post-, retention-test design was used, with avatar appearance held constant
182 across conditions (i.e., self-as-a-model), model skill level (i.e., novice vs. skilled) as a between-
183 participants factor, and time (i.e., pre, post, retention) as a within-participants factor (see Figure
184 1; for more details, see Procedures). Hence, participants in each condition watched an avatar of
185 themselves performing the squat, but the avatar's performance differed in skill level.
186 Specifically, participants in the Me-Novice group watched themselves performing a novice
187 squat as recorded during pre-test. Thus, participants watched themselves performing at their
188 current level of expertise. Participants in the Me-Skilled group watched themselves performing
189 a skilled squat. This was done by animating their own avatar using pre-recorded movements of
190 a skilled individual. Thus, participants watched themselves performing at a level that was above
191 their current level of expertise.

192 **Apparatus**

193 *Cave automated virtual environment*

194 We conducted the study in an immersive, closed-loop virtual reality environment. The
195 2-sided, L-shaped Cave Automated Virtual Environment (CAVE) was equipped with two walls
196 sized 3m x 2.3 m (front and floor wall), and a resolution of 2100 x 1600 pixel. The virtual reality
197 was realized by way of four projectors, two projecting onto the front wall and two onto the floor

198 from the back, and run by a single computer (2 Intel Xeon CPU E5-2609 @2.4GHz, 16GB
199 Ram, 2 Nvidia Quadro P6000 GPUs). INFITEC filters allowed for passive stereoscopic vision.
200 The scene was rendered by using a self-developed, single-computer multi pipe approach for
201 rendering the two images for left/ right eye for each projection wall in the CAVE at approx. 95
202 fps, resulting in a low latency of approx. 60 ms (cf. Waltemate et al., 2015). Inside the CAVE,
203 the participant's movements were tracked using an optical motion tracking system (OptiTrack,
204 Corvallis, Oregon, U. S. A.; for details on the system's architecture, see de Kok et al., 2017;
205 Waltemate et al., 2015).

206 *Scanning*

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

224 *Virtual coaching environment*

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

229 **Task and Measures**

230 *Motor task*

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

243 *Motor performance*

244 We recorded participants' squats by way of a motion capture system (OptiTrack,
245 Corvallis, Oregon). Specifically, we tracked the execution of the squat using ten Prime 13W
246 cameras, with a sampling frequency of 240 Hz and a spatial resolution of 1280 x 1024 pixels.
247 We collected data from 41 markers placed around the relevant joints for tracking whole body
248 movements (standard set by OptiTrack). To quantify the participants' performance, we

249 analysed three variables: participants' overall performance, error patterns and kinematics at the
250 deepest point of the squat (see Data Analysis).

251 *Cognitive representation structure*

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

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

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

282 *Self-efficacy*

283 Four questions, one on the overall performance of the squat and three relating to
284 different details of the squat, served to measure self-efficacy based on Bandura's (2006
285 guidelines for efficacy measurement. Specifically, we asked participants how confident they
286 were to execute the squat properly, to reach the proper depth of the squat, to distribute their
287 weight appropriately, and to coordinate their arms and legs accurately during the squat.
288 Participants rated each of the questions on a scale from 0 to 100 percent in steps of ten (i.e., 0,
289 10, 20 etc.).

290 *Imagery ability*

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

295 *Virtual reality experience*

296 To check for simulator sickness, we administered the simulator sickness questionnaire
297 in the beginning of the study as well as after the intervention (Kennedy et al. 1993). This served
298 to exclude participants who may be susceptible to sickness in VR environments in general and

299 those who experiences sickness during acquisition phase. To learn more about the participants'
300 VR experience, we asked questions on sense of agency, body ownership, perceived latency,
301 plausibility, and two control questions (see Table 2). Questions were answered on 7-point Likert
302 scales, ranging from -3 to 3 (3 indicating maximum agreement and -3 indicating maximum
303 disagreement).

304 *Imagery and observation experience*

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

314 **Procedure**

315 *Pre-test*

316 On the first day, participants signed informed consent forms, provided demographic
317 information and filled out the questionnaires on simulator sickness. To create a virtual version
318 of each participant, we scanned participants in our scanning laboratory. While the experimenter
319 further processed the data, participants completed the MIQ-R. Participants then completed the
320 split procedure on a computer as part of the SDA-M to assess initial cognitive representation
321 structure for the squat. Participants then put on the motion capture suit. The experimenter placed
322 41 retro-reflective markers on pre-defined anatomical landmarks. To assess initial self-efficacy
323 levels, participants reported on the four self-efficacy questions regarding the squat. Next,

324 participants entered the CAVE wearing 3D glasses. Participants were asked to attentively
325 observe a virtual character performing two repetitions of a skilled squat. To assess initial squat
326 performance, participants were asked to perform the squats as similarly as possible to the
327 recordings shown in the skilled model they had previously seen with respect to speed, posture
328 and depth. Participants then performed two blocks of five single squats. The virtual mirror was
329 disabled during test phases so that participants did not receive any augmented feedback on their
330 performances during testing.

331 *Acquisition phase*

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

336 During AOMI, participants saw an avatar of themselves performing a body weight squat
337 (i.e., Me-Novice or Me-Skilled) in front of the virtual mirror in real-time from an angle of 45°
338 (see Figure 1A and 1B). This view combined the front and side view to best serve motor
339 performance and learning of novice learners (characteristics chosen according to the Applied
340 Model for the Use of Observation (AMUO); Ste-Marie et al., 2012). We asked participants to
341 try and observe the squats as attentively as possible whilst simultaneously imagining the
342 feelings that they would experience when executing a squat themselves. We repeated this
343 instruction before the first, third and fifth blocks. During EXE, they saw themselves (i.e., their
344 own avatar) performing in the virtual mirror in real-time like in a real mirror, but 45° rotated
345 (see Figure 1A). To this end, we used participants' movements captured via Optitrack to
346 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).

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

349 *Post-test*

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

356 *Retention-test*

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

360 **Data Analysis**

361 *Imagery ability*

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

364 *Imagery and observation experience*

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

368 *Virtual reality experience*

369 To check for simulator sickness, we calculated each participant’s median prior to and
370 after the virtual reality experience. For the questionnaire on participants’ virtual reality

371 experiences (cf. Table 2), we used independent samples t-tests for each item to test whether
372 participants' responses significantly differed between the two groups.

373 *Motor performance*

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

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

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

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

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

399 *Cognitive representation*

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

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

414 *Self-efficacy*

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

418 **Results**

419 *Imagery ability*

420 Overall, participants reported acceptable visual imagery ability ($M = 22.65$, $SD = 2.58$.;
421 5.66 per item) as well as acceptable kinesthetic imagery ability ($M = 20.73$, $SD = 4.31$.; 5.18
422 per item). On average, imagining the motor actions was *easy to see* and *somewhat easy to feel*
423 for participants. In addition, independent t -tests on imagery ability revealed no difference
424 between groups, neither for overall imagery ability, $t(24) = -.531$, $p = .600$, nor for visual
425 imagery ability, $t(24) = -.224$, $p = .825$, or kinesthetic imagery ability, $t(24) = -.583$, $p = .565$.
426 This indicates that imagery ability was similar for each of the two groups.

427 ***Imagery and observation experience***

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

433 ***Virtual reality experience***

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

440 ***Motor performance***

441 **Overall performance.** In comparison to the participants' own performance at baseline,
442 a 2 x 4 repeated measures ANOVA revealed a significant main effect of time for spatial
443 deviation, $F(3,72) = 4.803$, $p = .004$, $\eta_p^2 = .167$. The interaction effect, $F(3,72) = .631$, $p = .598$,
444 $\eta_p^2 = .026$, and the main effect of group, $F(1,24) = .239$, $p = .629$, $\eta_p^2 = .010$, were not

445 significant. Furthermore, analyses revealed a significant main effect of time for temporal
 446 deviation, $F(3,72) = 11.810, p < .001, \eta_p^2 = .330$. The interaction effect, $F(3,72) = .870, p =$
 447 $.461, \eta_p^2 = .035$, and the main effect of group, $F(1,24) = .634, p = .434, \eta_p^2 = .026$, were not
 448 significant. Post hoc comparisons showed that both the spatial and temporal deviation increased
 449 across acquisition, post-test and retention-test, as compared to the pre-test (all $ps < 0.05$),
 450 indicating that participants' performance differed from their initial performance.

451 In comparison to the skilled performance of the model, analyses on the participants'
 452 spatial error revealed neither a significant main effect of time, $F(3,72) = 2.587, p = .060, \eta_p^2 =$
 453 $.097$, nor a significant group x time interaction effect, $F(3,72) = .809, p = .493, \eta_p^2 = .033$. The
 454 main effect of group was also not significant, $F(1,24) = .067, p = .798, \eta_p^2 = .003$. Similarly,
 455 for temporal error, the main effect of time, $F(3,72) = .625, p = .601, \eta_p^2 = .025$, the group x
 456 time interaction, $F(3,72) = .323, p = .809, \eta_p^2 = .013$, and the main effect of group, $F(1,24) =$
 457 $1.277, p = .270, \eta_p^2 = .051$, were not significant.

458 **Error patterns.** For the EP 'Incorrect weight distribution', a 2 x 4 repeated measures
 459 ANOVA revealed no significant main effect of time, $F(3,72) = 1.576, p = .203, \eta_p^2 = .062$, nor
 460 a group x time interaction, $F(3,72) = .571, p = .493, \eta_p^2 = .023$. The main effect of group was
 461 also not significant, $F(1,24) = .617, p = .440, \eta_p^2 = .025$. For the EP 'Too deep', the group x
 462 time interaction effect was significant, $F(3,72) = 5.323, p = .002, \eta_p^2 = .82$. Post hoc
 463 comparisons revealed an increase in error for the Me-Novice group for acquisition phase and
 464 post-test compared to pre-test (all $ps < .05$). Both the main effect of time, $F(3,72) = .365, p =$
 465 $.778, \eta_p^2 = .015$ and the main effect of group, $F(1,24) = 1.391, p = .250, \eta_p^2 = .055$, were not
 466 significant. For the EP 'Wrong movement dynamics', analyses showed no main effect of time,
 467 $F(3,72) = 1.881, p = .140, \eta_p^2 = .073$, or group x time interaction, $F(3,72) = .658, p = .580, \eta_p^2$
 468 $= .027$. The main effect of group was not significant either, $F(1,24) = 1.688, p = .206, \eta_p^2 =$
 469 $.066$.

470 **Kinematics.** To further validate whether changes in motor performance were
471 functional, we conducted two separate 2 x 4 mixed measures ANOVAs on the two directions
472 of the center of mass (com) at the deepest point of the movement (i.e., up/ down: depth; back/
473 forth: weight distribution). Results revealed a significant effect for depth, but not for weight
474 distribution at the deepest point. For depth, we found a significant group x time interaction
475 effect, $F(3,72) = 7.717, p < .001, \eta_p^2 = .243$. Post hoc comparisons revealed changes in the Me-
476 Novice group for acquisition, post-test and retention-test compared to pre-test (all $ps < 0.05$),
477 with squats becoming deeper over time. Both the main effect of time, $F(3,72) = 1.289, p = .285,$
478 $\eta_p^2 = .051$ and the main effect of group were not significant, $F(1,24) = 2.259, p = .146, \eta_p^2 =$
479 $.086$. For weight distribution at the deepest point, we found no significant main effect of time,
480 $F(3,72) = .328, p = .805, \eta_p^2 = .013$, or group x time interaction effect, $F(3,72) = 2.039, p =$
481 $.116, \eta_p^2 = .078$. The main effect of group was not significant either, $F(1,24) = .004, p = .952,$
482 $\eta_p^2 = .000$.

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

490 ***Cognitive representation***

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

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

498 The Me-Novice group's tree diagrams at pre-test was comprised of one cluster holding
499 four BACs ([1 3 6 8]) pertaining to two different phases (i.e., preparation phase [BAC 1 and 3]
500 and main phase [BAC 6 and 8] of the squat). At retention-test, this cluster was comprised of
501 three BACs ([1 3 8]), two relating to the preparation phase and one to the main phase of the
502 squat. The Me-Skilled group's tree diagram at pre-test revealed two clusters ([1 3 6 8]; [4 10]),
503 one comprised of four BACs of two different phases (i.e., preparation phase [BAC 1 and 3] and
504 main phase [BAC 6 and 8] of the squat) and one comprised of two BACs of the main phase
505 [BAC 4 and 10]. Similarly, two clusters were evident at retention-test ([3 6 8 12]; [4 10]).
506 However, while one cluster was the same at retention-test (that of the main phase: [BAC 4 and
507 10]), the mixed cluster had changed and finally involved three BACs of the main phase and one
508 BAC of the preparation phase ([BAC 3 and BAC 6, 8 and 12]). This means that the number of
509 BACs of the preparation phase decreased in this particular cluster, while the number of BACs
510 of the main phase had increased.

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

517 *Self-efficacy*

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

520 .107, $p = .899$, $\eta_p^2 = .004$. The main effect of group was also not significant, $F(1,24) = .740$, p
521 $= .398$, $\eta_p^2 = .03$. For the subscale depth, we found a main effect of time, $F(2,48) = 3.537$, $p =$
522 $.037$, $\eta_p^2 = .128$. The interaction effect, $F(2,48) = .524$, $p = .596$, $\eta_p^2 = .021$, and the main effect
523 of group, $F(1,24) = .455$, $p = .507$, $\eta_p^2 = .019$, were not significant. For the subscale weight
524 distribution, the mixed measures ANOVA revealed a main effect of time, $F(2,48) = 9.880$, $p =$
525 $.000$, $\eta_p^2 = .292$. The interaction effect, $F(2,48) = .093$, $p = .911$, $\eta_p^2 = .004$, and the main effect
526 of group, $F(1,24) = .110$, $p = .743$, $\eta_p^2 = .005$, were not significant. For the subscale movement
527 dynamics, we found a main effect of time, $F(2,48) = 4.647$, $p = .014$, $\eta_p^2 = .162$. The interaction
528 effect, $F(2,48) = .623$, $p = .541$, $\eta_p^2 = .025$, and the main effect of group, $F(1,24) = .885$, $p =$
529 $.356$, $\eta_p^2 = .036$, were not significant. Post hoc comparisons showed that self-efficacy related
530 to weight distribution increased from pre-test to post-test and from pre-test to retention-test (all
531 $ps < 0.05$) across groups, and self-efficacy related to depth and movement dynamics increased
532 from pre- to retention-test (all $ps < 0.05$).

533

Discussion

534 In this study we investigated the impact of feedforward modeling of a complex motor
535 action on motor performance, cognitive representation, and self-efficacy using a pre-post-
536 retention-test design. To this end, we used virtual reality to differentiate the model's appearance
537 and the model's performance level. This allowed to contrast model performance level (i.e.,
538 novice vs. skilled) whilst controlling the familiarity of the model (i.e., myself). Novices watched
539 an avatar of themselves and simultaneously imagined themselves (AOMI) performing a body
540 weight squat either at an advanced skill level (Me-Skilled) or at their current skill level (Me-
541 Novice). We predicted that both types of AOMI would lead to improvements in motor
542 performance, cognitive representation, and self-efficacy, and expected greater improvements in
543 the Me-Skilled group compared to the Me-Novice group. Overall, results were partly in line

544 with our hypotheses. Motor performance of the squat changed compared to participants' initial
545 performances in both groups, with participants in the Me-Novice group showing more
546 erroneous performance after the intervention. Moreover, cognitive representations in the Me-
547 Skilled group became more functional. Finally, self-efficacy relating to selected specific aspects
548 of the squat increased in both groups.

549 Regarding motor performance of the squat, overall movement quality changed over the
550 course of the study for both groups. In line with studies showing that AOMI practice can affect
551 movement quality (e.g., Marusic et al., 2018; Romano-Smith et al., 2019) and motor
552 performance (e.g., Kim et al., in press; Marshall et al., 2020; Marusic et al., 2018; Robin et al.,
553 2019; Romano-Smith et al., 2018), movement quality in both groups deviated from participants'
554 initial performances temporally and spatially after the intervention, as well as after one day of
555 retention. Our results thus confirm findings from prior research showing that AOMI has the
556 potential to change behavior, which is important not only for different sports contexts (e.g.,
557 Robin et al., 2019), but also for (re-)learning contexts such as rehabilitation (e.g., Marusic et
558 al., 2018).

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

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

587 While motor performance did not develop towards that of a skilled performance,
588 cognitive representation structures became more functional in the Me-Skilled group after
589 feedforward AOMI, as revealed by an increase of similarity of the mean group tree diagram
590 compared to a reference structure. This corroborates findings from studies showing that AO and
591 AOMI of a skilled performer leads to functional changes in one's cognitive action
592 representation (Frank et al., 2018; Kim et al., 2020; Kim et al., in press), and extends the
593 findings by showing that novices' cognitive representations reveal functional changes after

594 watching and imagining oneself being the skilled performer. Moreover, previous research
595 indicates that changes in cognitive representation structure after MI and/ or AO training precede
596 performance changes, and come into effect only after task execution (Frank et al., 2014; Frank
597 et al., 2016; Frank et al., 2018). It may therefore be that learning has occurred on the cognitive
598 levels in the present study (cognitive stage: Fitts & Posner, 1967), and may transfer to
599 sensorimotor levels of action organization after longer term practice (i.e., perceptual-cognitive
600 scaffolding; Schack et al., 2016). Contrary to our hypotheses, however, self-review AOMI did
601 not result in functional changes in memory over time. One potential explanation might be that
602 watching and imagining one's own novice performance corresponds exactly to one's own
603 current cognitive representation, and thus does not provide useful information to aid the
604 development of the representation beyond the current level.

605 Finally, self-efficacy increased in both groups for all items related to specific aspects of
606 the squat indicating that AOMI practice can improve self-efficacy in performers. In contrast to
607 our hypotheses, feedforward AOMI did not lead to higher self-efficacy compared to self-review
608 AOMI in the present study. This might be attributed to the fact that we did not inform
609 participants in the Me-Skilled group explicitly that they were watching the technique of a skilled
610 other. Consequently, these participants may have assumed that they were watching their own
611 current performance standard, given that the self-related visual characteristics of the avatar. In
612 contrast, in previous modeling and feedforward modeling studies that show beneficial effects
613 of watching skilled performance (for reviews, see Feltz et al., 2008; Ste-Marie et al., 2011,
614 2020) participants are usually aware of the fact that they watch a skilled performer. Independent
615 of group, this may have led participants to think that they saw their own performance leading
616 to similar changes in their beliefs.

617 A potential limitation of the present study was that we did not include action observation
618 or motor imagery control groups. From the design of the present study, it is not possible to draw

619 any conclusions about the impact of MI, or whether the combination of AOMI is better than
620 AO alone. While the focus of the study lay on the impact of feedforward modeling during
621 AOMI, it would be interesting to learn about whether feedforward AOMI has additive effects
622 compared to AO or MI alone in future studies. Moreover, the relative short length of the study
623 and relatively few practice trials during acquisition phase may have resulted in the lack of clear
624 differences between the groups and a clear development in direction of the skilled performance.
625 Larger differences would probably emerge over a greater length of practice. Another possible
626 reason for the small effect between groups could be that the number of squat repetitions may
627 have caused physical fatigue which in turn may have led to decreased imagery accuracy in both
628 groups (Di Rienzo et al., 2012). Future studies, therefore, should consider utilizing more
629 practice sessions over several days or weeks during the acquisition phase, and control for
630 physical fatigue. Although we consider the squat a complex task with many degrees of freedom
631 that must be coordinated during the movement, it is self-paced and relatively slow and simple.
632 While feedforward AOMI might not come into effect in simpler sports tasks, it may be more
633 effective for more complex tasks of higher speeds or with larger ranges of motion. Feedforward
634 AOMI across tasks and across different dimensions of complexity should therefore be examined
635 in future studies. Finally, watching an avatar of themselves was a novel experience for most of
636 the participants and may consequently promote emotional responses that in turn influence
637 participants' actions. It may be worthwhile to measure and control for emotional aspects in
638 future studies when watching a realistic, personalized avatar representing the self during
639 learning and coaching interactions in VR (Latoschik et al., 2017; Ratan, 2012; Waltemate et al.,
640 2018).

641 In sum, the present study partly confirmed our idea that feedforward AOMI, that is
642 watching and imagining oneself performing at an advanced skill level, can be beneficial.
643 Findings revealed that feedforward AOMI maintained motor performance but improved

644 cognitive representation structure. Self-efficacy improved after both feedforward and self-
645 review AOMI. In comparison to watching and imagining oneself performing at the current
646 novice skill level, watching and imagining oneself performing at a more advanced skill level
647 prevented from making errors and led to functional changes in underlying representations. This
648 improved cognitive representation structure may be indicative of perceptual-cognitive
649 scaffolding during motor learning (Frank et al., 2014; Frank et al., 2020; Schack et al., 2016)
650 that might be beneficial in promoting longer term performance changes. Simultaneous imagery
651 whilst observing future states of action may therefore help to establish cognitive prerequisites
652 that enable better motor performance.

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

669 rehabilitation from injury. As it becomes more affordable, VR becomes more and more
670 accessible to practitioners and will hopefully become a standard tool in applied sport
671 psychology one day.

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

682 **Data Availability Statement**

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

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971

972 Figure captions

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

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

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

988

989 Table 1

990 *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]	

991

992 Table 2

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

	AOMI Experience	
	Me-Novice	Me-Skilled
	<i>n</i> = 13	<i>n</i> = 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

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

998

999

1000 Table 3

1001 *Descriptives of participants' virtual reality experience per group and item.*

	Virtual Reality Experience	
	Me-Novice	Me-Skilled
	<i>n</i> = 13	<i>n</i> = 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

1002 *Note:* Means and standard deviations of items investigating participants' experience toward the
 1003 virtual character in the two groups. The scale ranged from -3 to +3 (+3 indicated maximum
 1004 agreement).

1005 Table 4

1006 *Descriptives of participants' motor performance.*

	Motor performance							
	Me-Novice (<i>n</i> = 13)				Me-Skilled (<i>n</i> = 13)			
	Pre	Intervention	Post	Retention	Pre	Intervention	Post	Retention
Overall movement quality								
<i>Deviation from initial performance</i>								
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
<i>Deviation from skilled performance</i>								
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

1007 *Note:* Means and standard deviations of the different motor performance variables per group and test phase.

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