Can Stephen Curry really know? - Conscious access to outcome prediction of motor actions

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Abstract

The NBA player Stephen Curry has a habit of turning away from the basket right after taking three-point shots, presumably because he can predict the success of his shot. For such a consciously accessible prediction to be possible, Stephen Curry needs access to internal processes of outcome prediction and valuation. Computational simulations and empirical data suggest that the quality of internal prediction processes is related to motor expertise. Whether the results of internal predictions can reliably be consciously accessed is less clear. In the current study, 30 participants each practiced a virtual goal-oriented throwing task for 1000 trials. Every second trial, they were required to verbally predict the success of the current throw. Results showed that on average, conscious prediction accuracy was above an

individually computed chance level, taking into account individual success rates and response strategies. Furthermore, prediction accuracy was related to throwing performance. Participants with better performance predicted the success of their throws more accurately than participants with poorer performance. Moreover, for the poorer performing individuals, movement execution was negatively affected by the verbalized predictions required, and they did not show variation in speech characteristics (response latency) between correct and incorrect predictions. This indicates reduced quality of conscious access to internal processes of outcome prediction.

Keywords: action outcome prediction, conscious access, forward model, response latency, response amplitude

1 Introduction

Theories of internal models claim that the predictive outcomes of forward models play an essential role in motor learning (McNamee & Wolpert, 2019). Forward models are a set of neural processes that integrate information from the current state of the system and its environment with motor commands and sensory signals from movement execution to predict sensory consequences of that movement (Miall & Wolpert, 1996). Sensory and motor noise increase the uncertainty in the state estimate of the system. Forward models act as filters capable of reducing this uncertainty and attenuating unwanted information, or highlighting information critical for control. Furthermore, forward models can be used to transform motor errors, which are differences between desired and actual sensory outcomes of a movement into corresponding corrections in motor commands, thereby providing appropriate signals for motor learning (Wolpert et al., 1995). Based on computational simulations, it is suggested that learning is faster the better the forward model is able to model the dynamics of the movement and its effects (Jordan & Rumelhart, 1992). In line with this, empirical and anecdotal evidence confirm that processing and valuation of motor errors based on forward model predictions is strongly related to learning. First, it has been shown that neurophysiological correlates of predictive error valuation increase with learning (Beaulieu et al., 2014; Lutz et al., 2013; Maurer et al., 2021). Second, participants with extended experience in a throwing task particularly motor experts, that is throwers with high accuracy show more distinct signs of predictive error valuation on the neurophysiological level (Joch et al., 2017; Maurer et al., 2015; Maurer et al., 2021). Third, there is anecdotal evidence that motor experts are aware of their own errors and can consciously predict them even before they perceive

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24   any external feedback: The alleged predictive abilities of NBA players like Stephen Curry

25   can be observed in both professional and amateur game videos, and in them it can be

26   observed that shortly after the ball leaves the player's hand, the players already cheer in

27   cases of successful throws or express their disappointment in cases of missed throws.

28   But is it really possible to gain conscious access to the predictive output of forward

29   models in highly complex motor tasks like basketball shooting? And taken even further,

30   might conscious access to prediction processes influence forward model computations?

31   If so, would this influence be beneficial, as it has been shown in an apparent motion

32   paradigm (Vetter et al., 2014), or detrimental, as proposed by the theory of reinvestment

33   (Masters et al., 1993; Masters & Maxwell, 2008), and indicated by studies on perception-

34   action coupling (Beilock et al., 2002; Farrow & Abernethy, 2003)? Without delving deeply

35   into theories and models of consciousness, it has to be acknowledged that the term

36   "consciousness" has different meanings, such as reaching from a waking state or

37   subjectivity to an experimental variable of brain differences attributable to

38   consciousness (Baars, 2015). In the present study "conscious access" is defined as the

39   ability to report contents of perceptual states; according to this definition, perception

40   itself is not limited to the processing of sensory (afferent) signals, as perception can arise

41   from afferent and efferent information as well as cognitive (top-down) signals. Hence, if

42   people with reliably working forward models have conscious access to the output of the

43   forward model, they should be able to verbally predict the outcome of a motor action

44   before any external feedback about the outcome is available. Arbuzova and colleagues

45   (2021) examined metacognitive abilities in the discrimination of two different outcomes

46   based on predictions in a virtual goal-oriented throwing task. Discrimination accuracy

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47   was governed by an online staircase procedure aimed at fixing performance at

48   approximately 71% correct. Results from this study do not allow conclusions about

49   absolute discrimination accuracy (i.e., effect prediction), but, confidence about the

50   discrimination ratings (metacognitive ability) was relatively high across different

51   informational domains (visual, visuomotor, motor). This shows that aspects of one's own

52   movement execution are principally available for conscious use, at least with respect to

53   the monitoring of performance.

54   The conscious accessibility of sensorimotor prediction with respect to action outcomes

55   has been investigated in athletes involved in different sports. The focus of most studies

56   has been on anticipatory estimates of other players' actions, based purely on visual

57   information, for example in basketball shooting (e.g., Abreu et al., 2012; e.g., Aglioti et

58   al., 2008; Li & Feng, 2020; Özkan et al., 2019), volleyball smashes (e.g., Cañal-Bruland et

59   al., 2011; Wright et al., 1990), soccer penalty kicks (Tomeo et al., 2013), or other game

60   situations (for a review see Abreu et al., 2017). Since predictions in these studies were

61   exclusively based on observations of motor actions, available sensorimotor information

62   was incomplete, and visual information differed compared to when actions were

63   executed. That is, observers lacked internal efferent information about motor

64   commands, and did not have access to proprioceptive or haptic information associated

65   with the related movement either. But, in contrast to performers, observers take a third-

66   person perspective. Hence, they can use visual information from whole body kinematics.

67   Other studies examined predictions in both observers and performers (Cañal-Bruland et

68   al., 2015), or in performers alone (Maglott et al., 2019). Performers had to rate outcomes

69   of basketball shots after their vision was occluded by shutter googles immediately after

70   ball release. Results showed that, on average, performers were able to verbally predict

71   the results of their shots above the level of chance. But, both of these studies reported a

72   strong judgment bias regarding shooting position and outcome (hits vs. misses).

73   Performances of shots from the foul line were generally overestimated as compared to

74   shots taken from other distances (Canal-Bruland et al., 2015), and expert players in

75   particular had higher biases towards predicting their shots as hits (Maglott et al., 2019).

76   The authors took that bias into account when calculating the base rate of correct

77   judgements (i.e., the number of all actual hits being predicted as hits plus the number of

78   all misses being predicted as misses, relative to the total number of trials) that could be

79   accounted for by pure chance. Yet, the base rate reflecting pure chance also depends on

80   the actual individual hit rate, which, however, was not included in the base rate

81   estimations provided by the authors. Furthermore, in both studies, the shutter googles

82   were manually controlled, which presumably introduced relatively large temporal

83   variations of the occlusions, and it must be assumed that some post-release information

84   about ball trajectory could have been received and processed by participants.

85   The present study aimed to verify that subjects with experience in a motor task can

86   consciously predict outcomes of their own actions without any external feedback about

87   action outcomes being available to them. For the experimental task, a virtual goal-

88   oriented throwing task with parallels to basketball shooting was used. One significant

89   advantage of studying throwing in this context is the natural delay between movement

90   (throwing) termination and the availability of outcome feedback. Moreover, since the

91   task was virtual and movement execution was captured online, the visual information

92   available to subjects could be precisely controlled. Thus, outcome predictions could be

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93   based exclusively on information gathered during movement planning (efferent

94   information) and during movement execution (haptic, proprioceptive, or visual

95   information), but not on external information about movement effects (e.g., trajectory of

96   the object to be thrown). Hence, information on the level of an individual's accuracy in

97   consciously accessing outcome predictions (predictive accuracy) would provide novel

98   insight into the quality of forward models and the easiness or efficiency of conscious

99   access to forward models. Predictive accuracy was quantified by the rate of correct

100   verbal predictions of throwing outcome, relative to a baseline (chance) level accounting

101   for individual hit rates and response strategies.

102   Successful verbalized predictions require at least two separate functions: a predictor and

103   conscious access to its predictions. Or, conversely, poor predictive accuracy may arise

104   from two reasons: (i) individuals have poor prediction quality (due to poor forward

105   models), or (ii) they have difficult or inefficient conscious access to their forward models.

106   Thus, it is expected that individuals with superior throwing performances (inferring good

107   forward models) and easy conscious access to internal processes, would be able to

108   predict their throwing outcomes above the level of chance. In the present study design,

109   the integrated effect of both aspects was examined, and experimental separation was

110   not directly possible. But, post-hoc interpretations of the different influences of

111   prediction quality (i) and easiness of access (ii) on prediction accuracy are provided. As

112   additional variables contributing to this differentiation, throwing performance and

113   speech characteristics of verbal responses were analyzed. A possible back wash effect of

114   conscious access to internal prediction processes results in interference with throwing

115   performance: The preparation of conscious verbal predictions following movement

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116   execution might disrupt the motor control process, and hence affect throwing

117   performance (Beilock et al., 2002; Masters & Maxwell, 2008). These costs of conscious

118   processing might also manifest themselves in longer verbal response latencies and lower

119   response volumes due to hesitation (Collins et al., 2000; Seymour, 1970).

120   ## 2   Materials and Methods

121   ### 2.1   Participants

122   Thirty participants (18 female, 12 male) from the student population of the Justus Liebig

123   University, Giessen, Germany with an average age of 24.13 (*SD* = 5.77) years participated in

124   the study. Participants were healthy and had normal or corrected-to-normal vision. Two left-

125   handed subjects practiced the task with the right hand, which had been shown to produce

126   similar learning curves to right-handed participants in pilot studies. Participants received

127   course credit or monetary compensation of €8 per hour. The experiment was conducted in

128   accordance with the ethical standards laid down in the Declaration of Helsinki. The protocol

129   was approved by the Ethical Review Board of the Justus Liebig University, Giessen.

130   ### 2.2   Experimental task and apparatus

131   Participants practiced a novel and complex goal-oriented throwing task that has previously

132   been used to study motor learning (e.g., Cohen & Sternad, 2009; Maurer et al., 2021; Müller

133   & Sternad, 2004; Pendt et al., 2011). The task is inspired by the British pub game "Skittles",

134   where a ball attached to the top of a post by a string has to be swung around the post to hit

135   target objects on the opposite side. In addition to the ballistic nature of the task preventing

136   online corrections during movement execution, this throwing task allows a temporal

137   separation of movement execution and its terminal outcome, because the outcome is

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138   temporally delayed with respect to the movement. The task was executed semi-virtually.

139   That is, participants executed a real ballistic throwing movement using a metal lever device

140   (manipulandum), while the movement and its outcome were only visible on a computer

141   screen from an overhead perspective (see Fig. 1).
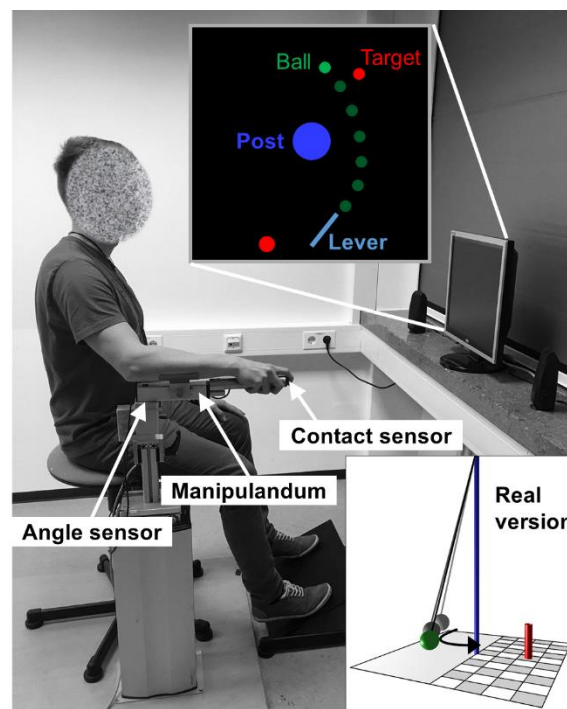

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143   Figure 1. Experimental setup of the Skittles task. The participant uses a manipulandum
144   to throw the virtual ball (green) with a horizontal rotational movement. The ball is
145   released by lifting off the index finger from a contact sensor at the tip of the
146   manipulandum. The ball travels on an elliptical pathway around the blue post to hit a
147   red target.
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149   The Skittles task was carried out using MATLAB R2018a (The Mathworks, Inc.) using the

150   Psychophysics Toolbox version 3.0.14 (Brainard, 1997). On the screen in front of each

151   subject, a virtual equivalent of the metal lever was displayed, which participants used to pick

152   up and throw a green virtual ball (radius on screen = 4.2 mm) around a blue center post

153   (radius on screen = 21 mm) in order to hit a red target (radius on screen = 4.2 mm). The

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154   elliptical trajectory of the ball around the center post was defined by the angle and velocity

155   of the manipulandum at the moment of ball release. The calculation of the ball trajectory

156   was based on a physical model of the task (Müller & Sternad, 2004) with the following

157   parameters: center post (radius = 0.25 m; position: x = 0.0 m, y = 0.0 m), target (radius = 0.05

158   m; position: x = 0.8 m, y = 0.9 m), ball (radius = 0.05 m; mass = 0.1 kg), spring constant (1.0

159   N/m). In the regular version of the task, participants were able to see the ball moving

160   towards the target after ball release. Whenever the minimum distance between the

161   trajectory of the ball center and the center of the target (D_{min}) was less than or equal to

162   twice the radius of the ball/target, the ball collided with the target (hit). For the subjects, this

163   was apparent visually, because the target was pushed away from its position, and

164   acoustically by the sound of two colliding billiard balls. In trials where D_{min} was larger than

165   twice the radius of the ball/target, the ball missed the target. In the experimental version, in

166   every second trial the ball vanished from the screen immediately after its release from the

167   virtual lever. In these trials, subjects did not receive any information about the movement

168   outcome.

169   *2.3   Study procedure*

170   Task execution was accomplished as follows: Participants sat on a stool placed 100 cm in

171   front of a 19-inch, 4:3 computer monitor (model: Dell P190St, screen resolution: 1280 x 1024

172   pixels, refresh rate: 60 Hz). Their right arms rested on the foam padded manipulandum,

173   which was fixed on a height-adjustable stand at the vertical rotation axis below the elbow

174   joint of the participant (Figure 1). An integrated magnetic angle sensor with a resolution of

175   12 bit (0.09 deg) measured the lever rotation with a sampling rate of 1000 Hz. Movement

176   was restricted to the horizontal plane, more specifically, to rotation around a fixed vertical

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177   axis. To pick-up the virtual ball, participants placed their index fingers on an electrical

178   contact sensor at the tip of the lever to close an electrical circuit. They then "threw" the ball

179   by moving the manipulandum in an outward horizontal movement similar to a Frisbee toss,

180   and starting in front of their bodies. As soon as the participant's finger was lifted from the

181   manipulandum, the virtual ball was released from the virtual lever. To explain the task to the

182   participants, a miniature model of the real Skittles game was used to clarify the task. To

183   prevent a fast, rhythmic execution of subsequent trials, participants were instructed to start

184   every trial by moving the tip of the virtual lever into a red circle positioned left of the fixed

185   end of the lever (35° clockwise relative to the horizontal axis; see Figure 1). Immediately

186   after the tip of the virtual lever reached the circle, it turned yellow. The circle turned green

187   when the lever was held steady within the yellow circle for one second. The green starting

188   circle signaled that participants were free to start the movement at any time. Note,

189   however, that the subjects did not start the movement in reaction to the green signal. The

190   aim of the task was to hit the target as frequently as possible.

191   The movement result was to be predicted verbally by the subjects within 2.5 seconds after

192   ball release by the German words for hit ("Treffer") or miss ("Fehler"). The verbal utterances

193   were recorded for later analysis. For this purpose, a clip-on microphone (Monacor ECM-

194   501L/SK), a phantom power adapter (MG STAGELINE EMA-1), and a microphone

195   preamplifier (IMG STAGELINE MPA-202) were used. The output signal from the preamplifier

196   was captured using a 16-bit data acquisition device (National Instruments PCIe-6321), and

197   Matlab Data Acquisition Toolbox time synchronized with the data from the Skittles

198   apparatus (angular and touch sensor) with a sampling frequency of 10.000 Hz.

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199 *2.4   Study design*

200   Practice took place over two sessions with 500 trials each. Trials were categorized with

201   respect to practice and experimental conditions (overview in Tab. 1). The first 100 trials of

202   session one served as a first practice of the task. The regular version of the task was used for

203   all of these trials. From trial 101 to trial 150, the experimental version was used where ball

204   flight information was masked for every second trial as described above ("Experimental task

205   and apparatus"). In these trials, participants did not receive any outcome feedback, while

206   feedback was normally presented in the other 50 % of trials. From trial 151 to trial 1000, the

207   regular version of the task was alternated with the experimental version in every other trial

208   and, additionally, participants were asked to verbally predict the outcomes of their throws in

209   the trials without ball flight information and outcome feedback (*prediction condition*). Trials

210   151-200 served as practice of the verbal prediction. Only trials 201 to 1000 were used for

211   analyses where the *prediction condition* (verbal prediction and no outcome feedback) was

212   contrasted with the *regular condition* (no verbal prediction, but available outcome

213   feedback). The alternation of throws with and without feedback was chosen because pilot

214   data indicated that it was not possible to perform the task successfully without "drifting

215   away" from the solution manifold of the task without regular feedback.

216   **Tab. 1. Overview of the experimental procedure**

	Trials 1-100	**Trials 101-150**	**Trials 151-200**	**Trials 201-1000**
Experimental phases	Practice: Regular task version	Practice: Alternation of regular task	Practice: Alternation of regular task	Experiment: Alternation of regular task

		version and experimental version in every trial	version and prediction condition in every trial	version and prediction condition in every trial
Implementation of feedback and verbal prediction in the different phases	100 % of trials with outcome feedback	50 % of trials with outcome feedback and 50 % of trials without outcome feedback	50 % of trials with outcome feedback and 50 % of trials without outcome feedback and with verbal prediction	50 % of trials with outcome feedback and 50 % of trials without outcome feedback and with verbal prediction

217

2.5   Analysis of throwing performance

219   Behavioral analyses as well as the analyses of verbal responses were done in MATLAB

220   R2020b (The Mathworks, Inc.). The execution variables (release angle and velocity) and

221   outcomes in the Skittles task are related in a nonlinear fashion. Furthermore, the task is

222   redundant, what means that hits and misses are not functions of a dichotomous difference

223   in throwing execution, but can arise from very different combinations in release angle and

224   velocity. As a consequence, outcome prediction is not trivial. To account for this difficulty,

225   only clear target hits (with $D_{min} \leq 7$ cm) and clear misses (with $D_{min} \geq 12$ cm) were analyzed

226   (following Joch et al., 2017; note that trials with Dmin ≤ 10 cm lead to hits). Throwing

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227   performance was defined as the rate of clear hits in percent of blocks of 100 trials (10 blocks

228   in total) averaged over all participants. Since conscious verbal predictions could influence

229   throwing performance, hit rates between the *prediction condition* and the *regular condition*

230   were compared. In these cases, hit rate was determined over 50 trials of each block for both

231   conditions, because prediction trials and regular trials were alternated every trial.

2.6   Analysis of verbal responses

233   Verbal predictions of throwing outcomes were examined along two dimensions: First,

234   prediction accuracy was analyzed in order to test whether participants were able to

235   consciously access their internal processing of movement errors. Second, characteristics of

236   speech, concretely variance in the onset and amplitude of verbal responses provided further

237   information about the ease of conscious access to the predictions. It was assumed that

238   faster (easier) conscious access would be manifested in earlier and louder prediction

239   responses.

2.6.1   Prediction accuracy

241   Prediction accuracy was defined as the rate of correct predictions relative to an individual

242   baseline or chance level. This was accomplished in several steps. First, the rate of correct

243   predictions ($\%C_{Pred}$) was defined as the percentage of correctly predicted clear hits and

244   misses of all trials in the *prediction condition*. This empirical prediction rate was compared to

245   the individually calculated prediction baselines ($\%C_{Chance}$). This baseline depends on two

246   factors: first, the rate at which participants actually hit ($\%Act_{Hit}$) or missed ($\%Act_{Miss}$) the

247   target in the experimental condition and, second, the rate at which they verbally report hits

248   ($\%Verb_{Hit}$) or misses ($\%Verb_{Miss}$).

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249 Based on the null hypothesis that verbal estimates are unrelated to the actual occurrence of

250 hits and misses, we estimated $\%C_{Chance}$ in the following way:

251 $\%C_{Chance} = \%Act_{Hit} * \%Verb_{Hit} + \%Act_{Miss} * \%Verb_{Miss}$

252 Prediction accuracy ($\%Acc_{Pred}$) was then computed as the percentage of correct predictions

253 above $\%C_{Chance}$, normalized with respect to perfect predictions:

254 $\%Acc_{Pred} = (\%C_{Pred} - \%C_{Chance}) / (100 - \%C_{Chance})$

255 Thus, $\%Acc_{Pred}$ represented the ability of participants to consciously and verbally predict the

256 outcomes of their throwing movements.

257 2.6.2   Speech characteristics

258 To analyze verbal utterances, voltage values from the microphone output were offset-

259 corrected, rectified, and then a moving average calculation (window width 250 values, i.e. 25

260 ms) was performed. The onset time of a verbal utterance was identified when the averaged

261 profile exceeded 0.1 V. To determine the amplitudes, the maximum value in the averaged

262 voltage curve was first determined. To account for general differences in loudness resulting

263 from different positioning of the microphone and speaking volumes of subjects, all

264 maximum amplitude values of each test session and subject were divided by their medians.

265 Finally, the medians of onset latencies and response amplitudes were determined for all

266 trials in the four different categories $Act_{Hit}/Verb_{Hit}$, $Act_{Hit}/Verb_{Miss}$, $Act_{Miss}/Verb_{Hit}$,

267 $Act_{Miss}/Verb_{Miss}$.

268   *2.7   Statistical analyses*

269   Statistical analysis was performed in JASP (Version 0.14.1). The alpha level was set to .05 for

270   all statistical analyses. Data normality was checked with the Shapiro-Wilk test, and sphericity

271   was checked using the Mauchly's W test. In case of violation of sphericity, the Greenhouse-

272   Geisser correction was used. Changes in performance were tested with repeated

273   measurement ANOVAs over all sessions, which included *Holm* corrected post-hoc testing of

274   single sessions. Direct comparisons of performances between the experimental conditions

275   (*regular* vs. *prediction*) was done using Wilcoxon signed-rank test (due to violation of

276   normality assumptions), using the rank-biseral correlation coefficient as effect size. A one-

277   sample *t*-test was used to examine whether prediction accuracy (%Acc_{Pred}) was above

278   baseline prediction, with effect sizes determined by Cohen's *d*. It was expected that

279   prediction accuracy would be a function of forward-model quality, and quality of conscious

280   access. Hence, a Spearman correlation between prediction accuracy and hit rate as well as

281   between prediction accuracy and the differences in hit rates between the *regular condition*

282   and the *prediction condition* (conscious processing costs) was conducted. Speech

283   characteristics (response latency and amplitude) were tested by a 2 (actual hit or miss) × 2

284   (verbalized hit or miss) repeated measures ANOVA, with the difference in hit rate between

285   the *regular condition* and the *prediction condition* as a covariate. In addition, a Bayesian

286   inference approach was used, with Bayes factors (*BF*) interpreted as the amount of evidence

287   for the null and the alternative-hypothesis before versus after inspection of the data

288   (Verdinelli & Wasserman, 1995). The size of the *BFs* were interpreted according to Raftery

289   (1995). *BFs* 1 - 3 were interpreted as weak evidence for the alternative hypothesis against

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290   the null hypothesis, 3 - 20 as positive, 20 - 150 as strong, and *BFs* > 150 as very strong

291   evidence.

3   Results

3.1   Throwing performance

294   Figure 2 depicts the development of throwing performance (hit rate). Figure 2A shows the

295   hit rate over all trials executed. In Figure 2B, only trials carried out under regular conditions

296   are shown (from trial 201 on), and Figure 2C illustrates the hit rates of only those trials of the

297   *prediction condition* (from trial 201 on). Hit rates started at around 50 % on average, and

298   rose with practice until they levelled off around block seven. ANOVA analyses carried out

299   with repeated measures showed a significant main effect of block ($F(4.65, 134.85) = 18.92$, *p*

300    $< .001$, $\eta_p^2 = .40$, $BF_{10} > 150$). Post hoc tests revealed significant differences between blocks

301   1-6 and block 10, practically no differences between block 7 and 10, and no differences

302   between blocks 8, 9 and 10 (see Tab. 2). Interindividual variance was relatively large in

303   general (standard deviation of the hit rate of all trials was 13.49 %, see Tab. 3), and even

304   larger in the *prediction condition* (SD = 22.71 %). The average hit rate also differed

305   significantly between the *regular condition* and the *prediction condition* ($W = 61$, $p < .001$,

306   *rank-biserial correlation* = -0.74, $BF_{10} > 150$), but there was also large variance between

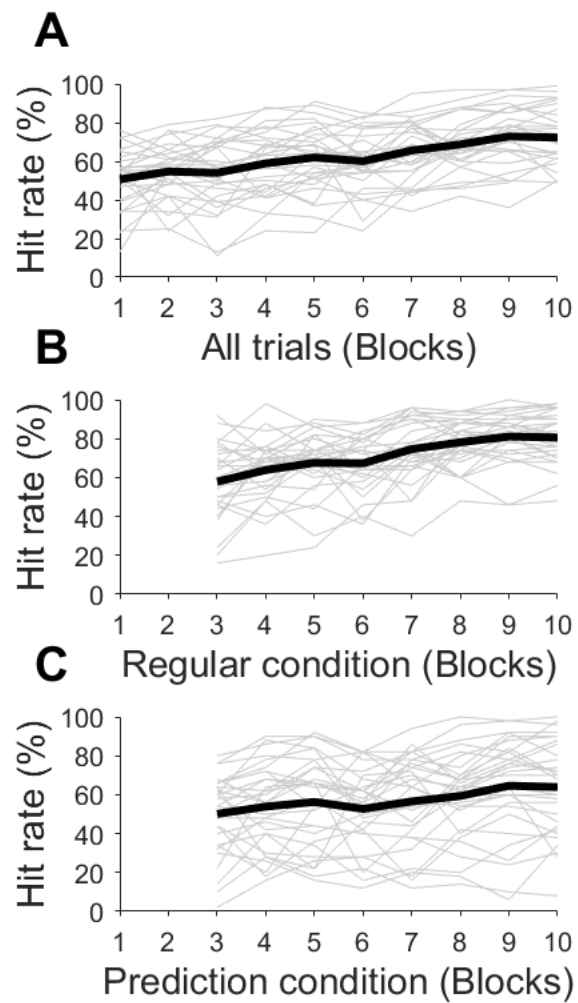307   participants (SD = 20.73 %, Min = -5.24 %, Max = 60.33 %).

Figure 2. Development of throwing performance over all trials (A), over trials under the regular condition (B), and over trials under the prediction condition (C). Thick black lines represent the group average; thin grey lines represent individual data.

Table 2. Post-hoc comparisons between blocks 1-9 and block 10.

Session	Hit rate Mean difference	SE	t	p_{holm}	BF_{10}
1 vs. 10	-0.22	0.03	-8.58	< .001	> 150
2 vs. 10	-0.18	0.03	-6.98	< .001	> 150
3 vs. 10	-0.19	0.03	-7.24	< .001	> 150
4 vs. 10	-0.14	0.03	-5.31	< .001	> 150
5 vs. 10	-0.11	0.03	-4.10	< .001	> 150
6 vs. 10	-0.01	0.03	-4.85	< .001	> 150
7 vs. 10	-0.13	0.03	-2.66	.15	6.094
8 vs. 10	-0.07	0.03	-1.40	1.00	1.760
9 vs. 10	-0.04	0.03	0.23	1.00	0.210

Table 3. Descriptive data of hit rates in the two experimental conditions and both conditions together (All trials)

	N	Mean	SD
Hit rate *All trials*	30	64.28	13.49
Hit rate *Regular*	30	72.26	13.77
Hit rate *Prediction*	30	56.00	22.71
Difference between *Prediction* and *Regular*	30	16.27	20.73

SD = Standard deviation

3.2 Prediction accuracy

The prediction baseline was on average 55.41 % (SD = 12.83 %), which corresponds to the

average chance level for the participants' predictions. Average prediction accuracy

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325   (%ACC_{Pred}) exceeded the prediction baseline by 6.01 % (SD = 9.61 %) of the potential

326   accuracy gain by predicting, which was significant ($t(29)$ = 3.42, p = .002, d = .63, BF_{10} =

327   19.19). Prediction accuracy, however, varied greatly between participants (see Fig. 3). There

328   was a significant positive correlation of %Acc_{Pred} and hit rate over all trials (r = .44, p = .014,

329   BF_{10} = 4.03; Fig. 3A). Since throwing performance differed between the *regular condition* and

330   the *prediction condition* with large variance between participants, it was tested whether this

331   variance also accounted for the differences in prediction accuracies. A significant negative

332   correlation of %Acc_{Pred} with the difference in hit rate between the *regular condition* and the

333   *prediction condition* was found (r = -0.52, p = .003, BF_{10} = 4.62; see Fig. 3B). This means that

334   participants with lower hit rates in the *prediction condition* relative to the *regular condition*

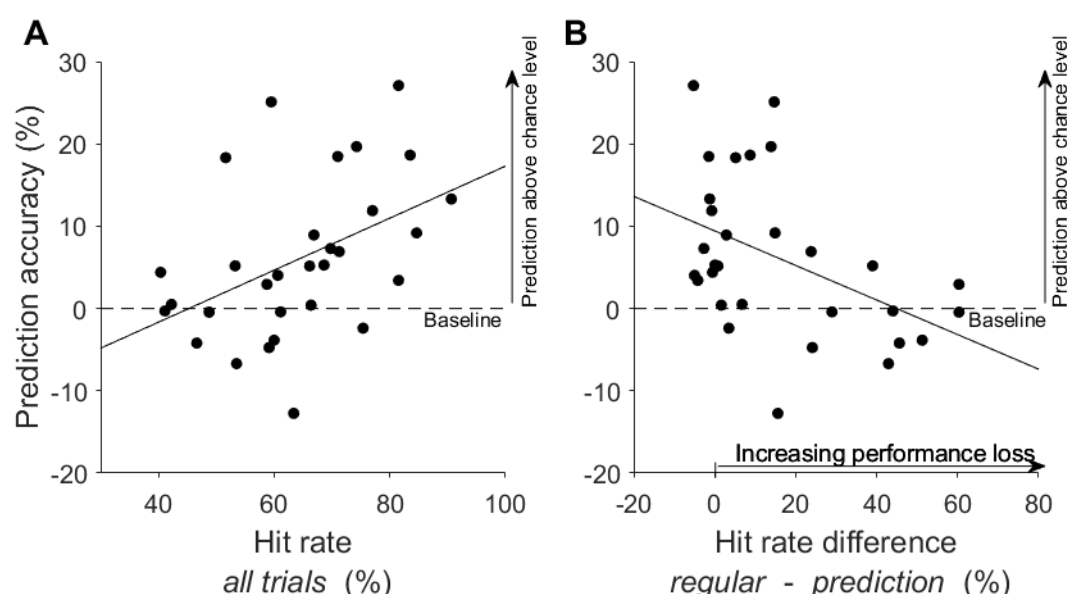335   showed poorer prediction accuracy, in the lowest cases even below baseline level.

336

337   Fig. 3. Correlations of throwing performance with prediction accuracy relative to
338   individual chance level (see 2.6 "Analysis of verbal responses"). Each dot represents
339   the average values of a single participant. The dashed line marks the baseline
340   prediction level (equivalent to chance level). **A:** Correlation of prediction accuracy
341   with hit rates over all experimental trials (*prediction condition* and *regular condition*
342   together). **B:** Correlation of prediction accuracy with the difference in hit rates

343 between the *prediction condition* and the *regular condition*. The larger the difference
344 value, the lower the performance in the *prediction condition*.
345

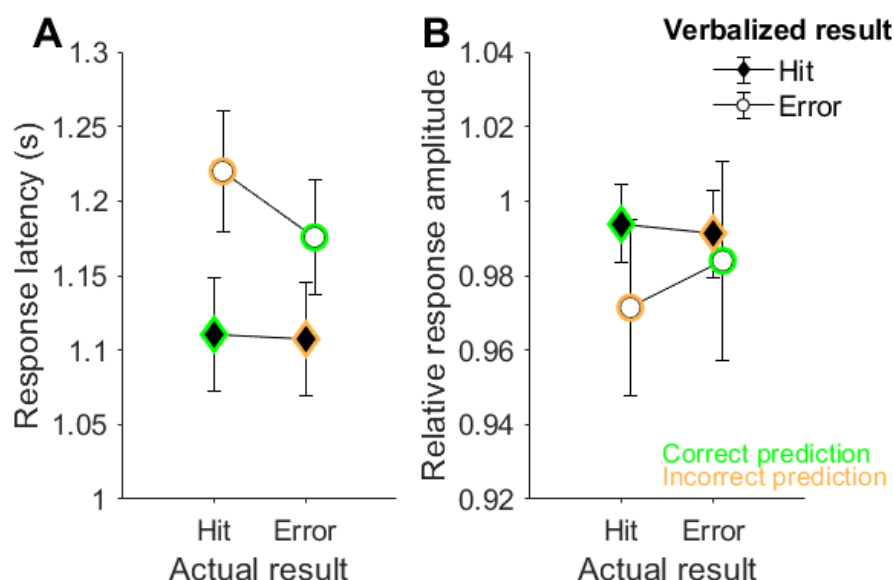346 *3.3   Speech characteristics*

347

348 Fig. 4. Average response latencies (**A**) and response amplitudes (**B**) differentiated after
349 actual results of trials (actual hits or misses) and the verbalized responses (verbalized
350 hits or misses). Error bars represent standard errors of the mean. Correction
351 predictions are marked in green, incorrect predictions are marked in orange.
352

353 Figure 4 shows the response latencies (A) and amplitudes (B) with respect to the *verbalized*

354 *prediction as a function of actual outcome*. It can be observed that responses predicting

355 misses were generally slower, and tended to also be quieter, than responses predicting hits.

356 The latency difference was confirmed by a main effect regarding the *verbalized result* ($F(1,$

357 $28) = 12.90$, $p = .001$, $\eta_p^2 = .32$, $BF_{10} > 150$), but there was no main effect of *verbalized result*

358 for the amplitude variable ($F(1, 28) = 0.79$, $p = .38$, $\eta_p^2 = .03$, $BF_{10} = .26$). There was also a

359 small main effect for *actual result* in response latencies ($F(1, 28) = 4.78$, $p = .037$, $\eta_p^2 = .15$),

360 which could, however, be ascribed to an interaction effect (see below). Bayesian statistics

361 confirmed that the data was not sufficiently informative to allow a strong conclusion to be

21

362   drawn about the main effect *actual result* (BF_{10} = 0.434). Nevertheless, later responses of

363   trials being incorrectly predicted as misses could clearly be observed relative to trials

364   correctly predicted as misses, and this difference was not observable in the trials predicted

365   as hits. Classical ANOVA revealed an interaction effect between *actual result* and *verbalized*

366   *result* ($F(1, 28)$ = 5.41, p = .028, η_p^2 = .16). A Bayesian mixed-factor ANOVA also determined

367   that the data were well represented by a model that included both main factors, *actual*

368   *result* and *verbalized result*, and the *actual × verbalized* interaction. The BF_{10} was 7459,

369   indicating decisive evidence in favor of this model when compared to the null model.

370   Moreover, the BF_{10} in favor of indicating the interaction effect on top of the main effect

371   *actual result* was 5.82. A tendency for a similar interaction (incorrectly predicted misses

372   seem to be expressed most quietly) could be observed in amplitude data, which was,

373   however, neither confirmed by classical nor by Bayesian ANOVA ($F(1, 28)$ = .57, p = .46, η_p^2 =

374   .02, BF = .01). There were also no interactions with the covariate *performance loss*

375   (differences in hit rates between the *regular condition* and the *prediction condition*) in the

376   amplitude results.

377   Regarding response latency, the three-way interaction with the covariate *actual result ×*

378   *prediction × performance loss* did not achieve significance, but showed a trend for a different

379   interaction depending on the size of performance loss ($F(1, 28)$ = 5.50, p = .07, η_p^2 = .11). In

380   addition, the Bayes model, including the main factors *actual result* and *verbalized result* and

381   the *performance loss* covariate, strongly outperformed the null model (BF_{10} > 150), and

382   weakly outperformed the model including the *actual × verbalized* interaction (BF_{10} = 1.48).

383   To analyze how this trend was supported by the data, a median split was applied with

384   respect to *performance loss*: one group showed virtually no performance loss (< 7.76 %) and

22

385   the other showed performance loss (> 7.76 %). Figure 5 illustrates that the interaction

386   between *actual result* and *prediction* exists only in the group of participants who showed no

387   performance loss in the *prediction condition*.
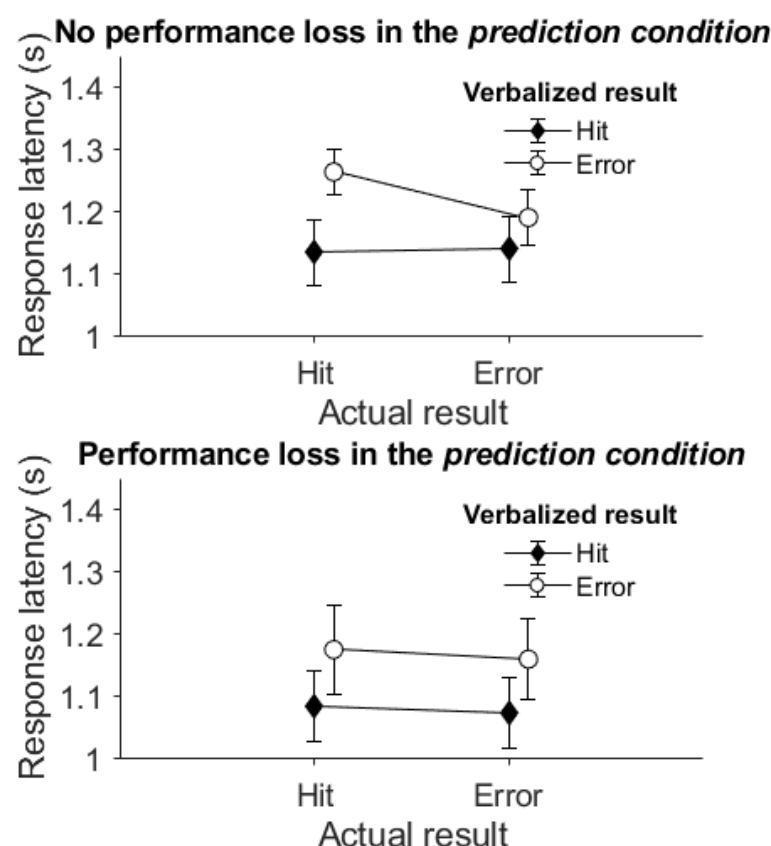

388

389   Fig. 5. Average response latencies differentiated after actual results of trials and
390   verbalized results for two groups separated based on whether they experienced
391   performance loss in the *prediction condition* or not. Error bars represent standard
392   errors of the mean.

4   Discussion

394   The present study examined whether subjects experienced in a motor task can consciously

395   predict outcomes of their own actions without receiving any external feedback about action

396   outcomes. To this end, participants practiced a virtual goal-oriented throwing task for 200

397   trials. In every other of the remaining trials, they were then asked to verbally predict

23

398   whether the ball they had just released would hit or miss the target (*prediction condition*).

399   They had 2.5 seconds after releasing the ball to make their predictions. No feedback was

400   given about the trajectory of the ball. In the other half of the trials, participants did not have

401   to predict outcomes and they could see the ball moving towards the target and hitting or

402   missing it (*regular condition*). Results in terms of throwing performance, prediction accuracy,

403   and speech characteristics of verbal responses were analyzed and compared between the

404   *prediction condition* and the *regular condition*.

405   **Conscious access to outcome predictions is possible, but varies interindividually**

406   On average, prediction accuracy (as the measure of conscious access to outcome

407   predictions) exceeded baseline levels by about 6 % of the potential gain in accuracy. This

408   means that 6 % of what, in theory, could have been achieved above chance when using

409   internal information was achieved. 100 % in that measure would indicate predictions where

410   every trial is correctly classified as error or hit, while 0 % represented the prediction

411   accuracy that can be achieved without conscious access to internal prediction processes. In

412   this case, verbalized reports of anticipated outcome predictions could only be made at the

413   chance level. Chance level was reflected in the individual baseline level, taking into account

414   actual hit rates (%Act$_{Hit}$ and %Act$_{Miss}$) and verbal report rates (%Verb$_{Hit}$ and %Verb$_{Miss}$). Thus,

415   for accuracies above this level, any improvement in accuracy must have resulted from

416   information gathered during the throwing movement, particularly from internal sources

417   including correlates of efferent commands. Variance of above-baseline gains in accuracy

418   prediction was relatively large between participants, with some individuals achieving gains

419   of around and above 20 %, while others fluctuated around chance level. As described in the

420   introduction, predictive accuracy is a function of prediction quality (quality of a task forward

24

421   model) and ease or efficiency of conscious access to the forward model predictions. So,

422   individuals with higher prediction accuracies must have had good prediction quality and easy

423   access to their internal processes, while the reason for poorer prediction accuracy may have

424   been poorer prediction quality and/or more difficult access to internal processes, as quality

425   of prediction has already been associated with experience or expertise. Forward model

426   computations contribute to learning (Jordan & Rumelhart, 1992), and extended experience

427   in a motor task correlates with distinct signs of predictive error processing on the

428   neurophysiological level (Lutz et al., 2013; Beaulieu et al, 2014; Maurer et al. 2015; Joch et

429   al., 2017; Maurer et al., 2021). Furthermore, it has been shown that motor experts (sports

430   athletes) can anticipate the outcomes of other players' actions with relatively little

431   information about action parameters, and that this ability rises with skill level (Abreu et al.,

432   2012; Aglioti et al., 2008; Li & Feng, 2020; Tomeo et al., 2013). In these studies, temporal

433   occlusion paradigms were used, where participants with varying expertise levels watched

434   videos of motor actions and had to predict the outcomes of the actions shown at different

435   points in time. In the Aglioti and colleagues' study (2008), professional basketball players

436   were capable of correctly predicting shooting outcomes above the level of chance even

437   before players on the videos released the ball. These motor experts, which professional

438   players are, were contrasted with participants with high visual experience (sports journalists

439   and basketball coaches). Pure visual experts needed significantly more information to

440   correctly judge the outcomes above the level of chance. This difference indicates that motor

441   expertise facilitates perceptual abilities in general and, more specifically, at least partially

442   through predictive functions.

25

443   The present study extended these findings to predictive abilities with respect to subjects'

444   own movement outcomes. Although experience and expertise in the task used here was not

445   comparably high to natural experts in terms of practice trials, participants reached a learning

446   plateau, and similar studies with the same task have shown that hit rates of more than 60 %

447   coincided with a neurophysiological marker of forward model predictions (Maurer et al.,

448   2015, Joch et al., 2017). In the present study, participants reached an average hit rate of

449   over 50 % within the first 100 trials, and increased their hit rate average to 72 % in the last

450   100 trials, taking into account both experimental conditions (*prediction* and *regular*). In the

451   *regular condition* alone, they even reached a hit rate of over 80 %, although interindividual

452   variance in performance was relatively high. Thus, individuals with higher hit rates could be

453   assumed to have had a better forward model of the task and, hence, better prediction

454   quality than individuals with lower hit rates. This was demonstrated by a positive correlation

455   between prediction accuracy and hit rates. The second factor of prediction accuracy, ease of

456   access, also contributed to the clarification of variances between subjects. There was a clear

457   difference in hit rates between the *regular condition* and the *prediction condition*. Hit rates

458   in the *regular condition* were on average higher, but there were again large differences

459   between participants. While about half of the participants did not show much change in hit

460   rates between the two conditions, the other half experienced large decreases in

461   performance when throwing outcomes had to be predicted verbally. This difference in hit

462   rates between the *regular condition* and the *prediction condition* correlated negatively with

463   prediction accuracy. Prediction accuracy was higher when performance loss in the *prediction*

464   *condition* was smaller. This means that the experimental demands of the *prediction*

465   *condition* affected motor task performance more in some individuals than in others. What

466   may be the reason for this? During the experimental procedure, participants had to respond

467   verbally no later than 2.5 seconds after releasing the ball. Hence, preparation of the

468   response and the focus on accessing relevant internal information for the outcome

469   prediction might have interfered with motor control processes, leading to a performance

470   loss in the *prediction condition*. This observation is in line with well-established findings that

471   have shown that attention to performance can become counterproductive (Masters, 1992;

472   Masters et al., 1993). This detrimental effect is suggested to be strongest with skill-focused

473   attention (internal focus) of step-by-step monitoring and control (Beilock et al., 2002; Beilock

474   & Carr, 2001; Wulf et al., 1998). Conscious access of internal prediction processes, however,

475   does not necessarily require attention to step-by-step components of a movement. The

476   activation of this access may be more comparable to an external, goal-oriented focus of

477   attention, which typically only affects less-skilled participants (Wulf & Su, 2007). Thus, the

478   less-skilled participants in the present study were more impaired by the verbal prediction

479   requirement, presumably because they had less effective access to information relevant for

480   outcome predictions, and needed to reallocate attention from motor execution. The results

481   from analysis of the speech characteristics of the verbal responses support this

482   interpretation.

483   **Response latency and amplitude are related to throwing performance and prediction**

484   **accuracy**

485   Speech production is sensitive, and hesitation and uncertainty of responses can be observed

486   in measures of response latency and amplitude (Seymour, 1970; Collins et al., 2000). Hence,

487   possible detrimental effects of conscious access to movement outcome predictions may be

488   represented by these variables. Movement outcome predictions are based on different

489   sources of information gathered during movement planning (efference copy) and movement

490   execution (haptic, proprioceptive, or visual information; Wolpert et al., 1995), with each of

491   these modalities producing different time delays and resulting in varying degrees of accuracy

492   (Cameron et al., 2014; Pasma et al., 2015; Thorpe et al., 1996). It can be assumed that

493   outcome estimates are continuously produced, resulting in an increase in accuracy of the

494   input information while the movement is evolving. Hence, responses can be quick if

495   sufficiently accurate information is available early on, or if predictions are, instead, based on

496   experience, or are "thoughtlessly" uttered without the subject's consideration of the actual

497   input information when making predictions.

498   In the present study, there was a general observation of quicker (and in tendency also

499   louder) responses when a hit was predicted, irrespective of whether this turned out to be

500   true or not. In contrast, response latency differed between correctly and incorrectly

501   predicted misses: Predictions of trials that were incorrectly predicted as misses were

502   verbalized more slowly than predictions of trials correctly verbalized as misses. This

503   difference was only observable in participants without performance loss in the *prediction

504   condition*. Moreover, correctly predicted hits and correctly predicted misses had similar

505   response latencies (and amplitudes), especially in the "no performance loss" group. Hence,

506   in these cases, input information was probably clear and accurate relatively early, leading to

507   relatively fast outcome estimates. In contrast, incorrectly predicted misses resulted in slower

508   response latencies. This indicates that the information gathered here was more ambiguous

509   for outcome predictions, and that this ambiguity did not resolve over time. Nevertheless,

510   participants waited longer, apparently hoping for better information resolution, and ended

511   up answering incorrectly. That this effect was not observed in the "performance loss" group

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512   indicates limited access to internal prediction processes in these participants. They were

513   apparently not able to differentiate between accurate and ambiguous input information

514   and, hence, showed similar response times between correctly and incorrectly predicted

515   trials. As already described, the latency effect was generally not present in incorrectly

516   predicted hit trials. The reason for the difference between hit and miss predictions could be

517   a general bias toward hit responses, as has been observed in other studies (Canal-Bruland et

518   al., 2015; Maglott et al., 2019). Response bias in the computation of prediction accuracy was

519   controlled for, but it may have still been inherent in verbal responses. Hence, it is possible

520   that responses predicting hits were expressed based on experiences instead of waiting for

521   accurate input information, which led participants to respond (too) early. However, further

522   experiments would be needed to confirm this assumption.

523   Taking together results of prediction accuracy, throwing performance, and speech

524   characteristics of verbal responses, it can be concluded that task expertise allows rapid

525   access to accurate motor predictions without interference with motor control processes. On

526   the contrary, when throwing performance is poor, conscious access to internal predictions

527   negatively affects movement execution, presumably in the form of conscious processing

528   costs. In light of these results, the question posed in the title can be answered in the

529   affirmative: Yes, he can! Given the fact that Stephen Curry has exceptionally good throwing

530   skills, it can be assumed that he has an excellent forward model and good access to internal

531   predictions.

532   **Limitations**

533   There are limitations in this study that need to be taken into consideration when

534   interpreting results. First, no neurophysiological measures were recorded, which could have

535   provided more direct information about internal prediction processes. Temporal

536   characteristics of error-related potentials in electroencephalogram measures, such as the

537   error-related negativity (Falkenstein et al., 1991; Gehring et al., 1993) could have supported

538   interpretations about the response latency effects. In addition, there might be another

539   explanation for the variances in prediction accuracy aside from conscious processing costs

540   that cannot be fully ruled out. In the prediction condition, participants had no visual

541   feedback about throwing effects (i.e., the ball was masked as soon as it was released).

542   Although feedback in the form of information about ball trajectory could not have had any

543   influence on performance in the current trial (since the throwing movement was already

544   terminated at that point), such feedback might have affected the participants anticipatively.

545   That is, knowing that a trial would be without feedback could have unsettled and blocked

546   them. This explanation is regarded as not very likely, but only an experimental separation of

547   missing visual feedback information about action outcomes from conscious processing costs

548   can provide a clear differentiation.

549   5   Acknowledgments

6   Literaturverzeichnis

Abreu, A. M., Candidi, M. & Aglioti, S. M. (2017). Catching on it early: Bodily and brain anticipatory mechanisms for excellence in sport. *Progress in brain research*, *234*, 53–67. https://doi.org/10.1016/bs.pbr.2017.08.006

Abreu, A. M., Macaluso, E., Azevedo, R. T., Cesari, P., Urgesi, C. & Aglioti, S. M. (2012). Action anticipation beyond the action observation network: a functional magnetic resonance imaging study in expert basketball players. *European Journal of Neuroscience*, *35*(10), 1646–1654. https://doi.org/10.1111/j.1460-9568.2012.08104.x

Aglioti, S. M., Cesari, P., Romani, M. & Urgesi, C. (2008). Action anticipation and motor resonance in elite basketball players. *Nat Neurosci*, *11*(9), 1109–1116. https://doi.org/10.1038/nn.2182

Arbuzova, P., Peters, C., Röd, L., Koß, C., Maurer, H., Maurer, L., Müller, H., Verrel, J. & Filevich, E. (in press). Measuring metacognition of direct and indirect parameters of voluntary movement. *Journal of Experimental Psychology: General*.

Baars, B. (2015). Consciousness. *Scholarpedia*, *10*(8), 2207. https://doi.org/10.4249/scholarpedia.2207

Beaulieu, C., Bourassa, M.-È., Brisson, B., Jolicoeur, P. & Beaumont, L. de (2014). Electrophysiological correlates of motor sequence learning. *BMC Neuroscience*, *15*, 102. https://doi.org/10.1186/1471-2202-15-102

Beilock, S. & Carr, T. (2001). On the fragility of skilled performance: What governs choking under pressure? *Journal of Experimental Psychology: General*, *130*(4), 701–725.

573   Beilock, S., Carr, T., MacMahon, C. & Starkes, J. (2002). When paying attention becomes

574   counterproductive: Impact of divided versus skill-focused attention on novice and

575   experienced performance of sensorimotor skills. *Journal of Experimental Psychology:*

576   *Applied*, *8*(1), 6–16.

577   Brainard, D. H. (1997). The Psychophysics Toolbox. *Spatial Vision*, *10*(4), 433–436.

578   Cameron, B. D., La Malla, C. de & López-Moliner, J. (2014). The role of differential delays in

579   integrating transient visual and proprioceptive information. *Frontiers in Psychology*, *5*, 50.

580   https://doi.org/10.3389/fpsyg.2014.00050

581   Cañal-Bruland, R., Balch, L. & Niesert, L. (2015). Judgement bias in predicting the success of

582   one's own basketball free throws but not those of others. *Psychological Research*, *79*(4),

583   548–555. https://doi.org/10.1007/s00426-014-0592-2

584   Cañal-Bruland, R., Mooren, M. & Savelsbergh, G. J. P. (2011). Differentiating experts'

585   anticipatory skills in beach volleyball. *Research Quarterly for Exercise and Sport*, *82*(4),

586   667–674. https://doi.org/10.1080/02701367.2011.10599803

587   Cohen, R. & Sternad, D. (2009). Variability in motor learning: relocating, channeling and

588   reducing noise. *Experimental Brain Research*, *193*(1), 69–83.

589   https://doi.org/10.1007/s00221-008-1596-1

590   Collins, L. H., Powell, J. L. & Oliver, P. V. (2000). Those who hesitate lose: the relationship

591   between assertiveness and response latency. *Perceptual and Motor Skills*, *90*(3 Pt 1), 931–

592   943. https://doi.org/10.2466/pms.2000.90.3.931

593   Falkenstein, M., Hohnsbein, J., Hoormann, J. & Blanke, L. (1991). Effects of crossmodal

594   divided attention on late ERP components. II. Error processing in choice reaction tasks.

595   *Electroencephalography and Clinical Neurophysiology*, *78*(6), 447–455.

596   https://doi.org/10.1016/0013-4694(91)90062-9

597   Farrow, D. & Abernethy, B. (2003). Do expertise and the degree of perception-action

598   coupling affect natural anticipatory performance? *Perception*, *32*(9), 1127–1139.

599   https://doi.org/10.1068/p3323

600   Gehring, W. J., Goss, B., Coles, M. G. H., Meyer, D. E. & Donchin, E. (1993). A Neural System

601   for Error Detection and Compensation. *Psychological Science*, *4*(6), 385–390.

602   https://doi.org/10.1111/j.1467-9280.1993.tb00586.x

603   Joch, M., Hegele, M., Maurer, H., Müller, H. & Maurer, L. K. (2017). Brain negativity as an

604   indicator of predictive error processing: the contribution of visual action effect

605   monitoring. *Journal of Neurophysiology*, *118*(1), 486–495.

606   https://doi.org/10.1152/jn.00036.2017

607   Jordan, M. & Rumelhart, D. (1992). Forward models: Supervised learning with a distal

608   teacher. *Cognitive Science*, *16*(3), 307–354. https://doi.org/10.1016/0364-0213(92)90036-

609   T

610   Li, Y. & Feng, T. (2020). The effects of sport expertise and shot results on basketball players'

611   action anticipation. *PLoS ONE*, *15*(1), e0227521.

612   https://doi.org/10.1371/journal.pone.0227521

613   Lutz, K., Puorger, R., Cheetham, M. & Jancke, L. (2013). Development of ERN together with

614   an internal model of audio-motor associations. *Frontiers in Human Neuroscience*, *7*, 471.

615   https://doi.org/10.3389/fnhum.2013.00471

616   Maglott, J. C., Chiasson, D. & Shull, P. B. (2019). Influence of skill level on predicting the

617   success of one's own basketball free throws. *PLoS ONE*, *14*(3), e0214074.

618   https://doi.org/10.1371/journal.pone.0214074

619   Masters, R. (1992). Knowledge, knerves and know-how: The role of explicit versus implicit

620   knowledge in the breakdown of a complex motor skill under pressure. *British Journal of*

621   *Psychology*, *83*, 343–358.

622   Masters, R. & Maxwell, J. (2008). The theory of reinvestment. *International Review of Sport*

623   *and Exercise Psychology*, *1*(2), 160–183. https://doi.org/10.1080/17509840802287218

624   Masters, R., Polman, R. & Hammond, N. V. (1993). 'Reinvestment': A dimension of

625   personality implicated in skill breakdown under pressure. *Personality and Individual*

626   *Differences*, *14*(5), 655–666. https://doi.org/10.1016/0191-8869(93)90113-H

627   Maurer, L. K., Joch, M., Hegele, M., Maurer, H. & Müller, H. (2021). Relevance of predictive

628   and postdictive error information in the course of motor learning. *Manuscript under*

629   *revision*.

630   Maurer, L. K., Maurer, H. & Müller, H. (2015). Neural correlates of error prediction in a

631   complex motor task. *Frontiers in behavioral neuroscience*, *9*, 209.

632   https://doi.org/10.3389/fnbeh.2015.00209

633   McNamee, D. & Wolpert, D. M. (2019). Internal Models in Biological Control. *Annual review*

634   *of control, robotics, and autonomous systems*, *2*, 339–364.

635   https://doi.org/10.1146/annurev-control-060117-105206

636   Miall, R. C. & Wolpert, D. M. (1996). Forward Models for Physiological Motor Control. *Neural*

637   *Networks*, *9*(8), 1265–1279. https://doi.org/10.1016/s0893-6080(96)00035-4

638   Müller, H. & Sternad, D. (2004). Accuracy and variability in goal-oriented movements:

639   Decomposition of gender differences in children. *Journal of Human Kinetics*, *12*, 31–50.

640   Özkan, D. G., Pezzetta, R., Moreau, Q., Abreu, A. M. & Agliotti, S. M. (2019). Predicting the

641   fate of basketball throws: an EEG study on expert action prediction in wheelchair

642   basketball players. *Experimental Brain Research*, *237*(12), 3363–3373.

643   https://doi.org/10.1007/s00221-019-05677-x

644   Pasma, J. H., Engelhart, D., Maier, A. B., Schouten, A. C., van der Kooij, H. & Meskers, C. G. M.

645   (2015). Changes in sensory reweighting of proprioceptive information during standing

646   balance with age and disease. *Journal of Neurophysiology*, *114*(6), 3220–3233.

647   https://doi.org/10.1152/jn.00414.2015

648   Pendt, L. K., Reuter, I. & Müller, H. (2011). Motor skill learning, retention, and control deficits

649   in Parkinson's disease. *PLoS ONE*, *6*(7), e21669.

650   https://doi.org/10.1371/journal.pone.0021669

651   Raftery, A. E. (1995). Bayesian Model Selection in Social Research. *Sociological Methodology*,

652   *25*, 111. https://doi.org/10.2307/271063

653   Seymour, P. H. (1970). Conceptual uncertainty and the latency of judgements of the

654   congruence of word-shape pairs. *Acta Psychologica*, *34*, 451–461.

655   https://doi.org/10.1016/0001-6918(70)90038-7

656   Thorpe, S., Fize, D. & Marlot, C. (1996). Speed of processing in the human visual system.

657   *Nature*, *381*(6582), 520–522. https://doi.org/10.1038/381520a0

658   Tomeo, E., Cesari, P., Aglioti, S. M. & Urgesi, C. (2013). Fooling the kickers but not the

659   goalkeepers: behavioral and neurophysiological correlates of fake action detection in

660   soccer. *Cereb Cortex*, *23*(11), 2765–2778. https://doi.org/10.1093/cercor/bhs279

661   Verdinelli, I. & Wasserman, L. (1995). Computing Bayes Factors Using a Generalization of the

662   Savage-Dickey Density Ratio. *Journal of the American Statistical Association*, *90*(430), 614.

663   https://doi.org/10.2307/2291073

664   Vetter, P., Sanders, L. L. O. & Muckli, L. (2014). Dissociation of prediction from conscious

665   perception. *Perception*, *43*(10), 1107–1113. https://doi.org/10.1068/p7766

666   Wolpert, D. M., Ghahramani, Z. & Jordan, M. I. (1995). An internal model for sensorimotor

667   integration. *Science*, *269*(5232), 1880–1882.

668   Wright, D. L., Pleasants, F. & Gomez-Meza, M. (1990). Use of Advanced Visual Cue Sources in

669   Volleyball. *Journal of Sport & Excercise Psychology*, *12*(4), 406–414.

670   https://doi.org/10.1123/jsep.12.4.406

671   Wulf, G., Höß, M. & Prinz, W. (1998). Instructions for motor learning: Differential effects of

672   internal versus external focus of attention. *Journal of Motor Behavior*, *30*(2), 169–179.

673   Wulf, G. & Su, J. (2007). An external focus of attention enhances golf shot accuracy in

674   beginners and experts. *Research Quarterly for Exercise and Sport*, *78*, 384–389.

675