

# 1 **Motor learning in real-world pool billiards**

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## 19 **Abstract**

20 The neurobehavioral mechanisms of human motor-control and learning evolved in free  
21 behaving, real-life settings, yet this is studied mostly in reductionistic lab-based experiments. Here  
22 we take a step towards a more real-world motor neuroscience using wearables for naturalistic full-  
23 body motion-tracking and the sports of pool billiards to frame a real-world skill learning  
24 experiment. First, we asked if well-known features of motor learning in lab-based experiments  
25 generalize to a real-world task. We found similarities in many features such as multiple learning  
26 rates, and the relationship between task-related variability and motor learning. Our data-driven  
27 approach reveals the structure and complexity of movement, variability, and motor-learning,  
28 enabling an in-depth understanding of the structure of motor learning in three ways: First, while  
29 expecting most of the movement learning is done by the cue-wielding arm, we find that motor-  
30 learning affects the whole body, changing motor-control from head to toe. Second, during learning,  
31 all subjects decreased their movement variability and their variability in the outcome. Subjects who  
32 were initially more variable were also more variable after learning. Lastly, when screening the link  
33 across subjects between initial variability in individual joints and learning, we found that only the  
34 initial variability in the right forearm supination shows a significant correlation to the subjects'  
35 learning rates. This is in-line with the relationship between learning and variability: while learning  
36 leads to an overall reduction in movement variability, only initial variability in specific task-  
37 relevant dimensions can facilitate faster learning.

## 38 Introduction

39 Motor learning is a key feature of our development and daily lives, from a baby learning  
40 to crawl, an adult learning a new sport, or a patient undergoing rehabilitation after a stroke. The  
41 process of learning a real-world motor skill is usually long and complex, and difficult to quantify  
42 as tasks are naturally unconstrained and highly variable. Most of the motor learning literature  
43 focuses on relatively simple tasks, performed in a laboratory setup or even within an MRI scanner,  
44 such as force-field adaptations<sup>1-4</sup>, visuomotor perturbations<sup>5-9</sup>, and sequence-learning of finger  
45 tapping or pinching tasks<sup>10-13</sup>. These laboratory-based learning tasks enable us to isolate specific  
46 features of motor learning and dissect them individually, thus provide elegant experiment designs  
47 to verify the experimenters' hypothesis. As a result, motor learning in the real world is rarely  
48 studied. While laboratory-tasks play an important role in our understanding of sensorimotor control  
49 and learning, they address a very restricted range of behaviours that do not capture the full  
50 complexity of real-world motor control and may overlook fundamental principles of motor control  
51 and learning in real-life<sup>14,15</sup>.

52 Neurobehavioral mechanisms are subject to evolutionary selection pressures and survive  
53 only if they are relevant in natural tasks. Thus, studying operation in natural contexts allows us to  
54 evaluate mechanisms the nervous system has been designed for<sup>16,17</sup>. E.g. in sensory neuroscience  
55 the use of natural sensory stimuli has led to a revolution of our mechanistic understanding of  
56 perception<sup>18,19</sup>. Over the past decade, there were a few notable efforts to study motor learning in  
57 unconstrained tasks. One line of research devised more complex tasks for skill learning<sup>20-22</sup> (e.g.  
58 skittles) which were implemented as computer-based gamified tasks that emulate real-world tasks.  
59 Others moved away from the computer screen but were still highly constrained; e.g. throwing a  
60 frisbee while the subject's trunk is strapped to the chair to prevent trunk movement<sup>23</sup>. Another line  
61 of inquiry used free-behaviour in real-world tasks such as tool-making or juggling<sup>17,24-27</sup>. In these  
62 studies, we and others focused on anatomical and functional MRI measurable changes following  
63 learning. In a 3-year long complex tool-making apprenticeship experiment<sup>17</sup> we were able to  
64 quantify changes in motor control precision and improvements of task outcomes, but given the 100s  
65 of hours of training involved and complexity of the task itself, we were not able to record trial-by-  
66 trial learning effects. Therefore, the findings and insights of learning studied in the computational  
67 motor control literature – at the level of actual changes in motor coordination and control policies  
68 – has received little attention in previous real-world learning studies.

69 One of the main challenges of understanding real-world behaviour and specifically motor  
70 learning is to identify underlying simplicities in a highly variable stream of movements that are not  
71 well constrained. We take a data-driven approach to analyse a real-world task and thereby illustrate  
72 a process by which one can investigate a real-world motor learning task in a principled manner. We  
73 aim to inject as few assumptions a priori as possible about task-relevant joints or mechanisms of

74 learning, instead we aim to use plausible methods to reveal these to us. The paradigm we choose is  
75 the game of pool table billiards. Pool is a real-world task that involves many different sub-tasks  
76 (precision, alignment, ballistic movements, high-level sequential planning and sequencing of shots  
77 and ball positions) which requires advanced skills – hence it is a highly competitive sport. While  
78 our ultimate goal is to move to a data analysis framework for real-world motor learning in arbitrary  
79 tasks, we find that the game of pool offers a useful intermediate goal that frames the behavioural  
80 data in a way that makes our approach amenable to be understood in the currently dominant  
81 framework of laboratory-tasks and measures. Pool billiards has natural spatial constraints (the area  
82 in and around the pool table), divisibility of behaviour into trials (shots of the ball) allowing us to  
83 visualize results in the same framework of lab-based motor learning tasks and a clear outcome (sink  
84 the ball into the pocket). Subjects had to do a pool shot to put the ball in the pocket using  
85 unconstrained full-body, self-paced movement, with as many preparatory movements as the subject  
86 needs for each shoot, the only constraints arose from the placement of the white cue ball which the  
87 subjects shoot with the cue stick and the red target ball (that needs to go into the pocket). We  
88 implemented this as a real-world experiment, effectively only adding sensors to the subject and the  
89 pool table, i.e. subjects use the normal pool cue, balls, and pool table they would in a leisure setting  
90 and thus carry out natural motor commands, receive the natural somatosensory feedback and  
91 experience the same satisfaction (rewards) when they put the ball in the pocket as this is a real-  
92 world task. Crucially, the skill of subjects in putting the ball into the pocket is learnable in the time  
93 course of 1-2 hours, allowing us to record and analyse the experiments as one session.

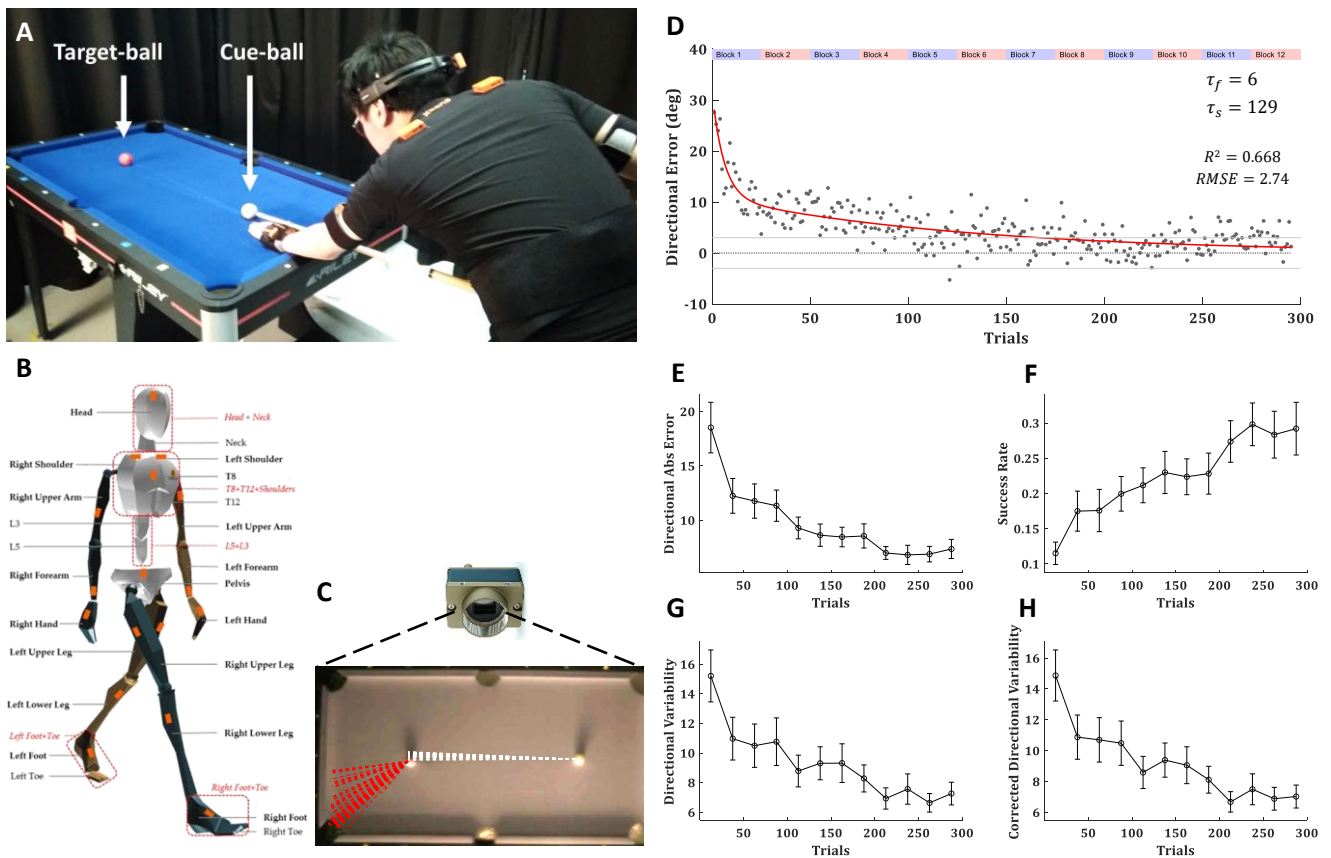
94 To tackle the complexity of the high dimensional full-body motor control and task-space  
95 (game objects) movement, we recorded continuously the full-body movement during the entire  
96 learning period (about an hour and a half) and measured balls movements automatically on the  
97 table. EEG activity was also recorded during the task via mobile brain imaging, but to focus here  
98 on the motor kinematics learning we chose to report the neural activity results elsewhere<sup>28</sup>. We  
99 quantify the trends in full-body movement and task performance separately during the entire  
100 learning process, and look for correlations between the changes in the body movement and the  
101 performance in the task.

102 We structured the results as follows: We ground our results in previous work on laboratory-  
103 tasks, to show that our unconstrained task and its task goal (directional error of the target ball  
104 relative to the pocket it is meant to go in) displays the well-known features of human motor  
105 learning, namely learning curves with characteristic double exponential shape. We then  
106 characterize full-body movement structure during the task, and how learning changes the  
107 kinematics of every of the measured 18 joints. In our analysis, we will alternate between taking a  
108 data-driven view that attempts to be task-ignorant to identify underlying simplicities indicative of  
109 biological mechanisms in the data, and a task-based view to interpret the data-driven findings by

110 using task-domain knowledge. Finally, we compare across subjects to characterize how their  
 111 performance, motor variability, and learning rates are linked.

## 112 Results

113 30 right-handed volunteers, with little to no previous experience playing billiards,  
 114 performed 300 repeated trials (6 sets of 50 trials each with short breaks in-between) where the cue  
 115 ball and target ball were placed in the same locations, and subjects were asked to shoot the target  
 116 ball towards the far-left corner pocket (Figure 1A). During the entire learning process, we recorded  
 117 the subjects' full-body movements with a 'suit' of inertial measurement units (IMUs; Figure 1B),  
 118 and the balls on the pool table were tracked with a high-speed camera to assess the outcome of each  
 119 trial (Figure 1C).



**Figure 1. Experimental setup and task performance.** (A) 30 right-handed healthy subjects performed 300 repeated trials of billiards shoots of the target (red) ball towards the far-left corner. (B) Full body movement was recorded with a 'suit' of 17 wireless IMUs (Xsens MVN Awinda). (C) The pool balls were tracked with a high-speed camera. Dashed lines show the trajectories of the cue (white) and target (red) balls over 50 trials of an example subject. (D) The trial-by-trial directional error of the target-ball (relative to the direction from its origin to the centre of the target pocket), averaged across all subjects, with a double-exponential fit (red curve). The time constant of the fast and slow components were 6 and 129 trials, respectively. Grey lines mark the range of successful trials (less than 3 degrees from the centre of the pocket). (E) The mean absolute directional error of the target-ball. (F) The success rates. (G) directional variability, and (H) directional variability corrected for learning (see text). (E-H) presented over blocks of 25 trials, averaged across all subjects, error bars represent SEM.

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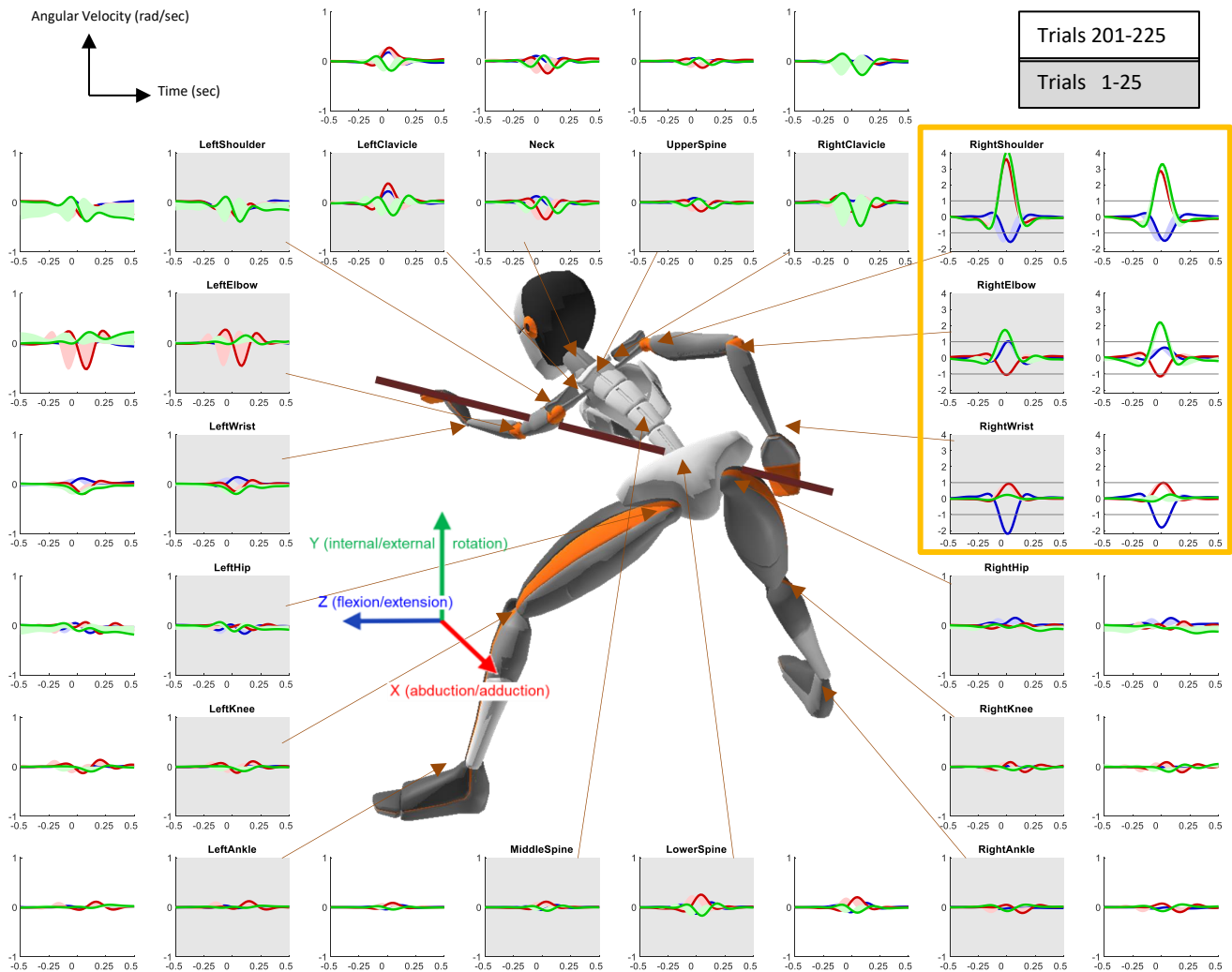
## 121 **Movement and Learning in a real-world pool task**

122           The ball tracking data showed learning curve for the decay in the directional error of the  
123 target ball (relative to the direction from its origin to the centre of the target pocket) over trials  
124 (Figure 1D). This learning curve was best fit with a double exponential curve (Supplementary  
125 Figure 1). The direction of the error in the initial trials was consistent across subjects as they tended  
126 to hit the centre of the target ball and shot it forward towards the centre of the table. For measuring  
127 success rates and intertrial variability we divided the trials into blocks of 25 trials (each  
128 experimental set of 50 trials was divided into two blocks to increase the resolution in time). To  
129 improve robustness and account for outliers, we fitted the errors in each block with a t-distribution  
130 and used the location and scale parameters ( $\mu$  and  $\sigma$ ) as the blocks' centre and variability measures.  
131 The learning curve over blocks (Figure 1E) emphasised the reduction in the inter-subject variability  
132 during learning (decreasing error bars). The success rate over blocks (percentage of successful trials  
133 in each block; Figure 1F) showed similar learning to the directional error.

134           Learning was also evident in the intertrial variability in the shooting direction which  
135 decayed over learning (Figure 1G). Since learning also occurred within a block (especially during  
136 the first block) and the variability might be driven by the learning gradient, we corrected for it by  
137 calculating intertrial variability over the residuals from a regression line fitted to the ball direction  
138 in each block (while the learning curve is exponential, within the small blocks of 25 trials it is  
139 almost linear). This corrected intertrial variability showed only minor reduction in the initial blocks,  
140 relative to the uncorrected variability, and showed the same decay pattern over the learning (Figure  
141 1H). Overall, the task performance data suggested that subjects reached peak performance by the  
142 fifth experimental set (blocks 9-10, trials 200-250) and were doing the same (or even slightly worse)  
143 on the last experimental set (blocks 11-12, trials 250-300). Thus, we refer to the last two  
144 experimental sets (blocks 9-12, trials 201-300) as the 'learning plateau', while being mindful that  
145 professional pool players train over months and years to improve or maintain their skills.

146           Kinematic data were recorded using a wearable motion tracking 'suit' of wireless IMUs,  
147 where individual wireless sensors (matchbox-sized) were attached via Velcro to elastic straps fixed  
148 around the subjects' body without constraining movement. The full-body kinematics were analysed  
149 in terms of joint angles using 3 degrees of freedom for each joint following the International Society  
150 of Biomechanics (ISB) recommendations for Euler angle extractions of Z (flexion/extension), X  
151 (abduction/adduction), and Y (internal/external rotation). Note, this standard approach includes  
152 hinge joints of the body which have only 1 degree of freedom being recorded as 3 Euler angles.  
153 The full-body movements were analysed over the angular joint velocity profiles of all joints. The  
154 data allowed us to reconstruct the full-body pose at any given moment, which we checked for visual  
155 correctness on a subject-by-subject basis against video ground truth. However, we chose not to look  
156 at joint angle's probability distributions, as those are more sensitive to potential drifts in the IMUs  
157 (and contain small changes not spottable by the human eye). We previously showed that joint

158 angular velocity probability distributions are more subject invariant than joint angle distributions  
 159 suggesting these are the reproducible features across subjects in natural behavior<sup>29</sup>. In the current  
 160 study, this robustness is quite intuitive: all subjects stood in front of the same pool table and used  
 161 the same cue stick, thus the subjects' body size influenced their joint angles distributions (taller  
 162 subjects with longer arms had to bend more towards the table and flex their elbow less than shorter  
 163 subjects with shorter limbs) but not joints angular velocity probability distributions (Figure 2).



**Figure 2.** Angular velocity profiles. Angular velocity profiles in 3 degrees of freedom (DoF) for each joint (blue: flexion/extension, red: abduction/adduction; green: internal/external rotation) averaged across subjects and trials over the first block of trials (1-25) in the inner circle (grey background) and the first block after learning plateau (201-225) in the outer circle (white background). Shaded areas represent the standard error of the mean. Data was recorded in 60 Hz, X axis is in seconds, covering a 1 second window around the timepoint the cue hit the ball. Y axis is in radians per second. The joints of the right arm which do most of movement in the task are highlighted in orange box and have a different scale on the Y axis and grey line to indicate the Y axis limits of all other joints.

164

165 In the first step of our data-driven analysis, we wanted to identify the key joints for the  
 166 task: we analysed the angular velocity profiles of all joints, averaged across the initial block trials  
 167 of all subjects, and found that most of the movement is done by the right arm, and specifically in  
 168 the right shoulder (Figure 2 inner circle). This is expected as all subjects were right-handed and

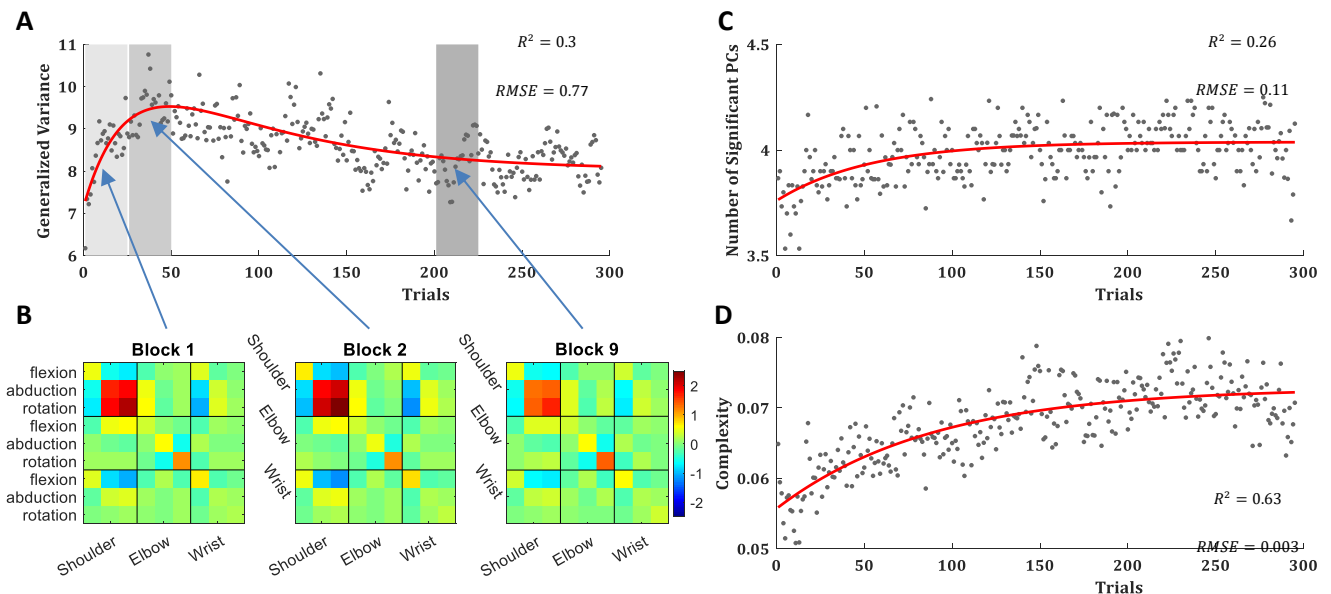
169 used their right hand to hold the cue stick and make the shot. Taking domain understanding of the  
170 task into account, we can explain the shoulder movement by the naivety of the subjects, as pool  
171 billiards guidebooks<sup>30–33</sup> emphasize that the shooting movement should be from the elbow down  
172 while the shoulder should be kept still. Correspondingly, the angular velocity profiles averaged  
173 across the initial block of the learning plateau (trials 201–225) showed similar distributions with an  
174 overall decrease in peak velocities relative to the initial trials but an increase in the peak angular  
175 velocity of ‘right elbow rotation’, which is the rotation between the upper arm and the forearm  
176 sensor and is equivalent to forearm supination (Figure 2 outer circle).

177 The angular velocities of all other joints were much smaller than those of the shooting  
178 (right) arm. For visibility, we increased the y-axis range of the right arm joints by a factor of 3  
179 relative to all other joints (Figure 2). The high variance (relative to the mean) in some of the non-  
180 shooting arm joints that do move (such as the left elbow) suggests variability across trials and  
181 subjects in the movement of this joint and specifically in its timing relative to the shot. While some  
182 subjects in some shots had a small left elbow movement just before the peak of the shot, others had  
183 it shortly after. The sensor noise was much smaller than variability across trials and subjects, as  
184 demonstrated in a recent work where we provide the noise floor for the IMU, specifically, angular  
185 velocity precision evaluated against ground-truth marker-based optical motion tracking<sup>34</sup>.

186 To quantify the overall change in the within-trial variability structure of the body over  
187 trials, we use the generalised variance, which is the determinant of the covariance matrix<sup>35</sup> and is  
188 intuitively related to the multidimensional scatter of data points around their mean. We measured  
189 the generalised variance over the angular velocity profiles of all joints and found that it increased  
190 rapidly over the first ~40 trials and later decreased slowly (Figure 3A). To understand what drives  
191 the generalised variance peak we plotted the variance-covariance matrixes of the first block, the  
192 second block (over the peak generalised variance), and ninth block (after learning plateaus) (Figure  
193 3B). It shows that the changes in the generalised variance were driven by an increase in the variance  
194 of all DoFs of the right shoulder and the negative covariance between the abduction/adduction and  
195 internal/external rotation of the right shoulder to the flexion/extension of the right shoulder and  
196 wrist. The internal/external rotation of the right elbow showed a continuous increase in its variance,  
197 which did not follow the trend of the generalised variance.

198 Next we set to study the complexity of the movement – as defined by the number of degrees  
199 of freedom used by the subject – since the use of multiple degrees of freedom in the movement is  
200 a hallmark of skill learning<sup>36</sup>. For that purpose, we applied Principal component analysis (PCA)  
201 across joints for the angular velocity profiles per trial for each subject and used the number of PCs  
202 that explain more than 1% of the variance to quantify the degrees of freedom in each trial  
203 movement. While in all trials of all subjects most of the variance can be explained by the first PC  
204 (Supplementary Figure 2), there is a slow but consistent rise in the number of PCs that explain more  
205 than 1% of the variance in the joint angular velocity profiles (Figure 3C). The manipulative

206 complexity, suggested by Belić and Faisal<sup>37</sup> as a way to quantify complexity for a given number of  
 207 PCs on a fixed scale ( $C = 1$  implies that all PCs contribute equally, and  $C = 0$  if one PC explains  
 208 all data variability), showed cleaner trajectory with the same trend (Figure 3D). This suggests that  
 209 over trials subjects use more degrees of freedom in their movement.

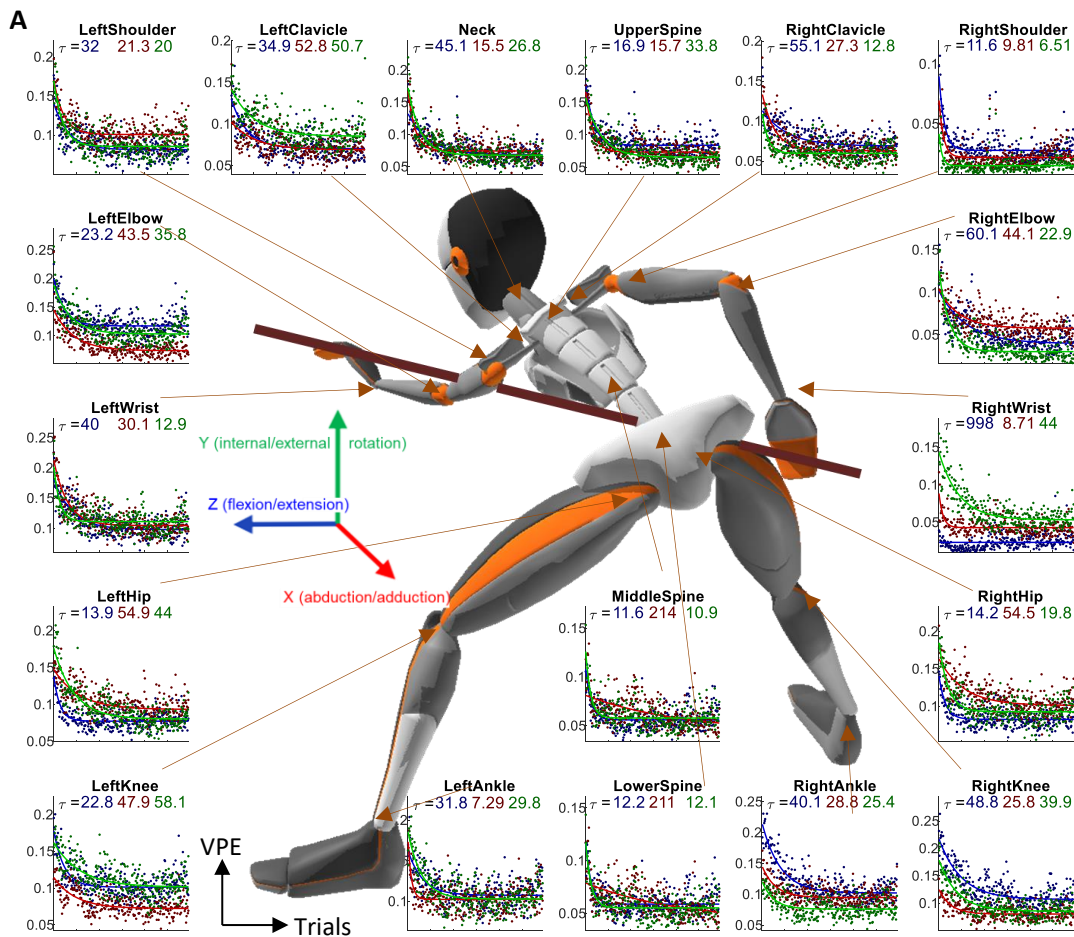


**Figure 3. Variance and Complexity.** (A) The trial-by-trial generalised variance, with a double-exponential fit (red curve). (B) The variance covariance matrix of the right arm joints angular velocity profiles averaged across subjects and trials over the initial block (trials 1-25), the second block (trials 26-50), in which the generalised variance peaks, and first block after learning plateau (block 9, trials 201-225). The order of the DoF for each joint is: flexion/extension, abduction/adduction, internal/external rotation. (C) The number of principal components (PCs) that explain more than 1% of the variance in the angular velocity profiles of all joints in a single trial, with an exponential fit (red curve). (D) The manipulative complexity (Belić and Faisal, 2015), with an exponential fit (red curve). (A, C, D) Averaged across all subjects over all trials.

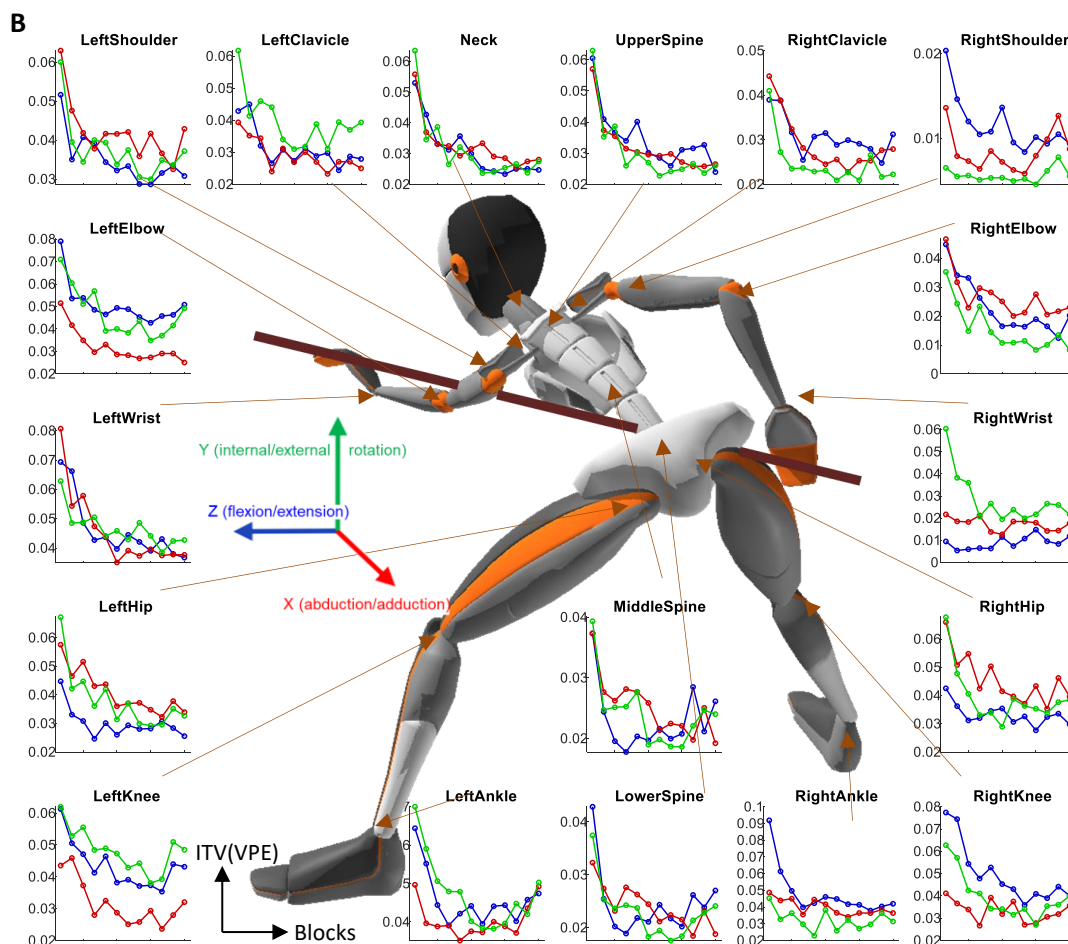
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211 In the next step of our data-driven analysis, we wanted to identify signatures of learning  
 212 joint-by-joint. For that, we defined a measure of task performance in single-joint space, which we  
 213 named the Velocity Profile Error (VPE). VPE is the minimal correlation distances between the  
 214 angular velocity profile of each joint in each trial to the angular velocity profiles of that joint in all  
 215 successful trials (for more see methods). For all joints, VPE showed a clear pattern of decay over  
 216 trials in an exponential learning curve (Figure 4A). We fitted it with a single exponential learning  
 217 curve (see fits time constants and goodness of fit in Supplementary Table 1). A proximal-to-distal  
 218 gradient in the time constant of these learning curves was observed across the right arm, from the  
 219 shoulder to the elbow and the wrist rotation (Supplementary Figure 3). Intertrial variability in joint  
 220 movement was measured over the VPEs in each block. Learning was also evident in the decay of  
 221 the VPE intertrial variability during the learning over most joints across the body (Figure 4B).





**Figure 4. Learning over Joints. (A)** Trial-by-trial Velocity Profile Error (VPE) for all 3 DoF of all joints, averaged across all subjects, with an exponential fit. The time constants of the fits are reported under the title. **(B)** VPE intertrial variability (ITV) over blocks of 25 trials, averaged across all subjects. The color code of the DoF is the same as in figure 2 (blue: flexion/extension; red: abduction/adduction; green: internal/external rotation).



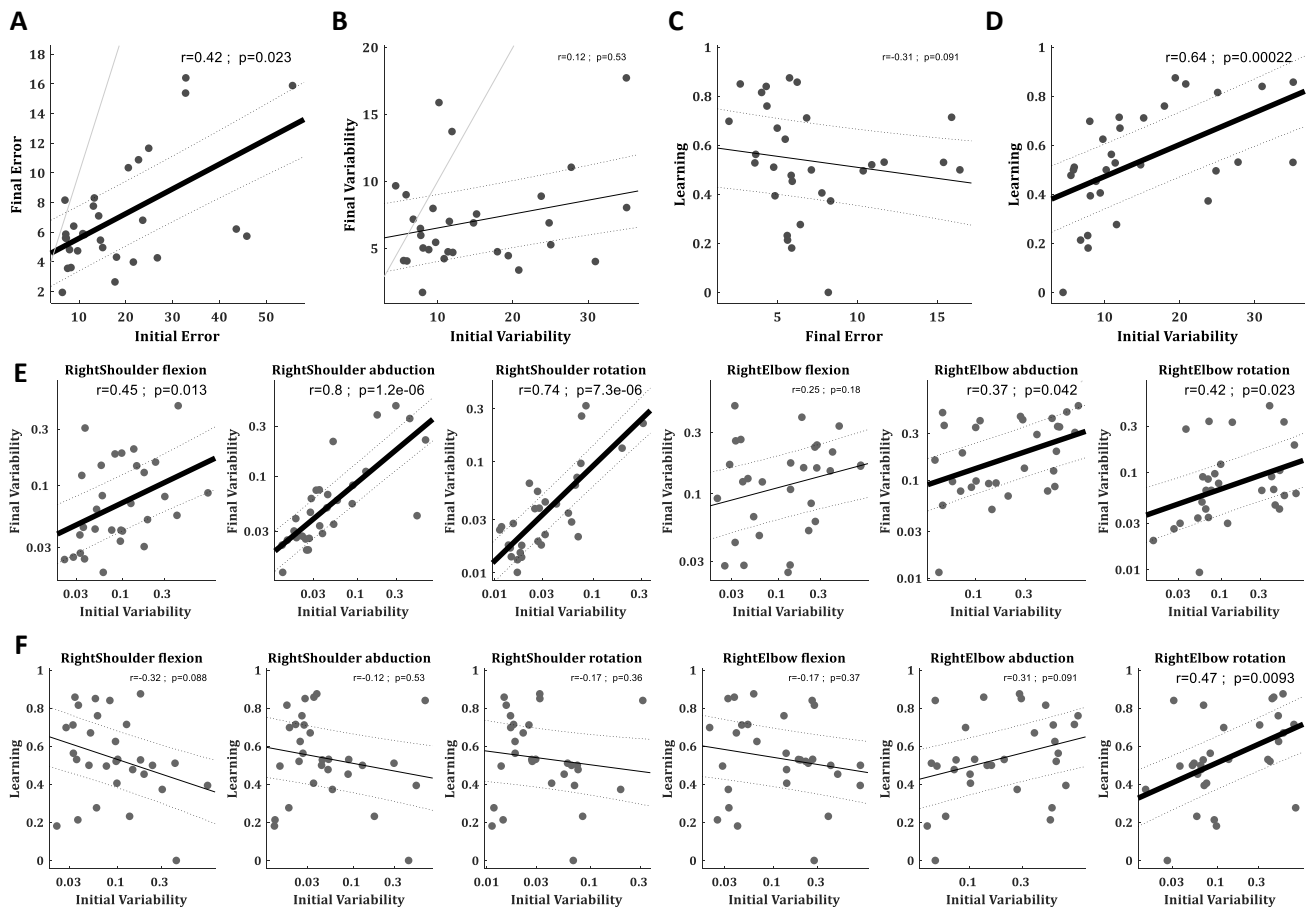
## 223 **Inter-subject differences in variability and learning**

224 In the final step of our data-driven analysis, we addressed the individuality of the subjects  
225 and looked across subjects for correlations between their task performance, learning rate, and joint  
226 movements. Since this is an exploratory study, all statistical tests are reported with caution and thus  
227 are not presented in the text but only in the figure ([Figure 5](#)) – where the readers can see the data  
228 points and make their judgment as for the true significance. The statistics are presented in Spearman  
229 rank correlation, to deal account for outliers and non-linear trends, and p-values are FDR corrected  
230 for multiple comparisons. The regression lines are presented only for visual account and include  
231 their 95% confidence intervals to address outlier biases. We found substantial differences between  
232 subjects in their initial errors, final errors, intertrial variability, and learning, which are overlooked  
233 in the group average results. One subject, who had low initial errors, showed no learning, i.e. did  
234 not reduce her error over trials from the first block (trials 1-25) to the learning plateau (trials 201-  
235 300). For all other subjects, the final errors were smaller than the initial errors ([Figure 5A](#)). There  
236 was a significant correlation between the initial and the final errors, meaning subjects with higher  
237 initial errors tended to have higher final errors as well.

238 While over the learning most subjects decreased their intertrial variability in the outcome  
239 (ball direction; [Figure 1H & 5B](#)) there was some tendency (though non-significant) for subjects  
240 who were initially more variable to be also more variable after learning ([Figure 5B](#)). The intertrial  
241 variability of the joint angular velocity profiles, which also decreased over learning ([Figure 4B](#)),  
242 showed a clearer and stronger correlation between the initial and the final intertrial variability  
243 ([Figure 5E & Supplementary Figure 4](#)). While this phenomenon was observed in various joints  
244 across the body, and dominant in the abduction across the spine joints, it was most dominant in the  
245 right shoulder abduction and rotation, the two joint angles that do most of the movement and carry  
246 most of its variance ([Figure 2](#)).

247 Learning was defined as the difference between the initial error (over the first block: trials  
248 1-25) and the final error (over the learning plateau: trials 201-300) normalised by the initial error.  
249 For the one subject who showed no learning (had bigger errors during the learning plateau than  
250 during the first block), we set learning to zero to avoid negative learning value. While there is a  
251 negative relation between learning and final error by definition, due to the normalization by the  
252 initial error (which was highly variant), there was no significant correlation between the learning  
253 and the final error (as subjects who started worse could have learned more but still not perform  
254 better after learning), but there was only a trend that more learning leads to smaller final errors  
255 ([Figure 5C](#)). We speculated that the manipulative complexity (the degrees of freedom in the  
256 movement) might explain part of the inter-subject variability in learning rates. Presumably, subjects  
257 that learn more also show a higher increase in their manipulative complexity. Yet, we found no  
258 such relation. Both the initial (over the first block: trials 1-25) and the final (over the learning  
259 plateau: trials 201-300) manipulative complexity levels showed only a weak, non-significant,

260 correlation to learning, and the increase in manipulative complexity showed no correlation to  
 261 learning (Supplementary Figure 5).



**Figure 5. Variability and learning across subjects.** (A) Correlation between subjects' mean absolute directional error (in degrees) over the first block (trials 1-25) and the learning plateau (trials 201-300). (B) Correlation between subjects' directional variability (in degrees) over first block (corrected for learning trend, see text) and over the learning plateau. (C) Correlation between subjects' mean absolute directional error over the learning plateau and their learning. (D) Correlation between subjects' directional variability over the first block (corrected for learning trend, see text) and their learning. (E) Correlation between subjects' VPE variability (in logarithmic scale) over the first block and the learning plateau for the right arm joints. (F) Correlation between subjects' VPE variability (in logarithmic scale) over the first block and their learning for the right arm joints. (A-F) Correlation values are Spearman rank correlation, p-values are FDR corrected for multiple comparisons, regression lines (black) are linear fits with 95% confidence intervals (dotted lines). (A, B) unity lines are in grey.

262

263 We then tested if higher levels of initial task-relevant motor variability (variability in the  
 264 directional error of the target ball) in this complex real-world task could predict faster learning  
 265 across individuals, as found in simple lab experiments<sup>38</sup>. We indeed found that individuals with  
 266 higher intertrial variability in the directional error of the target ball over the first block showed more  
 267 learning (Spearman rank correlation  $r=0.64$ ,  $p<0.001$ ; Figure 5D). Importantly, this is the corrected  
 268 intertrial variability (as in Figure 1H) which is calculated over the residuals from a regression line  
 269 fitted to the ball direction to correct for the learning that is happening within the block. As a control,  
 270 we also tested for correlation with the initial variability in the target ball velocity – which is a task-  
 271 irrelevant motor variability – and found no correlation (Spearman rank correlation  $r=0.06$ ,  $p=0.77$ ).

272            Since much of the learning is happening during the first 25 trials, calculating learning over  
273 blocks can lead to a ceiling effect. Therefore, to test the robustness of the correlation between  
274 learning and variability, we re-calculated the learning rate based on the 5, 7, 10, 15, and 20 initial  
275 trials (Supplementary Figure 6). All choices of more than 5 trials showed a significant correlation  
276 between the initial variability and the learning. In the case of 5 trials, there were 2 outlier subjects  
277 with high variability and little learning who damaged the correlation. These 2 subjects had an initial  
278 ‘lucky shot’ which biased the learning calculation. Once including more trials, this effect was  
279 washed out.

280            Next, we tested the link between learning and initial variability over the joint angular  
281 velocity profiles of the right arm (Figure 5F). We found that the only joint angle where the intertrial  
282 variability showed a significant correlation to learning was the right elbow rotation (Spearman rank  
283 correlation  $r=0.47$ ,  $p=0.0086$ ), which is the forearm supination. We further tested the link over the  
284 full-body kinematics (Supplementary Figure 7) and found no other joint that showed this  
285 correlation. Thus, while learning leads to an overall reduction in movement variability, only initial  
286 variability in specific, task-relevant, dimensions can facilitate/predict learning.

## 287 **Discussion**

288            In this paper, we introduce a new paradigm for studying naturalistic motor learning during  
289 whole-body movement in a complex real-world motor skill task. Our results present new insights  
290 into motor learning in the real-world. While the learning curves in this in-the-wild paradigm are  
291 within the same range of those reported in reductionistic motor adaptation tasks<sup>2,39</sup> we find that this  
292 learning is taking place not only in the task-relevant joints but across the entire body. Also, we  
293 found that task-relevant initial variability in the ball direction (movement outcome) can predict  
294 learning, like in laboratory-tasks<sup>38</sup>, and so can the initial variability in the right forearm supination  
295 which is the task-relevant joint angle variability.

296            While pushing towards real-world neuroscience, we started here with a relatively  
297 constrained version of the real-world task, asking subjects to perform repeated trials of the same  
298 pool shot. This was to enable analysis using well-developed methods of laboratory-tasks.  
299 Nonetheless, it is a major step in the direction of a naturalistic study. First, we allow full-body  
300 unconstrained movement. Second, we do not use any artificial go cue and allow self-paced  
301 movement and as many preparatory movements as the subject needs for each shoot. Third, subjects  
302 receive natural somatosensory feedback. And last, we do not perturb the feedback to induce  
303 learning.

## 304 **Fundamentals of real-world motor learning**

305 Across all subjects, we found that motor learning is a holistic process - the body is affected  
306 as a whole by learning the task. This was evident in the decrease in the VPE and the intertrial  
307 variability over learning (Figure 4A & B). This result should not come as a surprise considering  
308 decades of research in sport science showing this relationship. For example, baseball pitcher's torso,  
309 pelvis, and leg movements are directly associated with ball velocity<sup>40-42</sup>. Recently it was also  
310 demonstrated with full-body motion capture in a ball throwing task<sup>43</sup>. And yet, unlike baseball  
311 pitches, basketball throws, or any unconstrained overarm throw, where the whole body is moving,  
312 in a pool shot the shooting arm is doing most of the movement and there is very little body  
313 movement. Thus, the whole-body learning is not trivial and suggestive that even in arm movement  
314 laboratory-tasks there is probably a whole-body learning aspect that is overlooked.

315 We also found a proximal-to-distal gradient in the learning rates over the right arm joints  
316 (Figure 4A & Supplementary Figure 3). This is especially interesting in light of the well-known  
317 phenomenon of proximal-to-distal sequence in limb movements in sports science<sup>44</sup> and  
318 rehabilitation<sup>45</sup>. While there are records of proximal-to-distal sequence at multiple time scales<sup>46</sup>,  
319 our results are the first to suggest that this gradient also occur over repetitions as part of the learning  
320 process.

## 321 **Variability & learning**

322 Intertrial variability is a fundamental characteristic of human movements and its underling  
323 neural activity<sup>47</sup>. It was recently reported that individuals exhibit distinct magnitudes of movement  
324 variability, which are consistent across movements and effectors, suggesting individual traits in  
325 movement variability<sup>48</sup>. Our results show that subjects who were initially more variable tended to  
326 be also more variable after learning in many joints across the body (Figure 5E & Supplementary  
327 Figure 4) and specifically in those of right shoulder that carry most of the variance in the movement.  
328 This result is in-line with the notion that there is an individual trait in movement variability.

329 Intertrial kinematic variability is also thought to be critical for motor learning<sup>49-53</sup>. It was  
330 suggested that individuals with higher levels of task-relevant movement variability exhibit faster  
331 motor learning in both skill learning and motor adaptation error-based paradigms<sup>38</sup>. The failures to  
332 reproduce this result in visuomotor adaptation studies<sup>54,55</sup>, led to the idea that experiments with  
333 task-relevant feedback (which is common in visuomotor studies) emphasize execution noise over  
334 planning noise, whereas measurements made without feedback (as in<sup>38</sup>) may primarily reflect  
335 planning noise<sup>53</sup>. This is in-line with a recent modelling work in a visuomotor adaptation study  
336 (with task-relevant feedback) in which subjects with higher planning noise showed faster learning,  
337 but the overall movement variability was dominated by execution noise that was negatively  
338 correlated with learning<sup>56</sup>. In our task there were no manipulations or perturbations, thus, task-  
339 relevant feedback was fully available to the participants. On the other hand, in real-world, there is  
340 no baseline variability, and the variability was measured during early learning and therefore is

341 probably dominated by planning noise, as subjects explore, regardless of the visual feedback.  
342 Indeed, subjects with higher variability in the target ball direction over the first block showed higher  
343 learning rates (Figure 5D). Our results straighten the link between variability and learning and are  
344 the first to show that it applies to real-world tasks. Moreover, the only joint angle that showed a  
345 significant correlation between initial variability and learning was the right forearm supination  
346 (measured by the right elbow rotation in our IMUs setup, Figure 5F & Supplementary Figure 7).  
347 Following the idea that task-relevant variability predicts learning, it would suggest that the right  
348 elbow rotation is the task-relevant joint angle to adjust during the initial learning of a simple pool  
349 shoot. Indeed, guidebooks for pool and billiards emphasize that while shooting one should keep  
350 one's body still and move only the back (right) arm from the elbow down. While the elbow flexion  
351 movement gives the power to the shoot, the forearm supination (also known as 'screwing' in  
352 billiards) maintains the direction of the cue.

353 It is important to note that this refers specifically to the forearm supination around the  
354 elbow and not around the wrist. This is due to the nature of the data collected with the sensors suit  
355 where the joint angles are recorded with 3 degrees of freedom based on the angles between the  
356 sensors from both sides of each joint. Thus, hinge joints of the body which have only one anatomical  
357 degree of freedom been recorded as 3 Euler angles. Specifically, the elbow rotation is the rotation  
358 between the upper arm sensor and the forearm sensor and is equivalent to forearm supination around  
359 the elbow. The wrist rotation is the rotation between the forearm sensor and the hand sensor and is  
360 equivalent to hand supination.

361 It is also important to highlight that the above are correlational and cannot address the  
362 question of causality: i.e. can higher initial variability cause faster learning? While the study of  
363 real-world tasks takes us closer to understanding real-world motor-learning, it is lacking the key  
364 advantage of laboratory tasks (which made them so popular) of highly controlled manipulations of  
365 known variables, to isolate specific movement/learning components. To address this issue and  
366 introduce manipulations to this real-world task and establish causality, we developed an embodied  
367 virtual reality version of our pool task<sup>57</sup>. The VR-based approach can overcome this limitation.

## 368 **Conclusions**

369 In this study, we demonstrate the feasibility and importance of studying human  
370 neuroscience in-the-wild, and specifically in naturalistic real-world skill tasks. While finding  
371 similarities in learning structure between our real-world paradigm and lab-based motor learning  
372 studies, we highlight crucial differences, namely, real-world motor learning is a holistic full-body  
373 process. Looking at the motor behaviour over learning across the entire body enabled us to explore  
374 the relationship between variability and learning and define task-relevant variability that can  
375 facilitate learning.

376

## 377 **Methods**

378 *Ethics statement.* All experimental procedures were approved by Imperial College  
379 Research Ethics Committee and performed in accordance with the declaration of Helsinki. All  
380 subjects gave informed consent prior to participating in the study.

381 *Experimental Setup and Design.* 30 right-handed healthy human volunteers with normal or  
382 corrected-to-normal visual acuity (12 women and 18 men, aged 24±3) participated in the study.  
383 The recruitment criteria were that they played pool/billiards/snooker for leisure fewer than 5 times  
384 in their life, never in the recent 6 months, and had never received any pool game instructions. All  
385 volunteers gave informed consent before participating in the study, and all experimental procedures  
386 were approved by the Imperial College Research Ethics Committee and performed in accordance  
387 with the declaration of Helsinki. The volunteers stood in front of a 5ft pool table (Riley Leisure,  
388 Bristol, UK) with 1 7/8" (48mm diameter) pool balls. Volunteers performed 300 repeated trials  
389 where the cue ball (white) and the target ball (red) were placed in the same locations. We asked  
390 volunteers to shoot the target ball towards the pocket of the far-left corner (Figure 1A). Trials were  
391 split into 6 sets of 50 trials with a short break in-between to allow the subjects to rest a bit and  
392 reduce potential fatigue. Each experimental set (of 50 trials) took 8 to 12 minutes. For the data  
393 analysis, we further split each set into two blocks of 25 trials each, resulting in 12 blocks. During  
394 the entire learning process, we recorded the subjects' full-body movements with a motion-tracking  
395 'suit' of 17 wireless inertial measurement units (IMUs; Figure 1B). The balls on the pool table were  
396 tracked with a high-speed camera (Dalsa Genie Nano, Teledyne DALSA, Waterloo, Ontario) to  
397 assess the subjects' success in the game and to analyze the changes throughout learning, not only  
398 in the body movement but also in its outcome – the ball movement (Figure 1C).

399 *Balls tracking.* The balls movement on the pool table were tracked with a computer vision  
400 system mounted from the ceiling. The computer vision camera was a Genie Nano C1280 Color  
401 Camera (Teledyne Dalsa, Waterloo, Canada), colour images were recorded with a resolution of  
402 752x444 pixels and a frequency of 200Hz. This Ethernet-based camera was controlled via the  
403 Common Vision Blox Management Console (Stemmer Imaging, Puchheim, Germany) and image  
404 videos recorded with our custom software written in C++ based on a template provided by Stemmer  
405 Imaging. Our software captured the high-performance event timer, the camera frames and  
406 converted the images from the camera's proprietary CVB format to the open-source OpenCV  
407 (<https://opencv.org/>) image format for further processing in OpenCV. The video frames were  
408 stored as an uncompressed AVI file to preserve the mapping between pixel changes and timings  
409 and the computer's real-time clock time-stamps were recorded to a text file. Each trial was subject-  
410 paced, so the experimenter observed the subject and hit the spacebar key as an additional trigger  
411 event to the time-stamps text file. This timing data was later used to assist segmentation of the  
412 continuous data stream into trials. The positions of the two pool balls (white cue ball and red target

413 ball) were calculated from the video recordings offline using custom software written in C++ using  
414 OpenCV. Then, with custom software written in MATLAB (R2017a, The MathWorks, Inc., MA,  
415 USA), we segmented the ball tracking data and extracted the trajectory of the balls in each trial.  
416 For each trial, a 20 x 20 pixels (approx 40 x 40 mm) bounding box was set around the centre of the  
417 48 mm diameter cue ball. The time the centre of the ball left the bounding box was recorded as the  
418 beginning of the cue ball movement. The pixel resolution and frame rate were thus sufficient to  
419 detect movement onset, acceleration and deceleration of the pool balls. The target (red) ball initial  
420 position and its position in the point of its peak velocity were used to calculate the ball movement  
421 angle (relative to a perfectly straight line between the white cue ball and the red target ball). We  
422 subtracted this angle from the centre of the pocket angle (the angle the target ball initial position  
423 and the centre of the pocket relative to the same straight line between the balls) to calculate the  
424 directional error for each shot.

425 *Full-Body Motion Tracking.* Kinematic data were recorded at 60 Hz using a wearable  
426 motion tracking ‘suit’ of 17 wireless IMUs (Xsens MVN Awinda, Xsens Technologies BV,  
427 Enschede, The Netherlands). Data acquisition was controlled via a graphical interface (MVN  
428 Analyze, Xsens Technologies BV, Enschede, The Netherlands). Xsens MVN uses a biomechanical  
429 model and proprietary algorithms to estimate 3D joint kinematics<sup>58,59</sup>. The Xsens sensors shows  
430 high accuracy<sup>34</sup>, and the Xsens MVN system was used and validated in tracking real-world  
431 behaviour in many sports including football<sup>60</sup>, horse riding<sup>61</sup>, ski<sup>62</sup> and snowboarding<sup>63</sup>. The Xsens  
432 3D joint kinematics were exported as XML files and analysed using custom software written in  
433 MATLAB (R2017a, The MathWorks, Inc., MA, USA). The Xsens full-body kinematics were  
434 extracted in joint angles in 3 degrees of freedom for each joint that followed the International  
435 Society of Biomechanics (ISB) recommendations for Euler angle extractions of Z  
436 (flexion/extension), X (abduction/adduction) Y (internal/external rotation). This standard approach  
437 includes hinge joints of the body which have only 1 degree of freedom being recorded as 3 Euler  
438 angles.

439 *Angular Velocity Profile Analysis.* From the Xsens 3D joint angles we extracted the angular  
440 velocity profiles of all joints in all trials. We defined the peak of the trial as the peak of the average  
441 absolute angular velocity across the DoFs of the right shoulder and the right elbow. We aligned all  
442 trials around the peak angular velocity of the trial and cropped a window of 1 sec around the peak  
443 for the analysis of joint angular velocity profiles during the shot and its follow-through. This time  
444 window covered the entire movement of the pool shoot while eliminating the preparatory  
445 movement and the mock shoots (Figure 2).

446 *Task performance & learning measures.* The task performance was measured by the trial  
447 error which was defined as an absolute angular difference between the target ball movement vector  
448 direction and the desired direction to land the target ball in the centre of the pocket. The decay of  
449 error over trials is the clearest signature of learning in the task. For measuring success rates and



450 intertrial variability we divided the trials into blocks of 25 trials by dividing each experimental set  
451 of 50 trials to two blocks. This was done to increase the resolution in time from calculating those  
452 on the full sets. Success rate in each block was defined by the ratio of successful trial (in which the  
453 ball fell into the pocket). To improve robustness and account for outliers, we fitted the errors in  
454 each block with a t-distribution and used the location and scale parameters ( $\mu$  and  $\sigma$ ) as the blocks'  
455 centre and variability measures. To correct for learning within a block, we also calculated a  
456 corrected intertrial variability, which was the intertrial variability over the residuals from a  
457 regression line fitted to the ball direction in each block. This correction for the learning trend within  
458 a block does not change the variability measure by much (Figure 1G&H). This is since our  
459 variability measure is not the standard deviation, but the scale parameter of a t-distribution fitted to  
460 the errors. When correcting the change in the distribution fitted was mostly an increase in the  
461 degrees of freedom and a not decrease in the scale. I.e. the early trials which were much higher than  
462 the mean and the late trials which were much lower become closer to the mean and therefore the  
463 distribution is more normal as it loses the heavy tails). This is highlighting the robustness of the  
464 scale measure for variability.

465 To quantify the within-trial variability structure of the body movement, we use the  
466 generalised variance, which is the determinant of the covariance matrix<sup>35</sup> and is intuitively related  
467 to the multidimensional scatter of data points around their mean. We measured the generalised  
468 variance over the velocity profiles of all joints in each trial to see how it changes with learning. To  
469 study the complexity of the body movement which was defined by the number of degrees of  
470 freedom used by the subject we applied principal component analysis (PCA) across joints for the  
471 velocity profiles per trial for each subject and used the number of PCs that explain more than 1%  
472 of the variance to quantify the degrees of freedom in each trial movement. We also calculated the  
473 manipulative complexity which was suggested by Belić and Faisal<sup>37</sup> as a way to quantify  
474 complexity for a given number of PCs on a fixed scale ( $C = 1$  implies that all PCs contribute equally,  
475 and  $C = 0$  if one PC explains all data variability).

476 *Statistical Analysis.* Trial by trial learning curves of single-trial performance measure  
477 (directional error of the target ball relative to the centre of the pocket) were fitted with a single,  
478 double, and triple exponential learning curve using Matlab fit function. As in most motor learning  
479 datasets, the double exponential curve showed the best fit ([Supplementary Figure 1](#)).

480 As a measure of task performance in body space, correlation distances (one minus Pearson  
481 correlation coefficient) were calculated between the angular velocity profile of each joint in each  
482 trial to the angular velocity profiles of that joint in all successful trials. The minimum over these  
483 correlation distances produced a single measure of Velocity Profile Error (VPE) for each joint in  
484 each trial.

485 
$$VPE_i = \min_s(\text{corrDist}(\text{velProf}_i, \text{velProf}_s))$$

486            Thus, VPE in trial  $i$  was the minimal correlation distances between the angular velocity  
487 profile in trial  $i$  ( $velProf_i$ ) and the angular velocity profiles in successful trials  $s$  ( $velProf_s$ ). While  
488 there are multiple combinations of body variables that can all lead to successful task performance,  
489 this measure looks for the distance from the nearest successful solution used by the subjects and  
490 thus provides a metric that accounts for the redundancy in the body.

491            All correlations between error, variability, and learning are Spearman's rank correlation  
492 coefficients to be robust to outliers and non-linear trends, and their p-values are FDR corrected for  
493 multiple comparisons. Regression lines are based on linear regression fits (in logarithmic scale for  
494 VPE variability) and are presented with 95% confidence intervals.

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