

Goldsmiths Research Online

*Goldsmiths Research Online (GRO)
is the institutional research repository for
Goldsmiths, University of London*

Citation

Tecilla, Margherita; Michael, Grossbach; Gentile, Giovanni; Holland, Peter; Antonini, Angelo and Herrojo Ruiz, Maria. 2023. Modulation of Motor Vigor by Expectation of Reward Probability Trial-by-Trial Is Preserved in Healthy Ageing and Parkinson's Disease Patients. *The Journal of Neuroscience*, 43(10), pp. 1757-1777. ISSN 1529-2401 [Article]

Persistent URL

<https://research.gold.ac.uk/id/eprint/33047/>

Versions

The version presented here may differ from the published, performed or presented work. Please go to the persistent GRO record above for more information.

If you believe that any material held in the repository infringes copyright law, please contact the Repository Team at Goldsmiths, University of London via the following email address: gro@gold.ac.uk.

The item will be removed from the repository while any claim is being investigated. For more information, please contact the GRO team: gro@gold.ac.uk

Title: Modulation of motor vigour by expectation of reward probability trial-by-trial is preserved in healthy ageing and Parkinson's disease patients

Abbreviated title: Motor invigoration by reward probabilities

Author names and affiliations, including postal codes:

1. Margherita Tecilla, Department of Psychology, Goldsmiths, University of London, London SE146NW, UK
2. Michael Großbach, Institute of Music Physiology and Musicians' Medicine, Hannover University of Music Drama and Media, Hannover 30175, Germany
3. Giovanni Gentile, Parkinson and Movement Disorders Unit, Study Center for Neurodegeneration (CESNE), Department of Neuroscience, University of Padua, 35131 Padua, Italy
4. Peter Holland, Department of Psychology, Goldsmiths, University of London, London SE146NW, UK
5. Sebastian Sporn, Department of Clinical and Movement Neuroscience, Queens Square Institute of Neurology, UCL, London WC1N3BG, UK
6. Angelo Antonini, Parkinson and Movement Disorders Unit, Study Center for Neurodegeneration (CESNE), Department of Neuroscience, University of Padua, 35131 Padua, Italy
7. Maria Herrojo Ruiz, Department of Psychology, Goldsmiths, University of London, London SE146NW, UK

Corresponding author email address: Margherita Tecilla, mteci003@gold.ac.uk

Number of pages: 66

Number of figures, tables: 9 figures, 5 tables

Number of words for abstract, introduction, and discussion: abstract (250 words), introduction (650 words), discussion (1499)

Conflict of interest statement: The authors declare no competing financial interests

Acknowledgments: We would like to thank Osama Shah for programming the task in JavaScript. The authors also thank Caterina Tagliavini and McKenna Hedman for helping in data collection of Study 3.

Data and code availability

The data that support the main findings of these studies are available from the Open Science Framework Data Repository under the accession code 7kfbj:<https://osf.io/7kfbj/>

Code for the main brms and HGF analyses has also been deposited in <https://osf.io/7kfbj/>

1 **ABSTRACT**

2 Motor improvements, such as faster movement times or increased velocity, have been
3 associated with reward magnitude in deterministic contexts. Yet whether individual
4 inferences on reward probability influence motor vigour dynamically remains undetermined.
5 We investigated how dynamically inferring volatile action-reward contingencies modulated
6 motor performance trial-by-trial. We conducted three studies that coupled a one-armed
7 bandit decision-making paradigm with a motor sequence task and used a validated
8 hierarchical Bayesian model to fit trial-by-trial data. In Study 1, we tested healthy younger
9 (HYA, 37 [13 males]) and older adults (HOA, 37 [20 males]), and medicated Parkinson's
10 Disease patients (PD, 20 [13 males]). We showed that stronger predictions about the
11 tendency of the action-reward contingency led to faster performance tempo—commensurate
12 with movement time—on a trial-by-trial basis without robustly modulating reaction time (RT).
13 Using Bayesian linear mixed models, we demonstrated a similar invigoration effect on
14 performance tempo in HYA, HOA and PD, despite HOA and PD being slower than HYA. In
15 Study 2 (HYA, 39 [10 males]), we additionally showed that retrospective subjective inference
16 about credit assignment did not contribute to differences in motor vigour effects. Last, Study
17 3 (HYA, 33 [6 males]) revealed that explicit beliefs about the reward tendency (confidence
18 ratings) modulated performance tempo trial-by-trial.
19 Our study is the first to reveal that the dynamic updating of beliefs about volatile action-
20 reward contingencies positively biases motor performance through faster tempo. We also
21 provide robust evidence for a preserved sensitivity of motor vigour to inferences about the
22 action-reward mapping in ageing and medicated PD.

23 **SIGNIFICANCE STATEMENT**

24 Navigating a world rich in uncertainty relies on updating beliefs about the probability that our
25 actions lead to reward. Here we investigated how inferring the action-reward contingencies
26 in a volatile environment modulated motor vigour trial-by-trial in healthy younger and older
27 adults, and in Parkinson's Disease patients on medication. We found an association
28 between trial-by-trial predictions about the tendency of the action-reward contingency and
29 performance tempo, with stronger expectations speeding the movement. We additionally
30 provided evidence for a similar sensitivity of performance tempo to the strength of these
31 predictions in all groups. Thus, dynamic beliefs about the changing relationship between
32 actions and their outcome enhanced motor vigour. This positive bias was not compromised
33 by age or Parkinson's disease.

34 INTRODUCTION

35 The prospect of obtaining rewards invigorates motor performance, with incentives leading to
36 faster and more accurate movements (Summerside et al., 2018; Sedaghat-Nejad et al.,
37 2019; Codol et al., 2020). Several non-mutually exclusive mechanisms have been proposed
38 to account for the beneficial effects of reward on movement. These include the reward-
39 driven strengthening of motor representations at the cortical level (Galaro et al., 2019;
40 Adkins & Lee, 2021), enhanced feedback-control processes (Padmala & Pessoa, 2011;
41 Carroll et al., 2019; Manohar et al., 2019), increased limb stiffness (Codol et al., 2020) and
42 coarticulation (Sporn et al., 2022; Aves et al., 2021). Despite the growing number of studies
43 demonstrating how rewards positively bias motor behaviour, the evidence so far is limited to
44 simple manipulations of reward magnitude (presence/absence; large/small). Yet, in our
45 everyday life we are exposed to environments rich in uncertainty, where adaptive behaviour
46 relies on estimating the changing relationship between actions and their outcomes. How
47 beliefs about the probabilistic structure of reward contingencies modulate motor performance
48 remains largely unexplored. In addition, whether this modulation is compromised with age
49 and in neurological conditions is unclear.

50 Hierarchical Bayesian inference models explain how individuals learn and make decisions
51 under uncertainty (den Ouden et al., 2010; Feldman & Friston, 2010). On a neural level,
52 processing uncertainty and updating beliefs about action-reward contingencies likely
53 involves the anterior cingulate cortex (ACC, Behrens et al., 2007; Hayden et al., 2011),
54 medial prefrontal cortex (mPFC; Rouault et al., 2019) and orbitofrontal cortex (OFC; Rolls et
55 al., 2019). In multi/one-armed bandit tasks, these models describe learning as governed by
56 inferences on the probabilistic stimulus-outcome mappings, as well as higher-level beliefs
57 about the rate of change of these contingencies over time, labelled volatility (de Berker et al.,
58 2016; Sheffield et al., 2022). In Bayesian predictive coding, beliefs about the probable
59 causes of sensory data are updated via prediction errors weighted by uncertainty or
60 precision (Friston et al., 2014; Mathys et al., 2014). Thus, dynamic estimates of uncertainty
61 allow for the expression of individual differences in belief updating. If motor vigour is

62 modulated by beliefs about the action-reward contingencies, then individual differences in
63 uncertainty estimates could explain differences in motor vigour. Alternatively, under
64 equivalent signatures of decision-making behaviour, individuals could exhibit differential
65 sensitivity of motor performance to the expectation of reward probability.

66 We tested these hypotheses in three behavioural studies that used a reward-based motor
67 decision-making task based on a one-armed bandit paradigm with changing stimulus-
68 outcome contingencies over time.

69 In the first study we investigated whether dynamic predictions about volatile action-reward
70 contingencies influence motor sequence performance trial-by-trial. We additionally assessed
71 whether the sensitivity of motor performance to the strength of these expectations
72 undergoes changes in later stages of life and in patients with Parkinson's Disease (PD) on
73 their dopamine-replacement medication. This is motivated by the lack of evidence regarding
74 how reward sensitivity and reversal learning interact to modulate motor vigour in PD and
75 older adults. On the one hand, evidence supports preserved sensitivity to rewards and
76 probabilistic learning in ageing and medicated PD (Fera et al., 2005; Euteneuer et al., 2009;
77 Aves et al., 2021). Yet other work suggests impoverished decision making and reward-
78 based learning in both groups. Specifically, ageing and medicated PD can underperform in
79 tasks using volatile probabilistic stimulus-outcome mappings (Cools et al., 2001; Eppinger et
80 al., 2011; Nassar et al., 2016). However, the medication effects on decision making in PD
81 (on/off states) is still under debate (Ryterska et al., 2013; Kjær et al., 2019). Accordingly,
82 whether ageing and medicated PD can use their dynamic belief estimates to invigorate
83 motor performance trial-by-trial remains unspecified.

84 In the second study we evaluated the potential contribution of retrospective subjective
85 inferences about credit assignment to explain the motor vigour results. Last, we assessed
86 how explicit beliefs about the reward tendency (confidence ratings) modulated motor
87 performance trial-by-trial. This aimed at providing a more comprehensive understanding of
88 the motor invigoration effect by beliefs about volatile reward probabilities.

89

90 MATERIALS AND METHODS

91 Participants

92 All studies received ethical approval by the review board of Goldsmiths (healthy sample),
93 University of London, and the Neurology Clinic, Padua University Hospital (Parkinson's
94 Disease [PD] sample). Informed consent was acquired for each participant. Healthy younger
95 (HYA) and older adults (HOA) were recruited through online advertisement and via the
96 Research Participation Scheme (RPS) at Goldsmiths University, while PD were enrolled at
97 the Neurology Clinic, Padua University Hospital.

98

99 *Study 1*

100 37 HYA (13 males, age 18-40, mean age 27.8, standard error of the mean [SEM] 0.67;
101 hereafter we follow the intrinsic measures of precision for rounding descriptive and inferential
102 statistics as reported in Cousineau, 2020), 20 PD patients (13 males, age 40-75, mean age
103 58.9, SEM 1.32) and an age-matched group of 37 HOA (20 males, age 40-75, mean age
104 61.5, SEM 1.25) participated in this research. The sample size for healthy samples was
105 informed by previous work assessing differences between HYA and HOA in decision-making
106 under uncertainty (de Boer et al., 2017: N = 30, 30) and our own work assessing group
107 effects in parameters of hierarchical Bayesian models (Hein et al., 2021; 2022; N = 20, 20).
108 We increased the sample size to allow for variability being introduced due to the nature of
109 the online study.

110 All participants were right-handed, had normal or corrected vision and were able to perform
111 controlled finger movements. Amateur/professional pianists and participants diagnosed with
112 a mental health disorder were excluded from the study. Additionally, exclusion criteria for PD
113 patients were: implanted with Deep Brain Stimulation (DBS), taking antidepressant
114 medications, diagnosed with dementia and displaying tremor as an onset symptom. One PD
115 patient declared to take Laroxyl, yet confirmed not to be diagnosed with depression. PD
116 were evaluated through ITEL-Mini Mental state examination (ITEL-MMSE; Metitieri et al.,
117 2001), Unified Parkinson's Disease Rating Scale part III (UPDRS-III; Fahn & Elton, 1987),

118 Hospital Anxiety and Depression Scale (HADS; Zigmond & Snaith, 1983) and State-Trait
119 Anxiety Inventory (STAI Y2; Spielberger, 1983). Supplementary disease-related information
120 was also gathered (**Table 1**). Patients completed the experiment in the ON medication state
121 according to their usual dopamine-replacement treatment. The individual dopaminergic
122 medication details were collected and converted to a levodopa-equivalent daily dose (LEDD)
123 value (**Table 1**).

124 All participants took part in the study remotely (online), except for five PD patients, who
125 completed the study in the laboratory facilities of the Neurology Clinic of Padua. An Italian
126 translation of the original experimental instructions in English was created to test some of the
127 HOA participants (N = 24) and all PD patients (see the Results section for details on our
128 control analyses to assess the effect of the language of the instructions). The previously
129 validated Italian translations of the HADS, ITEL-MMSE, UDPRS-III and STAI Y2 scales were
130 used. HYA and HOA participants received a monetary compensation of £5 (5€ for those
131 completing the task in Italian), which could be increased up to £10 (10€) as a function of
132 their task performance. PD patients did not receive a monetary prize, in line with the clinical
133 research policies at the Neurology Clinic of Padua.

134

135 *Study 2*

136 A separate sample of 39 HYA took part in Study 2, which was aimed at evaluating the
137 potential contribution of subjective inferences about task-related reward (credit) assignment
138 to explain our results (McDougle et al., 2016). HYA participants in this control experiment
139 were divided into two subsamples as a function of their reply (True/False) to a post-
140 performance question (Q8; **Table 2**). Group Q8_T consisted of 26 participants (8 males, age
141 18-40, mean age 24.1, SEM 1.13) and Q8_F of 13 participants (2 males, age 18-40, mean age
142 25, SEM 1.7). The same inclusion/exclusion criteria and compensation as for HYA in Study 1
143 applied.

144

145 *Study 3*

146 For Study 3, we recruited 33 HYA (6 males, age 18-40, mean age 22.4, SEM 1.14) with the
147 aim of understanding how trial-by-trial explicit confidence ratings about action-reward
148 contingencies modulate motor performance. The same inclusion/exclusion criteria and
149 compensation as for HYA in Study 1 applied.

150 **Table 1**

151

152 **Experimental design**

153 In Study 1 and 2, the experiment ran completely online on the Qualtrics platform
154 (<https://www.qualtrics.com>) and was accessible through a study link. The task was
155 programmed in JavaScript and embedded into the Qualtrics form. We provide more details
156 of the data acquisition below (see Acquisition of online data using JavaScript section).

157 Participants performed a novel computerised reward-based motor decision-making task
158 based on a one-armed bandit paradigm with changing stimulus-outcome contingencies over
159 time (e.g., de Berker et al., 2016). Participants were instructed to play one of two sequences
160 of finger movements on a virtual piano to express their decision, which is an extension of
161 standard one-armed bandit tasks that instruct participants to manifest their choice by
162 pressing a right or left button (Hein et al., 2021).

163 The task consisted of a familiarisation and a reward-based learning phase. In the
164 familiarisation phase participants learned how to play two short sequences (seq1 and seq2)
165 of four finger presses each. Each sequence was uniquely represented by one of two
166 different fractal images (**Figure 1A**). They were asked to position their right hand on the
167 keyboard as follows: index finger on “g” key, middle finger on “h” key, ring finger on “j” key
168 and little finger on “k” key. Each key press reproduced a distinct auditory tone, simulating a
169 virtual piano. Participants were trained to press “g-j-h-k” for seq1 (red fractal) and “k-g-j-h” for
170 seq2 (blue fractal). Online videos showing the correct hand position on the keyboard and
171 how to perform the two sequences were provided to increase inter-individual consistency.
172 The familiarisation phase terminated when an error-free performance was achieved for five

173 times in succession for both sequences. The number of sequence renditions during
174 familiarisation was recorded and used for subsequent analyses.

175 The reward-based learning phase consisted of 180 trials. On each trial, participants were
176 instructed to choose between two coloured fractals (blue and red) and correctly play the
177 associated sequence (seq1 and seq2) in order to receive a reward (five points; **Figure 1B**).
178 Trial-by-trial reward feedback about participants' choices was provided on the screen
179 (binary: "You earned 5 points!" or "You earned 0 points"). The reward probability associated
180 with each sequence (or icon) changed every 30-42 trials (as in de Berker et al., 2016). The
181 mapping governing the likelihood of sequences being rewarded was reciprocal ($p(\text{win}|\text{seq1})$
182 $= 1-p(\text{win}|\text{seq2})$) and consisted of five stimulus-outcome contingency blocks (90/10, 70/30,
183 50/50, 30/70, 10/90) (**Figure 1C**). The order of the contingency blocks was randomly
184 generated for each participant.

185 After the first key press, subjects had 5000 ms to perform the sequence, terminating in a
186 Stop signal. Visual hints suggesting the first key to press for both sequences were displayed:
187 "It starts with a "g"" – for seq1 (red fractal); "It starts with a "k"" – for seq2 (blue fractal).
188 Participants were instructed to press key "q" if they needed a reminder of the order of finger
189 presses for each sequence. No participant required this reminder.

190 Correctly playing the rewarded sequence added five points to the participants' total score
191 (win trial). Thus, receiving five points indicated that participants chose the rewarded
192 sequence on the trial and did not make performance execution errors when playing it. Zero
193 points, however, could reflect participants choosing an unrewarded sequence on that trial or,
194 alternatively, choosing a rewarded sequence but performing it incorrectly (performance
195 execution error) (McDougle et al., 2016). No reward was provided when sequence
196 performance exceeded the 5000 ms limit (no response trial) and participants were informed
197 they played too slowly.

198 Thus, to maximise the total cumulative points over the experiment, participants had to infer
199 the probability of reward associated with each sequence and adapt their choices when
200 contingencies changed. They also had to perform the sequences correctly. Participants were

201 informed at the beginning of the experiment that the stimulus-outcome mapping would
202 change from time to time. However, they received no detailed information regarding the
203 frequency or magnitude of those changes. We validated that each participant group
204 completed the task correctly using two measures: (a) the percentage of trials that they
205 performed either seq1 or seq2 (percPlayed, referring to playing seq1); and (b) percPlayed by
206 contingency phase. In the first case, percPlayed was used to demonstrate that participants
207 did not have a preference towards one of the sequences, which could emerge if they
208 perceived one sequence to be easier with regard to motor skills. On average, we expected
209 percPlayed to be 50%. Next, (b) was used to assess whether their chosen sequences
210 tracked the contingency changes over time. To compute percPlayed by contingency phase,
211 we estimated the rate of choosing seq1 in each contingency phase, separately in each
212 participant. We then pooled these data across participants in each group, sorted by phases
213 of increasing contingency values [0.1, 0.3, 0.5, 0.7, 0.9], as defined for seq1. See further
214 details below (Behavioural and computational data analysis and Results sections).

215 In Study 2 we additionally asked participants at the end of the reward-based learning phase
216 to reply to some questions about their performance. We were particularly interested in
217 assessing whether participants could correctly infer what zero points meant, that is, whether
218 they could distinguish between a performance execution error or a decision to play a
219 sequence that was unrewarded on the trial. Both scenarios would result in zero points. We
220 reasoned that participants who could not always infer the meaning of zero might show a
221 reduced invigoration effect. **Table 2** lists the questions of the post-performance
222 questionnaire, which required binary responses (True/False) and was designed based on
223 previous work (McDougle et al., 2016; Herrojo Ruiz et al., 2017). The binary answer to
224 Question 8 “I could *always* distinguish whether 0 points reflected a performance error or a
225 bad decision” was used as criterion to split the control sample into Q8_T (i.e., participants
226 were *always* sure about the hidden causes for the lack of reward) and Q8_F (i.e., participants
227 were *not always* sure about the hidden causes for receiving zero points). Among other
228 questions, participants were asked whether the subjective number estimate of performance

229 errors was less than 10, between 10 and 30 or more than 30. This information was used to
230 investigate whether $Q8_T$ and $Q8_F$ differed in the rate of subjective execution errors. The
231 rationale here was that $Q8_F$ participants relative to $Q8_T$ could attribute more zeros to
232 performance errors rather than inferring that their choice was not rewarded on that trial.
233 Alternatively, they could misattribute zeros to bad decision outcomes. In both cases, their
234 biased credit assignment would be reflected in a more pronounced difference between
235 estimated and empirical error rates in $Q8_F$. However, their belief updating would differ; in the
236 first case, $Q8_F$ participants relative to $Q8_T$ would not update their beliefs following a zero
237 outcome, as this would be rendered as not informative feedback regarding the underlying
238 probabilistic structure. Thus, differences in credit assignment could explain differences in
239 decision making and, potentially, associated motor vigour effects. Finally, we also assessed
240 the strategy that participants used to memorise the sequences (79.5% of participants
241 declared to have memorised the sequences focusing both on the finger movements and the
242 tones; Q7).

243 In Study 3, we conducted an offline version of the task described above. The paradigm was
244 coded in psychtoolbox (<http://psychtoolbox.org>) and run in MATLAB (version 2021b). In
245 order to better capture measures of trial-wise reaction times (RT), excluding deliberation
246 time, the 5000 ms time window for performing the sequence started at the fractals
247 presentation (and not when the first key was pressed, as in Study 1 and 2). Hence, reward
248 delivery was contingent on RT and movement time.

249 Importantly, after each sequence performance we asked participants how certain they were
250 to be rewarded on that round (following Frömer et al, 2021). This aimed at unveiling a
251 potential association between trial-by-trial explicit beliefs about the reward tendency
252 (confidence ratings) and motor performance. Participants were instructed to type a number
253 in the 0–99 range on the computer keyboard with their left hand. Value 0 denoted having no
254 clue about receiving the points, while 99 reflected being absolutely certain of being
255 rewarded. Participants were encouraged to explore the full 0–99 range. They were
256 additionally asked to press the key “z” if they thought to have committed a performance

257 execution error. This allowed us to estimate the percentage of correctly identified errors,
258 which expands on Study 2 findings by informing about trial-by-trial (real-time) subjective
259 inference on credit assignment.

260 **Figure 1**

261 **Table 2**

262

263 **Acquisition of online data using JavaScript**

264 In Study 1 and 2, due to the nature of the online experiment, cross-browser issues could
265 emerge. A potential issue was that participants could use a variety of computer hardware,
266 running on different web browsers, operating systems and keyboard types (e.g., tablets vs
267 laptops). To mitigate the effect of hardware variability on the acquisition of motor
268 performance data, we instructed participants to complete the task on a desktop or laptop
269 computer. An inspection of browser user agent data suggests that the experiment was
270 performed on a mixture of desktops or laptops running the Chrome & Safari browsers on
271 Windows and Macintosh operating systems.

272 Timing data was collected using the web browser's high-resolution timer. This browser
273 resolution timer has an upper resolution limit of 2 ms on some web browsers. Therefore, all
274 analysis scripts *truncated* timing data to 2 ms precision. When estimating the mean and
275 standard error of the mean in time variables, we therefore considered a systematic error of 1
276 ms (2 ms precision means that our time measures were on average 1 ms too short).

277 For each participant, keypresses, timing data, points, contingency mapping, outcome, and
278 other data were extracted on each trial, then stored and uploaded via JSON to the data
279 folder in Pavlovia (see <https://gitlab.pavlovia.org/oshah001/reward-learning-experiment>).

280

281 **The hierarchical gaussian filter**

282 To model intra-subject trial-by-trial performance in our task, we used a validated hierarchical
283 Bayesian inference model, the Hierarchical Gaussian Filter (HGF; Mathys et al. 2011, 2014;
284 Frässle et al., 2021). The HGF toolbox is an open source software and is freely available as

285 part of TAPAS (<http://www.translationalneuromodeling.org/tapas>; Frässle et al., 2021). Here
286 we used the HGF version 6.1 implemented in MATLAB® 2020b. The HGF is a generative
287 model that describes how individual agents learn about a hierarchy of hidden states in the
288 environment, such as the latent causes of sensory inputs, probabilistic contingencies, and
289 their changes over time (labelled volatility). Beliefs on each hierarchical level are updated
290 through prediction errors (PEs) and scaled (weighted) by a precision ratio (precision as
291 inverse variance or uncertainty). The precision ratio effectively operates as a learning rate,
292 determining how much influence the uncertainty about the belief distributions has on the
293 updating process (Mathys et al., 2011, 2014).

294 In our studies, the HGF was used to characterise subject-specific trial-by-trial trajectories of
295 beliefs about stimulus-outcome contingencies (level 2) and their changes over time
296 (environmental volatility, level 3). These belief distributions are Gaussian, summarised by
297 the posterior mean (μ_2, μ_3) and the posterior variance (σ_2, σ_3). The latter represents
298 uncertainty about the hidden states on those levels, that is, our imperfect knowledge about
299 the true hidden states. On level 2, σ_2 is termed estimation or informational uncertainty. More
300 generally, the inverse $1/\sigma$ is termed precision, labelled π . The HGF provides trajectories of
301 updated beliefs on the current trial, k , after observing the outcome (posterior mean $\mu_i^{(k)}$ for
302 level $i = 2, 3$). Before observing the outcome, participants' predictions are denoted by the hat
303 operator $\hat{\mu}_i^{(k)}$ and correspond to the values in the previous trial ($\mu_i^{(k-1)}$). As in previous work
304 using one-armed bandit paradigms (Iglesias et al., 2013; Mathys et al., 2014; Hein et al.,
305 2021), we modelled learning using the 3-level HGF (HGF₃) for binary outcomes (**Figure 2A**).

306 In this hierarchical perceptual model, the hidden state on the lowest level, x_1 , represents the
307 binary categorical variable of the experimental stimuli (for each trial k , $x_1^{(k)} = 0$ if the red
308 icon/seq1 is rewarded [or blue/seq2 loses]; $x_1^{(k)} = 1$ when red fractal/seq1 is not rewarded [or
309 blue/seq2 wins]). Higher in the hierarchy, x_2 reflects the true value of the tendency of the
310 stimulus-outcome contingency, and x_3 the true volatility of the environment (i.e., of x_2). Belief
311 updating in the HGF depends on various parameters, which can be estimated in each

312 individual or fixed depending on the hypotheses. This allows for the assessment of individual
313 learning characteristics. Here we chose to individually estimate parameter ω_2 , representing
314 the tonic (time-invariant) volatility on the second level, and ω_3 , denoting the tonic volatility
315 on the third level. Generally, ω_2 and ω_3 parameters describe an individual's learning motif.
316 Larger ω_2 values are associated with faster learning about stimulus outcomes, and thus
317 greater update steps in μ_2 (see simulations in Hein et al., 2021). Similarly, greater levels of
318 tonic volatility on level 3, ω_3 , increase the update steps on μ_3 . See details on our priors in
319 **Table 3**. Using simulations to assess the accuracy of parameter estimation in the HGF₃, we
320 and others have previously demonstrated that ω_2 can be estimated accurately, while ω_3 is
321 not estimated well (Reed et al., 2020; Hein et al., 2021).

322 We then coupled the perceptual HGF model to a response model for binary outcomes, which
323 defined how beliefs about the tendency of the stimulus-outcome contingencies were mapped
324 onto decisions (e.g., which sequence should be chosen and played according to the beliefs
325 on the current trial; Mathys et al., 2014). Our response model was the unit-square sigmoid
326 observation model for binary responses (Iglesias et al., 2013; Mathys et al., 2014). This
327 model estimates on each trial k the probability that the agent's response y is either 0 or 1
328 (**Figure 2B**; $p[y^{(k)} = 1]$ and $p[y^{(k)} = 0]$), as a function of the predicted probability that the
329 icon/sequence is rewarding. This mapping from beliefs to decisions depends on the
330 response parameter ζ (interpreted as inverse decision noise). Higher ζ values indicate a
331 greater probability for the agents to select the option that is more likely to be rewarding
332 according to their beliefs. Simulations demonstrate that ζ is recovered well (Hein et al.,
333 2021).

334 In the following, as stimuli (red and blue icons) are one-to-one associated with motor
335 sequences (seq1 and seq2, respectively), we will use the term action-reward contingency
336 when referring to stimulus-reward or stimulus-outcome mappings.

337 **Figure 2**

338

339 **Models and priors**

340 In line with previous work (Iglesias et al., 2013; Hein et al., 2021) we fitted the empirical data
341 with different models. We started by modelling our data with the HGF₃ perceptual model +
342 sigmoid response model, as described above. In this model, the third hierarchical level
343 represents environmental volatility, that is the rate of change in the action-reward
344 contingencies. In our paradigm the true volatility was constant across participants, as the
345 reward contingencies changed approximately every 30-42 trials. In Study 1, using relatively
346 uninformative priors for ω_2 , ω_3 as in previous work (prior mean -4, -7, respectively; prior
347 variance 16 in both cases; Iglesias et al., 2017; de Berker et al., 2016; Hein et al., 2021) led
348 to numerical instabilities in the HGF₃ in 20% of our participants across all groups, in
349 particular in those exhibiting high win rates and thus learning well. The numerical instabilities
350 also manifested when using tight priors (small variance of 4 or 1 in the prior distribution of ω_2 ,
351 ω_3), and when using prior values estimated in our data using an ideal observer model. An
352 ideal observer is typically defined as the set of parameter values that minimise the overall
353 surprise that an agent encounters when processing the series of inputs (see an application
354 of an ideal observer model in e.g., Weber et al., 2020). It is likely that the divergence of the
355 HGF₃ in 20% of our datasets is due to the trial number being smaller than in previous studies
356 using the HGF₃ (180 instead of 320 or 400). We therefore proceeded to use the 2-level HGF
357 (HGF₂) in all our three studies, in which beliefs on volatility on the third level are fixed. Priors
358 for the perceptual HGF₂ model were chosen by simulating an ideal observer receiving the
359 series of inputs that the participants observed (**Table 3**). We then used the estimated
360 posterior values on those model parameters as priors for the HGF₂ perceptual model
361 coupled with our response model. Complementing the HGF, we used two standard
362 reinforcement learning models, the Rescorla-Wagner model (RW; fixed learning rate
363 determined by PEs; Rescorla & Wagner, 1971) and Sutton K1 model (SK1; flexible learning
364 rate driven by recent PEs; Sutton, 1992). Priors for reinforcement learning models were set
365 according to previous literature (Diaconescu, 2014; Hein et al., 2021).

366 The different models (HGF₂, RW, SK1) were fitted to the trial-by-trial inputs and responses in
367 each participant using the HGF toolbox, which generates maximum-a-posteriori (MAP)
368 parameter estimates in each individual. To identify the model that explained the behavioural
369 data across all participants best, we used random effects Bayesian model selection (BMS,
370 through the freely available MACS toolbox <https://github.com/JoramSoch/MACS>; Soch &
371 Allefeld, 2018). Importantly, in Study 1 we used the same priors in all participant groups
372 (HYA, HOA, PD) as in previous studies (Powers et al., 2017; Hein et al., 2021). Note,
373 however, that recent computational modelling work suggests that using different prior values
374 in each participant group may be more suitable to capture dissociable group effects (e.g., for
375 mental health: Valton et al., 2020). This approach, albeit interesting, would not favour a
376 standard statistical comparison between groups: any between-group differences could be
377 explained by the underlying models having been constructed differently.

378 **Table 3**

379

380 **Behavioural and computational data analysis**

381 First, we validated the task by assessing (a) the percentage of trials that each sequence type
382 was played (percPlayed) and (b) whether percPlayed followed the contingency changes.
383 See details in Experimental design. We additionally examined the percentage of trials in
384 which each sequence type was played without performance execution errors
385 (percCorrectlyPlayed).

386 General task performance in each participant was assessed by analysing the percentage of
387 errors (percError: rate of sequences with performance execution errors due to one or several
388 wrong key presses), win rate (percWin: rate of trials in which the rewarded sequence is
389 played without execution errors), the average of the trial-wise performance tempo (mIKI in
390 ms: trial-wise mean of the three inter-keystroke-intervals [IKI] across four key presses within
391 the same trial; see **Figure 1D** for trial-wise mIKI in Study 1) and the mean of the trial-wise
392 RT (in ms: time interval between the fractal presentation and first key press). Importantly,
393 mIKI is commensurate with movement time (MT), the time between the first and last key

394 press ($MT = mIKI * 3$). Finally, we also assessed the number of sequence renditions that
395 participants completed during the familiarisation phase (rendFam: average of renditions
396 across both sequence types). Time out trials and trials with performance execution errors
397 were excluded from analyses on performance tempo and RT to avoid potential confounds,
398 such as slowing following errors (Herrojo Ruiz et al., 2009).

399 Next, to investigate decision-making processes we analysed group effects on three
400 computational variables that characterised learning in each individual. The model that best
401 explained the behavioural data across all participants according to BMS was the HGF₂ (see
402 Results section). We therefore assessed the perceptual model parameter ω_2 (subject-
403 specific tonic volatility, which influences the speed of belief updating on level 2), ζ (the
404 decision noise of the response model), and the average across trials of σ_2 (posterior
405 variance of the belief distribution). The quantity σ_2 is particularly interesting, as it represents
406 informational uncertainty about the tendency of the action-reward contingency. Moreover,
407 beliefs on level 2 are updated as a function of PEs about the stimulus-outcome mapping (the
408 mismatch between the observed outcomes $u = 1$ or 0 and the agent's beliefs about the
409 probability of such an outcome) and weighted by σ_2 (the precision ratio on level 2).
410 Accordingly, if agents are more uncertain about the contingencies governing their
411 environment, they will rely more on PEs to update their beliefs on that level.

412 To test our main research hypothesis that the strength of expectations about the action-
413 reward contingency modulates the trial-by-trial motor performance, as a function of the
414 group, we focused on the trajectory $\hat{\mu}_2$ (dropping trial index k for simplicity; prediction about
415 the tendency of the action-reward contingency).

416 In Study 3, we also measured the explicit trial-wise confidence ratings (conf: number
417 between 0 and 99) about the reward outcome to assess whether motor performance was
418 sensitive to explicit beliefs about the reward tendency.

419

420 **Statistical analyses**

421 **Bayesian analyses on Study 1**

422 *General task performance and computational variables*

423 First, we calculated the mean and SEM as summary statistics for each of our general task
424 performance (mIKI, RT, percError, percWin, rendFam) and computation variables (ω^2 , ζ , σ^2).
425 Next, we evaluated between-group differences by computing Bayes Factors (BF) using the
426 bayesFactor toolbox (<https://github.com/klabhub/bayesFactor>) in MATLAB. This toolbox
427 implements tests that are based on multivariate generalisations of Cauchy priors on
428 standardised effects (Rouder et al., 2012). For each dependent variable (DV), we calculated
429 the BF on the model $DV \sim 1 + \text{group}$, where DV is explained by a fixed effect of group (HYA,
430 HOA, PD). The model was fitted using the fitlme function of the MATLAB Statistics toolbox.
431 Computing BF allowed us to quantify the evidence in support of the alternative hypothesis
432 (full model, in our case assessing the main effect of the group) relative to the null model
433 (intercept-only model, i.e., $DV \sim 1$). BF values were interpreted as in Andraszewicz et al.
434 (2015). As BF is the ratio between the probability of the data being observed under the
435 alternative hypothesis and the probability of the same data under the null hypothesis, a BF of
436 20 would indicate strong evidence for the alternative hypothesis. On the other hand, BF of
437 0.05 would provide strong evidence for the null hypothesis (see Table 1 by Andraszewicz et
438 al., 2015 for further details). Accompanying the BF results, we provided the outcomes of
439 standard one-way analysis of variance (ANOVA) for completion. In the case of main effects
440 being observed in the group-level BF analysis, we conducted follow-up BF analyses on
441 independent two-sample t-tests.

442 When analysing RT, we excluded outliers (RT values larger than three standard deviations
443 above the mean) at the subject level. For BF analyses, we used the individual average
444 across 180 trials for the mIKI, RT, and σ^2 variables. As mIKI and RT were not normally
445 distributed, values were log-transformed (natural logarithm, log_mIKI and log_RT). The
446 same preprocessing steps were applied to RT and mIKI values in Studies 2 and 3. The

447 number of renditions during the familiarisation phase was averaged between both types of
448 sequence.

449 Sanity checks were performed to assess that participants chose to play each sequence as a
450 function of the inferred action-reward contingencies and not based on individual sequence
451 preferences. These were carried out by computing mean and SEM along with BF analyses
452 for paired t-tests on the percentage of trials each sequence type was (correctly) played
453 (percPlayed; percCorrectlyPlayed; outcomes of standard paired t-test reported for
454 completion). We also report the group mean and SEM of percPlayed by contingency phases,
455 which allowed us to observe whether participants' choices followed the changes in
456 contingencies over time.

457

458 *Assessing the association between predictions about the action-reward contingency and*
459 *motor performance using Bayesian Linear Mixed Models*

460 Our main goal was to investigate whether trial-by-trial sequence performance tempo (mIKI)
461 is modulated by the expectation about the tendency of the action-reward contingency ($\hat{\mu}_2$) in
462 our participant groups. In addition, we aimed to determine whether the group factor
463 modulated the sensitivity of performance tempo to $\hat{\mu}_2$, resulting in different slopes of the
464 association.

465 We addressed these questions by implementing a series of Bayesian Linear Mixed Models
466 (BLMM) in R (version 4.0.3). We used the Bayesian Regression Models using Stan (brms;
467 Bürkner, 2017; 2018; 2021) package, freely available on
468 <https://cran.r-project.org/web/packages/brms/index.html>. Brms relies on the probabilistic
469 programming language Stan, which implements Bayesian inference using Markov Chain
470 Monte Carlo (MCMC) sampling methods to estimate approximate posterior probability
471 distributions for model parameters.

472 In the HGF for binary categorical inputs, the sign of $\hat{\mu}_2$ (and similarly μ_2) is not informative,
473 as it represents the tendency of an action-reward mapping for an *arbitrary* action (e.g., for

474 seq1). Yet, we could similarly define the model in reference to the other action (e.g., seq2).
475 In line with previous work (Stefanics et al., 2018; Hein et al., 2022), we therefore took the
476 absolute value of $\hat{\mu}_2$ ($|\hat{\mu}_2|$) for our analysis to represent the strength of predictions about the
477 tendency of the action-reward mapping. Trials with greater $|\hat{\mu}_2|$ values are trials in which the
478 participants will have a stronger expectation of receiving a reward, given they select the
479 correct action. Thus, $|\hat{\mu}_2|$ represents the *strength* of the predictions. In one participant (HYA),
480 we excluded $|\hat{\mu}_2|$ values of the last 27 trials, as the HGF trajectories diverged, despite the
481 participant exhibiting normative learning patterns. Next, we centred the $|\hat{\mu}_2|$ values ($|\hat{\mu}_2 \vee \hat{\mu}_2 - \bar{|\hat{\mu}_2|}$)
482 to allow the intercept estimate for mIKI to reflect the average $|\hat{\mu}_2|$ value. As for Bayesian
483 ANOVAs (see General task performance and computational variables), mIKI was log-
484 transformed to approach normality (log_mIKI). In one HOA participant, two log_mIKI values
485 were discarded from the analyses as they were not registered correctly in the JSON file (i.e.,
486 represented an impossible value of mIKI ~ 50 ms).

487 In BLMM with brms, it is standard to select one group as reference for the parameter
488 estimates. Brms then estimates the posterior distribution of parameter differences between
489 each group and the reference group, as well as the posterior distributions of parameters in
490 the reference group itself. We set HOA as the reference group, and therefore posterior
491 distributions of between-group differences on response variables were assessed for HOA vs
492 HYA and HOA vs PD.

493 We implemented six models of increasing complexity, with every model including a larger
494 number of explanatory variables (**Table 4**). For simplicity, in the following we used variable
495 label y to represent our dependent variable log_mIKI, and x to represent the explanatory
496 variable $|\hat{\mu}_2 \vee \hat{\mu}_2 - \bar{|\hat{\mu}_2|}$. To answer our research questions, we primarily focused on: (i) the fixed
497 effect of x (sensitivity [slope] of the performance tempo to the strength of predictions about
498 the action-reward contingency in the reference group, HOA); and (ii) the interaction effect x *
499 group (differences between groups in the sensitivity [slope] of the performance tempo to the
500 strength of expectations about the action-reward mapping).

501 For each model we ran four independent chains with 5000 iterations each, of which the first
502 1000 were discarded as warmup. This resulted in a total of 16000 posterior samples. In all
503 models we used default prior distribution for the intercept, and a normal distribution for each
504 fixed and random effect (fixed effects for group and x, normal [0,2]); interaction term group *
505 x, normal [0,1]; random effects for intercept by subject and intercept by trial, normal [0,2];
506 random effect x by subject, normal [0,1]). The prior on the LKJ-Correlation, the correlation
507 matrices in brms (Lewandowski, Kurowicka, & Joe, 2009), was set to 2 as recommended in
508 Bürkner and colleagues (2017). Chain convergence was assessed using the Gelman-Rubin
509 statistics (R-hat < 1.1; Gelman and Rubin, 1992).

510 Models were compared using leave-one-out cross-validation of the posterior log-likelihood
511 (LOO-CV) with Pareto-smoothed importance sampling (Vehtari et al., 2017). The
512 identification of the best fitting model was based on the highest expected log point-wise
513 predictive density (ELPD). We also checked that the absolute mean difference in ELPD
514 between two models (elpd_diff in brms) exceeded twice the standard error of the differences
515 (2*se_diff). LOO-CV identified the most complex model (model number 6 in **Table 4**) as the
516 best fitting model (see Results section for further details). This model explained the
517 performance tempo as the interaction between groups and the strength of the expectation
518 about the action-reward contingency (in addition to main effects). Further, it modelled the
519 effect of subjects on the intercept and $\hat{\mu}_2 \vee \hat{\epsilon}$ as a random effect, and the effect of trials on
520 the intercept as a random effect. We reported for each parameter the posterior point
521 estimate and the associated 95% credible interval (CI). See Results section for further
522 details.

523 Because reward expectations could also modulate RT as shown previously (Codol et al.,
524 2020), we conducted additional analyses to assess the effect of $\hat{\mu}_2 \vee \hat{\epsilon}$ on RT trial-by-trial.
525 Further, we evaluated whether the group factor influences the sensitivity of RT to $\hat{\epsilon} \hat{\mu}_2 \vee \hat{\epsilon}$. In
526 these analyses, we followed the same procedure as for the sequence performance tempo
527 analysis. In particular, the associations between RT (log-transformed) and $\hat{\mu}_2 \vee \hat{\epsilon}$ were

528 assessed by implementing and comparing six models of increasing complexity in brms
529 (**Table 4**; see Results for further details). RT values three standard deviations above the
530 mean were excluded from statistical analyses. This approach was also followed in Studies 2
531 and 3. As for performance tempo, in the results section we use the variable label y for the
532 dependent variable (\log_RT) and x for $|\hat{\mu}_2 \vee \hat{\sigma}_2|$.

533

Table 4

534

Bayesian analyses on Study 2

536 As described above, in Study 2 participants were allocated to two different analysis groups
537 ($Q8_T$ and $Q8_F$) depending on their answer to a post-performance question (“I could *always*
538 distinguish whether 0 points reflected a performance error or a bad decision”, binary answer:
539 True/False). This allowed us to test the potential influence of subjective inferences about
540 task-related reward assignment on the motor invigoration effect observed in Study 1.
541 Specifically, we reasoned that participants who could not always infer the meaning of zero
542 might show a reduced sensitivity of motor performance by beliefs about the reward
543 tendency.

544 As for Study 1, we computed the mean and SEM as summary statistics for each dependent
545 variable. Next, we used the bayesFactor toolbox to calculate the evidence in support of (or
546 against) group differences in general task performance (mIKI, RT, percError, percWin) and
547 computational variables (ω_2 , ζ , σ_2). We intentionally did not analyse the rate of sequence
548 renditions during the familiarisation phase as here we were only interested in assessing the
549 role of subjective inferences about credit assignment on motor sequence performance
550 decision-making behaviour. We performed BF analysis on independent two-sample t-tests to
551 assess between group-differences on the variables of interest (results on standard
552 independent t-tests also reported for completion). RT and mIKI were log transformed and
553 followed the same preprocessing steps as described for Study 1.

554 Next, to test potential between-group differences in the mIKI- $\hat{\mu}_{2 \vee \hat{\mu}_1}$ association, we
555 implemented six BLMM of increasing complexity (same models as in Study 1, **Table 4**). As
556 for Study 1, the most complex model (model number 6 in **Table 4**) was identified as the best
557 fit by LOO-CV (see Results section for further details). The same procedure was used to
558 investigate the associations between RT with $\hat{\mu}_{2 \vee \hat{\mu}_1}$.
559 Finally, we evaluated whether Q8_T and Q8_F differed in the rate of retrospective subjective
560 number estimate of performance errors. In particular, we were interested in assessing
561 between-group differences in the tendency of under/overestimating the number of
562 performance errors. For each participant, the rate of subjective performance execution errors
563 (subjective_percError) was calculated through the post-performance questionnaire (see
564 Questions 1,2,3 **Table 2**). We arbitrarily assigned a value of 0.028 (= 5/180) if subjects
565 thought to have committed less than 10 performance errors; 0.111 (= 20/180) for between
566 20 and 40 estimated performance errors; 0.222 (= 40/180) for more than 40 subjective
567 performance errors. To assess whether this rough estimate of the percentage of
568 performance errors reflected a general over or underestimation of the true performance error
569 rate in the total sample (N = 39), we first conducted a BF analysis on the correlation between
570 the subjective and empirical error rates (Pearson's r coefficient and p-value reported for
571 completion). Next, we identified potential group-related systematic biases in the subjective
572 estimate. This was done with a BF analysis using independent two-sample t-tests on the
573 normalised rate of subjective errors ([subjective_percError-percError]/percError; results on
574 standard independent t-tests reported for completion).

575

576 ***Bayesian analyses on Study 3***

577 In Study 3, we aimed at assessing the association between trial-by-trial explicit beliefs about
578 the reward tendency (confidence ratings) and motor performance. We were particularly
579 interested in understanding whether being more certain (following Frömer et al, 2021) about
580 obtaining the reward—given the right choice—would speed up motor responses.

581 First, following the same steps as for Study 1 and 2, we calculated the mean and SEM as
582 summary statistics for the general task performance variables (mIKI, RT, percWin, conf).
583 Trial-by-trial confidence ratings were converted to a 0-0.99 scale.
584 We aimed to use the confidence rating as a predictor in our BLMM analyses to assess the
585 sensitivity of motor performance (mIKI and RT) to explicit beliefs about the reward tendency.
586 This was tested by implementing four BLMM of increasing complexity (**Table 4**).
587 As for Study 1 and 2, we used the label y to represent our dependent variable (mIKI or RT),
588 and x for the explanatory variable (conf). To test our hypothesis, we specifically focused on
589 the fixed effect of x (sensitivity [slope] of the motor performance to the confidence ratings
590 about the predicted outcome). We used the same priors as in Study 1 for the corresponding
591 factors. The most complex model number 4 and the model number 3 (**Table 4**) were
592 identified as the best fit by LOO-CV for performance tempo and RT, respectively (see
593 Results section for further details).
594 In addition, as a sanity check, we evaluated the association of confidence ratings with the
595 strength of predictions about the action-reward contingency trial-by-trial. The investigation of
596 motor vigour effects in Study 1 and 2 assumed that the unsigned $|\hat{\mu}_2|$ values estimated in
597 the HGF reflect the strength of participants' expectation on the reward tendency. However,
598 whether this HGF quantity reflects true explicit beliefs, assessed as confidence ratings, is not
599 clear. We evaluated the association between confidence ratings and the unsigned $|\hat{\mu}_2|$
600 values using the formula $\text{conf} \sim 1 + |\hat{\mu}_2|_c + (1 + |\hat{\mu}_2|_c|\text{subj}) + (1|\text{trial})$ in brms. We chose a
601 default prior distribution for the intercept, and a normal distribution for the fixed and random
602 effects (fixed effect for $|\hat{\mu}_2|_c$, normal [0,2]); random effects for intercept by subject and
603 intercept by trial, normal [0,2]; random effect $|\hat{\mu}_2|_c$ by subject, normal [0,1]). The prior on
604 the LKJ-Correlation was set to 2 as recommended in Bürkner and colleagues (2017).
605 Finally, we provided summary statistics for the number of empirical performance errors and
606 the number of subjective performance errors (how many times the “z” key was pressed
607 throughout the experiment). This aimed at expanding on the findings of Study 2, informing

608 about participants' ability to correctly identify performance errors and thus infer the task-
609 related credit assignment.
610

611 RESULTS

612 Study 1

613 *Task validation*

614 Participants played on average seq1 and seq2 50% of the trials (seq1: mean 0.490, SEM
615 0.008; seq2: mean 0.508, SEM 0.008). This suggests that they did not express a preference
616 towards a sequence type (percPlayed, BF = 0.2295, moderate evidence in support of the
617 null hypothesis for no differences in the percentage of performances by sequence type, $t_{(93)} =$
618 -1.204 , $p = 0.232$). Participants committed fewer performance execution errors in seq1
619 (mean 0.958, SEM 0.005) than seq2 (mean 0.922, SEM 0.008; percCorrectlyPlayed, BF =
620 1126.7, suggesting extreme evidence for alternative hypothesis that the rate of correct
621 performance differed in seq1 and seq2, $t_{(93)} = 4.576$, $p < 0.001$). Next, we observed that
622 percPlayed in each group successfully tracked the contingency changes over time. For true
623 contingencies sorted according to increasing values, [0.1, 0.3, 0.5, 0.7, 0.9], HYA
624 participants played the corresponding sequence at these rates: [0.18 (0.02), 0.33 (0.02),
625 0.48 (0.02), 0.67 (0.02), 0.81 (0.02)]. Similar values were obtained for HOA participants:
626 [0.18 (0.02), 0.34 (0.02), 0.48 (0.02), 0.62 (0.02), 0.79 (0.02)]; and for PD patients: [0.16
627 (0.02), 0.32 (0.03), 0.47 (0.03), 0.63 (0.03), 0.79 (0.03)]. Accordingly, task performance
628 demonstrated that each group of participants learned to flexibly adapt to the changing
629 contingencies over time.

630

631 *General task performance*

632 Overall, as expected, our analyses revealed between-group differences in performance
633 tempo (mIKI in ms, HYA: 300, SEM:15.8; HOA: mean 424, SEM 19.6; PD: mean 537, SEM
634 26.9; **Figure 3A**), and reaction time (RT in ms, HYA: 634, SEM: 34.9; HOA: mean 838, SEM
635 49.4; PD: mean 918, SEM 77.5; **Figure 3B**), with movements progressively slowing down in
636 ageing and PD patients. BF analyses on performance tempo yielded extreme evidence for a
637 group effect (log_mIKI: BF = 1.1253e+09, demonstrating extreme evidence for the
638 alternative hypothesis; $F_{(2,91)} = 35.332$, $p < 0.001$). Post hoc pair-wise t-tests using BF

639 showed extreme evidence for between-group differences in HYA vs HOA (BF = 1.2044e+04)
640 and in HYA vs PD (BF = 3.3592e+07). We also found very strong evidence for the
641 alternative hypothesis in HOA vs PD (BF = 32.591). Thus, performance tempo (and
642 therefore movement time) was differently modulated between groups, with HYA being faster
643 than HOA and PD, and HOA faster than PD. Regarding RT, there was extreme evidence
644 supporting between-group differences (log_RT: BF = 404.521; $F_{(2,91)} = 11.383$, $p < 0.001$). BF
645 analysis on post hoc independent two-sample t-tests revealed extreme evidence for
646 between-group differences in HYA vs HOA (BF = 109.444) and HYA vs PD (BF = 239.335).
647 Yet, we only found anecdotal evidence in support of the null hypothesis in HOA vs PD (BF =
648 0.403). Hence, despite HYA displaying shorter RTs than HOA and PD, our analyses suggest
649 similar RTs in HOA and PD.

650 In addition, we found anecdotal evidence supporting that groups differed in the number of
651 sequence renditions during the familiarisation phase (rendFam, HYA: mean 5.6, SEM 0.1;
652 HOA: mean 6.0, SEM 0.2; PD: mean 7.1, SEM 0.8; BF = 1.733; $F_{(2,91)} = 4.448$, $p = 0.014$).
653 Post-hoc BF analyses to assess differences between pairs of groups revealed anecdotal and
654 moderate evidence for between-group differences in HYA and HOA (BF = 1.900) and HYA
655 and PD (BF = 3.030), respectively. Still, HOA and PD practised the two sequences to a
656 similar extent (BF = 0.853, revealing anecdotal evidence for the null hypothesis). Of note,
657 practising more during familiarisation was not associated with better win rates or average
658 performance tempo during task completion. A correlation analysis across all participants
659 between the number of repetitions during familiarisation and these variables demonstrated
660 some evidence for null correlation effects (percWin: BF = 0.290, Pearson $r = -0.134$, $p =$
661 0.200 ; log_mIKI: BF = 0.397; Pearson $r = 0.158$, $p = 0.131$; note that we excluded one PD
662 patient who practised 21 times during familiarisation as outlier in this correlation analysis).

663 The group effects observed above were not accompanied by a dissociation between groups
664 in the win rate or the rate of performance execution errors (**Figure 3C-D**). BF analysis on win
665 rates provided moderate evidence for the lack of a group effect (percWin, HYA: mean 0.590,
666 SEM 0.012; HOA: mean 0.561, SEM 0.014; PD: mean 0.553, SEM 0.021; BF = 0.210,

667 supporting moderate evidence for the null hypothesis; $F_{(2,91)} = 1.848$, $p = 0.163$). A similar
668 outcome was observed in the analysis of performance execution error rates (percError, HYA:
669 mean 0.061, SEM 0.009; HOA: mean 0.057, SEM 0.008; PD: mean 0.084, SEM 0.020; BF =
670 0.146, moderate evidence for the null hypothesis; $F_{(2,91)} = 1.456$, $p = 0.239$). In sum, we
671 found moderate evidence that HYA, HOA and PD did not differ in either the rate of win or
672 error trials.

673

674 *Computational parameters*

675 Decision making was assessed by looking at between-group differences in the
676 computational variables ω_2 , ζ and σ_2 . After excluding the HGF₃ from model comparison due
677 to numerical instabilities, BMS was conducted on the HGF₂ and two reinforcement learning
678 models (RW, SK1) using the individual log-model evidence (LME) values provided by the
679 HGF toolbox. The winning model was the HGF₂, with an exceedance probability of 0.95 and
680 an expected frequency of 0.90. Of note, although the HGF₃ model was not included in BMS,
681 a qualitative comparison of LME values for the HGF₃ and HGF₂ models in the 80%
682 participants in which HGF₃ did not lead to numerical instabilities revealed extremely similar
683 values (LME differences < 1). This observation suggested that both models described
684 behaviour in our task with constant true volatility to a similar degree.

685 Overall, we found no group effect on the signatures of reward-based learning and decision
686 making in our volatile task (**Figure 3E-G**). BF analysis on ω_2 demonstrated strong evidence
687 for the absence of a main effect of group (HYA: mean -1.332, SEM 0.282; HOA: mean -
688 1.686, SEM 0.438; PD: mean -1.843, SEM 0.609; BF = 0.059; $F_{(2,91)} = 0.380$ $p = 0.685$).
689 Similarly, we found strong evidence in favour of a lack of group effect on the informational
690 uncertainty about beliefs on the tendency of the action-reward contingency, σ_2 (HYA: mean
691 1.610, SEM 0.177; HOA: mean 1.663, SEM 0.158; PD: mean 1.559, SEM 0.218; BF =
692 0.045; $F_{(2,91)} = 0.074$, $p = 0.928$). Last, groups exhibited a similar mapping from beliefs to
693 responses, driven by the response model parameter ζ (HYA: mean 1.735, SEM 0.191; HOA:

694 mean 1.523, SEM 0.176; PD: mean 2.095, SEM 0.469; BF = 0.114, demonstrating moderate
695 evidence for the null hypothesis; $F_{(2,91)} = 1.1495$, $p = 0.321$).

696 A direct comparison between the Italian HOA subsample and (Italian) PD sample revealed
697 anecdotal or moderate evidence in support of the null hypothesis when assessing general
698 performance and decision-making variables (exception for log_mIKI). These findings thus
699 converge with the outcomes of the full HOA sample analysis. On the other hand, the very
700 strong evidence in support of group effects on the performance tempo in the full sample was
701 only anecdotal when directly comparing Italian HOA and PD samples on this variable
702 (log_mIKI: BF = 2.556; $t_{(42)} = -2.348$, $p = 0.024$). These results suggested that Italian healthy
703 ageing was associated with slower performance tempo relative to UK healthy ageing
704 participants (log_mIKI: BF = 6.637; $t_{(35)} = 2.871$, $p = 0.007$; moderate evidence supporting
705 differences in performance tempo). Hence, between-group effects on general task
706 performance and decision making cannot be accounted for by language differences.

707 **Figure 3**

708

709 *Sensitivity of motor performance to the strength of expectations about the action-reward*
710 *contingency*

711 For performance tempo, LOO-CV identified the most complex model (model number 6) as
712 the best fit. The absolute mean difference in ELPD between the winning model and the
713 second best fitting model (elpd_diff) was -665.8557 and the standard error of the differences
714 (se_diff) equals 39.0404 (elpd_diff > 2*se_diff). When ELPD differences between two
715 models are larger than four, and also if the number of observations is > 100, and the model
716 is moderately well specified, then the standard error is a good estimate of the uncertainty in
717 the difference between models (Vehtari et al., 2017; Sivula et al., 2022). Posterior predictive
718 checks revealed that the best model had strong predictive power for the range of the DV
719 (**Figure 4A**). In the following we use variable label y to represent our dependent variable
720 log_mIKI (in log-ms), and x to represent the explanatory variable $\hat{\mu}_2 \vee \hat{\mu}_c$. **Table 5** presents
721 a summary of the posterior distributions for the winning model.

722 **Table 5**

723

724 First, we found that groups differed in performance tempo, as expected. This is in line with
725 our previous between-group analyses showing a progressive slowness in execution tempo in
726 HOA and PD. The posterior estimate for the intercept in the reference group, HOA, was
727 6.00, CI = [5.91, 6.09] (in ms, 404, CI = [368, 443]). The distribution of the differences
728 between intercepts in HOA and HYA had a posterior estimated value of -0.34, CI = [-0.47, -
729 0.21] (in ms, -116, CI = [-163, -70]), while the distribution of the differences between
730 intercepts in HOA and PD yielded a posterior point estimate of 0.25, CI = [0.09, 0.41] (in ms,
731 114, CI = [41, 192]). As neither of the two distributions overlapped with zero, we concluded
732 that HYA performed the sequences faster than HOA, while PD was slower than HOA
733 **(Figure 4B)**.

734 Next, we evaluated how the strength of predictions about the action-reward contingency
735 modulated performance tempo on a trial-by-trial basis. The analyses supported our
736 hypothesis, showing that stronger expectations about the reward contingency invigorated
737 motor performance through faster execution tempo. Here, we focused on the distribution of
738 the fixed effect of x (slope of the association between y and x) in the reference group, HOA.
739 This distribution informs about the sensitivity of the performance tempo to the strength of
740 predictions about the action-reward contingency in HOA. The posterior estimate of x was
741 equal to -0.04, CI = [-0.07, -0.01]. As the distribution did not include zero, this highlights a
742 negative relationship between performance tempo and the strength of expectations about
743 the action-reward contingency in the reference group **(Figure 4C)**.

744 We were also interested in evaluating between-group differences in the sensitivity of
745 performance tempo to the strength of expectations about the action-reward contingency.
746 This was carried out by assessing the distribution of the interaction effect group * x on the
747 slope. Both the posterior distributions of slope differences between HOA and HYA and
748 between HOA and PD overlapped with zero, suggesting that the sensitivity was similar

749 between groups (HOA vs HYA: posterior estimate = -0.00, CI = [-0.04, 0.04]; HOA vs PD:
750 posterior estimate = -0.00, CI = [-0.05, 0.04]; **Figure 4D**).

751 Overall, our BLMM analysis demonstrated that motor performance tempo was influenced
752 trial-by-trial by the strength of predictions about the tendency of the action-reward
753 contingency, with stronger expectations leading to faster execution tempo. However, the
754 sensitivity of performance tempo to the strength of these predictions was not differently
755 modulated between groups, suggesting that all groups could successfully use the inferred
756 predictions to invigorate their motor performance to a similar degree.

757 **Figure 4**

758

759 In a separate analysis, we determined whether the motor invigoration effect extended to the
760 RT, reflecting the time to initiate the sequence performance (first key press). As for
761 performance tempo, LOO-CV identified model 6 as the best fit (elpd_diff = -378.2718, se_diff
762 = 30.69148; elpd_diff > 2*se_diff) and posterior predictive checks demonstrated good
763 predictive power for the range of the DV albeit less so than for performance tempo (**Figure**
764 **5A**). On the other hand, Gelman-Rubin statistics (R-hat values) demonstrated an excellent
765 chain convergence. **Table 5** presents a summary of the posterior distributions for the
766 winning model.

767 Our brms analysis on the best fitting model revealed shorter RT in HYA compared to HOA,
768 with no differences emerging between HOA and PD. The posterior point estimate for the
769 intercept in the reference group, HOA, was 6.65, CI = [6.54, 6.75] (in ms, 771, CI = [693,
770 856]). The distribution of the differences between intercepts in HOA and HYA was centred at
771 -0.28, CI = [-0.42, -0.13] (in ms, -188, CI = [-289, -88]), which did not overlap with zero. On
772 the other hand, the distribution of the differences between intercepts in HOA and PD yielded
773 a posterior point estimate of 0.09, CI = [-0.08, 0.27] (in ms, 77, CI = [-65, 231]) and included
774 zero (**Figure 5B**). These results demonstrated that HYA initiated the sequence faster than
775 HOA, consistent with our mIKI group results, whereas PD and HOA had a similar RT
776 intercept.

777 Regarding the association between the strength of predictions about the action-reward
778 contingency and RT, we observed no trial-by-trial modulation and no group effects. The
779 distribution of the fixed effect of x (slope of the association between y and x in the reference
780 group, HOA) had a posterior point estimate of -0.02 , CI $[-0.04, 0.01]$. As the distribution's
781 centre overlapped with zero, this demonstrates that the strength of predictions about the
782 action-reward contingency did not modulate RT in this group (**Figure 5C**). Potential
783 between-group differences in the slope were assessed by investigating the distribution of the
784 interaction effect group $\times x$. Both the posterior distributions of slope differences between
785 HOA and HYA and between HOA and PD included zero (HOA vs HYA: posterior estimate =
786 -0.01 , CI = $[-0.05, 0.03]$; HOA vs PD: posterior estimate = -0.03 , CI = $[-0.07, 0.02]$; **Figure**
787 **5D**). This outcome supported that the sensitivity of RT to the strength of expectations about
788 the reward mapping did not differ between groups. Thus, the strength of predictions about
789 the action-reward contingency invigorated performance tempo on a trial-by-trial basis without
790 affecting the RT.

791 **Figure 5**

792

793 **Study 2**

794 Subjective inference about task-related reward assignment

795 We conducted Bayesian analyses on the HYA sample of Study 2 to evaluate whether
796 subjective inferences about the hidden causes for the absence of reward could modulate the
797 motor invigoration effect observed in Study 1.

798 Overall, our analyses provided anecdotal and moderate evidence for the lack of differences
799 between $Q8_T$ and $Q8_F$ in the main markers of general task performance (log_mIKI: BF =
800 0.417 ; $t_{(37)} = -0.795$, $p = 0.432$; log_RT: BF = 0.329 ; $t_{(37)} = 0.156$, $p = 0.877$; percWin: BF =
801 0.408 ; $t_{(37)} = 0.758$, $p = 0.453$; percError: BF = 0.596 ; $t_{(37)} = -1.252$, $p = 0.219$; see **Figure 6A-**
802 **D** for summary statistics).

803 Random effects Bayesian model selection yielded substantially greater evidence in favour of
804 model HGF_2 (exceedance probability 0.94, and expected frequency 0.68). Using this model

805 to characterise decision-making processes in Q8_T and Q8_F samples, we observed that a BF
806 analysis on ω_2 , ζ and σ_2 provided anecdotal evidence for the absence of a group effect (ω_2 :
807 BF = 0.560; $t_{(37)} = -1.183$, $p = 0.244$; ζ : BF = 0.445; $t_{(37)} = 0.895$, $p = 0.377$; σ_2 : BF = 0.463; $t_{(37)}$
808 = -0.951, $p = 0.348$; see **Figure 6E-G** for summary statistics).
809 Hence, whether participants were *always* certain (Q8_T) or not (Q8_F) of the implications of
810 receiving zero points, their general motor sequence performance and decision-making
811 behaviour seemed similar, albeit this interpretation is based on anecdotal evidence.

812
813

Figure 6

814 We further investigated whether not being *always* sure about the causes for the lack of
815 reward could impact the sensitivity of motor performance (mIKI and RT) to the strength of
816 predictions about the action-reward contingency. As for the main experiment, LOO-CV
817 identified the most complex model (model number 6) as the best fit (mIKI, $\text{elpd_diff} = -$
818 144.9434 , $\text{se_diff} = 20.33661$; $\text{elpd_diff} > 2*\text{se_diff}$; RT, $\text{elpd_diff} = -106.3677$, $\text{se_diff} =$
819 17.4019 ; $\text{elpd_diff} > 2*\text{se_diff}$). **Table 5** presents a summary of the posterior distributions for
820 the winning models.

821 For performance tempo, the posterior predictive checks demonstrated a very strong
822 predictive power for the range of DV values in the best model (**Figure 7A**). Consistent with
823 our previous BF analyses on mIKI, the distribution of the differences between intercepts in
824 Q8_T and Q8_F overlapped with zero, suggesting that subjective inferences about credit
825 assignment did not impact performance tempo (**Figure 7B**). BLMM analyses also revealed a
826 negative association (slope) between the strength of predictions about the action-reward
827 contingency and performance tempo. This replicates our findings in Study 1, showing that
828 stronger predictions about the reward contingencies are followed by faster execution tempo
829 (**Figure 7C**). Yet, no between-group slope differences were observed. Thus, subjective
830 inferences about the causes for the absence of reward did not modulate the sensitivity of

831 performance tempo to the strength of expectations about the action-reward contingency
832 (**Figure 7D**).

833 **Figure 7**

834

835 Regarding RT, the predictive power for the range of RT values was weaker compared to
836 performance tempo (**Figure 8A**), yet Gelman-Rubin statistics demonstrated an excellent
837 chain convergence (R-hat values equal to 1.00). BLMM analyses showed no differences
838 between $Q8_T$ and $Q8_F$ (intercepts) on RT, which is in line with our BF results (**Figure 8B**).
839 We found no robust evidence for an association (slope) between the strength of predictions
840 about the action-reward contingency and RT (**Figure 8C**). The 95% CI of the slope
841 distribution ranged from -0.04 to 0.00. A closer look at the upper bound of the distribution
842 including three decimal digits revealed a value of 0.002, demonstrating that 0 was marginally
843 part of the 95% CI. This outcome suggests that RT is not robustly modulated by the strength
844 of predictions about the action-reward contingency, unlike performance tempo.
845 No between-group slope differences were observed. Thus, as for performance tempo,
846 subjective inferences about credit assignment did not modulate the association between RT
847 and the strength of expectations about the action-reward contingency (**Figure 8D**).

848 **Figure 8**

849

850 Finally, we investigated the effect of differences in inferences about reward assignment on
851 the post-performance subjective error rate. First, the subjective error rate estimation was
852 validated by computing BF analysis on the correlation between subjective and empirical
853 error rates. Results provided strong evidence for a positive association in the full sample (N
854 = 39; $BF = 10.204$; $r = 0.448$, $p = 0.004$). Next, we found no support for between-group
855 differences in the subjective error rate ($BF = 0.432$, demonstrating anecdotal evidence for
856 the null hypothesis; $t_{(36)} = -0.850$, $p = 0.401$). Thus, being not *always* sure about the causes
857 for the lack of reward did not influence the rate of subjective number estimate of
858 performance errors.

859 To conclude, our analyses provided evidence for the lack of differences between $Q8_T$ and
860 $Q8_F$ in the evaluated parameters, suggesting that subjective inferences about task-related
861 credit assignment do not modulate decision-making, general motor performance or the
862 association between expectation on reward probability and motor vigour. Thus, even if the
863 groups in Study 1 would have had differences in credit assignment, it is unlikely that this
864 would have led to a modulation of group effects. In addition, here we found further support
865 for our main research hypothesis, whereby stronger predictions about the action-reward
866 contingency enhanced motor vigour through faster movement.

867

868 **Study 3**

869 *Sensitivity of motor performance to confidence ratings about reward*

870 In this study we focused our BLMM analysis on the association between motor performance
871 (mIKI and RT) and confidence ratings to investigate how explicit beliefs about the reward
872 outcome modulated motor vigour. **Table 5** presents a summary of the posterior distributions
873 for the winning models.

874 For performance tempo, LOO-CV identified the most complex model (model number 4) as
875 the best fit (mIKI, $\text{elpd_diff} = -112.4178$, $\text{se_diff} = 15.74263$; $\text{elpd_diff} > 2 * \text{se_diff}$). The
876 posterior predictive checks demonstrated that the observed outcome variable y overlapped
877 well with the simulated datasets y^{rep} from the posterior predictive distribution (**Figure 9A**).
878 The y distribution exhibited two peaks, however, denoting two modes of mean performance
879 tempo in our sample. The BLMM analyses showed a negative association (slope) between
880 the confidence ratings and the performance tempo, with stronger explicit beliefs about the
881 reward tendency speeding up performance (**Figure 9B**). The slope estimate was -0.04 (95%
882 CI from -0.08 to -0.001 , including three decimal digits in the upper bound; **Figure 9C**).

883 In the case of RT, LOO-CV identified the model number 3 as the best fit ($\text{elpd_diff} = -$
884 45.046830 , $\text{se_diff} = 18.255767$; $\text{elpd_diff} > 2 * \text{se_diff}$). This model did not include trials as
885 random effect. The posterior predictive checks showed in this case that the y and y^{rep}
886 distributions overlapped perfectly (**Figure 9D**). As opposed to performance tempo, we found

887 no robust modulation of RT by confidence ratings (**Figure 9E**). The 95% CI of the slope
888 distribution ranged from -0.20 to 0.01. Thus, a zero effect was a credible value of the slope
889 distribution (**Figures 9F**).

890 Overall, these results support the conclusion that being more certain about obtaining the
891 reward speeds up performance tempo—and thus movement time—without having a clear
892 effect on RT. This expands our previous findings on the computational parameter $|\hat{\mu}_2 \vee \hat{\sigma}_c$,
893 supporting a motor invigoration effect by explicit beliefs about the reward tendency under
894 volatility.

895 In a separate sanity check, we assessed whether our measure of confidence was correlated
896 with $|\hat{\mu}_2 \vee \hat{\sigma}_c$ in the HGF₂. This would suggest that implicit beliefs about the tendency of the
897 action-reward contingency—captured with computational modelling—can be a proxy for
898 explicit ratings about the confidence of reward delivery. Indeed, a BLMM analysis
899 demonstrated a strong association between $|\hat{\mu}_2 \vee \hat{\sigma}_c$ and confidence ratings. The posterior
900 point estimate for the intercept was 0.53, CI = [0.47, 0.59]. The distribution of the fixed effect
901 of the association between $|\hat{\mu}_2 \vee \hat{\sigma}_c$ and the confidence ratings had a posterior point estimate
902 of 0.09, CI [0.04, 0.14]. R-hat values were below 1.1, indicating chain convergence (Gelman
903 and Rubin, 1992).

904 Last, descriptive statistics of performance variables in this task revealed values consistent
905 with HYA samples in Studies 1 and 2 (mIKI, in ms, mean 335, SEM 14.4; RT, in ms, mean
906 662, SEM 26.7; percWin, mean 0.542, SEM 0.011; conf, mean 0.527, SEM 0.028). Also, out
907 of the 180 trials, participants made 9.1 (SEM 1.6) performance errors on average, while they
908 subjectively reported making 4.8 (SEM 0.7) errors. Thus, they subjectively reported only
909 53% of the performance errors they committed.

910 **DISCUSSION**

911 We investigated how predictions about the tendency of the action-reward contingency
912 invigorated motor performance trial-by-trial in healthy younger adults (HYA), in medicated
913 Parkinson's Disease patients (PD), and in an age-matched sample of healthy older adults
914 (HOA). The task was a combination of a standard one-armed bandit decision-making
915 paradigm with a motor sequence task. We fitted the trial-by-trial behavioural data using the
916 Hierarchical Gaussian Filter (HGF; Mathys et al. 2011, 2014; Frässle et al., 2021) and
917 performed Bayesian analyses (Bayes Factor and Bayesian Linear Mixed Models [BLMM]).

918 Study 1 showed a trial-by-trial modulation of performance tempo—commensurate with
919 movement time—by the strength of expectations about the action-reward contingencies. The
920 invigoration effect was limited to performance tempo and was not observed for reaction time
921 (RT). Moreover, BLMM revealed a similar sensitivity of performance tempo to these
922 predictions in our three groups. This provides compelling evidence for a preservation of
923 motor invigoration by expectations of reward probability in HOA and PD, expanding the
924 understanding on how reward sensitivity and reversal learning interact to modulate motor
925 vigour in ageing and medicated PD.

926 Previous investigations of the beneficial effects of reward on motor behaviour (e.g., faster
927 and more accurate motor performance; Sedaghat-Nekad et al., 2019) have been limited to
928 manipulations of reward magnitude (presence/absence; large/small) in deterministic contexts
929 (Codol et al., 2020; Sporn et al., 2022; Aves et al., 2021). Our findings expand on
930 computational work that demonstrated the updating of beliefs in a perceptual task to speed
931 RT (Marshall et al., 2016). The authors found that, as participants learned to track the
932 transition probabilities between stimuli, different decision-making variables affected RT. Our
933 results show that the trial-by-trial influence of motor vigour by belief updating can be
934 extended beyond the perceptual domain to learning about action-reward contingencies.

935 Despite the preserved motor invigoration effect in HOA and PD, we found extreme evidence
936 for between-group differences in the mean performance tempo. HYA were faster than HOA
937 and PD, and HOA quicker than PD. The slower sequence execution in HOA is consistent
938 with a general slowness of hand movements in later stages of life (Ketcham et al., 2002;
939 Aves et al., 2021). Regarding PD, the slower performance is likely explained by a sequence
940 effect (SE). SE is a common bradykinetic symptom in PD, which manifests through slower
941 and attenuated sequential movements (Kang et al., 2010). Dopamine (DA) intake does not
942 ameliorate symptoms associated with SE, suggesting a non-DA involvement in the
943 pathophysiology of this effect (Bologna et al., 2016). Similar results were found for RT, with
944 HYA displaying shorter RT than HOA and PD. Yet, RT did not dissociate between HOA and
945 PD.

946 We additionally found evidence for similar win and error rates in our three groups. Empirical
947 findings on reward learning in ageing and medicated PD have been mixed. Some studies
948 have shown reduced probabilistic and reversal learning in older adults and PD ON
949 medication, suggesting difficulties in establishing new stimulus-outcome associations and
950 updating reward beliefs (Cools et al., 2001; Eppinger et al., 2011; Nassar et al., 2016).
951 Consistent with this, de Boer et al. (2017) demonstrated poorer probabilistic reversal
952 learning in ageing compared to young participants, with the attenuation of the anticipatory
953 values signals in the prefrontal brain accounting for the impoverished performance.
954 However, other work argued for preserved reward sensitivity and learning in older adults and
955 medicated PD (Fera et al., 2005; Euteneuer et al., 2009; Aves et al., 2021). Specifically, PD
956 ON medication have been found to successfully learn from rewards, and exhibit deficits in
957 reversal learning exclusively for negative feedback (Frank et al., 2004; Levy-Gigi, 2019).
958 Also, Hird et al. (2022) reported that age does not modulate the invigorating effect of reward

959 on motor responses. This is consistent with our findings, highlighting a preserved motor
960 invigoration effect by reward in ageing and medicated PD.

961 Our groups did not differ in the main markers of decision making. We provided some
962 evidence for the absence of a group effect on tonic volatility (ω_2 ; index of individual learning
963 about the action-reward mapping under volatility [Hein et al., 2021]), estimated uncertainty
964 about the action-reward tendency (σ_2) and on the mapping from beliefs to responses (ζ).
965 Accordingly, belief updating in our task with changing action-reward contingencies was
966 comparable across HYA, HOA and PD groups.

967 One aspect that was not identified in Study 1 was whether participants correctly inferred the
968 hidden causes for the lack of reward (McDougle et al., 2016). Study 2 demonstrated that
969 retrospective subjective inference about credit assignment did not contribute to differences in
970 general motor performance, decision making, motor vigour or the subjective estimate of
971 performance errors. Because the feedback that participants received was veridical (unlike in
972 McDougle et al., 2016), the effects of misattribution of the causes of zero reward in our study
973 are likely very small, as the anecdotal evidence suggests. A limitation of this study, however,
974 was that it relied on retrospective self-report. Accordingly, we conducted a third study to
975 determine whether trial-by-trial explicit beliefs about the reward tendency (confidence
976 ratings) are associated with faster motor performance.

977 Study 3 demonstrated that performance tempo is associated with confidence ratings trial-by-
978 trial: being more certain about obtaining the reward speeded up the movement. Moreover,
979 the confidence ratings were robustly correlated with the strength of the predictions. This
980 outcome supports that implicit beliefs about the tendency of the action-reward contingency—
981 captured with computational modelling—can be a proxy for explicit ratings about the
982 confidence of reward delivery.

983 The invigoration effect of beliefs (both implicit and explicit) did not extend to RT. Accordingly,
984 across our three studies, RT was not robustly modulated in the same dynamic trial-wise
985 manner as performance tempo was. In Study 1 and 2, RT included deliberation time (no
986 constraints on initiating the sequence), which could have introduced noise to the RT
987 distribution and weakened the motor vigour effects. By contrast, RT in Study 3 excluded
988 deliberation time.

989 According to current hypotheses, motor vigour is based on trading-off future efforts and
990 gains, reflecting a subject's willingness to invest energy to harvest future rewards (Shadmehr
991 et al., 2010; Yoon et al., 2020). Specifically, it increases when the option is inferred to be
992 valuable and decreases for perceived effort. This has been demonstrated both for movement
993 times and RT (Summerside et al., 2018, Codol et al., 2020). It follows that changes in vigour
994 should be modulated by inferences on the tendency of reward probability. We demonstrated
995 that exclusively performance tempo—commensurate with movement time—is affected by
996 beliefs about the action-reward contingency on a trial-by-trial basis. The lack of robust
997 invigoration effects on RT is consistent with sequential planning effects introducing noise to
998 the RT distribution. Recent work has demonstrated that the preparatory state of discrete
999 sequential finger movements reflects sequence planning skills (Mantziara et al., 2021).
1000 Accordingly, RT in our task would include trial-by-trial variability in sequence preparation,
1001 which may mask the underlying motor vigour effects. A prediction for future work would be a
1002 trial-by-trial invigoration of RT, beyond movement time, in motor tasks that do not require
1003 preparation of discrete movements.

1004 A limitation of the present work is that, due to the nature of our online experiment, we only
1005 tested PD ON medication. Future work should investigate the effect of DA on the trial-by-trial
1006 association between the expectations of reward probability and motor vigour. Interestingly, a
1007 recent study by Hird et al. (2022) found only a weak association between dopamine D1

1008 receptor availability and the invigorating effect of reward. This outcome, together with our
1009 finding of preserved dynamic motor vigour effects in medicated PD, raises an interesting
1010 question: if motor vigour and learning are driven by the dopaminergic system as previously
1011 postulated (Balleine et al., 2007; Eppinger et al., 2011), how robust is this association in
1012 more complex scenarios rich in uncertainty and with changing reward probabilities over
1013 time? Our results suggest that DA-replacement therapy could restore putative decision-
1014 making deficits during learning in volatile environments in PD.

1015 In addition, the interplay between dynamic decision making and motor performance might be
1016 driven by several neurotransmitter systems linked to precision weighting of prediction errors
1017 during belief updating: acetylcholine (Moran et al., 2013); noradrenaline (Dayan and Yu,
1018 2006); in addition to dopamine (Iglesias et al., 2013; Haarsma et al., 2021). On a neural
1019 level, learning uncertain stimulus-reward contingencies relies on the ACC, OFC, and
1020 portions of the mPFC (Hayden et al., 2011; Rolls et al., 2019; Rouault et al., 2019). The
1021 mPFC is also involved in mapping beliefs to actions during exploration-exploitation
1022 (Domenech et al., 2021). Follow-up neuroimaging studies could assess the role of these
1023 regions in the motor vigour effects reported here, including the preserved effects in ageing
1024 and PD.

1025 To conclude, this study is the first to demonstrate that inferring the probabilistic reward
1026 mappings positively biases motor performance through faster performance tempo.
1027 Additionally, we provided novel evidence for a preserved sensitivity of the motor invigoration
1028 effects in HOA and PD. Thus, healthy young, old and medicated PD can similarly obtain
1029 benefits in their motor performance when updating beliefs about the volatile action-reward
1030 contingencies.

1031 **REFERENCES**

- 1032 Adkins TJ, Lee TG (2021) Reward modulates cortical representations of action.
1033 NeuroImage 228:117708.
- 1034 Andraszewicz S, Scheibehenne B, Rieskamp J, Grasman R, Verhagen J,
1035 Wagenmakers E-J (2015) An Introduction to Bayesian Hypothesis Testing for
1036 Management Research. J Manag 41:521–543.
- 1037 Aves P, Moreau L, Alghamdi A, Sporn S, Galea JM (2021) Age-Related Differences
1038 in Reward-Based Modulation of Sequential Reaching Performance. bioRxiv
1039 461920. <https://doi.org/10.1101/2021.09.27.461920>.
- 1040 Balleine BW, Delgado MR, Hikosaka O (2007) The role of the dorsal striatum in
1041 reward and decision-making. J Neurosci 27:8161-8165.
- 1042 Behrens TEJ, Woolrich MW, Walton ME, Rushworth MFS (2007) Learning the value
1043 of information in an uncertain world. Nat Neurosci 10:1214–1221.
- 1044 Bologna M, Leodori G, Stirpe P, Paparella G, Colella D, Belvisi D, Fasano A, Fabbrini
1045 G, Berardelli A (2016) Bradykinesia in early and advanced Parkinson's
1046 disease. J Neurol Sci 369:286–291.
- 1047 Bürkner P-C (2017) brms: An R Package for Bayesian Multilevel Models Using Stan.
1048 J Stat Softw 80:1-28.
- 1049 Bürkner P-C (2018) Advanced Bayesian Multilevel Modeling with the R Package
1050 brms. R J 10:395-411.
- 1051 Bürkner P-C (2021) Bayesian Item Response Modeling in R with brms and Stan. J
1052 Stat Softw 100:1-54.
- 1053 Carroll TJ, McNamee D, Ingram JN, Wolpert DM (2019) Rapid Visuomotor
1054 Responses Reflect Value-Based Decisions. J Neurosci 39:3906–3920.

1055 Codol O, Holland PJ, Manohar SG, Galea JM (2020) Reward-Based Improvements
1056 in Motor Control Are Driven by Multiple Error-Reducing Mechanisms. 40:
1057 3604-3620.

1058 Cools R (2001) Enhanced or Impaired Cognitive Function in Parkinson's Disease as
1059 a Function of Dopaminergic Medication and Task Demands. Cereb Cortex
1060 11:1136–1143.

1061 Cousineau D (2020) How many decimals? Rounding descriptive and inferential
1062 statistics based on measurement precision. J Math Psychol 97:102362.

1063 Dayan P, Yu AJ (2006) Phasic norepinephrine: a neural interrupt signal for
1064 unexpected events. Netw Comput Neural Syst 17:335-350.

1065 de Berker AO, Rutledge RB, Mathys C, Marshall L, Cross GF, Dolan RJ, Bestmann S
1066 (2016) Computations of uncertainty mediate acute stress responses in
1067 humans. Nat Commun 7:10996.

1068 de Boer L, Axelsson J, Riklund K, Nyberg L, Dayan P, Bäckman L, Guitart-Masip M
1069 (2017) Attenuation of dopamine-modulated prefrontal value signals underlies
1070 probabilistic reward learning deficits in old age. eLife 6:e26424.

1071 den Ouden HEM, Daunizeau J, Roiser J, Friston KJ, Stephan KE (2010) Striatal
1072 Prediction Error Modulates Cortical Coupling. J Neurosci 30:3210–3219.

1073 Diaconescu AO, Mathys C, Weber LAE, Daunizeau J, Kasper L, Lomakina EI, Fehr
1074 E, Stephan KE (2014) Inferring on the Intentions of Others by Hierarchical
1075 Bayesian Learning. PLoS Comput Biol 10:e1003810.

1076 Domenech P, Rheims S, Koehlin E (2020) Neural mechanisms resolving
1077 exploitation-exploration dilemmas in the medial prefrontal cortex. Science
1078 369:eabb0184.

1079 Eppinger B, Hämmerer D, Li S-C (2011) Neuromodulation of reward-based learning
1080 and decision making in human aging: Eppinger et al. *Ann N Y Acad Sci*
1081 1235:1–17.

1082 Euteneuer F, Schaefer F, Stuermer R, Boucsein W, Timmermann L, Barbe MT,
1083 Ebersbach G, Otto J, Kessler J, Kalbe E (2009) Dissociation of decision-
1084 making under ambiguity and decision-making under risk in patients with
1085 Parkinson's disease: A neuropsychological and psychophysiological study.
1086 *Neuropsychologia* 47:2882–2890.

1087 Fahn S, Elton RL (1987) The unified Parkinson's disease rating scale. In: *Recent*
1088 *developments in Parkinson's disease, Vol 2* (Fahn S, Marsden CD, Calne
1089 DB, Goldstein M, eds), pp 153–163, 293–304. Florham Park, NJ. Macmillan
1090 Health Care Information.

1091 Feldman H, Friston KJ (2010) Attention, Uncertainty, and Free-Energy. *Front Hum*
1092 *Neurosci* 4:215.

1093 Fera F (2005) Neural Mechanisms Underlying Probabilistic Category Learning in
1094 Normal Aging. *J Neurosci* 25:11340–11348.

1095 Frank MJ, Seeberger LC, O'reilly RC (2004) By carrot or by stick: cognitive
1096 reinforcement learning in parkinsonism. *Science* 306:1940-1943.

1097 Frässle S, Aponte EA, Bollmann S, Brodersen KH, Do CT, Harrison OK, ... Stephan
1098 KE (2021) TAPAS: An Open-Source Software Package for Translational
1099 Neuromodeling and Computational Psychiatry. *Front Psychiatry* 12:68081.

1100 Frömer R, Nassar MR, Bruckner R, Stürmer B, Sommer W, Yeung N (2021)
1101 Response-based outcome predictions and confidence regulate feedback
1102 processing and learning. *Elife* 10.

1103 Friston KJ, Stephan KE, Montague R, Dolan RJ (2014) Computational psychiatry: the
1104 brain as a phantastic organ. *Lancet Psychiatry* 1:148–158.

1105 Galaro JK, Celnik P, Chib VS (2019) Motor Cortex Excitability Reflects the Subjective
1106 Value of Reward and Mediates Its Effects on Incentive-Motivated
1107 Performance. *J Neurosci* 39:1236–1248.

1108 Gelman A, Rubin DB (1992) Inference from Iterative Simulation Using Multiple
1109 Sequences. *Stat Sci* 7:457-472.

1110 Haarsma J, Fletcher PC, Griffin JD, Taverne HJ, Ziauddeen H, Spencer TJ, Miller C,
1111 Katthagen T, Goodyer I, Diederer KM, Murray GK (2021) Precision weighting
1112 of cortical unsigned prediction error signals benefits learning, is mediated by
1113 dopamine, and is impaired in psychosis. *Mol Psychiatry* 26:5320-33.

1114 Hayden BY, Heilbronner SR, Pearson JM, Platt ML (2011) Surprise signals in
1115 anterior cingulate cortex: neuronal encoding of unsigned reward prediction
1116 errors driving adjustment in behavior. *J Neurosci* 31: 4178–4187.

1117 Hein TP, de Fockert J, Ruiz MH (2021) State anxiety biases estimates of uncertainty
1118 and impairs reward learning in volatile environments. *NeuroImage*
1119 224:117424.

1120 Hein TP, Herrojo Ruiz M (2022) State anxiety alters the neural oscillatory correlates
1121 of predictions and prediction errors during reward-based learning.
1122 *NeuroImage* 249:118895.

1123 Herrojo Ruiz M, Jabusch H-C, Altenmüller E (2009) Detecting Wrong Notes in
1124 Advance: Neuronal Correlates of Error Monitoring in Pianists. *Cereb Cortex*
1125 19:2625–2639.

1126 Herrojo Ruiz M, Maess B, Altenmüller E, Curio G, Nikulin VV (2017) Cingulate and
1127 cerebellar beta oscillations are engaged in the acquisition of auditory-motor
1128 sequences. *Hum Brain Mapp* 38:5161–5179.

1129 Hird EJ, Beierholm U, De Boer L, Axelsson J, Backman L, Guitart-Masip M (2022)
1130 Dopamine and reward-related vigor in younger and older adults. *Neurobiol*
1131 *Aging* 118:34-43.

1132 Iglesias S, Mathys C, Brodersen KH, Kasper L, Piccirelli M, den Ouden HEM,
1133 Stephan KE (2013) Hierarchical Prediction Errors in Midbrain and Basal
1134 Forebrain during Sensory Learning. *Neuron* 80:519–530.

1135 Kang SY, Wasaka T, Shamim EA, Auh S, Ueki Y, Lopez GJ, Kida T, Jin S-H, Dang
1136 N, Hallett M (2010) Characteristics of the sequence effect in Parkinson's
1137 disease: Sequence Effect in Parkinson's Disease. *Mov Disord* 25:2148–2155.

1138 Ketcham CJ, Seidler RD, Van Gemmert AWA, Stelmach GE (2002) Age-Related
1139 Kinematic Differences as Influenced by Task Difficulty, Target Size, and
1140 Movement Amplitude. *J Gerontol B Psychol Sci Soc Sci* 57:P54–P64.

1141 Kjær SW, Damholdt MF, Callesen MB (2018) A systematic review of decision-making
1142 impairments in Parkinson's Disease: Dopaminergic medication and
1143 methodological variability. *Basal Ganglia* 14:31–40.

1144 Levy-Gigi E, Haim-Nachum S, Hall JM, Crouse JJ, Winwood-Smith R, Lewis SJ,
1145 Moustafa AA (2019) The interactive effect of valence and context on reversal
1146 learning in individuals with Parkinson's disease. *Neurosci Lett* 692:216-224.

1147 Lewandowski D, Kurowicka D, Joe H (2009) Generating random correlation matrices
1148 based on vines and extended onion method. *J Multivar Anal* 100:1989–2001.

1149 Mantziara M, Ivanov T, Houghton G, Kornysheva K (2021) Competitive state of
1150 movements during planning predicts sequence performance. *J Neurophysiol*
1151 125:1251-68.

1152 Manohar SG, Muhammed K, Fallon SJ, Husain M (2019) Motivation dynamically
1153 increases noise resistance by internal feedback during movement.
1154 *Neuropsychologia* 123:19–29.

1155 Marshall L, Mathys C, Ruge D, de Berker AO, Dayan P, Stephan KE, Bestmann S
1156 (2016) Pharmacological Fingerprints of Contextual Uncertainty. PLOS Biol
1157 14:e1002575.

1158 Mathys C (2011) A Bayesian foundation for individual learning under uncertainty.
1159 Front Hum Neurosci 5:1-20.

1160 Mathys CD, Lomakina EI, Daunizeau J, Iglesias S, Brodersen KH, Friston KJ,
1161 Stephan KE (2014) Uncertainty in perception and the Hierarchical Gaussian
1162 Filter. Front Hum Neurosci 8:1-24.

1163 MATLAB and Statistics Toolbox Release 2020b, The MathWorks, Inc., Natick,
1164 Massachusetts, United States.

1165 McDougle SD, Boggess MJ, Crossley MJ, Parvin D, Ivry RB, Taylor JA (2016) Credit
1166 assignment in movement-dependent reinforcement learning. Proc Natl Acad
1167 Sci 113:6797–6802.

1168 Metitieri T, Geroldi C, Pezzini A, Frisoni GB, Bianchetti A, Trabucchi M (2001) The
1169 Itel-MMSE: An Italian telephone version of the mini-mental state examination.
1170 Int J Geriatr Psychiatry 16:166-167.

1171 Moran RJ, Campo P, Symmonds M, Stephan KE, Dolan RJ, Friston KJ (2013) Free
1172 energy, precision and learning: the role of cholinergic neuromodulation. J
1173 Neurosci 33:8227-36.

1174 Nassar MR, Bruckner R, Gold JI, Li S-C, Heekeren HR, Eppinger B (2016) Age
1175 differences in learning emerge from an insufficient representation of
1176 uncertainty in older adults. Nat Commun 7:11609.

1177 Padmala S, Pessoa L (2011) Reward Reduces Conflict by Enhancing Attentional
1178 Control and Biasing Visual Cortical Processing. J Cogn Neurosci 23:3419–
1179 3432.

1180 Powers AR, Mathys C, Corlett PR (2017) Pavlovian conditioning–induced
1181 hallucinations result from overweighting of perceptual priors. *Science*
1182 357:596–600.

1183 R Core Team (2022). R: A language and environment for statistical computing. R
1184 Foundation for Statistical Computing, Vienna, Austria. URL [https://www.R-](https://www.R-project.org/)
1185 [project.org/](https://www.R-project.org/).

1186 Reed EJ, Uddenberg S, Suthaharan P, Mathys CD, Taylor JR, Groman SM, Corlett
1187 PR (2020) Paranoia as a deficit in non-social belief updating. *eLife* 9:e56345.

1188 Rescorla RA, Wagner AR (1972) A theory of Pavlovian conditioning: variations in the
1189 effectiveness of reinforcement and nonreinforcement. *Curr Res Theory* 2:64–
1190 99.

1191 Rolls ET, Deco G, Huang CC, Feng J (2022) The human orbitofrontal cortex,
1192 vmPFC, and anterior cingulate cortex effective connectome: emotion,
1193 memory, and action. *Cereb Cortex*.

1194 Rouault M, Drugowitsch J, Koechlin E (2019) Prefrontal mechanisms combining
1195 rewards and beliefs in human decision-making. *Nat Commun* 10:301.

1196 Rouder JN, Morey RD, Speckman PL, Province JM (2012) Default Bayes factors for
1197 ANOVA designs. *J Math Psychol* 56:356–374.

1198 Ryterska A, Jahanshahi M, Osman M (2013) What are people with Parkinson's
1199 disease really impaired on when it comes to making decisions? A meta-
1200 analysis of the evidence. *Neurosci Biobehav Rev* 37:2836–2846.

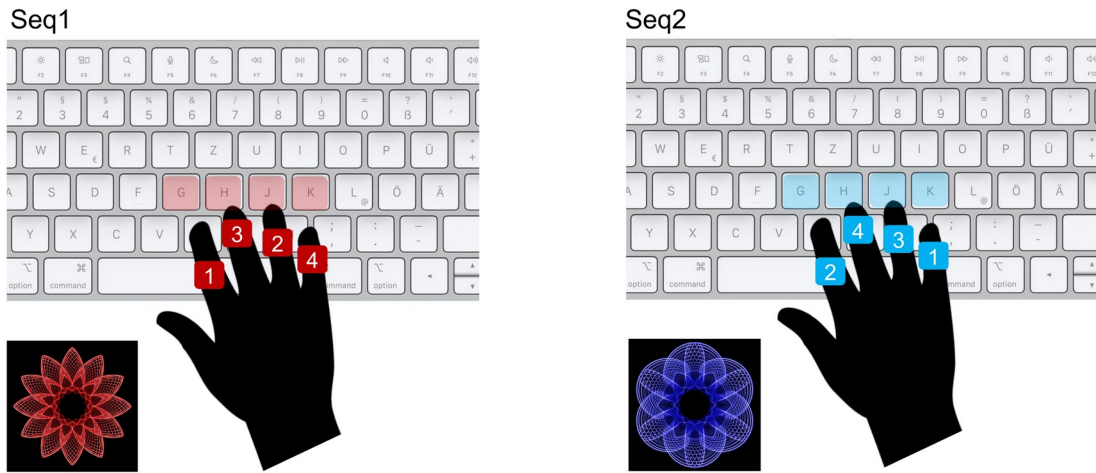
1201 Sedaghat-Nejad E, Herzfeld DJ, Shadmehr R (2019) Reward Prediction Error
1202 Modulates Saccade Vigor. *J Neurosci* 39:5010–5017.

1203 Shadmehr R (2010) Control of movements and temporal discounting of reward. *Curr*
1204 *Opin Neurobiol* 20:726-730.

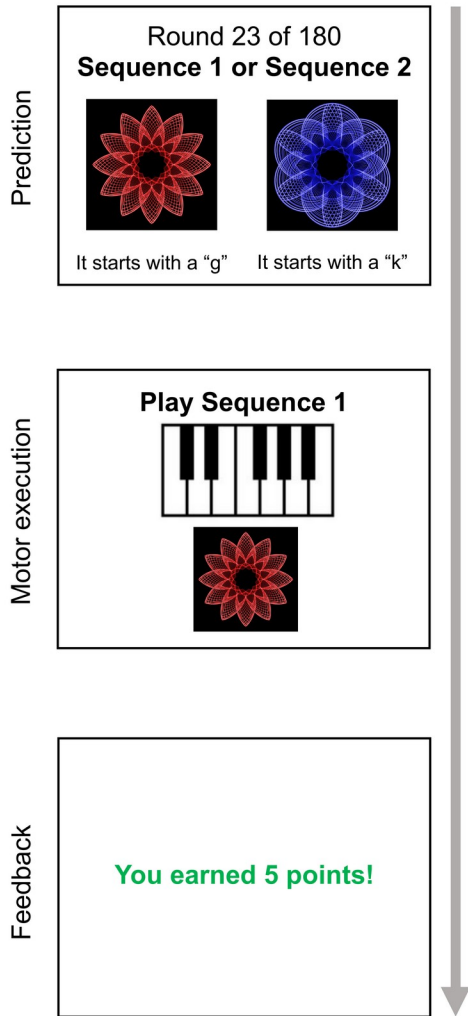
- 1205 Sheffield JM, Suthaharan P, Leptourgos P, Corlett PR (2022) Belief Updating and
1206 Paranoia in Individuals with Schizophrenia. *Biol Psychiatry Cogn Neurosci*
1207 *Neuroimaging*.
- 1208 Sivula T, Magnusson M, Matamoros AA, Vehtari A (2022) Uncertainty in Bayesian
1209 Leave-One-Out Cross-Validation Based Model Comparison. *arXiv*
1210 2008.10296. <https://doi.org/10.48550/arXiv.2008.10296>.
- 1211 Soch J, Allefeld C (2018) MACS – a new SPM toolbox for model assessment,
1212 comparison and selection. *J Neurosci Methods* 306:19–31.
- 1213 Spielberger CD, Gorsuch RL, Lushene R, Vagg PR, Jacobs GA (1983). *Manual for*
1214 *the State-Trait Anxiety Inventory*. Palo Alto, CA: Consulting Psychologists
1215 Press.
- 1216 Sporn S, Chen X, Galea JM (2022) The dissociable effects of reward on sequential
1217 motor behavior. *J Neurophysiol* 128:86-104.
- 1218 Stefanics G, Heinzle J, Horváth AA, Stephan KE (2018) Visual Mismatch and
1219 Predictive Coding: A Computational Single-Trial ERP Study. *J Neurosci*
1220 38:4020–4030.
- 1221 Summerside EM, Shadmehr R, Ahmed AA (2018) Vigor of reaching movements:
1222 reward discounts the cost of effort. *J Neurophysiol* 119:2347–2357.
- 1223 Sutton RS (1992) Gain adaptation beats least squares? Paper presented at the 7th
1224 Yale Workshop on Adaptive and Learning Systems, New Haven, CT, May.
- 1225 Valton V, Wise T, Robinson OJ (2020) Recommendations for Bayesian hierarchical
1226 model specifications for case-control studies in mental health. *arXiv*
1227 2011.01725. <https://doi.org/10.48550/arXiv.2011.01725>.
- 1228 Vehtari A, Gelman A, Gabry J (2017) Practical Bayesian model evaluation using
1229 leave-one-out cross-validation and WAIC. *Stat Comput* 27:1413–1432.

- 1230 Weber LA, Diaconescu AO, Mathys C, Schmidt A, Komater M, Vollenweider F,
1231 Stephan KE (2020) Ketamine Affects Prediction Errors about Statistical
1232 Regularities: A Computational Single-Trial Analysis of the Mismatch
1233 Negativity. *J Neurosci* 40: 5658-5668.
- 1234 Yoon T, Jaleel A, Ahmed AA, Shadmehr R (2020) Saccade vigor and the subjective
1235 economic value of visual stimuli. *J Neurophysiol* 123:2161-2172.
- 1236 Zigmond AS, Snaith RP (1983) The hospital anxiety and depression scale. *Acta*
1237 *Psychiatr Scand* 67:361-370.
- 1238

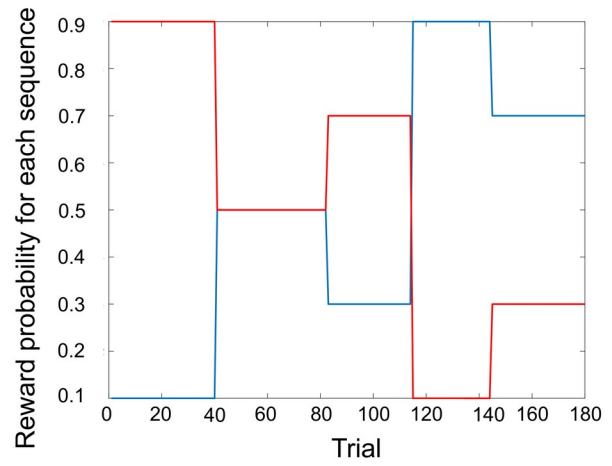
A



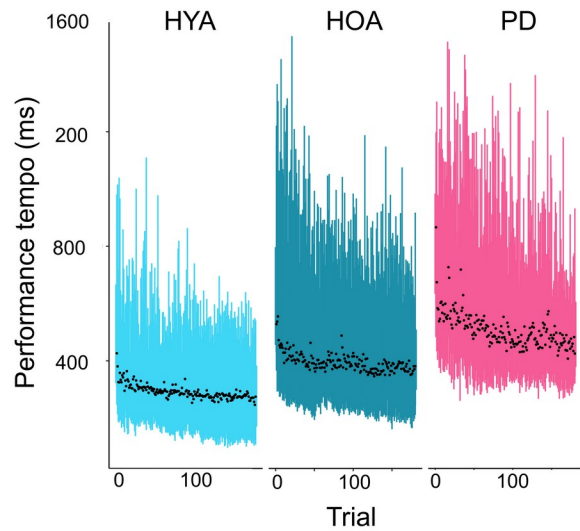
B



C



D



1241 **Figure 1. Task structure. A**, In the task familiarisation phase participants learnt to play two
1242 sequences associated with two images (red fractal – seq1 "g-j-h-k"; blue fractal – seq2 "k-g-
1243 j-h"). **B**, On each trial of the reward-based learning phase, subjects decided which sequence
1244 to play in order to get the reward. The two icons were always either red or blue and
1245 presented to the left or right part of the screen, respectively. First, participants made a
1246 prediction about which sequence (associated to the corresponding icon) was more likely to
1247 give them a reward. When a decision was reached, they played the corresponding sequence
1248 using the keyboard. Finally, the outcome (win +5p or 0p) was revealed. In the example, the
1249 participant played seq1 and obtained five points, suggesting correct prediction and
1250 execution. In Study 3, participants were instructed to rate how certain they were of being
1251 rewarded on each trial after they performed their chosen sequence. Confidence ratings were
1252 provided by typing any number between 0 and 99 (not shown in the figure). **C**, Displays the
1253 typical subject-specific mapping of probabilistic stimulus-outcome contingency over the
1254 course of 180 trials. In the example, the order of reward mappings for the blue icon (and
1255 corresponding seq2) is 10-50-30-90-70% (reciprocal for red icon and corresponding seq1).
1256 In order to obtain the maximal reward, participants needed to track these changes and adapt
1257 their choices throughout the experiment. **D**, The trial by trial changes in performance tempo
1258 in ms (mKI; mean inter-keystroke-intervals; see Behavioural and computational data
1259 analysis section for further details) for healthy younger adults (HYA; light blue), healthy older
1260 adults (HOA; dark blue) and patients with Parkinson's Disease (PD; in purple) across 180
1261 trials in Study 1. Black dots represent the trial-by-trial within-group averages of performance
1262 tempo. Bars indicate 95% interval probabilities. Participants tended to play the sequences
1263 faster towards the end of the experiment, possibly reflecting a practice effect.

1264

1265

1266

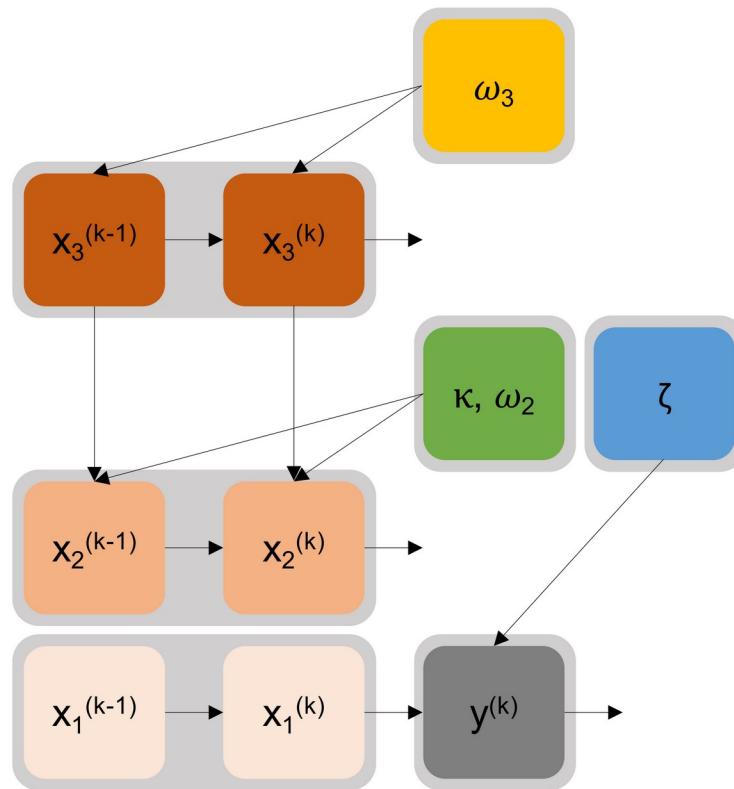
1267

1268

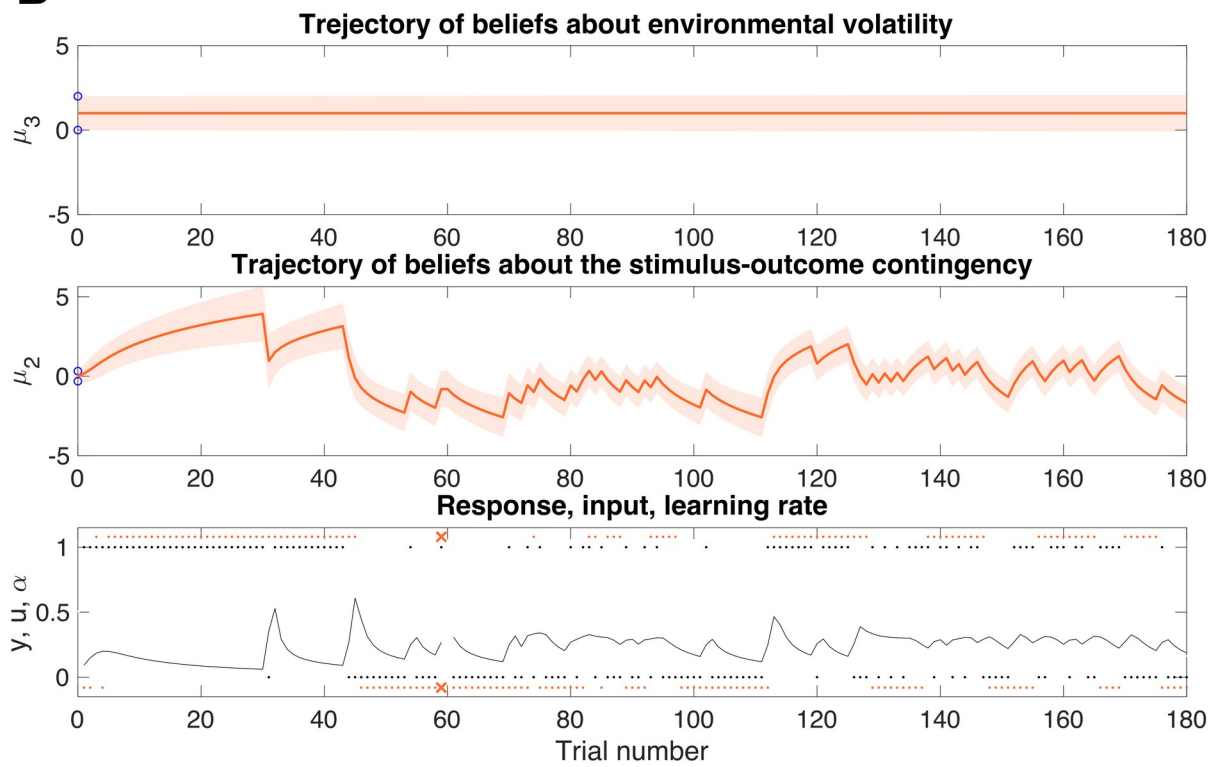
1269

1270

A

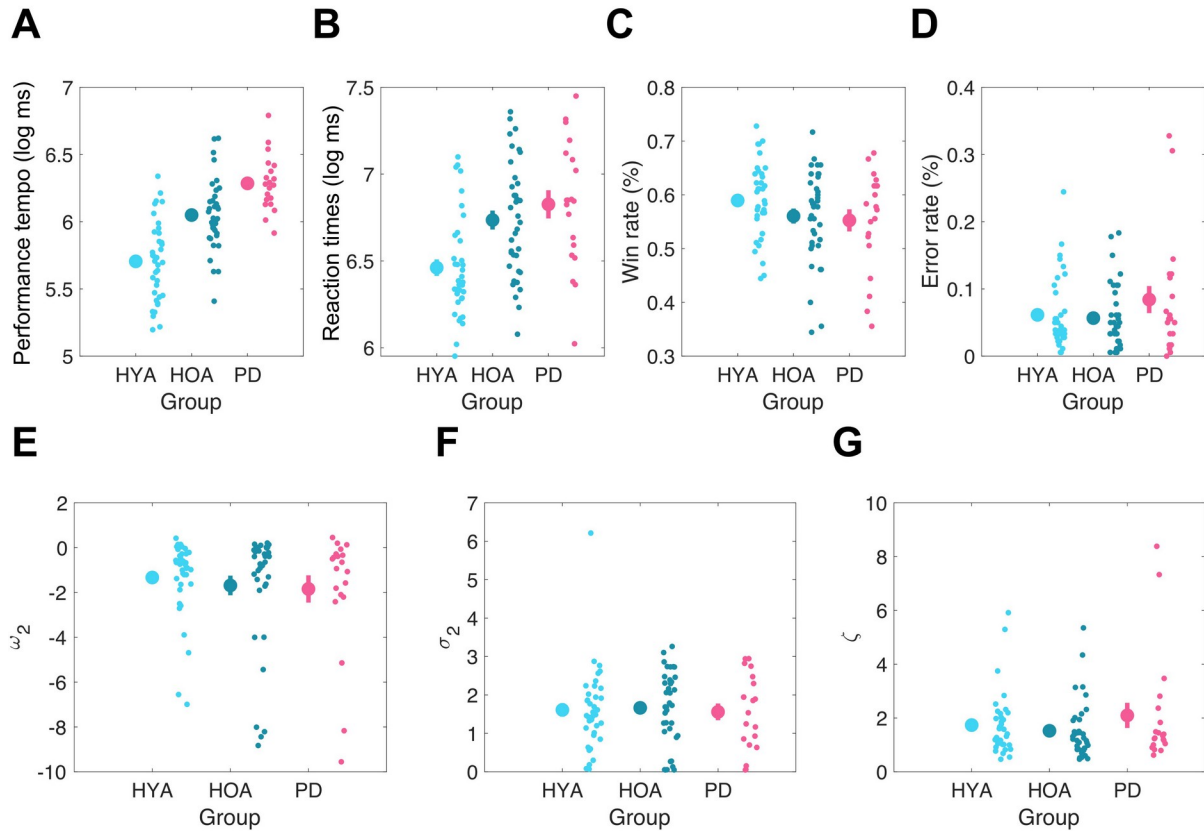


B



1271 **Figure 2. The Hierarchical Gaussian Filter (HGF) for binary outcomes. A**, Illustration of
1272 the 3-level HGF model (HGF₃) with relevant parameters modulating each level (adapted
1273 from Hein et al., 2021). Level x_1 represents the binary categorical variable of the
1274 experimental stimuli on each trial k ; x_2 reflects the true value of the tendency of the stimulus-
1275 outcome contingency, and x_3 the true volatility of the environment. In our experiment, ω_2 , ω_3
1276 and ζ were free parameters and were estimated by fitting individual responses and observed
1277 inputs with the HGF. κ represents the strength of coupling between level 2 and 3 (fixed to 1
1278 in our study; not shown in the text; see Mathys et al., 2014 for the model equations). **B**,
1279 Belief trajectories for the HGF₃ across the total 180 trials in a representative participant in
1280 Study 1. At the lowest level, black dots (u) represent the outcomes, denoting whether seq1
1281 was rewarded or not (1 = seq1 wins [seq2 loses]; 0 = seq2 wins [seq1 loses]); orange dots
1282 (y) represent the participant's choices (1 = seq1 is played; 0 = seq2 is played); orange
1283 crosses depict performance execution errors; the black line is a subject-specific learning rate
1284 about stimulus outcomes (α ; see Mathys et al. 2014 for the full HGF equations). At the
1285 second level, μ_2 (σ_2) is the trial-by-trial trajectory of beliefs (mean and variance) about the
1286 tendency of the stimulus-outcome contingencies (x_2). A mean estimate μ_2 shifted towards
1287 positive values on the y-axis indicates that the participant had a greater expectation that
1288 seq1 was rewarded relative to seq2. In addition, larger (absolute) μ_2 values on that axis
1289 denote a stronger expectation that given the correct sequence choice a reward will be
1290 received. The trajectory of beliefs about phasic (log)volatility (μ_3 [σ_3]) is displayed at the top
1291 level. The true volatility in our task, x_3 , was constant, as the stimulus-outcome contingencies
1292 changed every 25-35 trials. Participants could, however, express individual differences in
1293 their log-volatility estimates, which could be captured by the HGF₃ (e.g., Powers et al.,
1294 2017). In our three studies, the winning model was the 2-level HGF (HGF₂), in which volatility
1295 was fixed across participants. Blue circles on the y-axis denote the upper and lower priors of
1296 the posterior distribution of beliefs, $\mu_i^{(0)} \pm \sigma_i^{(0)}$, $i = 2, 3$.

1297



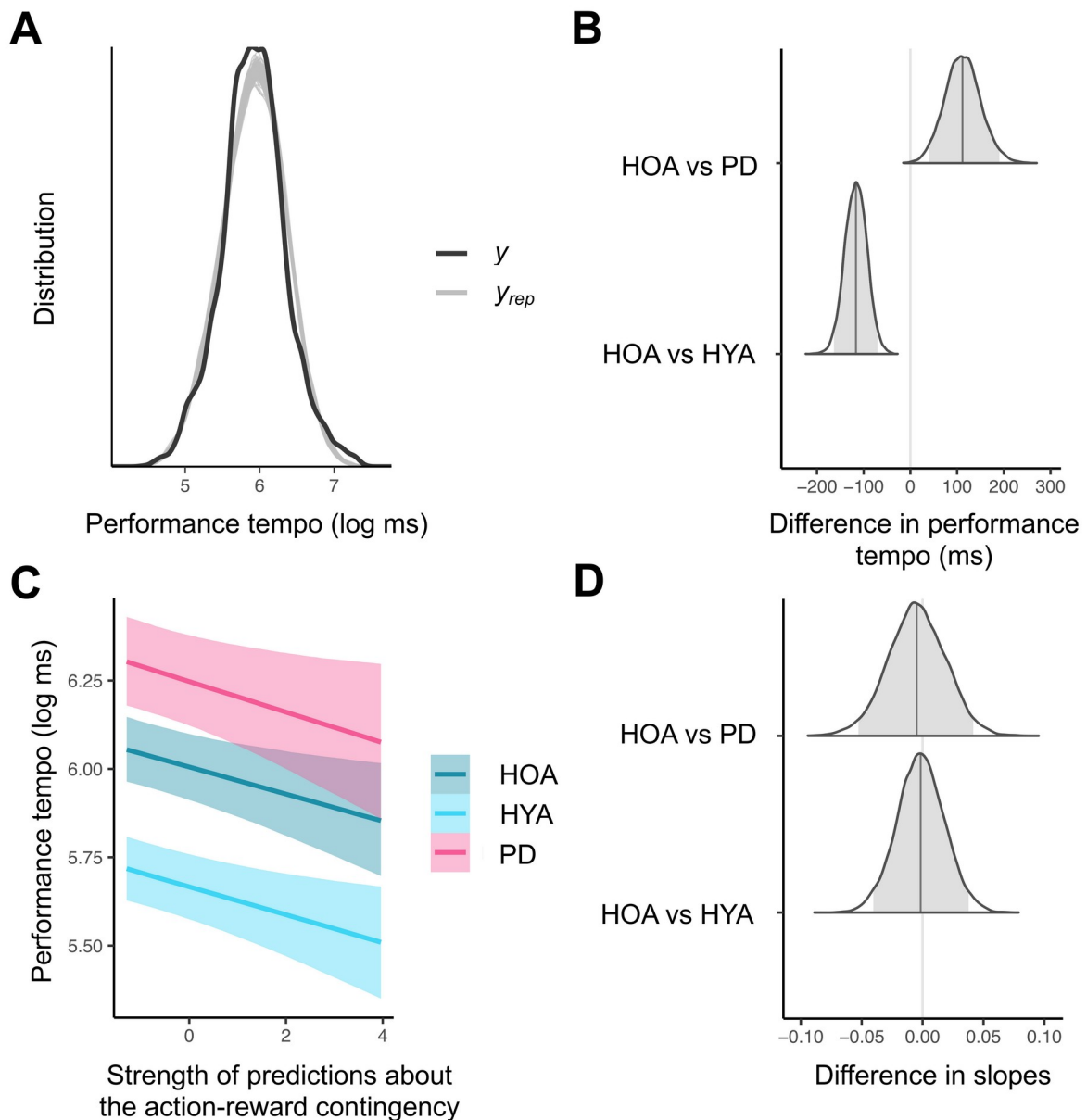
1299 **Figure 3. Markers of general task performance and decision making across groups.**

1300 Data presented for healthy younger adults (HYA; in light blue), healthy older adults (HOA; in
 1301 dark blue) and patients with Parkinson's Disease (PD; in purple) in Study 1. **A**, Performance
 1302 tempo (mIKI, mean inter-keystroke-interval, in ms); **B**, Reaction time (RT, in ms); **C**, Rate of
 1303 win trials (percWin); **D**, Rate of performance execution errors (percError); **E**, Tonic volatility
 1304 (ω_2); **F**, Informational uncertainty on level 2 (σ_2); **G**, Response model parameter (ζ). Values
 1305 mIKI, RT and σ_2 are averaged across 180 trials within each participant. mIKI and RT values
 1306 are log-transformed. In every plot, to the right of each mean (large dot) and standard error of
 1307 the mean (denoted by the vertical bar) the individual data points in each group are shown to
 1308 visualise group population variability.

1309

1310

1311



1313 **Figure 4. Invigoration of performance tempo by beliefs is preserved in healthy ageing**
 1314 **and in Parkinson's disease.** Bayesian Linear Mixed Model (BLMM; model number 6, $y \sim 1$
 1315 $+ \text{group} * x + [1 + x|\text{subject}] + [1|\text{trial}]$) with healthy older adults (HOA) as the reference
 1316 group in Study 1. **A**, Illustration of the posterior predictive checks where the distribution of
 1317 the observed outcome variable (y , in our case performance tempo) is compared to simulated
 1318 datasets (y_{rep}) from the posterior predictive distribution (100 draws). **B**, Distributions of the
 1319 difference in ms between performance tempo (intercept) in HOA and healthy younger adults
 1320 (HYA), and in HOA and patients with Parkinson's Disease (PD). For each distribution, the

1321 grey vertical bar indicates the posterior point estimate, while the grey area under the curve
1322 represents the 95% credible interval (CI). In the current plot, CIs do not overlap with zero
1323 (the null hypothesis). This indicates that there is a 95% probability of between-group
1324 differences in performance tempo. **C**, Results of the BLMM analysis. We analysed how the
1325 strength of predictions about the action-reward contingency modulates performance tempo
1326 separately for HYA (in light blue), HOA (in dark blue) and PD (in purple). Here, mIKI
1327 (performance tempo: mean inter-keystroke-interval) values are represented in the log-scale.
1328 The negative slopes suggest that stronger predictions about the action-reward contingency
1329 are associated with faster performance tempo. **D**, Distributions of the difference between
1330 slopes in HOA vs HYA, and HOA vs PD. Here, as CIs include zero we can conclude with
1331 95% probability that groups do not differ in how the strength of predictions about the reward
1332 contingency influences motor performance tempo. Thus, the sensitivity of performance
1333 tempo to the strength of predictions about the reward mapping is not differently modulated
1334 between groups.

1335

1336

1337

1338

1339

1340

1341

1342

1343

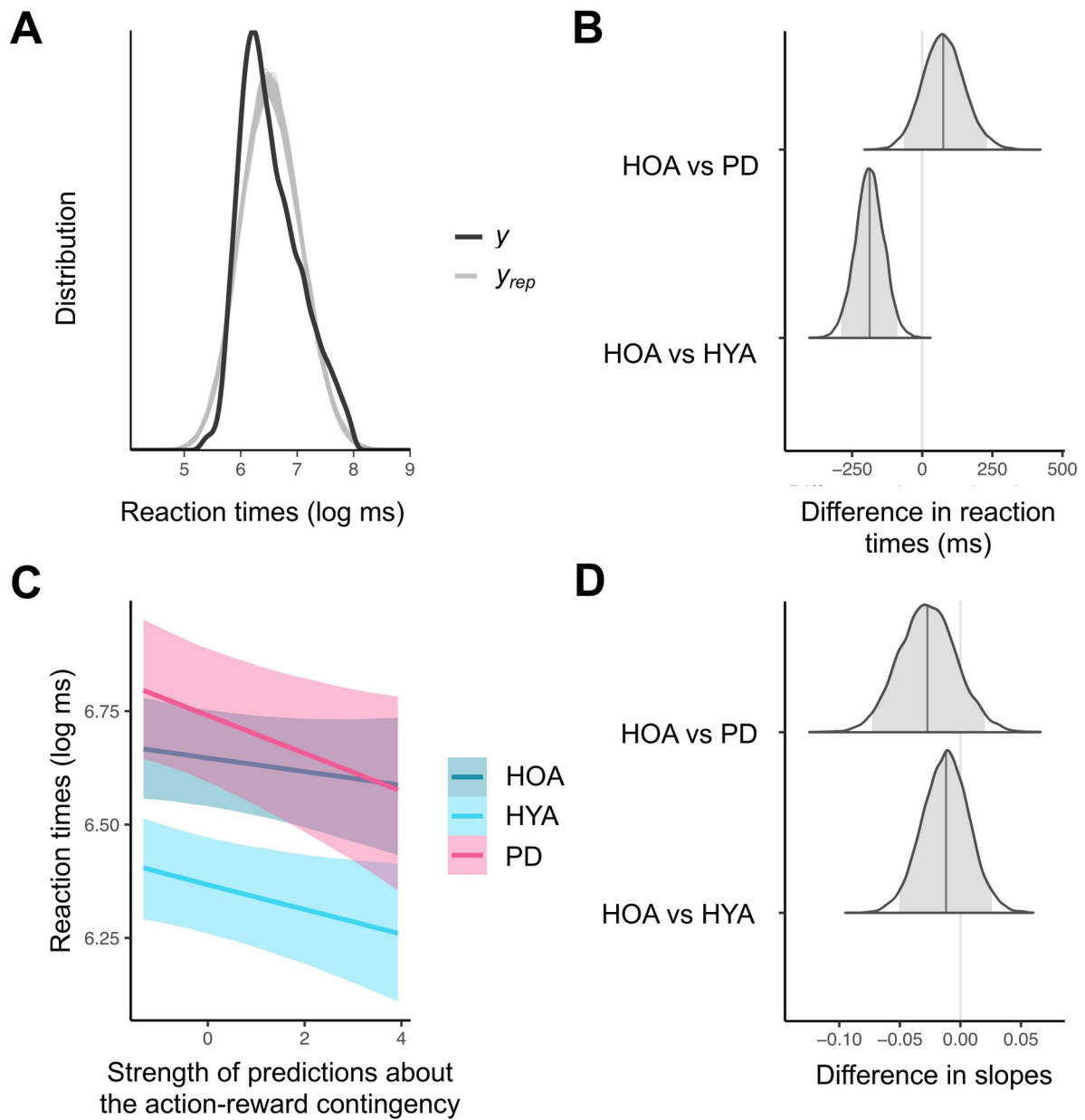
1344

1345

1346

1347

1348



1351 **Figure 5. Motor vigour effects on reaction times across healthy young, older and**
 1352 **Parkinson's participants.** Bayesian Linear Mixed Model (BLMM; model number 6, $y \sim 1 +$
 1353 $group * x + [1 + x|subject] + [1|trial]$) with healthy older adults (HOA) as the reference group
 1354 in Study 1. **A**, Illustration of the posterior predictive checks where the distribution of the
 1355 observed outcome variable (y , in our case reaction times [RT]) is compared to simulated
 1356 datasets (y_{rep}) from the posterior predictive distribution (100 draws). **B**, Distributions of the

1357 difference in ms between RT (intercept) in HOA and healthy younger adults (HYA), and in
1358 HOA and patients with Parkinson's Disease (PD). For each distribution, the grey vertical bar
1359 indicates the posterior point estimate, while the grey area under the curve represents the
1360 95% credible interval (CI). In the current plot, CI of the bottom distribution does not overlap
1361 with zero (the null hypothesis). This indicates that there is 95% probability of between-group
1362 differences in RT. On the other hand, the distribution at the top includes zero. This suggests
1363 that there is 95% probability of HOA and PD not differing in RT. **C**, Results of the BLMM
1364 analysis. We analysed how the strength of predictions about the action-reward contingency
1365 modulates RT separately for HYA (in light blue), HOA (in dark blue) and PD (in purple).
1366 Here, RT values are represented in the log-scale. We found no modulation of RT by the
1367 strength of expectations about the reward mapping. **D**, Distributions of the difference
1368 between slopes in HOA vs HYA, and HOA vs PD. Here, as CIs include zero we can
1369 conclude with 95% probability that groups do not differ in how the strength of predictions
1370 about the reward contingency influences RT. Thus, the sensitivity of RT to the strength of
1371 predictions about the reward mapping is not differently modulated between groups.

1372

1373

1374

1375

1376

1377

1378

1379

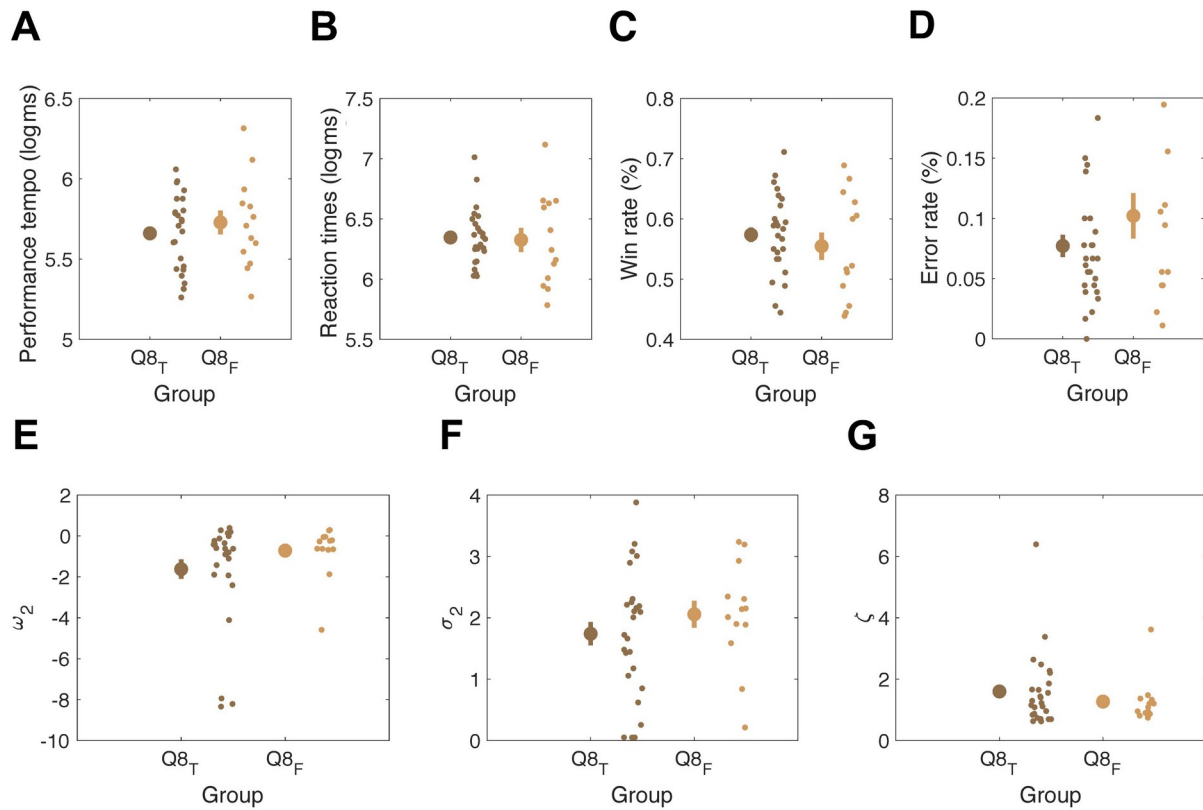
1380

1381

1382

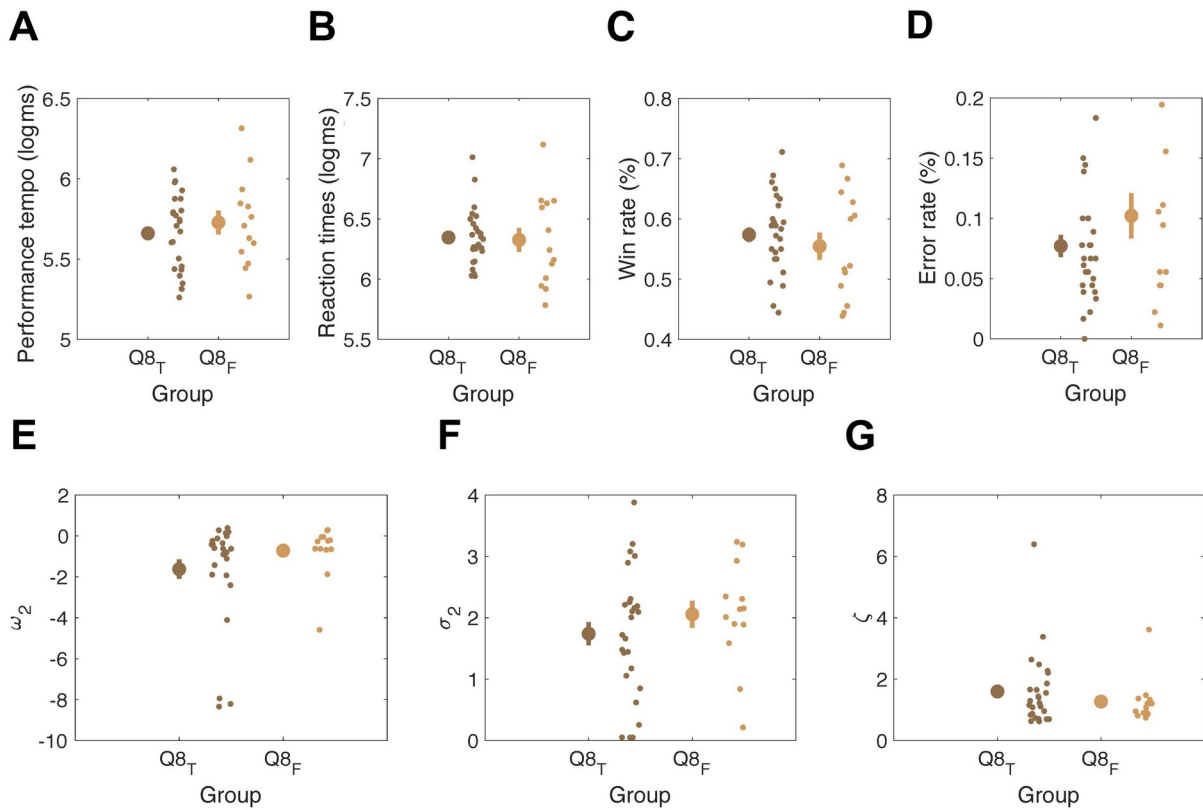
1383

1384



1386 **Figure 6. Effect of retrospective credit assignment on general task performance and**
 1387 **decision making.** Markers of general task performance and decision making in participants
 1388 that replied True to Question 8 (Q8_T; in dark brown) and participants that replied False to
 1389 Question 8 (Q8_F; in light brown) in the post-performance questionnaire (see **Table 2**) in
 1390 Study 2. **A**, Performance tempo (mIKI, mean inter-keystroke-interval; in ms, Q8_T: mean 287,
 1391 SEM 13.2; Q8_F: mean 307, SEM 27.2); **B**, Reaction times (RT; in ms, Q8_T: mean 564, SEM
 1392 30.5; Q8_F: mean 555, SEM 68.7); **C**, Rate of win trials (percWin; Q8_T: mean 0.574, SEM
 1393 0.013; Q8_F: mean 0.555, SEM 0.024); **D**, Rate of performance execution errors (percError;
 1394 Q8_T: mean 0.077, SEM 0.010; Q8_F: mean 0.102, SEM 0.020); **E**, Tonic volatility, (ω_2 ; Q8_T:
 1395 mean -1.624, SEM 0.510; Q8_F: mean -0.715, SEM 0.357); **F**, Informational uncertainty on
 1396 level 2 (σ_2 ; Q8_T: mean 1.740, SEM 0.203; Q8_F: mean 2.057, SEM 0.237); **G**, Response
 1397 model parameter, (ζ ; Q8_T: mean 1.599, SEM 0.237; Q8_F: mean 1.271, SEM 0.206). Values
 1398 mIKI, RT and σ_2 are averaged across 180 trials within each participant. mIKI and RT values
 1399 are log-transformed. In every plot, to the right of each mean (large dot) and standard error of

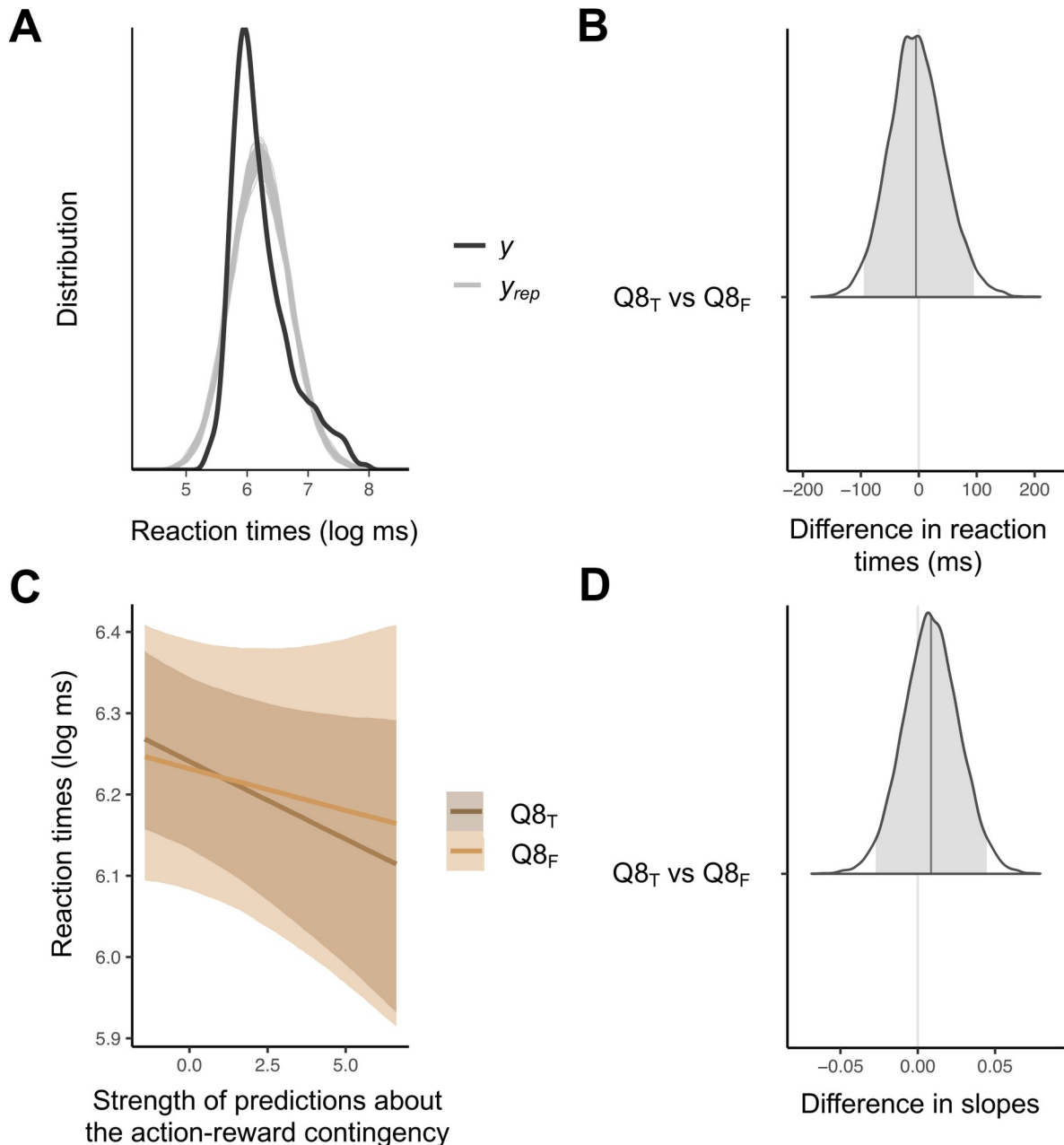
1400 the mean (denoted by the vertical bar) are displayed the individual data points in each group
 1401 to visualise group population variability.



1402 **Figure 7. No effect of retrospective credit assignment on motor vigour: performance**
 1403 **tempo.** Bayesian Linear Mixed Models (BLMM; model number 6, $y \sim 1 + \text{group} * x + [1 + x]$
 1404 $\text{subject}] + [1[\text{trial}]])$ with participants that replied True to Question 8 (Q8_T; see **Table 2**) as
 1405 reference group in Study 2. **A**, Illustration of the posterior predictive checks where the
 1406 distribution of the observed outcome variable (y , in our case performance tempo) is
 1407 compared to simulated datasets (y_{rep}) from the posterior predictive distribution (100 draws).
 1408 **B**, Distribution of the difference in ms between performance tempo (intercept) in Q8_T and in
 1409 participants that replied False to Question 8 (Q8_F; see **Table 2**). The grey vertical bar
 1410 indicates the posterior point estimate, while the grey area under the curve represents the
 1411 95% credible interval (CI). In the current plot, CI does overlap with zero (the null hypothesis).
 1412 This indicates that there is 95% probability of no between-group differences in performance
 1413 tempo. **C**, Results of the BLMM analysis. We analysed how the strength of predictions about

1414 the action-reward contingency modulates performance tempo separately for $Q8_T$ (in dark
1415 brown) and $Q8_F$ (in light brown). Here, mIKI (performance tempo: mean inter-keystroke-
1416 interval) values are represented in the log-scale. The negative slopes suggest that stronger
1417 predictions about the action-reward contingency are associated with faster performance
1418 tempo, which replicates our findings in the main experiment (see **Figure 4C**). **D**, Distribution
1419 of the difference between slopes in $Q8_T$ and $Q8_F$. Here, as CIs include zero we can conclude
1420 with 95% probability that groups do not differ in how the strength of predictions about the
1421 reward contingency influences motor performance tempo. Thus, the sensitivity of
1422 performance tempo to the strength of predictions about the reward mapping is not differently
1423 modulated between groups.

1424



1426 **Figure 8. No effect of retrospective credit assignment on motor vigour: reaction times.**

1427 Bayesian Linear Mixed Models (BLMM; model number 6, $y \sim 1 + \text{group} * x + [1 + x|\text{subject}] +$
 1428 $[1|\text{trial}]$) with participants that replied True to Question 8 (Q8_T; see **Table 2**) as reference
 1429 group in Study 2. **A**, Illustration of the posterior predictive checks where the distribution of
 1430 the observed outcome variable (y , in our case RT) is compared to simulated datasets (y_{rep})
 1431 from the posterior predictive distribution (100 draws). **B**, Distribution of the difference in ms
 1432 between RT (intercept) in Q8_T and in participants that replied False to Question 8 (Q8_F; see

1433 **Table 2).** The grey vertical bar indicates the posterior point estimate, while the grey area
1434 under the curve represents the 95% credible interval (CI). In the current plot, CI does overlap
1435 with zero (the null hypothesis). This indicates that there is 95% probability of no between-
1436 group differences in performance tempo. **C,** Results of the BLMM analysis. We analysed
1437 how the strength of predictions about the action-reward contingency modulates RT
1438 separately for Q8_T (in dark brown) and Q8_F (in light brown). Here, RT values are represented
1439 in the log-scale. We found no robust evidence for a modulation of RT by the strength of
1440 expectations about the reward mapping. The upper bound of the distribution including
1441 three decimal digits revealed a value of 0.002, demonstrating that 0 was marginally part
1442 of the 95% CI. **D,** Distribution of the difference between slopes in Q8_T and Q8_F. Here, as CIs
1443 include zero we can conclude with 95% probability that groups do not differ in how the
1444 strength of predictions about the reward contingency influences RT. Thus, the sensitivity of
1445 RT to the strength of predictions about the reward mapping is not differently modulated
1446 between groups.

1447

1448

1449

1450

1451

1452

1453

1454

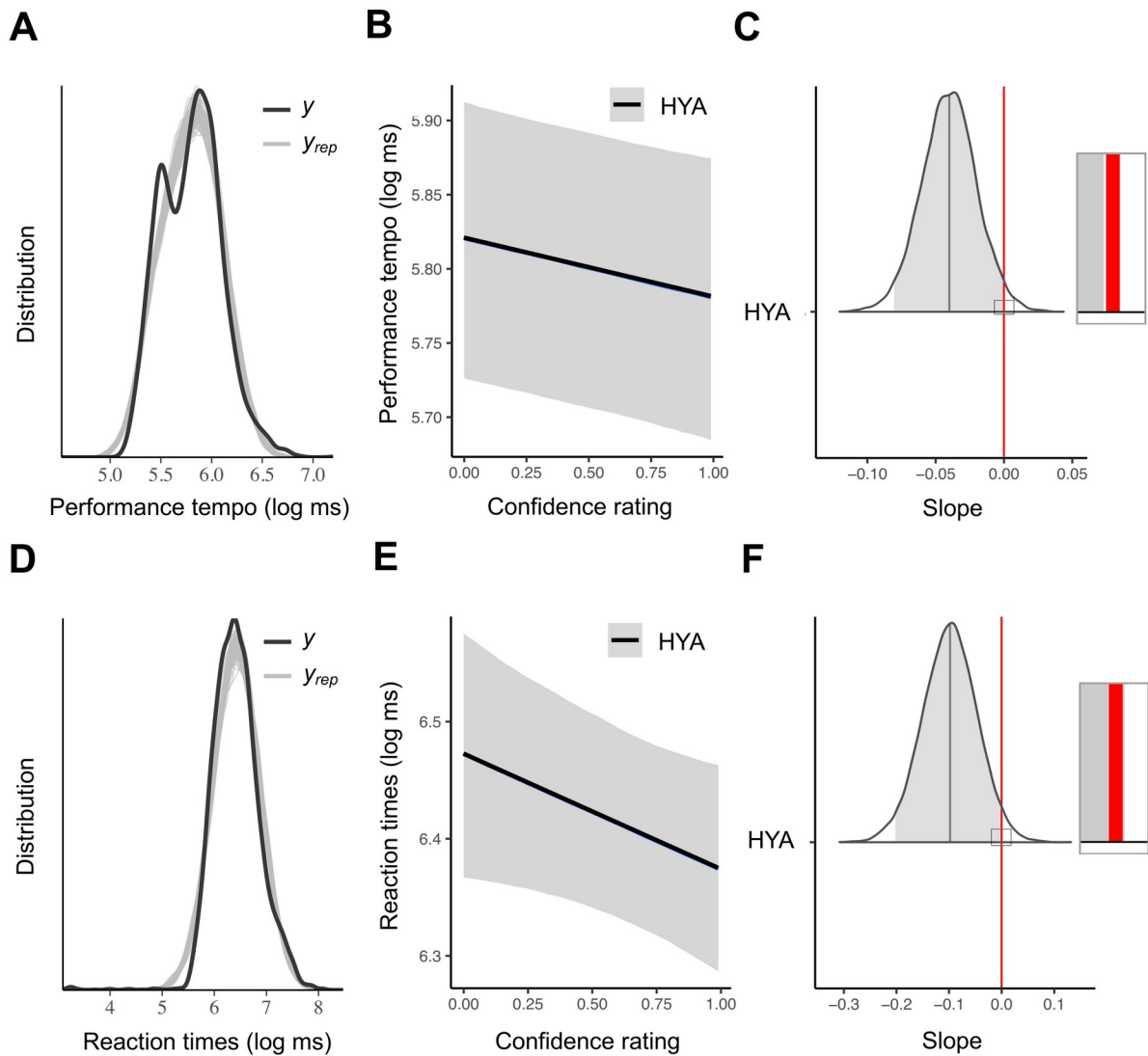
1455

1456

1457

1458

1459



1461 **Figure 9. Explicit confidence ratings invigorate performance tempo.** Bayesian Linear
 1462 Mixed Models (BLMM; model number 4, $y \sim 1 + x + [1 + x|\text{subject}] + [1|\text{trial}]$) in Study 3 for
 1463 performance tempo (left) and reaction times (RT; right). **A**, Illustration of the posterior
 1464 predictive checks where the distribution of the observed outcome variable (y , in our case
 1465 performance tempo) is compared to simulated datasets (y_{rep}) from the posterior predictive
 1466 distribution (100 draws). **B**, Results of the BLMM analysis. We analysed how explicit beliefs
 1467 about the reward tendency (confidence ratings) modulate performance tempo. Here, mIKI
 1468 (performance tempo: mean inter-keystroke-interval) values are represented in the log-scale.
 1469 The negative slope had a point estimate of -0.04 (95% credible interval [CI] from -0.08 to -
 1470 0.001, including three decimal digits in the upper bound). The 95% CI did not include zero.

1471 This suggest that being more certain about receiving a reward outcome is associated with
1472 faster performance tempo, which replicates our findings with the computational parameter
1473 $\hat{\mu}_2$ (see **Figure 4C** and **Figure 7C**). **C**, Distribution of the slope. The grey vertical bar
1474 indicates the posterior point estimate, while the grey area under the curve represents the
1475 95% CI. The vertical red line denotes zero. **D**, Illustration of the posterior predictive checks
1476 where the distribution of the observed outcome variable (y , in our case RT) is compared to
1477 simulated datasets (y_{rep}) from the posterior predictive distribution (100 draws). **E**, Results of
1478 the BLMM analysis. Here, RT values are represented in the log-scale. We found no robust
1479 evidence for a modulation of RT by the strength of expectations about the reward mapping
1480 (95% CI from -0.20 to 0.01). **F**, Distribution of the slope. The grey vertical bar indicates the
1481 posterior point estimate, while the grey area under the curve represents the 95% CI. The
1482 vertical red line denotes zero.

1489 TABLES

1490 Table 1. PD clinical information

Patient #	Age	UPDRS III ON	ITEL- MMSE	STAI Y2	HADS_A	HADS_D	Disease Duration (years)	Main Symptom	Most Impaired Side	Last Drug Intake (minutes)	LEDD	Active Substance
1	57	38	22	51	6	3	10	R/B	SX	30	920	Benserazide, Levodopa, Rasagiline, Ropinirole
2	46	17	22	40	10	16	7	R	SX	75	1197	Carbidopa, Entacapone, Levodopa
3	53	10	22	42	7	5	4	R/B	DX	120	100	Rasagiline
4	63	6	22	25	4	2	3	B	DX	720	50	Selegiline
5	57	6	22	33	7	7	2	R	DX	120	300	Benserazide, Levodopa
6	53	22	20	53	9	8	23	R/LE	BOTH	130	420	Carbidopa, Levodopa, Rotigotine
7	62	24	22	33	4	3	11	T	DX	120	1105	Benserazide, Levodopa, Pramipexole
8	62	6	22	28	3	5	8	R/B/D	DX	75	450	Carbidopa, Levodopa, Opicapone, Selegiline
9	62	17	22	25	4	3	8	T	SX	100	652	Benserazide, Levodopa, Pramipexole, Selegiline
10	69	7	21	45	5	6	3	B	SX	120	300	Benserazide, Levodopa
11	58	7	20	31	5	1	9	R	DX	30	970	Amantadine, Carbidopa, Entacapone, Levodopa, Pramipexole
12	54	25	19	32	2	5	7	R	SX	40	1780	Benserazide, Levodopa, Rasagiline, Rotigotine
13	66	16	19	34	4	10	12	R/B	DX	150	1580	Amantadine, Carbidopa, Levodopa, Opicapone, Pramipexole, Safinamide
14	53	21	22	44	5	5	8	R	BOTH	5	320	Ropinirole
15	55	4	22	37	4	1	2	R/T	DX	30	452	Benserazide, Levodopa, Pramipexole, Rasagiline
16	69	13	20	35	1	0	7	B	SX	437	470	Benserazide, Levodopa, Ropinirole, Selegiline
17	65	5	21	26	1	7	16	R/B	SX	360	100 + 3.9 ml/h	Levodopa, Opicapone, Pramipexole, Trihexyphenidyl

											levodopa	
											infusion	
											gel	
18	59	7	21	37	2	4	2	R/B	SX	5	150	Carbidopa, Levodopa
19	58	8	22	30	1	4	5	R/T	DX	100	452	Benserazide, Levodopa, Pramipexole
20	56	17	22	40	6	8	6	R	DX	185	1110	Amantadine, Benserazide, Levodopa, Pramipexole

1491 MMSE predicted score = 1.01 x ITEL-MMSE score + 5.16; HADS_A = anxiety score; HADS_D = depression score; R = rigidity, B =

1492 bradykinesia, LE = lack of energy, T = tremor, D = dyskinesia.

1493 **Table 2. Post-performance questionnaire**

Please, indicate whether the following statements are True or False.

Please note that performance errors mean pressing the wrong key(s) or key(s) in the wrong order, while bad choices mean playing a sequence that received no points on that attempt.

1. I made fewer than 10 performance errors [True/False]
2. I made between 10 and 30 performance errors [True/False]
3. I made more than 30 performance errors [True/False]
4. I recognised a performance error, because the tone sounded different than expected [True/False]
5. I recognised a performance error, because the finger movement felt different [True/False]
6. I memorised the sequences focusing on the finger movements, without paying attention to the tones [True/False]
7. I memorised the sequences focusing both on the finger movements and the tones [True/False]
8. I could *always* distinguish whether 0 points reflected a performance error or a bad decision [True/False]
9. I was *often* not sure whether 0 points reflected a performance error or a bad decision [True/False]

1494 Post-performance questionnaire included in Study 2. Question 8 (Q8) is aimed at evaluating
1495 subjective inferences about the task-related credit assignment.

1496

1497 **Table 3. Means and variances of the priors on perceptual parameters and starting**
 1498 **values of the beliefs of the winning HGF₂ model**

Prior	Mean	Variance
κ (all)	1	0
ω_2 (Study 1)	-2.17	16
ω_2 (Study 2)	-2.16	16
ω_2 (Study 3)	-2.22	16
ω_3 (all)	-7	0
$\mu_2^{(0)}$ (all)	0	0
$\sigma_2^{(0)}$ (all)	0.1	0
$\mu_3^{(0)}$ (all)	1	0
$\sigma_3^{(0)}$ (all)	1	0
ζ (all)	48	1

1499 Free parameter ω_2 was estimated in its unbounded (linear) space. The prior values on ω_2
 1500 (mean [variance]) were: -2.17 (16), -2.16 (16) and -2.22 (16) for Study 1, 2 and 3,
 1501 respectively. These prior values were obtained using an ideal observer model that received
 1502 the input that each participant had experienced. The response model parameter, ζ , was log-
 1503 transformed, to allow for its estimation in an unbounded space. The remaining parameters
 1504 were fixed and not estimated in each participant: $\sigma_2^{(0)}$, $\sigma_3^{(0)}$, κ , $\mu_2^{(0)}$, $\mu_3^{(0)}$. The coupling
 1505 strength between level 2 and 3 is κ , which was fixed to 1 (Hein et al., 2021). Among the fixed
 1506 parameters, the following ones operate in their log-transformed space: $\sigma_2^{(0)}$, $\sigma_3^{(0)}$, κ , $\mu_3^{(0)}$. The
 1507 prior variances are given in the space in which the parameters are typically estimated.

1508
 1509

1510 **Table 4. Models of increasing complexity used for Bayesian Linear Mixed Models**
 1511 **analyses**

Study #	Model #	Model
1 - 2		
	1	$y \sim 1 + (1 \text{subject})$
	2	$y \sim 1 + \text{group} + (1 \text{subject})$
	3	$y \sim 1 + \text{group} + x + (1 \text{subject})$
	4	$y \sim 1 + \text{group} * x + (1 \text{subject})$
	5	$y \sim 1 + \text{group} * x + (1 + x \text{subject})$
	6	$y \sim 1 + \text{group} * x + (1 + x \text{subject}) + (1 \text{trial})$
3		
	1	$y \sim 1 + (1 \text{subject})$
	2	$y \sim 1 + x + (1 \text{subject})$
	3	$y \sim 1 + x + (1 + x \text{subject})$
	4	$y \sim 1 + x + (1 + x \text{subject}) + (1 \text{trial})$

1512 Models of increasing complexity used in Study 1 and 2 (top) and Study 3 (bottom). In Study
 1513 1 and 2, y corresponds to the motor performance (log_mIKI or log_RT); x is the unsigned
 1514 centred value of the prediction about the tendency of the action-reward contingency (
 1515 $\hat{\mu}_2 \vee c$). This parameter represents the strength of the predictions. In model 1, y is
 1516 explained by a fixed effect of the intercept and a random effect of intercept by subject (the
 1517 latter accounts for repeated measurements); model 2 adds a fixed effect of group; model 3
 1518 includes the fixed effect of x, which allows to assess the sensitivity (slope) of performance
 1519 tempo or RT to $\hat{\mu}_2 \vee c$ in the reference group; model 4 incorporates the interaction term
 1520 between group and x, which allows to investigate the between-group differences in the
 1521 sensitivity (slope) of performance tempo or RT to $\hat{\mu}_2 \vee c$; model 5 includes the random

1522 effect of $\hat{\mu}_2$ by subject; last, model 6 includes a random effect of intercept by trial. In
1523 Study 3, y corresponds to the motor performance (log_mIKI or log_RT); x is the confidence
1524 rating. In model 1, y is explained by a fixed effect of the intercept and a random effect of
1525 intercept by subject (the latter accounts for repeated measurements); model 2 adds a fixed
1526 effect of x, which allows to assess the sensitivity (slope) of performance tempo or RT to
1527 confidence ratings; model 3 includes the random effect of confidence ratings by subject; last,
1528 model 4 includes a random effect of intercept by trial.
1529

1530 **Table 5. Summary of the posterior distributions for the fixed effects of the best fitting**
 1531 **Bayesian Linear Mixed Models**

Study #	Dependent Variable	Fixed Effect	Estimate	l-95% CI	u-95% CI	R-hat
1						
	Performance tempo					
		y: HOA	6.00	5.91	6.09	1.00
		y: HOA vs HYA	-0.34	-0.47	-0.21	1.00
		y: HOA vs PD	0.25	0.09	0.41	1.00
		x: HOA	-0.04	-0.07	-0.01	1.00
		group * x: HOA vs HYA	-0.00	-0.04	0.04	1.00
		group * x: HOA vs PD	-0.00	-0.05	0.04	1.00
	Reaction times					
		y: HOA	6.65	6.54	6.75	1.01
		y: HOA vs HYA	-0.28	-0.42	-0.13	1.00
		y: HOA vs PD	0.09	-0.08	0.27	1.00
		x: HOA	-0.02	-0.04	0.01	1.00
		group * x: HOA vs HYA	-0.01	-0.05	0.03	1.00
		group * x: HOA vs PD	-0.03	-0.07	0.02	1.00
2						
	Performance tempo					
		y: Q8 _T	5.62	5.51	5.72	1.00
		y: Q8 _T vs Q8 _F	0.07	-0.11	0.25	1.00
		x: Q8 _T	-0.04	-0.06	-0.01	1.00
		group * x: Q8 _T vs Q8 _F	-0.00	-0.04	0.04	1.00
	Reaction times					
		y: Q8 _T	6.24	6.13	6.34	1.00
		y: Q8 _T vs Q8 _F	-0.01	-0.19	0.18	1.00
		x: Q8 _T	-0.02	-0.04	0.002	1.00
		group * x: Q8 _T vs Q8 _F	0.01	-0.03	0.04	1.00

3

Performance tempo					
	y	5.82	5.73	5.91	1.00
	x	-0.04	-0.08	-0.001	1.00
Reaction times					
	y	6.47	6.37	6.58	1.00
	x	-0.10	-0.20	0.01	1.00

1532 Estimates, credible intervals (CIs) and R-hat values for the fixed effects of the best fitting
1533 models in Study 1, 2 (model number 6: $y \sim 1 + \text{group} * x + [1 + x|\text{subject}] + [1|\text{trial}]$) and in
1534 Study 3 (model number 4: $y \sim 1 + x + [1 + x|\text{subject}] + [1|\text{trial}]$). In Study 1, y: HOA refers to
1535 the posterior estimate for the intercept in the reference group (healthy older adults, HOA). y:
1536 HOA vs HYA and y: HOA vs PD reflect the posterior distributions of the differences between
1537 intercepts (HOA vs healthy younger adults [HYA]; HOA vs Parkinson's patients [PD],
1538 respectively). x: HOA is the posterior distribution of the association (slope) between motor
1539 performance (either performance tempo or reaction times) and the strength of predictions
1540 about the action-reward contingency in the reference group. group * x: HOA vs HYA and
1541 group * x: HOA vs PD are the posterior distributions of slope differences between HOA and
1542 HYA and between HOA and PD, respectively. In Study 2, y: Q8_T refers to the posterior
1543 estimate for the intercept in the reference group (participants that replied True to Question 8,
1544 Q8_T). y: Q8_T vs Q8_F reflects the posterior distribution of the difference between intercepts
1545 (Q8_T vs participants that replied False to Question 8 [Q8_F]). x: Q8_T is the posterior distribution
1546 of the association (slope) between motor performance (either performance tempo or reaction
1547 times) and the strength of predictions about the action-reward contingency in the reference
1548 group. The upper bound of the CI for the slope effect in the BLMM analyses for RT is given
1549 with three decimal digits to demonstrate that 0 was included in the 95% CI. group * x: Q8_T vs
1550 Q8_F is the posterior distribution of slope difference between Q8_T and Q8_F. In Study 3, y refers
1551 to the posterior estimate for the intercept. x is the posterior distribution of the association
1552 (slope) between motor performance (either performance tempo or reaction times) and the
1553 confidence ratings. The upper bound of the 95% CI estimate of the slope effect in the BLMM

1554 analyses for performance tempo was -0.001, when considering three decimal digits. In all
1555 studies, l-95% CI and u-95% CI refer to the lower and upper bound of the credible intervals
1556 of the posterior distributions of the fixed effects. For each parameter, we also reported the
1557 corresponding Gelman-Rubin statistics (R-hat values). Values < 1.1 indicates chain
1558 convergence (Gelman and Rubin, 1992).