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1 Motor inhibition prevents motor execution during typing imagery: evidence from an
2 action-mode switching paradigm

3 Ladislas Nalborczyk^{1,2,3}, F.-Xavier Alario¹, & Marieke Longcamp¹

4 ¹ Aix Marseille Univ, CNRS, CRPN, Marseille, France

5 ² Cognitive Neuroimaging Unit, CEA DRF/I2BM, INSERM, Université Paris-Sud,
6 Université Paris-Saclay, NeuroSpin Center, Gif/Yvette, France

7 ³ Inserm U 1127, CNRS UMR 7225, Sorbonne Universités, Institut du Cerveau, ICM,
8 Paris, France

9 Author Note

10 Correspondence concerning this article should be addressed to Ladislas Nalborczyk,
11 CRPN, CNRS & Aix-Marseille University, 3 place Victor Hugo, 13331 Marseille Cedex 3,
12 France. E-mail: ladislas.nalborczyk@gmail.com

Abstract

13

14 Motor imagery is accompanied by a subjective multisensory experience. This sensory
15 experience is thought to result from the deployment of internal models developed for the
16 execution and monitoring of overt actions. If so, how is it that motor imagery does not
17 lead to overt execution? It has been proposed that inhibitory mechanisms may prevent
18 execution during imagined actions such as imagined typing. To test this hypothesis, we
19 combined an experimental with a modelling approach. We conducted an experiment in
20 which participants ($N = 49$) were asked to alternate between overt (executed) and covert
21 (imagined) typing. We predicted that motor inhibition should lead to longer reaction and
22 movement times when the current trial is preceded by an imagined vs. an executed trial.
23 This prediction was borne out by movement times, but not by reaction times. We
24 introduced and fitted an algorithmic model of motor imagery to disentangle potentially
25 distinct inhibitory mechanisms underlying these effects. Results from this analysis suggest
26 that motor inhibition may affect different aspects of the latent activation function (e.g., the
27 shape of the activation function or the motor execution threshold) with distinct
28 consequences on reaction times and movement times. Overall, these results suggest that
29 typing imagery involves the inhibition of motor commands related to typing acts.
30 Preregistration, complete source code, and reproducible analyses are available at
31 <https://osf.io/y9a3k/>.

32

Keywords: typing, typing imagery, motor imagery, motor inhibition, response

33

inhibition, algorithmic modelling

34

Wordcount (excluding abstract, references, tables, and figures): 6238

Introduction

35

36 Motor imagery, defined as the mental rehearsal of an action, is a cornerstone of
37 human cognition. For most individuals, it is accompanied by a rich subjective multisensory
38 experience. A prominent proposal is that during motor imagery, the sensory consequences
39 of actions may be simulated mentally using pairs of internal models developed for the
40 control of overt actions (e.g., Grush, 2004; Jeannerod, 1994, 2001). More precisely, internal
41 forward models may predict the sensory consequences of (a copy of) motor commands
42 issued from internal inverse models. This view is supported by a wealth of chronometric,
43 electrophysiological, neuroimaging, and neurostimulation studies (for reviews, see Guillot,
44 Di Rienzo, et al., 2012; Guillot, Hoyek, et al., 2012; Guillot & Collet, 2005).

45 This simulationist perspective entails that the reuse of motor networks during motor
46 imagery should be accompanied by mechanisms preventing execution (Jeannerod, 2006;
47 O'Shea & Moran, 2017). Previous research has postulated at least three (non-exclusive)
48 potential inhibitory mechanisms that might operate during motor imagery (Guillot, Di
49 Rienzo, et al., 2012). First, the need to prevent execution could be integrated within the
50 representation of the action to be produced internally so that only “subthreshold” motor
51 commands are involved during motor imagery (see also Bach et al., 2022; Glover et al.,
52 2020). Second, motor inhibition could be applied broadly to all ongoing actions and to all
53 effectors involved in these actions (global motor inhibition). Third, motor inhibition may
54 be applied in a finer-grained manner, only to some effector (effector-specific inhibition).

55 To investigate these inhibitory mechanisms, Rieger et al. (2017) developed a protocol
56 called the action-mode switching paradigm in which participants have to rapidly alternate
57 between various overt (executed) and covert (imagined) hand movements. The authors
58 reasoned that, if motor imagery involves the inhibition of motor commands, then the
59 inhibition applied during some imagined trial may persist to the next trial and may slow
60 down its initiation, resulting in switching costs (for imagined-executed

61 vs. executed-executed sequences) or switching benefits (for imagined-imagined
62 vs. executed-imagined sequences). By further varying the effector used for the executed or
63 imagined action, this paradigm allows assessing the presence of effector-specific inhibition.
64 Using this paradigm, Rieger et al. (2017) showed that imagined hand movements involve
65 both global and effector-specific motor inhibition (see also Scheil & Liefoghe, 2018). It has
66 been further shown that these effects do not depend on the effector used to indicate the
67 onset and duration of imagined movements (Bart et al., 2020). These effects are influenced
68 by the proportion of imagined trials in mixed blocks (Bart et al., 2021b) and they decay
69 rapidly with increasing inter-trial interval (Bart et al., 2021a). In brief, the existence of
70 inhibitory mechanisms preventing motor execution during imagined hand reaching
71 movements has been successfully demonstrated and replicated in several distinct
72 experiments using this paradigm.

73 However, the evidence so far comes from ad-hoc pointing movements; it is unclear
74 whether the observed effects and inferred mechanisms generalise to more intricate and
75 automatised actions. Among our daily activities, typing provides an ideal test case of this
76 generalisation. Typing involves complex and often highly automatised sequential motor
77 actions, and it is ubiquitous in the everyday life of millions of persons. Cognitive models of
78 typing propose that all keystrokes programs of a word are activated in parallel prior to the
79 onset of execution, with a graded activation level allowing the ordering of the keystrokes
80 during execution (Logan & Crump, 2011; Pinet et al., 2016; Pinet et al., 2019; Rumelhart
81 & Norman, 1982; Snyder et al., 2014). Moreover, it has been hypothesised that during
82 typing imagery, forward models may predict the sensory consequences of (a copy of) typing
83 acts issued from inverse models (Dahm & Rieger, 2019). In support of the view of typing
84 imagery as mentally simulated typing, previous research suggests that the timing of typing
85 imagery is shorter but proportional to the timing of overt typing (Rieger, 2012) and that
86 typing imagery generally contains similar errors as overt typing, albeit to a lesser extent
87 (Dahm & Rieger, 2019; Rieger et al., 2011).

88 Here, we assessed the presence and scope (i.e., global and/or effector-specific) of
89 motor inhibition during typing imagery with an adapted version of Rieger et al. (2017)'s
90 action-mode switching paradigm. We asked participants to alternate between overt and
91 covert typing of unimanual words. We reasoned that, if typing imagery involves the
92 inhibition of motor commands (and if this inhibition persists until the next trial), then,
93 compared to typing execution, typing imagery should slow down the initiation of the next
94 trial (may this trial be imagined or executed). This should translate into a *switching cost*
95 in imagined-executed vs. executed-executed sequences, and into a *switching benefit* in
96 imagined-imagined vs. executed-imagined sequences. In contrast, if typing imagery does
97 not involve the inhibition of motor commands, we expected to observe a standard
98 switching cost (Kiesel et al., 2010; for reviews, see Monsell, 2003) in both executed and
99 imagined trials. Following Rieger et al. (2017), we hypothesised that effector-specific
100 inhibition should translate into longer reaction times (RTs) and movement times (MTs)
101 when the same hand is repeated than when it is not repeated, only in sequences in which
102 the first trial is an imagery trial.

103 Differences in RTs or MTs due to the action mode of the previous trial provide
104 important cues regarding the inhibitory mechanisms involved. However, these raw
105 contrasts may be inconclusive about the mechanistic implementation. For instance, motor
106 imagery could slow down the initiation of subsequent movements either by upregulating
107 the motor execution threshold or by delaying the spread of excitatory inputs (Nalborczyk
108 et al., 2024). In order to disentangle potentially distinct underlying inhibitory mechanisms,
109 we fitted a novel algorithmic model of motor imagery allowing to infer the effect of
110 inhibition in the previous trial on the underlying timecourse of motor activation during
111 typing imagery in the current trial (see the modelling section).

Methods

In this section, we report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study (Simmons et al., 2012). A pre-registered version of our protocol is available online: <https://osf.io/y9a3k/>.

Ethics information

The present research has been approved by the local ethics committee of Aix-Marseille University (agreement “HowFast”, number 2016-09-11-06). All participants provided informed consent and received course credits in exchange for their participation.

Participants

We recruited 49 French-speaking undergraduate students in Psychology from Aix-Marseille University, ranging in age from 18 to 23 years ($M = 19.41$, $SD = 1.32$, 39F, 10M), and with no reported history of psychiatric or neurological disorder, speech disorder, or hearing deficit. As preregistered (<https://osf.io/x5r67>), this sample size was defined based on temporal constraints (i.e., two full weeks of data collection) and previous research (i.e., more than double the number of participants in Rieger et al., 2017).

Linguistic material

Two classes of words were created based on the location of their constitutive letters on the keyboard (in relation to a median line located between the t-g-b and y-h-n letters on a regular AZERTY/QWERTY keyboard). Words made of letters located on the left of this median line were considered as “left-hand words” whereas words made of letters located on the right of this median line were considered as “right-hand words”. Left-hand words included words such as “averse” (rainfall) or “carafe” (carafe), whereas right-hand words included words such as “poumon” (lung) or “nylon” (nylon). These words were taken from the Lexique database (New et al., 2004). The groups of left-hand and

136 right-hand words were matched for per-word average bigram frequency, word frequency,
137 number of letters, and number of syllables (the complete list of stimuli is available in the
138 online supplementary materials).

139 **Design**

140 The experimental design was fully within-participant, with three crossed two-level
141 factors: current action mode (i.e., executed vs. imagined trials), previous action mode (i.e.,
142 executed vs. imagined trials), and hand alternation/repetition (i.e., same hand vs. other
143 hand), defining a total of eight sequences (i.e., pairs of successive trials) of interest.

144 **Procedure**

145 At the beginning of the experiment, typing expertise was assessed via an online copy
146 task (Leijten & Van Waes, 2013; Van Waes et al., 2019) and summarised by computing
147 average typing speed (ranging from 171 to 470.80 characters per minute, $M = 313.25$, SD
148 $= 65.13$) and accuracy (ranging from 88% to 99% of correctly typed characters, $M = 94.52$,
149 $SD = 2.77$). We also assessed typing habits via the questionnaire developed in Pinet et al.
150 (2022) (see the online supplementary materials).

151 Afterwards, we provided participants with extensive instructions about typing
152 imagery. Namely, we instructed them to imagine themselves from a first-person perspective
153 typing the words, insisting on the multisensory nature of motor imagery. We asked them to
154 focus on the tactile feelings and auditory percepts associated with typing (i.e., kinaesthetic
155 motor imagery). Participants were also instructed to perform both the overt and covert
156 typing tasks as fast and accurately as possible without correcting potential errors.

157 Participants started with a first training block which consisted only of overt typing
158 trials. They continued with a second training block consisting only of covert typing trials
159 followed by a third training block containing both overt and covert typing trials. Within
160 each trial, the action mode (i.e., executed vs. imagined trials) was indicated by a

161 geometrical shape (i.e., rectangle vs. circle) surrounding the word. The association between
 162 action mode and shape was counterbalanced across participants. The main experimental
 163 part (post-training) followed, consisting of six blocks of 65 trials each, yielding a total of
 164 390 trials per participant (Figure 1A). The order of word sequences (i.e., pairs of successive
 165 words/trials) in each block was randomised using Euler tours (Bakermans & Behrens,
 166 2021), ensuring that each of the eight trials sequences appeared equally often (i.e., 8 times
 167 per block).

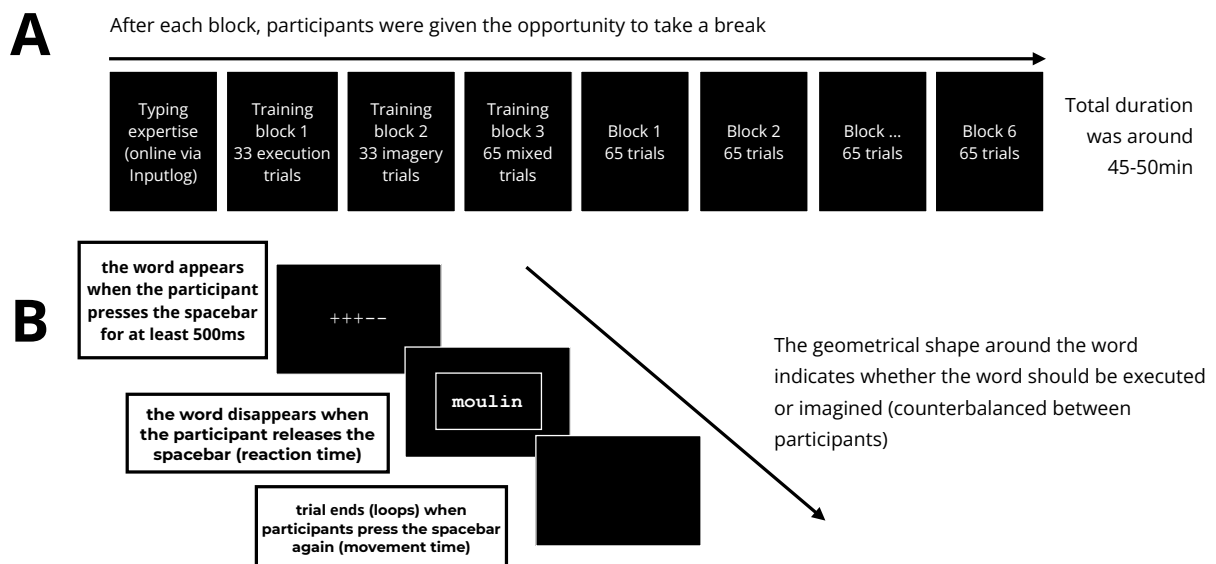


Figure 1. **A**: Experimental procedure. The main experimental part (post-training) involved 6 blocks of 65 trials each. **B**: Illustrated timecourse of a single trial.

168 The timecourse of each single trial is depicted in Figure 1B. Participants first needed
 169 to press the spacebar with their two thumbs for at least 500ms, visually represented by a
 170 progress bar displayed at the center of the screen. After these 500ms, the word appeared
 171 on the screen until the participant released the spacebar and started typing the word,
 172 either overtly or covertly. As soon as they finished, they had to return their thumbs to the
 173 spacebar. In each trial, we measured both the reaction time (RT) and the movement time

174 (MT). The reaction time was defined as the time interval between the appearance of the
175 stimulus (i.e., the word) and the release of the spacebar by the participant (i.e., the
176 disappearance of the stimulus from the screen). The movement time was defined as the
177 time interval between the release of the spacebar by the participant and the next spacebar
178 keypress (Figure 1B).

179 The first trial of each block was discarded (as it was not preceded by any other trial),
180 yielding a total of 48 repetitions of each of the eight sequences of interest per participant.
181 Following these six blocks, participants had to fill out the typing habits questionnaire
182 developed in Pinet et al. (2022). The experimental procedure was developed using the
183 PsychoPy software (Peirce et al., 2019) and took approximately 45 min. At the end of the
184 experiment, participants were fully informed about the theoretical rationale for the study
185 and compensated (in course credits) for their participation.

186 Data analysis

187 Statistical analyses were conducted using R version 4.2.3 (2023-03-15) (R Core Team,
188 2017) and are reported with the `papaja` (Aust & Barth, 2017) and `knitr` (Xie, 2015)
189 packages. To assess the effects of motor inhibition on RTs and MTs, we built and fitted
190 several Bayesian multilevel generalised linear models using the `brms` package (Bürkner,
191 2017).¹ Data were analysed using *current action mode* (2 levels, executed vs. imagined,
192 recoded using a -0.5/+0.5 sum contrast), *previous action mode* (2 levels, executed
193 vs. imagined, recoded using a -0.5/+0.5 sum contrast), and *hand alternation/repetition* (2
194 levels, same vs. different, recoded using a -0.5/+0.5 sum contrast) as within-subject
195 categorical predictors, and the RT or MT as a dependent variable. We analysed RTs and
196 MTs separately (i.e., we built separate models for each of these two measures). All models
197 allowed intercepts and slopes to vary by participant.

¹ An introduction to Bayesian statistics is outside the scope of this paper. The interested reader is referred to Nalborczyk et al. (2019) for an introduction to Bayesian multilevel modelling using the `brms` package.

198 Models were fitted using weakly informative priors (see the supplementary materials
199 for code details). Four Markov Chain Monte-Carlo (MCMC) were ran for each model to
200 approximate the posterior distribution, including each 5000 iterations and a warmup of
201 2000 iterations. Posterior convergence was assessed examining trace plots as well as the
202 Gelman-Rubin statistic \hat{R} . Constant effect estimates were summarised via their posterior
203 mean and 95% credible interval (CrI), where a credible interval can be considered as the
204 Bayesian analogue of a classical confidence interval. When applicable, we also report Bayes
205 factors (BFs), computed using the Savage-Dickey method, which consists in taking the
206 ratio of the posterior density at the point of interest divided by the prior density at that
207 point. These BFs can be interpreted as an updating factor, from prior knowledge (what we
208 knew before seeing the data) to posterior knowledge (what we know after seeing the data).

209 As pre-registered, we excluded trials in which participants performed the wrong
210 action mode, that is, trials in which participants typed some letters in the imagined typing
211 condition or did not type in the executed typing condition. This amounted to 149 trials,
212 that is, less than 0.01% of the total number of trials.

213 Results

214 This section is divided into four parts. First, we present a visual exploration of the
215 data. Second, we present results from confirmatory (preregistered) analyses, aiming at
216 assessing the sequential effects of motor inhibition on reaction times (RTs) and movement
217 times (MTs). Third, we present results from exploratory (non-preregistered) analyses,
218 aiming at distinguishing participants that effectively performed the imagery task from
219 those who did not. These were motivated by various indications that the task may not
220 have been performed equally well by all participants. Fourth, we discuss results obtained
221 by fitting a novel algorithmic model of motor imagery to these data and how it can be used
222 to disentangle different underlying inhibitory mechanisms.

223 **Visual exploration of the data**

224 Figure 2 shows the distributions of RTs, MTs, and total response times (TTs) for the
225 different sequences of trials (i.e., pair of successive trials): imagined-imagined,
226 executed-imagined, imagined-executed, and executed-executed sequences (from left to
227 right). Given this visual arrangement, if imagined typing involves motor inhibition, this
228 should translate into negative slopes from left to right columns, in each panel. In short,
229 such general pattern was observed for MTs (and TTs), whereas the inverse pattern was
230 observed for RTs.

231 **Confirmatory (preregistered) analyses**

232 To estimate these effects while accounting for the skewness of the collected data (for
233 more details, see the online supplementary materials), we fitted two multilevel
234 distributional Log-Normal models (one model for RTs and one model for MTs), where
235 “distributional” means that not only the means but also the standard deviations were
236 allowed to vary across conditions (for more details, see for instance Williams et al., 2021).
237 This was justified by the observation that the amount of variability (both within and
238 between participants) strongly differed across executed and imagined trials (as can be seen
239 from Figure 2). The distributional model allows estimating the effects of interest while
240 taking into account the effects the predictor variables may have on dispersion, thus
241 producing more precise (less biased) estimates of the effects on means or medians.
242 Estimates from these models are reported in Table 1 and Table 2 and discussed in the next
243 two paragraphs.

244 **Reaction times.** RTs were slightly shorter when the previous trial was imagined
245 rather than executed ($\beta = -0.006$, 95% CrI [-0.013, 0], $\text{BF}_{10} = 1.65$, $\text{BF}_+ = 0.036$) and
246 longer when the current trial was imagined rather than executed ($\beta = 0.066$, 95% CrI

Table 1

Estimates from the multilevel Log-Normal model fitted on reaction times

Predictor	Estimate	SE	Lower	Upper	Rhat	BF ₁₀	BF ₊
previous mode	-0.006	0.004	-0.013	0.000	1.001	1.65	0.036
current mode	0.066	0.004	0.059	0.073	1.000	6×10^{18}	∞
same hand	-0.004	0.003	-0.011	0.003	1.001	0.666	0.151
previous mode:current mode	-0.015	0.006	-0.027	-0.003	1.000	11.985	0.006
previous mode:same hand	-0.001	0.006	-0.013	0.010	1.000	0.614	0.665
current mode:same hand	-0.007	0.006	-0.018	0.005	1.000	1.107	0.154
previous mode:current mode:same hand	0.004	0.008	-0.012	0.021	1.000	0.946	2.360

Note. The 'Estimate' column represents the estimated group-level effect (slope) of each predictor included in the model (in terms of standardised AUCs). The 'Lower' and 'Upper' columns contain the lower and upper bounds of the 95% CrI, whereas the 'Rhat' column reports the Gelman-Rubin statistic. The last two columns report the BF in favour of the alternative hypothesis (relative to the null) and the directional (i.e., one-sided) BF, respectively.

247 [0.059, 0.073], BF₁₀ = 6×10^{18} , BF₊ = Inf).² There was strong evidence in favour of a
 248 non-null interaction effect between the effect of the previous mode and the effect of the
 249 current mode ($\beta = -0.015$, 95% CrI [-0.027, -0.003], BF₁₀ = 11.985, BF₊ = 0.006),
 250 indicating that the effect of the previous mode was stronger in imagined trials than in
 251 executed trials (where the effect of the previous trial was null). This equates to a switch
 252 cost in executed-imagined compared to imagined-imagined sequences, whereas there was no
 253 evidence for such an effect in imagined-executed compared to executed-executed sequences.
 254 These results are more readily understandable visually and are presented in the original
 255 scale of the RTs in Figure 3.

² For one-sided hypotheses, BF₊ represents the ratio of the posterior probability of the effect being positive and the posterior probability of the effect being negative.

Table 2

Estimates from the multilevel Log-Normal model fitted on movement times

Predictor	Estimate	SE	Lower	Upper	Rhat	BF ₁₀	BF ₊
previous mode	0.016	0.004	0.009	0.023	1.000	1041.083	23999.000
current mode	0.037	0.004	0.029	0.045	1.000	5×10^{15}	∞
same hand	0.001	0.004	-0.006	0.008	1.000	0.382	1.420
previous mode:current mode	-0.011	0.006	-0.023	0.001	1.000	2.97	0.036
previous mode:same hand	0.000	0.006	-0.012	0.012	1.000	0.61	0.904
current mode:same hand	-0.005	0.006	-0.017	0.007	1.000	0.826	0.282
previous mode:current mode:same hand	0.007	0.008	-0.009	0.024	1.000	1.195	4.079

Note. The 'Estimate' column represents the estimated group-level effect (slope) of each predictor included in the model (in terms of standardised AUCs). The 'Lower' and 'Upper' columns contain the lower and upper bounds of the 95% CrI, whereas the 'Rhat' column reports the Gelman-Rubin statistic. The last two columns report the BF in favour of the alternative hypothesis (relative to the null) and the directional (i.e., one-sided) BF, respectively.

256 **Movement times.** MTs were longer when the previous trial was imagined rather
257 than executed ($\beta = 0.016$, 95% CrI [0.009, 0.023], $\text{BF}_{10} = 1041.083$, $\text{BF}_{+} = 23999$) and
258 longer when the current trial was imagined rather than executed ($\beta = 0.037$, 95% CrI
259 [0.029, 0.045], $\text{BF}_{10} = 5 \times 10^{15}$, $\text{BF}_{+} = \text{Inf}$). This equates to a switching benefit in
260 executed-imagined compared to imagined-imagined sequences, and to a switching cost in
261 imagined-executed compared to executed-executed sequences. There was moderate
262 evidence in favour of a non-null interaction effect between the effect of the previous mode
263 and the effect of the current mode ($\beta = -0.011$, 95% CrI [-0.023, 0.001], $\text{BF}_{10} = 2.97$, BF_{+}
264 $= 0.036$), suggesting that the effect of the previous mode was smaller in imagined trials
265 than in executed trials. These results are also depicted in Figure 3.

266 The predictions regarding effector-specific inhibition could not be appropriately
267 tested, as highlighted by a reviewer. The participants included were not necessarily touch

268 typists. Therefore, some letters may have been typed with either the left or the right hand
269 according to the context or to individual preferences rather than to their keyboard
270 position; words containing central letters on the keyboard (e.g., T, G, or B) may have been
271 typed with both hands. This uncertainty blurs the experimental manipulation we
272 implemented and prevents us from drawing conclusions regarding effector-specific
273 inhibition effects. For the sake of completeness, though, we report the results from these
274 analyses in the supplementary materials.

275 **Preliminary summary.** To sum up, results from these analyses revealed that, as
276 predicted, imagery in the previous trial increased the *duration* of executed or imagined
277 movements, suggesting that typing imagery does involve the inhibition of motor
278 commands. However, contrary to our predictions and results from previous studies
279 studying pointing movements (e.g., Bart et al., 2020, 2021a, 2021b; Rieger et al., 2017), the
280 *initiation* of executed or imagined movements (i.e., the RT) was sped up rather than
281 slowed by typing imagery in the previous trial.

282 **Exploratory (non-preregistered) analyses - Assessing task compliance**

283 In this section, we report the results of exploratory (i.e., non-preregistered) analyses,
284 aiming at distinguishing participants who effectively performed the imagery task from
285 those who did not. How can we make sure that participants effectively performed the task
286 as expected in imagined trials? This is a common concern in studies involving covert
287 operations such as mental or motor imagery. Although there is no possible direct
288 verification, we considered an ensemble of a priori and a posteriori precautions. A priori,
289 we took great care of explaining the task to the participants in details and planned an
290 extensive training period during which the experimenter could monitor the (overt)
291 behaviour of the participant to provide more details about the task, if needed.

292 A posteriori (after data collection), we sought to separate participants who were
293 plausibly engaged in the imagery task from those who were not, based on the collected

294 movement times. We reasoned that if the imagined action follows a “faithful” mental
295 simulation of the corresponding overt action, we could expect the time it takes to imagine
296 an action to be correlated to the time it takes to execute the same action (similar to what
297 has been observed for handwriting or walking, for review see Guillot & Collet, 2005).

298 Figure 4 depicts the relation between the average movement time in executed and
299 imagined trials, averaged per word and participant, for a few exemplary participants. In
300 the data, we can distinguish between two profiles of participants: those who show a
301 positive relation between executed and imagined movements times (left panel, in green)
302 and those who do not (right panel, in orange), thereafter labelled as “on-task” and
303 “off-task” participants, respectively. We can then construct groups of participants (of
304 similar size) according to the correlation between the executed and imagined movement
305 times and assess the effect of interest according to this new grouping factor.

306 Figure 5 shows that the predicted effects of the previous action mode on MTs was
307 only found in participants with a non-null correlation between executed and imagined MTs
308 (middle and right panels) and was the strongest in participants with a strong positive
309 correlation between executed and imagined MTs (right panel). This visual intuition was
310 confirmed by fitting the model described in the previous section and adding interaction
311 terms with the correlation coefficient. This analysis revealed a strong interaction between
312 the effect of the previous action mode and the correlation coefficient, suggesting that higher
313 correlation coefficients (between executed and imagined MTs) were associated with higher
314 slowing effects of the previous action mode. This strongly suggests that typing imagery,
315 when performed correctly, does involve the inhibition of motor commands. However, this
316 figure also shows that even for “on-task” participants (right panel), we did not find the
317 effect predicted based on previous studies for the RTs. Finally, this analysis revealed that
318 participants with the strongest positive correlation coefficients had longer RTs on average.

319 **Modelling latent inhibitory processes**

320 Differences in RTs or MTs due to the action mode of the previous trial provide
 321 important cues regarding the inhibitory mechanisms involved. However, these raw
 322 contrasts may be inconclusive about the mechanistic implementation. For instance, motor
 323 imagery could slow down the initiation of subsequent movements either by upregulating
 324 the motor execution threshold or by delaying the spread of excitatory inputs (Nalborczyk
 325 et al., 2024). We developed an algorithmic model intended to capture alternative inhibitory
 326 mechanisms, and to distinguish between modulations of the motor execution threshold and
 327 modulations in the shape of the underlying activation function (Nalborczyk et al., 2024).
 328 This model provides a simplified overarching description of how the motor system is
 329 involved over the timecourse of a trial during motor imagery, roughly corresponding to the
 330 underlying activity of populations of excitatory and inhibitory neurons (adapted from
 331 MacDonald et al., 2014, 2017).³ The overall level of motor activation is modelled as a
 332 time-varying rescaled lognormal function defined as:

$$f(t; A, \mu, \sigma) = A \cdot \exp \left[-\frac{(\ln t - \mu)^2}{2\sigma^2} \right], \quad t > 0$$

333 where A represents the amplitude (i.e., the maximum value) of the activation function
 334 and is usually fixed to an arbitrary value (e.g., $A = 1$). This leaves three free parameters:
 335 μ (the peak latency or “peak time” of the function), σ (its width or “curvature”), and one

³ In the initial stages of the model development, we thought that this model could be used to account for both motor imagery and execution. However, it soon became clear that this model could not be applied as it is for motor execution because in such cases it leads to nonsensical predictions. For instance, assuming both a motor imagery threshold and a motor execution threshold make sense for motor imagery. However making the same assumption for motor execution would imply a stage of conscious (experienced) motor imagery preceding execution, which we think is not cognitively plausible. Primarily for this reason, we introduced this model as a model of motor imagery alone and therefore fitted it to imagined trials only.

336 parameter for the imagery threshold T (expressed relative to A and such that $T < A$).
 337 From a psychological perspective, $A - T$ may be related to the vividness of motor imagery
 338 percepts, μ may be related to the speed at which these mental percepts are established, and
 339 σ may be related to their duration (Nalborczyk et al., 2024). In this model, the reaction
 340 time is defined as the time at which the activation function crosses the threshold for motor
 341 imagery and the movement time is defined as the time “spent” above the threshold (Figure
 342 6) (similar to what has been proposed for conscious access, e.g., Pereira et al., 2022).

343 We fitted this model to data coming from each participant individually. The fit
 344 procedure was adapted from Ratcliff and Smith (2004) and is commonly used to fit
 345 sequential sampling models to behavioural data (e.g., Servant et al., 2019). The model was
 346 simultaneously fitted to RTs and MTs quantiles (0.1, 0.3, 0.5, 0.7, 0.9), to take into account
 347 the entire RTs and MTs distributions (instead of only the mean or median values). The
 348 following loss function (likelihood-ratio chi-square statistic) was minimised:

$$G^2 = 2 \left(\sum_{i=1}^2 \sum_{j=1}^6 p_{ij} \log \frac{p_{ij}}{\pi_{ij}} \right)$$

349 where the outer summation over i refers to RTs and MTs, and the inner summation
 350 over j extends refers to the 6 bins bounded by RT/MT quantiles. The quantities p_{ij} and
 351 π_{ij} are the observed and predicted proportions of trials in RT/MT bin j . This G^2 statistic
 352 characterises the goodness-of-fit of the model to the joint distributions of RT and MT. It
 353 was minimised using differential evolution (Storn & Price, 1997) and 200 simulated trials
 354 per condition (with $F = 0.9$ and $CR = 0.95$) using the `DEoptim` package (Mullen et al.,
 355 2011). The code underlying this model and the fitting routine are implemented in the
 356 `momimi` package (available on Github: <https://github.com/lnalborczyk/momimi>).

Table 3

Average (group-level) parameter estimates from the algorithmic model of motor imagery

Condition (trial sequence)	Execution threshold	Peak time	Curvature
executed_imagined	1.34	1.23	0.68
imagined_imagined	1.24	1.22	0.68

357 Estimates from these models are reported in Figure 6 and Table 3. Recall that
 358 whereas in previous studies both RTs and MTs increased following imagined trials, in the
 359 present study group-level results showed that MTs increased but RTs decreased following
 360 imagined trials. Parameter estimates obtained by fitting the algorithmic model to these
 361 data suggest that these differences may be due to different underlying inhibitory
 362 mechanisms. More precisely, the shortening of RTs (jointly observed with the lengthening
 363 of MTs) following imagined trials is compatible with a *decrease* in the motor execution
 364 threshold (as reported in Table 3), whereas the lengthening of both RTs and MTs following
 365 imagined trials is compatible with a delay in the peak time of the activation function (as
 366 previously suggested by Nalborczyk et al., 2024).

367

Discussion

368 We investigated the presence of motor inhibition during typing imagery with an
 369 adapted version of Rieger et al. (2017)'s action-mode switching paradigm. Overall, our
 370 results show that typing imagery slows down the realisation of subsequent executed or
 371 imagined movements (as assessed by differences in MTs), but speeds up the initiation of
 372 subsequent executed or imagined movements (as assessed by differences in RTs). Taken
 373 together, these results suggest that motor inhibition prevents the execution of typing acts
 374 during typing imagery. The algorithmic modelling revealed a possible implementation of
 375 inhibition in terms of threshold modulation or delay. In the following, we discuss this

376 interpretation in more detail, including potential explanations for the discrepancies between
377 our results and previous results obtained using the action-mode switching paradigm.

378 **Unexpected effects on reaction times**

379 Based on previous studies using a similar paradigm with imagined and executed
380 pointing movements, we hypothesised that motor inhibition during imagined movements
381 may slow down both the RT and MT. However, we did not observe such an effect on the
382 RTs. The discrepancy between our results and those of previous studies may come from the
383 nature of the task(s) participants had to realise during the time period considered as the
384 “reaction time” in our experiment. During this time period, participants had to identify
385 the action of the current trial (as indicated by the geometrical shape surrounding the word
386 displayed on the screen), but they also had *to read the word*, and possibly process it at
387 different linguistic stages, which differs considerably from the RT period of previous studies
388 involving simpler hand movements and during which participants only had to identify the
389 spatially congruent target to which they should next reach (or imagined reaching). We
390 assessed this possibility in a second follow-up preregistered study (cf. supplementary
391 materials). The overall procedure was similar to the main experiment, except for the
392 linguistic material. In this experiment, we sought design an experiment closer to the
393 protocol of Rieger et al. (2017). To this end, we used bigrams instead of words while
394 taking care of maximising the distance between left-hand and right-hand bigrams on the
395 keyboard. Moreover, we added an association training during which participants learned to
396 associate four bigrams to a geometrical shape. This was intended to remove or reduce the
397 effect of reading the item on screen during the period considered as “reaction time” and, as
398 such, to provide a more direct comparison to the procedure of Rieger et al. (2017). Overall,
399 we observed no difference across sequences in average RTs or MTs, but we observed longer
400 RTs and MTs variability following imagined trials, in a direction compatible with the
401 expected effects on average RTs and MTs (cf. supplementary materials, Table S1 and S2).

402 Another possibility, suggested by a reviewer, is that cue repetition (i.e., the geometric
403 shape indicating the action mode) in successive trials of the same action mode may have
404 provided a perceptual benefit, which could counteract the hypothesised effect (especially on
405 RTs). In other words, the effect of task-switching may be confounded with the effect of
406 cue-switching (e.g., Schneider & Logan, 2011). Whereas this could explain why we did not
407 observe the predicted effect on RTs in II vs. EI sequences (where the effect of cue repetition
408 and action mode switching may cancel out), this could not explain the lack of effects on
409 RTs in IE vs. EE sequences. Indeed, in executed trials, perceptual benefits related to cue
410 (action mode) should be congruent (in the same direction) with inhibition effects and
411 should therefore result in longer RTs for IE vs. EE sequences, which is not what was
412 observed. Nevertheless, the effect of cue-switching could be assessed in a future extension
413 of the present study by using a 2:1 cue-task mapping to assess the impact of this
414 manipulation on the pattern of RTs/MTs and the model's parameters (in the vein of
415 Schmitz & Voss, 2014).

416 **Distinct inhibitory mechanisms**

417 We introduced and fitted an algorithmic model of motor imagery allowing to
418 disentangle distinct underlying inhibitory mechanisms. Results from this analysis showed
419 that motor inhibition may have different effects on patterns of RTs and MTs, suggesting
420 that it may affect different aspects of the latent activation function (i.e., the shape of the
421 activation function or the motor execution threshold). More precisely, the shortening of
422 RTs jointly observed with the lengthening of MTs following imagined trials (as observed in
423 the present study) is compatible with a *decrease* in the motor execution threshold (as
424 reported in Table 3), whereas the lengthening of both RTs and MTs following imagined
425 trials (as observed in previous studies such as Bart et al., 2020, 2021a, 2021b; Rieger et al.,
426 2017) is compatible with a delay in the peak time of the activation function (as previously
427 suggested by Nalborczyk et al., 2024).

428 As mentioned previously, task requirements during the RT period in the present
429 study differed considerably from that of previous studies. These differences in task
430 requirements may have impacted the patterns of RTs/MTs as well as the model's
431 estimates. We further speculate that across typing and pointing, motor inhibition resulting
432 from imagery affects different aspects of the execution/imagery initiation in the following
433 trial. For instance, Haith et al. (2016) showed that motor preparation (i.e., preparing a
434 movement) and motor initiation (i.e., initiating a movement once it is prepared) may be
435 modulated independently and suggested that these two components have distinctly neural
436 correlates. We therefore speculate that these two components of the RT (i.e., preparation
437 + initiation) may be impacted differently in typing vs. pointing movements and may be
438 mapped to distinct parameters of the algorithmic model. More precisely, because motor
439 preparation is associated with activity in motor and premotor cortices and may share
440 resources with motor execution, we might expect it to impact the shape of the activation
441 function – this would correspond to modulations of the peak time and/or the curvature
442 parameter. In contrast, motor initiation is not expected to affect the shape of the
443 activation function and may therefore be related to modulations of the threshold parameter
444 (whose modulations do not change the shape of the activation function), with correlates in
445 brain regions such as the SMA (as suggested for motor initiation by Haith et al., 2016).
446 Relating this discussion to the two tasks mentioned previously (typing vs. pointing), we
447 could speculate that motor inhibition in the pointing action-mode switching tasks impacts
448 the shape of the activation function (thus, slowing down motor preparation) whereas motor
449 inhibition in the typing action mode switching tasks would impact the motor execution
450 threshold (thus, slowing down or delaying motor initiation). This remains to be assessed in
451 future studies combining behavioural measures with neuroimaging or electrophysiological
452 measures of motor preparation and motor imagery.

453 Perhaps surprisingly, fitting the algorithmic model of motor imagery presented in
454 Nalborczyk et al. (2024) to our data revealed that the motor execution threshold was

455 *decreased* in imagined-imagined sequences relative to executed-imagined sequences.
456 Whereas this interpretation may seem unintuitive at first, it reflects the *increase* of the
457 motor execution threshold in the first (previous) imagined trial, which then drifts back to
458 an average value. In other words, the motor execution threshold decreases in the second
459 trial of an imagined-imagined sequence (relative to the first trial) because it has increased
460 in the first trial of this sequence (relative to the trial preceding this sequence) and has no
461 reason to increase further. This could reflect strategic modulations of the execution
462 threshold in sequences of trials wherein the threshold is modulated according to task
463 demands in order to minimise a putative cost associated with upregulating the threshold
464 higher than necessary. This hypothesis is supported by considering what happens in
465 sequences of three successive trials (i.e., imagined-imagined-imagined
466 vs. executed-imagined-imagined sequences). In such sequences, the motor execution
467 threshold in the last trial of this sequence is *lower* in imagined-imagined-imagined than in
468 executed-imagined-imagined sequences (RTs/MTs are smaller/longer in III than EII
469 sequences, cf. Figure S3 in supplementary materials).

470 These inhibitory mechanisms may be subserved by brain regions such as the
471 pre-supplementary motor area (Kasess et al., 2008) or the right inferior frontal gyrus,
472 which may plausibly be responsible for weakening the motor commands that are emitted
473 during motor imagery (e.g., Angelini et al., 2015, 2016; Nalborczyk et al., 2022).
474 Downstream regions in the cerebellum (e.g., Lotze et al., 1999), in the brainstem (e.g.,
475 Jeannerod, 2001, 2006), or at the spinal level (e.g., Grosprêtre et al., 2016) may also
476 contribute to motor inhibition at a later stage. Alternatively, the need for explicit
477 inhibitory mechanisms counteracting motor commands has been questioned by studies
478 looking at population-level neuronal activity during motor preparation or motor imagery
479 (e.g., Dekleva et al., 2024; Kaufman et al., 2014). Analyses of intracranial recordings in
480 monkeys have revealed that neuronal activity within the primary motor cortex cancels out
481 at the population level during motor preparation, explaining how the motor cortex may

482 prepare movement without executing it (Kaufman et al., 2014). Dekleva et al. (2024)
483 further showed, in a implanted human tetraplegic patient, that motor imagery and motor
484 execution do not occupy completely orthogonal neural subspaces. Rather, population-level
485 neural activity can be decomposed in a common subspace plus orthogonal subspaces for
486 executed and imagined movements. This population-level view does not necessarily
487 contradict the algorithmic perspective of the model fitted on the present data, however.
488 Indeed, premotor areas (such as the dorsal premotor cortex) may be responsible for sending
489 “trigger” signals responsible for switching from the execution or imagery neural subspaces
490 (similar to what has been hypothesised for motor preparation and execution, e.g., Zimnik
491 & Churchland, 2021), with similar behavioural consequences (e.g., on imagined RTs and
492 MTs) than the threshold modulation perspective. Moreover, the “activation timecourse”
493 assumed by the algorithmic model may correspond to the population-level aggregate
494 activity within the primary motor cortex. Whether this assumption holds (or whether the
495 activation timecourse may be related to fluctuations in the vividness of motor imagery
496 percepts) remains to be assessed in future studies using TMS or intracranial measurements
497 together with continuous subjective reports.

498 **Conclusions**

499 In summary, we adapted the action mode switching paradigm (Rieger et al., 2017) to
500 typing imagery and observed that typing imagery slows down subsequent imagined or
501 executed typing movements. We further used and discussed a novel algorithmic model of
502 motor imagery allowing to infer the underlying continuous timecourse of motor activation
503 throughout the trial and to distinguish between different potential inhibitory mechanisms.
504 The assumptions and novel predictions derived from this framework remain to be assessed,
505 thus providing promising avenues for future research on the rich subjective experience of
506 motor imagery and the neural mechanisms supporting it.

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518

Data availability statement

519 Data and supplementary materials are available via the Open Science Framework:
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521

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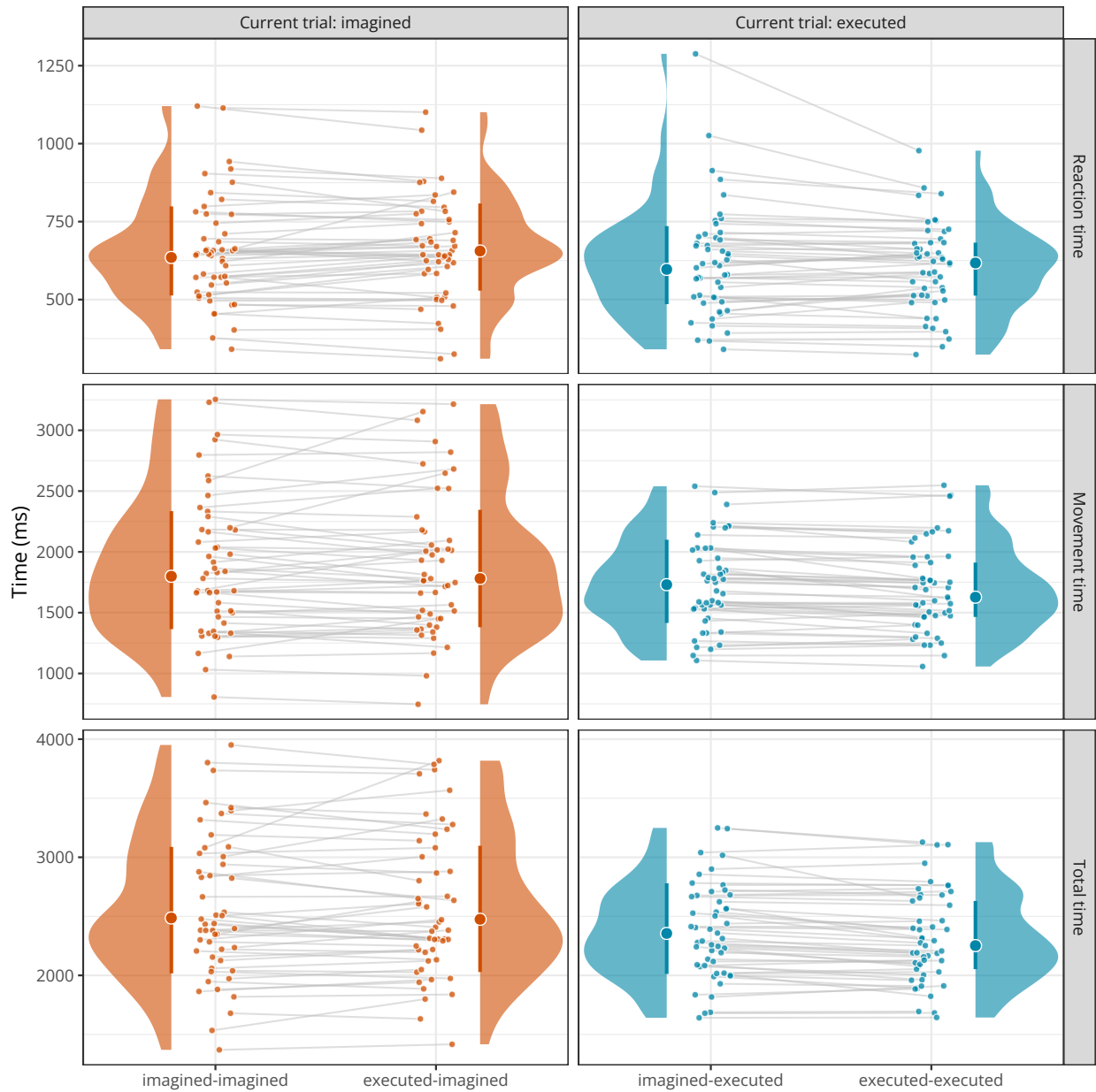


Figure 2. Average reaction time (top), movement time (middle), and total response time (bottom) across conditions. The error bars represent the 25th and 75th percentiles. Each dot represents the by-participant median reaction time (top row) or movement time (bottom) computed across 96 trials per condition. Left panel: imagined trials. Right panel: executed trials. Sequences of trials (i.e., pair of successive trials) are represented on the x-axis, which corresponds to (from left to right): imagined-imagined, executed-imagined, imagined-executed, and executed-executed sequences.

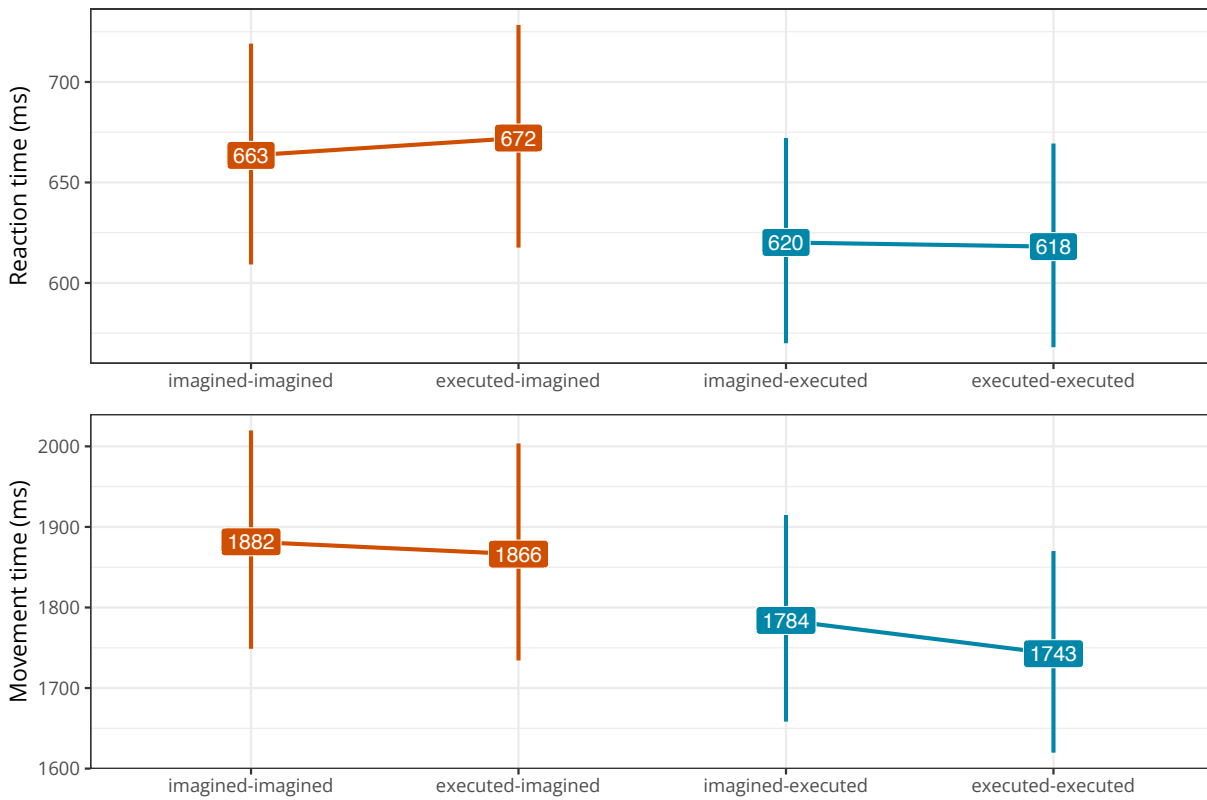


Figure 3. Estimated mean reaction time (top) and movement time (bottom) across conditions in Experiment 1. The error bars represent the 95% credible intervals. Sequences of trials (i.e., pair of successive trials) are represented on the x-axis, which corresponds to (from left to right): imagined-imagined, executed-imagined, imagined-executed, and executed-executed sequences.

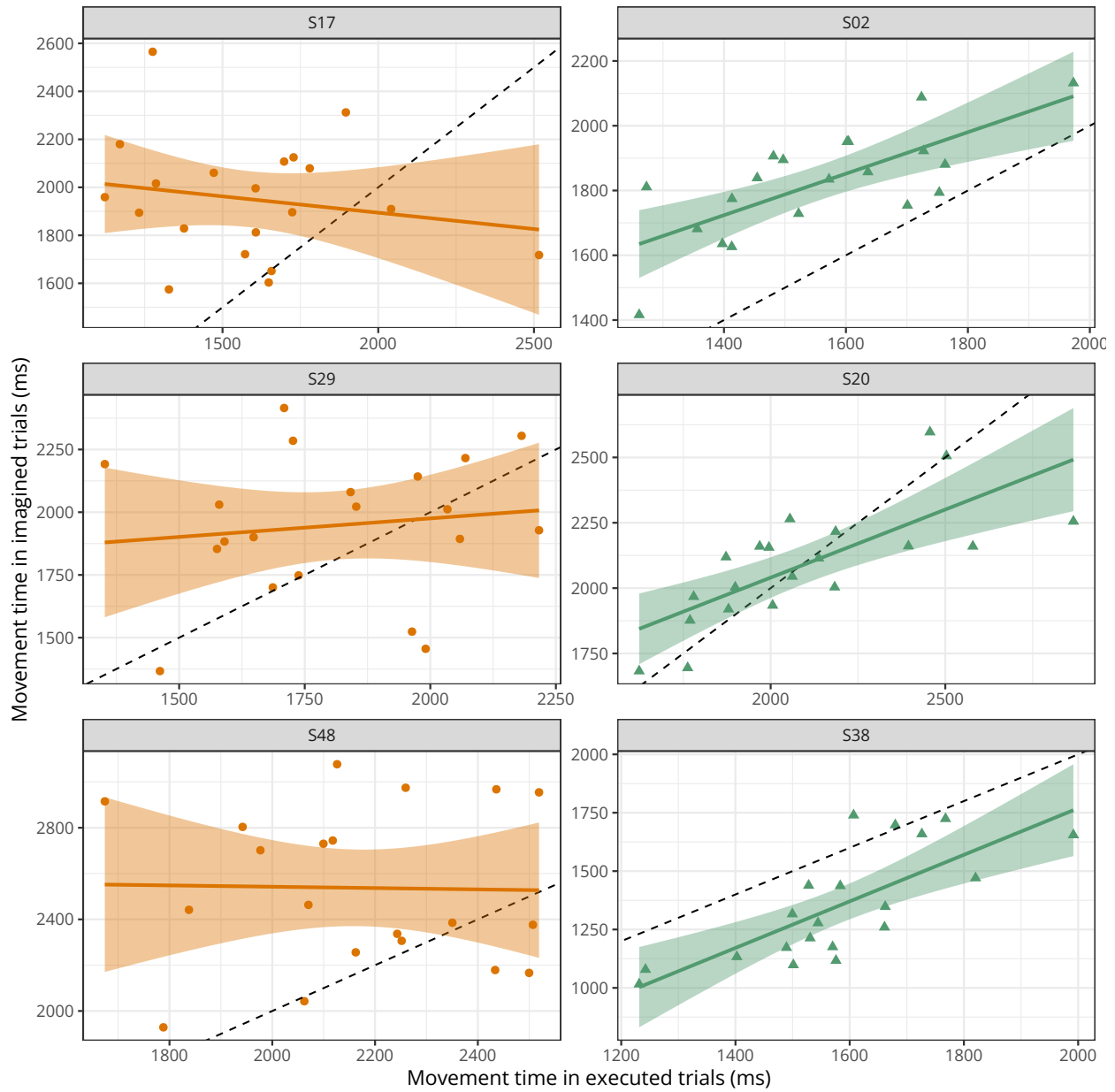


Figure 4. Relation between the average movement time in executed and imagined trials. Each panel represents a participant, each dot/triangle represents the per-word average MT in executed and imagined trials for this participant. Dashed lines represent the isochrony lines for which executed and imagined MTs are equal. Participants classified as 'off-task' according to this correlation are depicted in orange on the left whereas participants classified as 'on-task' according to the correlation between executed and imagined MTs are depicted in green on the right.

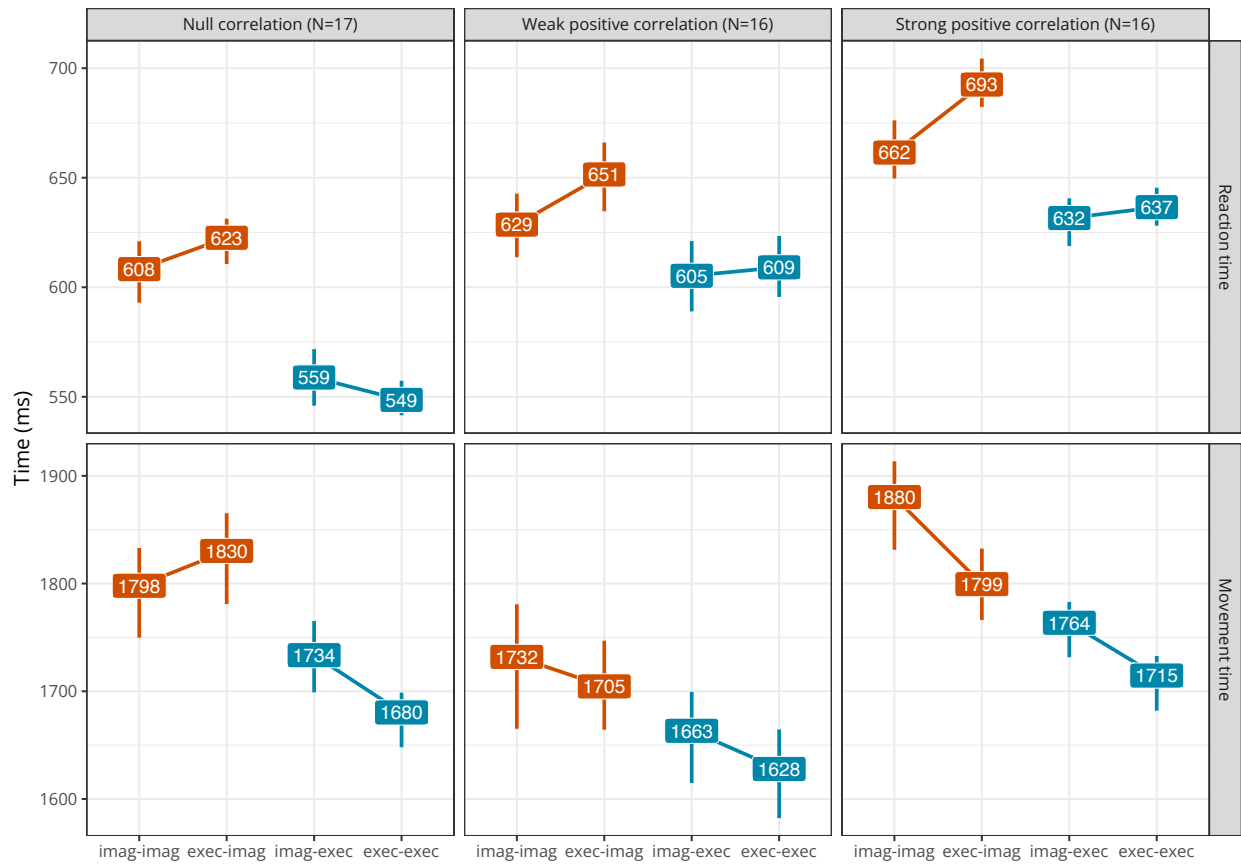


Figure 5. Average (median) reaction time and movement time per condition for participants with a null correlation between average executed and imagined movement times (left panel), those with a weak positive correlation (middle panel), and those with a strong positive correlation (right panel).

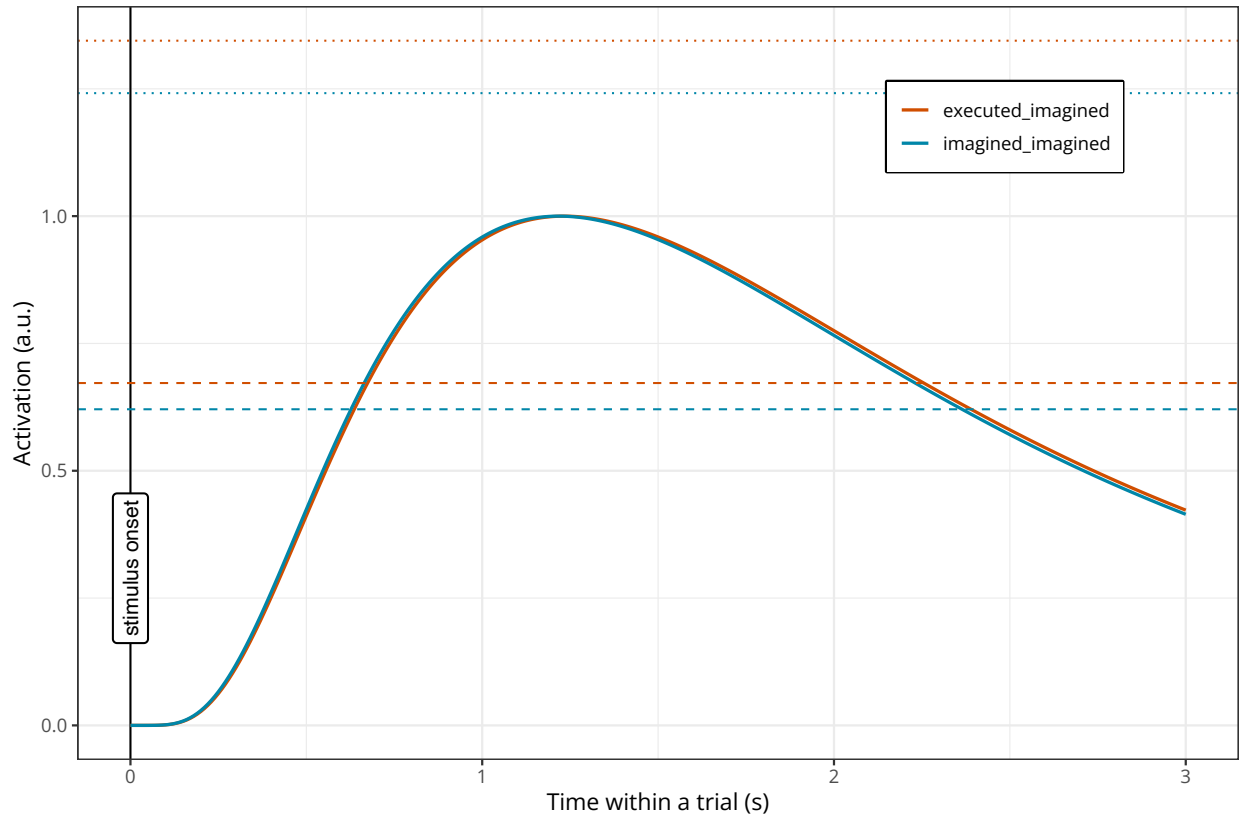


Figure 6. Average latent activation function as estimated by the model in imagined-imagined (blue) and executed-imagined (orange) sequences from stimulus onset (time = 0) to RT (first threshold crossing) onto to MT (difference between the second and first threshold crossing). The horizontal dotted lines represent the motor execution thresholds whereas the dashed horizontal lines represent the motor imagery thresholds. Only participants with a strong positive correlation between executed and imagined MTs ($N = 16$) were included.