

Full length article

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

Ladislav Nalborczyk^{a,b,c,*}, F.-Xavier Alario^a, Marieke Longcamp^a^a Aix Marseille Univ, CNRS, CRPN, Marseille, France^b Cognitive Neuroimaging Unit, CEA DRF/I2BM, INSERM, Université Paris-Sud, Université Paris-Saclay, NeuroSpin Center, Gif/Yvette, France^c Inserm U 1127, CNRS UMR 7225, Sorbonne Universités, Institut du Cerveau, ICM, Paris, France

ARTICLE INFO

Dataset link: <https://osf.io/y9a3k/>

Keywords:

Typing
 Typing imagery
 Motor imagery
 Motor inhibition
 Response inhibition
 Algorithmic modelling

ABSTRACT

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

1. Introduction

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

This simulationist perspective entails that the reuse of motor networks during motor imagery should be accompanied by mechanisms preventing execution (Jeannerod, 2006; O'Shea & Moran, 2017). Previous research has postulated at least three (non-exclusive) potential inhibitory mechanisms that might operate during motor imagery (Guillot, Di Rienzo et al., 2012). First, the need to prevent execution could

be integrated within the representation of the action to be produced internally so that only “subthreshold” motor commands are involved during motor imagery (see also Bach, Frank, & Kunde, 2022; Glover, Bibby, & Tuomi, 2020). Second, motor inhibition could be applied broadly to all ongoing actions and to all effectors involved in these actions (global motor inhibition). Third, motor inhibition may be applied in a finer-grained manner, only to some effector (effector-specific inhibition).

To investigate these inhibitory mechanisms, Rieger, Dahm, and Koch (2017) developed a protocol called the action-mode switching paradigm in which participants have to rapidly alternate between various overt (executed) and covert (imagined) hand movements. The authors reasoned that, if motor imagery involves the inhibition of motor commands, then the inhibition applied during some imagined trial may persist to the next trial and may slow down its initiation, resulting in switching costs (for imagined–executed vs. executed–executed sequences) or switching benefits (for imagined–imagined vs. executed–imagined sequences). By further varying the effector used for the

* Correspondence to: Ladislav Nalborczyk, CRPN, CNRS & Aix-Marseille University, 3 place Victor Hugo, 13331, Marseille Cedex 3, France.
 E-mail address: ladislav.nalborczyk@gmail.com (L. Nalborczyk).

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

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

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

Differences in RTs or MTs due to the action mode of the previous trial provide important cues regarding the inhibitory mechanisms involved. However, these raw contrasts may be inconclusive about the mechanistic implementation. For instance, motor imagery could slow down the initiation of subsequent movements either by upregulating the motor execution threshold or by delaying the spread of excitatory inputs (Nalborczyk, Longcamp, Gajdos, Servant, & Alario, 2024). In order to disentangle potentially distinct underlying inhibitory mechanisms, we fitted a novel algorithmic model of motor imagery allowing to infer the effect of inhibition in the previous trial on the underlying timecourse of motor activation during typing imagery in the current trial (see Section 3.4).

2. 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, Nelson, & Simonsohn, 2012). A pre-registered version of our protocol is available online: <https://osf.io/y9a3k/>.

2.1. 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.

2.2. 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, 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).

2.3. 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, Pallier, Brysbaert, & Ferrand, 2004). The groups of left-hand and right-hand words were matched for per-word average bigram frequency, word frequency, number of letters, and number of syllables (the complete list of stimuli is available in the online supplementary materials).

2.4. Design

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

2.5. Procedure

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

Afterwards, we provided participants with extensive instructions about typing imagery. Namely, we instructed them to imagine themselves from a first-person perspective typing the words, insisting on the multisensory nature of motor imagery. We asked them to focus

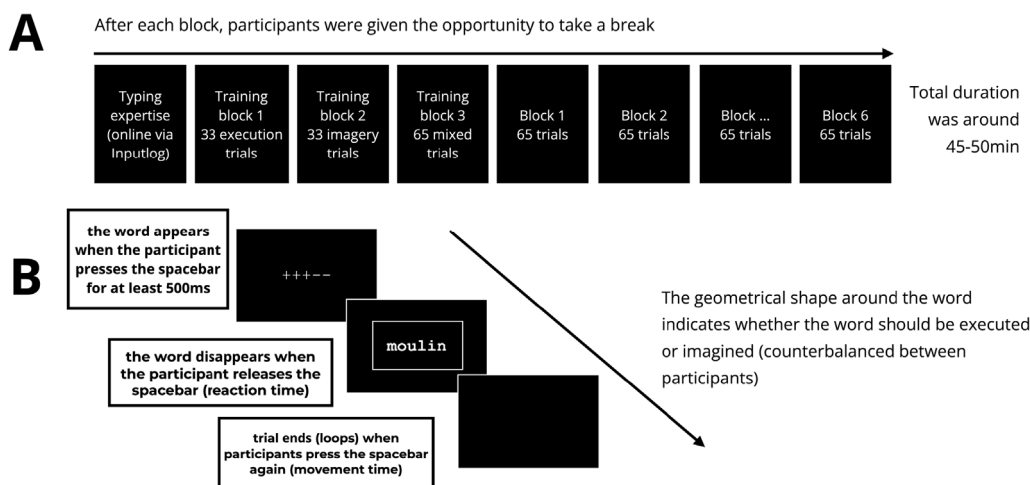


Fig. 1. A: Experimental procedure. The main experimental part (post-training) involved 6 blocks of 65 trials each. B: Illustrated timecourse of a single trial.

on the tactile feelings and auditory percepts associated with typing (i.e., kinaesthetic motor imagery). Participants were also instructed to perform both the overt and covert typing tasks as fast and accurately as possible without correcting potential errors.

Participants started with a first training block which consisted only of overt typing trials. They continued with a second training block consisting only of covert typing trials followed by a third training block containing both overt and covert typing trials. Within each trial, the action mode (i.e., executed vs. imagined trials) was indicated by a geometrical shape (i.e., rectangle vs. circle) surrounding the word. The association between action mode and shape was counterbalanced across participants. The main experimental part (post-training) followed, consisting of six blocks of 65 trials each, yielding a total of 390 trials per participant (Fig. 1A). The order of word sequences (i.e., pairs of successive words/trials) in each block was randomised using Euler tours (Bakermans & Behrens, 2021), ensuring that each of the eight trials sequences appeared equally often (i.e., 8 times per block).

The timecourse of each single trial is depicted in Fig. 1B. Participants first needed to press the spacebar with their two thumbs for at least 500 ms, visually represented by a progress bar displayed at the centre of the screen. After these 500 ms, the word appeared on the screen until the participant released the spacebar and started typing the word, either overtly or covertly. As soon as they finished, they had to return their thumbs to the spacebar. In each trial, we measured both the reaction time (RT) and the movement time (MT). The reaction time was defined as the time interval between the appearance of the stimulus (i.e., the word) and the release of the spacebar by the participant (i.e., the disappearance of the stimulus from the screen). The movement time was defined as the time interval between the release of the spacebar by the participant and the next spacebar keypress (Fig. 1B).

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

2.6. Data analysis

Statistical analyses were conducted using R version 4.2.3 (2023-03-15) (R. Core Team, 2017) and are reported with the *papa* (Aust & Barth, 2017) and *knitr* (Xie, 2015) packages. To assess the effects of

motor inhibition on RTs and MTs, we built and fitted several Bayesian multilevel generalised linear models using the *brms* package (Bürkner, 2017).¹ Data were analysed using *current action mode* (2 levels, executed vs. imagined, recoded using a $-0.5/+0.5$ sum contrast), *previous action mode* (2 levels, executed vs. imagined, recoded using a $-0.5/+0.5$ sum contrast), and *hand alternation/repetition* (2 levels, same vs. different, recoded using a $-0.5/+0.5$ sum contrast) as within-subject categorical predictors, and the RT or MT as a dependent variable. We analysed RTs and MTs separately (i.e., we built separate models for each of these two measures). All models allowed intercepts and slopes to vary by participant.

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

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

3. Results

This section is divided into four parts. First, we present a visual exploration of the data. Second, we present results from confirmatory (preregistered) analyses, aiming at assessing the sequential effects of motor inhibition on reaction times (RTs) and movement times (MTs). Third, we present results from exploratory (non-preregistered) analyses, aiming at distinguishing participants that effectively performed the imagery task from those who did not. These were motivated by various

¹ An introduction to Bayesian statistics is outside the scope of this paper. The interested reader is referred to Nalborczyk, Batailler, Loevenbruck, Vilain, and Bürkner (2019) for an introduction to Bayesian multilevel modelling using the *brms* package.

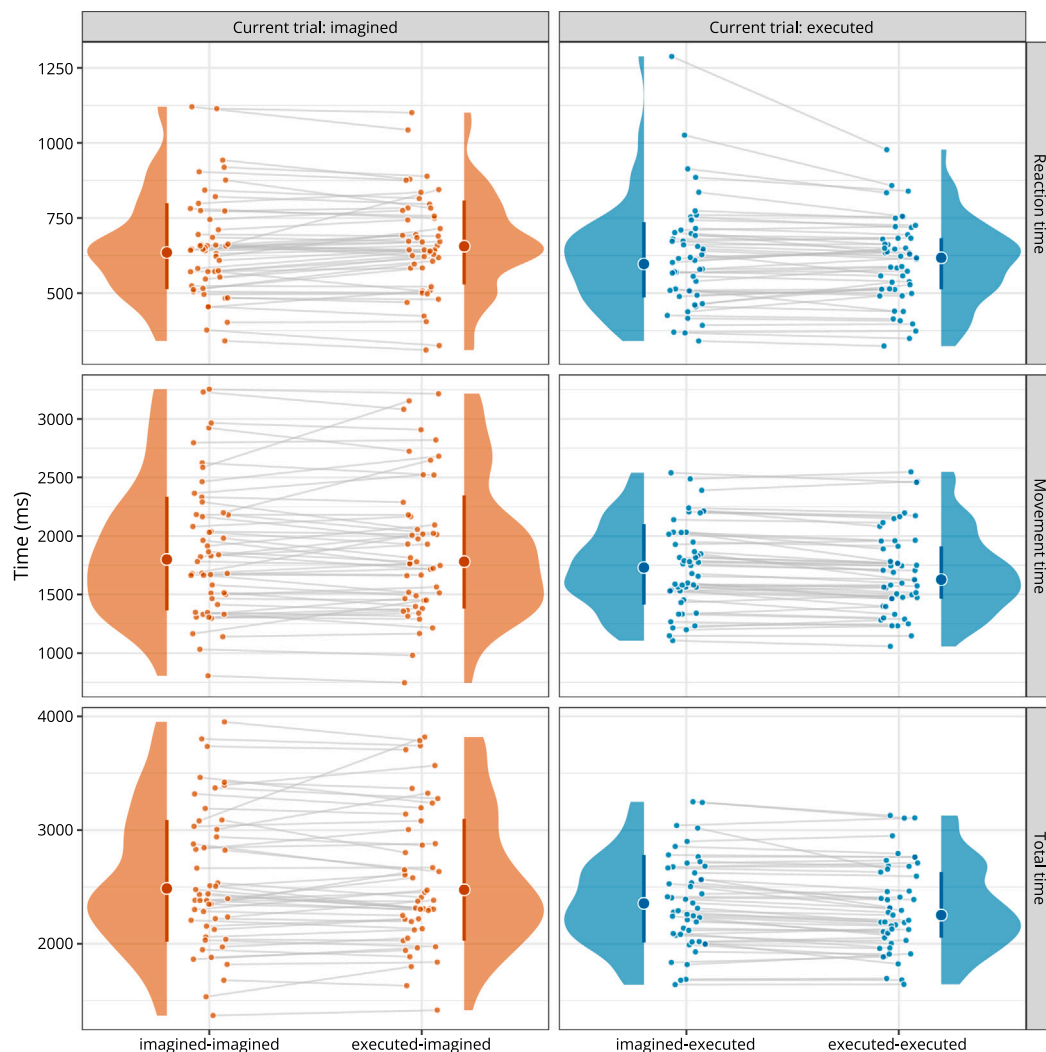


Fig. 2. Average reaction time (top), movement time (middle), and total response time (bottom) across conditions. The error bars represent the 25th and 75th percentiles. Each dot represents the by-participant median reaction time (top row) or movement time (bottom) computed across 96 trials per condition. 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.

indications that the task may not have been performed equally well by all participants. Fourth, we discuss results obtained by fitting a novel algorithmic model of motor imagery to these data and demonstrating how it can be used to disentangle different underlying inhibitory mechanisms.

3.1. Visual exploration of the data

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

3.2. Confirmatory (preregistered) analyses

To estimate these effects while accounting for the skewness of the collected data (for more details, see the online supplementary materials), we fitted two multilevel distributional Log-Normal models (one model for RTs and one model for MTs), where “distributional” means

that not only the means but also the standard deviations were allowed to vary across conditions (for more details, see for instance Williams, Mulder, Rouder, & Rast, 2021). This was justified by the observation that the amount of variability (both within and between participants) strongly differed across executed and imagined trials (as can be seen from Fig. 2). The distributional model allows estimating the effects of interest while taking into account the effects the predictor variables may have on dispersion, thus producing more precise (less biased) estimates of the effects on means or medians. Estimates from these models are reported in Table 1 and Table 2 and discussed in the next two paragraphs.

3.2.1. Reaction times

RTs were slightly shorter when the previous trial was imagined rather than executed ($\beta = -0.006$, 95% CrI [-0.013, 0], $BF_{10} = 1.65$, $BF_{+} = 0.036$) and longer when the current trial was imagined rather than executed ($\beta = 0.066$, 95% CrI [0.059, 0.073], $BF_{10} = 6 \times 10^{18}$, $BF_{+} = \text{Inf}$).² There was strong evidence in favour of a non-null interaction

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 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.

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	23 999.000
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.

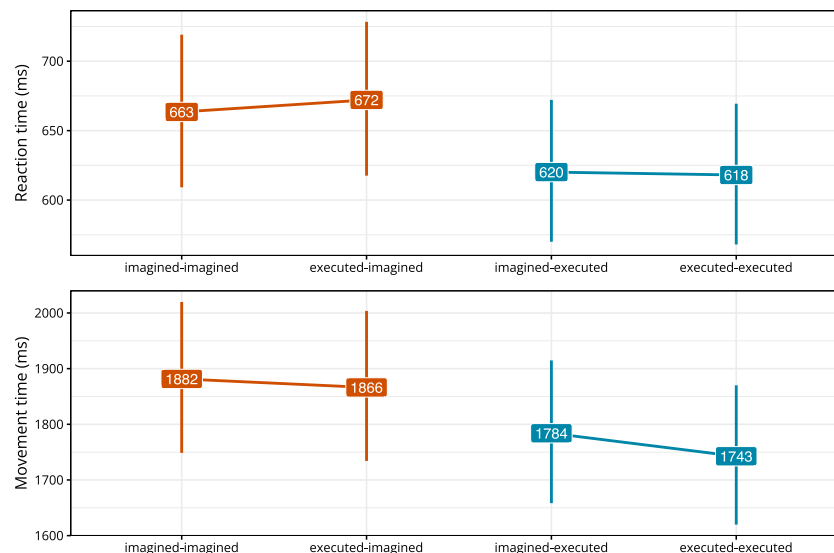


Fig. 3. Estimated mean reaction time (top) and movement time (bottom) across conditions in Experiment 1. The error bars represent the 95% credible intervals. Sequences of trials (i.e., pair of successive trials) are represented on the x-axis, which corresponds to (from left to right): imagined-imagined,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

effect between the effect of the previous mode and the effect of the current mode ($\beta = -0.015$, 95% CrI [-0.027, -0.003], $BF_{10} = 11.985$, $BF_+ = 0.006$), indicating that the effect of the previous mode was stronger in imagined trials than in executed trials (where the effect of the previous trial was null). This equates to a switch cost in executed-imagined compared to imagined-imagined sequences, whereas there was no evidence for such an effect in imagined-executed compared to executed-executed sequences. These results are more readily understandable visually and are presented in the original scale of the RTs in Fig. 3.

3.2.2. Movement times

MTs were longer when the previous trial was imagined rather than executed ($\beta = 0.016$, 95% CrI [0.009, 0.023], $BF_{10} = 1041.083$, BF_+

$= 23999$) and longer when the current trial was imagined rather than executed ($\beta = 0.037$, 95% CrI [0.029, 0.045], $BF_{10} = 5 \times 10^{15}$, $BF_+ = \text{Inf}$). This equates to a switching benefit in executed-imagined compared to imagined-imagined sequences, and to a switching cost in imagined-executed compared to executed-executed sequences. There was moderate evidence in favour of a non-null interaction effect between the effect of the previous mode and the effect of the current mode ($\beta = -0.011$, 95% CrI [-0.023, 0.001], $BF_{10} = 2.97$, $BF_+ = 0.036$), suggesting that the effect of the previous mode was smaller in imagined trials than in executed trials. These results are also depicted in Fig. 3.

The predictions regarding effector-specific inhibition could not be appropriately tested, as highlighted by a reviewer. The participants included were not necessarily touch typists. Therefore, some letters may have been typed with either the left or the right hand according to

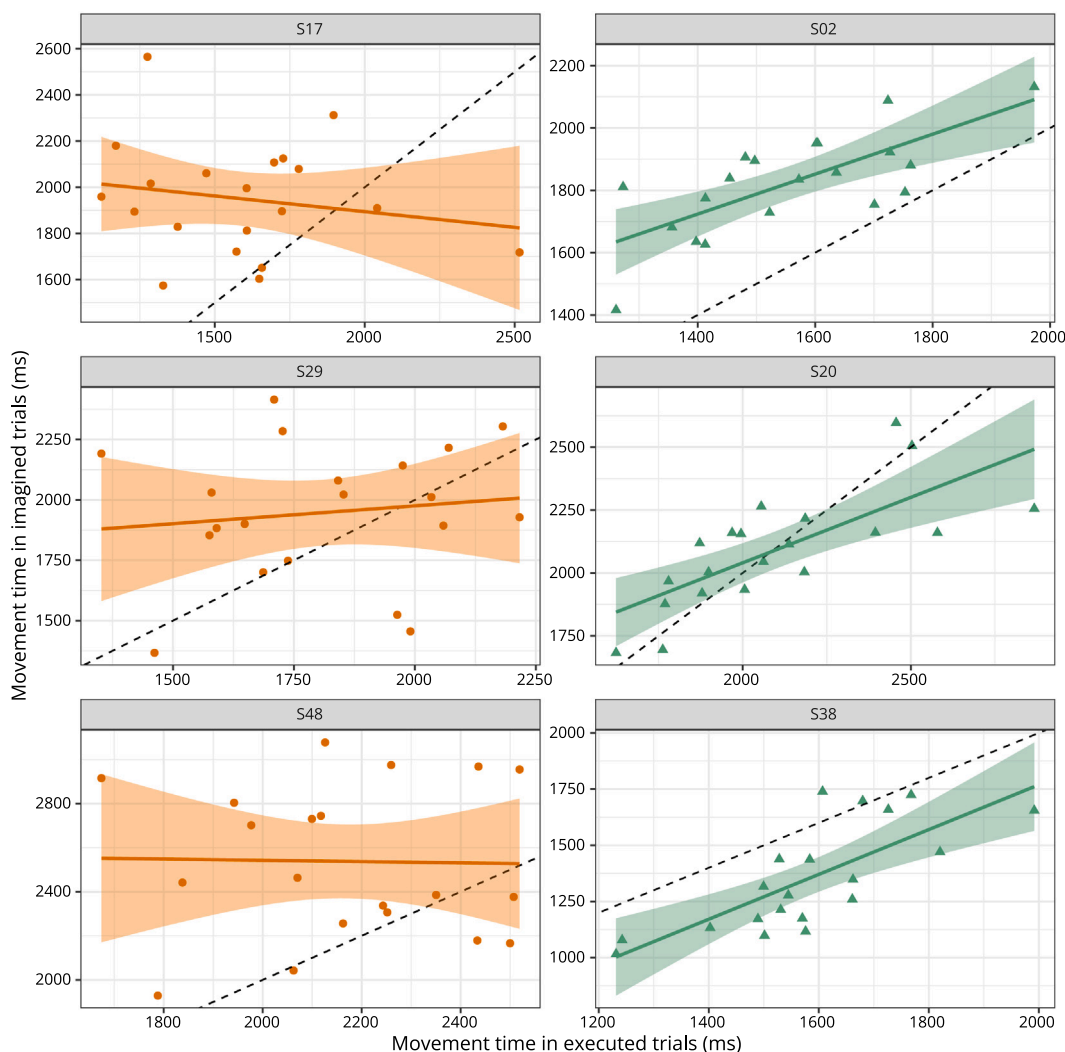


Fig. 4. Relation between the average movement time in executed and imagined trials. Each panel represents a participant, each dot/triangle represents the per-word average MT in executed and imagined trials for this participant. Dashed lines represent the isochrony lines for which executed and imagined 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.

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

3.2.3. Preliminary summary

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

3.3. Exploratory (non-preregistered) analyses — assessing task compliance

In this section, we report the results of exploratory (i.e., non-preregistered) analyses, aiming at distinguishing participants who effectively performed the imagery task from those who did not. How

can we make sure that participants effectively performed the task as expected in imagined trials? This is a common concern in studies involving covert operations such as mental or motor imagery. Although there is no possible direct verification, we considered an ensemble of a priori and a posteriori precautions. A priori, we took great care of explaining the task to the participants in details and planned an extensive training period during which the experimenter could monitor the (overt) behaviour of the participant to provide more details about the task, if needed.

A posteriori (after data collection), we sought to separate participants who were plausibly engaged in the imagery task from those who were not, based on the collected movement times. We reasoned that if the imagined action follows a “faithful” mental simulation of the corresponding overt action, we could expect the time it takes to imagine an action to be correlated to the time it takes to execute the same action (similar to what has been observed for handwriting or walking, for review see Guillot & Collet, 2005).

Fig. 4 depicts the relation between the average movement time in executed and imagined trials, averaged per word and participant, for a few exemplary participants. In the data, we can distinguish between two profiles of participants: those who show a positive relation between executed and imagined movements times (left panel, in green) and

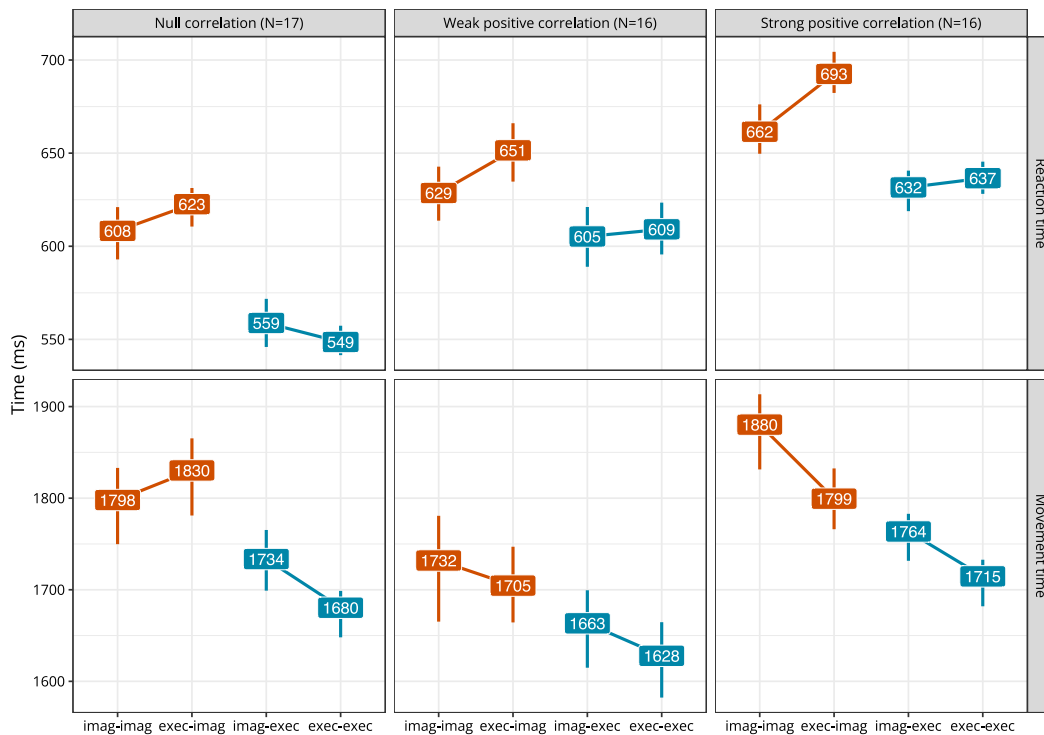


Fig. 5. Average (median) reaction time and movement time per condition for participants with a null correlation between average executed and imagined movement times (left panel), those with a weak positive correlation (middle panel), and those with a strong positive correlation (right panel).

those who do not (right panel, in orange), thereafter labelled as “on-task” and “off-task” participants, respectively. We can then construct groups of participants (of similar size) according to the correlation between the executed and imagined movement times and assess the effect of interest according to this new grouping factor.

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

3.4. Modelling latent inhibitory processes

Differences in RTs or MTs due to the action mode of the previous trial provide important cues regarding the inhibitory mechanisms involved. However, these raw contrasts may be inconclusive about the mechanistic implementation. For instance, motor imagery could slow down the initiation of subsequent movements either by upregulating the motor execution threshold or by delaying the spread of excitatory inputs (Nalborczyk et al., 2024). We developed an algorithmic model intended to capture alternative inhibitory mechanisms, and to distinguish between modulations of the motor execution threshold and modulations in the shape of the underlying activation function (Nalborczyk et al., 2024). This model provides a simplified overarching

description of how the motor system is involved over the timecourse of a trial during motor imagery, roughly corresponding to the underlying activity of populations of excitatory and inhibitory neurons (adapted from MacDonald, Coxon, Stinear, & Byblow, 2014; MacDonald, McMorland, Stinear, Coxon, & Byblow, 2017).³ The overall level of motor activation is modelled as a time-varying rescaled lognormal function defined as:

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

where A represents the amplitude (i.e., the maximum value) of the activation function and is usually fixed to an arbitrary value (e.g., $A = 1$). This leaves three free parameters: μ (the peak latency or “peak time” of the function), σ (its width or “curvature”), and one parameter for the imagery threshold T (expressed relative to A and such that $T < A$). From a psychological perspective, $A - T$ may be related to the vividness of motor imagery percepts, μ may be related to the speed at which these mental percepts are established, and σ may be related to their duration (Nalborczyk et al., 2024). In this model, the reaction time is defined as the time at which the activation function crosses the threshold for motor imagery and the movement time is defined as the time “spent” above the threshold (Fig. 6) (similar to what has been proposed for conscious access, e.g., Pereira, Perrin, & Faivre, 2022).

We fitted this model to data coming from each participant individually. The fit procedure was adapted from Ratcliff and Smith (2004)

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.

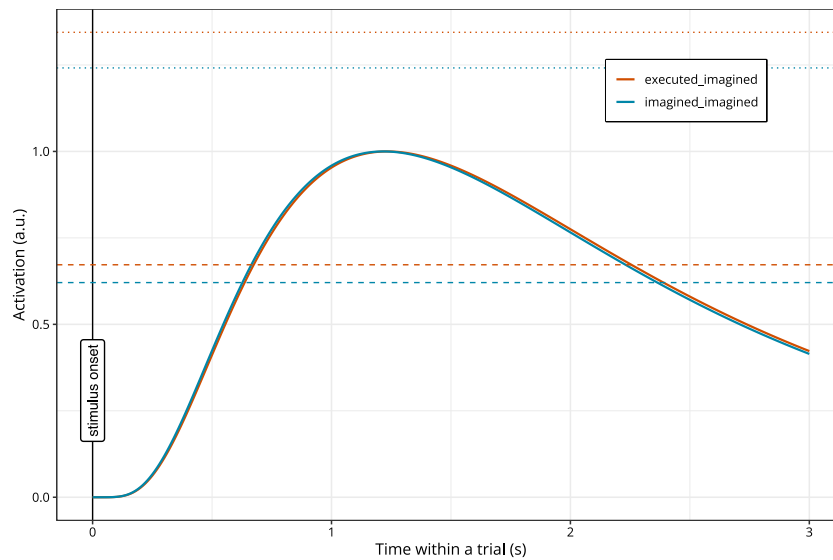


Fig. 6. Average latent activation function as estimated by the model in imagined–imagined (blue) and executed–imagined (orange) sequences from stimulus onset (time = 0) to RT (first threshold crossing) onto to MT (difference between the second and first threshold crossing). The horizontal dotted lines 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.

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

and is commonly used to fit sequential sampling models to behavioural data (e.g., Servant, Tillman, Schall, Logan, & Palmeri, 2019). The model was simultaneously fitted to RTs and MTs quantiles (0.1, 0.3, 0.5, 0.7, 0.9), to take into account the entire RTs and MTs distributions (instead of only the mean or median values). The following loss function (likelihood-ratio chi-square statistic) was minimised:

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

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

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

4. Discussion

We investigated the presence of motor inhibition during typing imagery with an adapted version of Rieger et al. (2017)’s action-mode switching paradigm. Overall, our results show that typing imagery slows down the realisation of subsequent executed or imagined movements (as assessed by differences in MTs), but speeds up the initiation of subsequent executed or imagined movements (as assessed by differences in RTs). Taken together, these results suggest that motor inhibition prevents the execution of typing acts during typing imagery. The algorithmic modelling revealed a possible implementation of inhibition in terms of threshold modulation or delay. In the following, we discuss this interpretation in more detail, including potential explanations for the discrepancies between our results and previous results obtained using the action-mode switching paradigm.

4.1. Unexpected effects on reaction times

Based on previous studies using a similar paradigm with imagined and executed pointing movements, we hypothesised that motor inhibition during imagined movements may slow down both the RT and MT. However, we did not observe such an effect on the RTs. The discrepancy between our results and those of previous studies may come from the nature of the task(s) participants had to realise during the time period considered as the “reaction time” in our experiment. During this time period, participants had to identify the action of the current trial (as indicated by the geometrical shape surrounding the word displayed on the screen), but they also had to read the word, and possibly process it at different linguistic stages, which differs considerably from the RT period of previous studies involving simpler hand movements and during which participants only had to identify the spatially congruent target to which they should next reach (or imagined reaching). We assessed this possibility in a second follow-up preregistered study (cf. supplementary materials). The overall procedure was similar to the main experiment, except for the linguistic material. In this experiment, we sought design an experiment closer to the protocol of Rieger et al. (2017). To this end, we used bigrams instead of words while taking care of maximising the distance between left-hand and right-hand bigrams on the keyboard. Moreover, we added an association training during which participants learned to associate four bigrams to a geometrical shape. This was intended to remove or reduce the effect of reading the

item on screen during the period considered as “reaction time” and, as such, to provide a more direct comparison to the procedure of Rieger et al. (2017). Overall, we observed no difference across sequences in average RTs or MTs, but we observed longer RTs and MTs variability following imagined trials, in a direction compatible with the expected effects on average RTs and MTs (cf. supplementary materials, Table S1 and S2).

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

4.2. Distinct inhibitory mechanisms

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

As mentioned previously, task requirements during the RT period in the present study differed considerably from that of previous studies. These differences in task requirements may have impacted the patterns of RTs/MTs as well as the model’s estimates. We further speculate that across typing and pointing, motor inhibition resulting from imagery affects different aspects of the execution/imagery initiation in the following trial. For instance, Haith, Pakpoor, and Krakauer (2016) showed that motor preparation (i.e., preparing a movement) and motor initiation (i.e., initiating a movement once it is prepared) may be modulated independently and suggested that these two components have distinctly neural correlates. We therefore speculate that these two components of the RT (i.e., preparation + initiation) may be impacted differently in typing vs. pointing movements and may be mapped to distinct parameters of the algorithmic model. More precisely, because motor preparation is associated with activity in motor and premotor cortices and may share resources with motor execution, we might expect it to impact the shape of the activation function — this would correspond to modulations of the peak time and/or the curvature parameter. In contrast, motor initiation is not expected to affect the shape of the activation function and may therefore be related to modulations of the threshold parameter (whose modulations do not change the shape of the activation function), with correlates in brain regions such as the SMA (as suggested for motor initiation by Haith et al., 2016). Relating this discussion to the two tasks mentioned previously (typing vs. pointing), we could speculate that motor inhibition in the pointing

action-mode switching tasks impacts the shape of the activation function (thus, slowing down motor preparation) whereas motor inhibition in the typing action mode switching tasks would impact the motor execution threshold (thus, slowing down or delaying motor initiation). This remains to be assessed in future studies combining behavioural measures with neuroimaging or electrophysiological measures of motor preparation and motor imagery.

Perhaps surprisingly, fitting the algorithmic model of motor imagery presented in Nalborczyk et al. (2024) to our data revealed that the motor execution threshold was *decreased* in imagined–imagined sequences relative to executed–imagined sequences. Whereas this interpretation may seem unintuitive at first, it reflects the *increase* of the motor execution threshold in the first (previous) imagined trial, which then drifts back to an average value. In other words, the motor execution threshold decreases in the second trial of an imagined–imagined sequence (relative to the first trial) because it has increased in the first trial of this sequence (relative to the trial preceding this sequence) and has no reason to increase further. This could reflect strategic modulations of the execution threshold in sequences of trials wherein the threshold is modulated according to task demands in order to minimise a putative cost associated with upregulating the threshold higher than necessary. This hypothesis is supported by considering what happens in sequences of three successive trials (i.e., imagined–imagined–imagined vs. executed–imagined–imagined sequences). In such sequences, the motor execution threshold in the last trial of this sequence is *lower* in imagined–imagined–imagined than in executed–imagined–imagined sequences (RTs/MTs are smaller/longer in III than EII sequences, cf. Figure S3 in supplementary materials).

These inhibitory mechanisms may be subserved by brain regions such as the pre-supplementary motor area (Kasess, Windischberger, Cunnington, Lanzenberger, Pezawas, & Moser, 2008) or the right inferior frontal gyrus, which may plausibly be responsible for weakening the motor commands that are emitted during motor imagery (e.g., Angelini et al., 2015, 2016; Nalborczyk, Debarnot, Longcamp, Guillot, & Alario, 2022). Downstream regions in the cerebellum (e.g., Lotze et al., 1999), in the brainstem (e.g., Jeannerod, 2001, 2006), or at the spinal level (e.g., Grosprêtre, Lebon, Papaxanthi, & Martin, 2016) may also contribute to motor inhibition at a later stage. Alternatively, the need for explicit inhibitory mechanisms counteracting motor commands has been questioned by studies looking at population-level neuronal activity during motor preparation or motor imagery (e.g., Dekleva et al., 2024; Kaufman, Churchland, Ryu, & Shenoy, 2014). Analyses of intracranial recordings in monkeys have revealed that neuronal activity within the primary motor cortex cancels out at the population level during motor preparation, explaining how the motor cortex may prepare movement without executing it (Kaufman et al., 2014). Dekleva et al. (2024) further showed, in a implanted human tetraplegic patient, that motor imagery and motor execution do not occupy completely orthogonal neural subspaces. Rather, population-level neural activity can be decomposed in a common subspace plus orthogonal subspaces for executed and imagined movements. This population-level view does not necessarily contradict the algorithmic perspective of the model fitted on the present data, however. Indeed, premotor areas (such as the dorsal premotor cortex) may be responsible for sending “trigger” signals responsible for switching from the execution or imagery neural subspaces (similar to what has been hypothesised for motor preparation and execution, e.g., Zimnik & Churchland, 2021), with similar behavioural consequences (e.g., on imagined RTs and MTs) than the threshold modulation perspective. Moreover, the “activation timecourse” assumed by the algorithmic model may correspond to the population-level aggregate activity within the primary motor cortex. Whether this assumption holds (or whether the activation timecourse may be related to fluctuations in the vividness of motor imagery percepts) remains to be assessed in future studies using TMS or intracranial measurements together with continuous subjective reports.

4.3. Conclusions

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

CRedit authorship contribution statement

Ladislav Nalborczyk: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **F.-Xavier Alario:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. **Marieke Longcamp:** Writing – review & editing, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization.

Acknowledgments

We want to thank Camille Grasso and Thibault Gajdos for insightful comments at various stages of the present research and Martina Rieger for her suggestions regarding the data analysis and interpretation. This work, carried out within the Institute of Convergence ILCB (ANR-16-CONV-0002), has benefited from support from the French government (France 2030), managed by the French National Agency for Research (ANR) and the Excellence Initiative of Aix-Marseille University (A*MIDEX). A CC-BY public copyright license has been applied by the authors to the present document and will be applied to all subsequent versions up to the Author Accepted Manuscript arising from this submission, in accordance with the grant's open access conditions. The funders have/had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

Data availability

Data, preregistration, and code are available at <https://osf.io/y9a3k/>.

References

- Angelini, M., Calbi, M., Ferrari, A., Sbriscia-Fiochetti, B., Franca, M., Gallese, V., et al. (2015). Motor inhibition during overt and covert actions: an electrical neuroimaging study. *PLOS ONE*, *10*(5), Article e0126800. <http://dx.doi.org/10.1371/journal.pone.0126800>.
- Angelini, M., Calbi, M., Ferrari, A., Sbriscia-Fiochetti, B., Franca, M., Gallese, V., et al. (2016). Proactive control strategies for overt and covert go/NoGo tasks: an electrical neuroimaging study. *PLOS ONE*, *11*(3), Article e0152188. <http://dx.doi.org/10.1371/journal.pone.0152188>.
- Aust, F., & Barth, M. (2017). papaja: Create APA manuscripts with R markdown. <https://github.com/crsh/papaja>.
- Bach, P., Frank, C., & Kunde, W. (2022). Why motor imagery is not really motoric: Towards a re-conceptualization in terms of effect-based action control. *Psychological Research*, <http://dx.doi.org/10.1007/s00426-022-01773-w>.
- Bakermans, J. J. W., & Behrens, T. E. J. (2021). Controlling precedence in sequential stimulus presentation with Euler tours [preprint]. <http://dx.doi.org/10.31234/osf.io/y8r6k>, PsyArXiv.
- Bart, V. K. E., Koch, I., & Rieger, M. (2020). Inhibitory mechanisms in motor imagery: Disentangling different forms of inhibition using action mode switching. *Psychological Research*, *85*(4), 1418–1438. <http://dx.doi.org/10.1007/s00426-020-01327-y>.
- Bart, V. K. E., Koch, I., & Rieger, M. (2021a). Decay of inhibition in motor imagery. *Quarterly Journal of Experimental Psychology*, *74*(1), 77–94. <http://dx.doi.org/10.1177/1747021820949388>.

- Bart, V. K. E., Koch, I., & Rieger, M. (2021b). Expectations affect the contribution of tonic global inhibition, but not of phasic global inhibition to motor imagery. *Journal of Experimental Psychology: Human Perception and Performance*, *47*(12), 1621–1646. <http://dx.doi.org/10.1037/xhp0000961>.
- Bürkner, P.-C. (2017). brms: An R package for bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1), 1–28. <http://dx.doi.org/10.18637/jss.v080.i01>.
- Dahm, S. F., & Rieger, M. (2019). Errors in imagined and executed typing. *Vision (Basel, Switzerland)*, *3*(4), <http://dx.doi.org/10.3390/vision3040066>.
- Dekleva, B. M., Chowdhury, R. H., Batista, A. P., Chase, S. M., Yu, B. M., Boninger, M. L., et al. (2024). Motor cortex retains and reorients neural dynamics during motor imagery. *Nature Human Behaviour*, <http://dx.doi.org/10.1038/s41562-023-01804-5>.
- Glover, S., Bibby, E., & Tuomi, E. (2020). Executive functions in motor imagery: Support for the motor-cognitive model over the functional equivalence model. *Experimental Brain Research*, *238*(4), 931–944. <http://dx.doi.org/10.1007/s00221-020-05756-4>.
- Grosprêtre, S., Lebon, F., Papaxanthis, C., & Martin, A. (2016). New evidence of corticospinal network modulation induced by motor imagery. *Journal of Neurophysiology*, *115*(3), 1279–1288. <http://dx.doi.org/10.1152/jn.00952.2015>.
- Grush, R. (2004). The emulation theory of representation: Motor control, imagery, and perception. *Behavioral and Brain Sciences*, *27*(3), 377–396. <http://dx.doi.org/10.1017/S0140525X04000093>.
- Guillot, A., & Collet, C. (2005). Duration of mentally simulated movement: A review. *Journal of Motor Behavior*, *37*(1), 10–20. <http://dx.doi.org/10.3200/JMBR.37.1.10-20>.
- Guillot, A., Di Rienzo, F., MacIntyre, T., Moran, A., & Collet, C. (2012). Imagining is not doing but involves specific motor commands: A review of experimental data related to motor inhibition. *Frontiers in Human Neuroscience*, *6*, <http://dx.doi.org/10.3389/fnhum.2012.00247>.
- Guillot, A., Hoyek, N., Louis, M., & Collet, C. (2012). Understanding the timing of motor imagery: Recent findings and future directions. *International Review of Sport and Exercise Psychology*, *5*(1), 3–22. <http://dx.doi.org/10.1080/1750984X.2011.623787>.
- Haith, A. M., Pakpoor, J., & Krakauer, J. W. (2016). Independence of movement preparation and movement initiation. *The Journal of Neuroscience*, *36*(10), 3007–3015. <http://dx.doi.org/10.1523/jneurosci.3245-15.2016>.
- Jeannerod, M. (1994). The representing brain: Neural correlates of motor intention and imagery. *Behavioral and Brain Sciences*, *17*(02), 187. <http://dx.doi.org/10.1017/S0140525X00034026>.
- Jeannerod, M. (2001). Neural simulation of action: A unifying mechanism for motor cognition. *NeuroImage*, *14*(1), S103–S109. <http://dx.doi.org/10.1006/nimg.2001.0832>.
- Jeannerod, M. (2006). *Motor cognition: what actions tell the self*. Oxford University Press.
- Kasess, C. H., Windischberger, C., Cunnington, R., Lanzenberger, R., Pezawas, L., & Moser, E. (2008). The suppressive influence of SMA on M1 in motor imagery revealed by fMRI and dynamic causal modeling. *NeuroImage*, *40*(2), 828–837. <http://dx.doi.org/10.1016/j.neuroimage.2007.11.040>.
- Kaufman, M. T., Churchland, M. M., Ryu, S. I., & Shenoy, K. V. (2014). Cortical activity in the null space: Permitting preparation without movement. *Nature Neuroscience*, *17*(3), 440–448. <http://dx.doi.org/10.1038/nn.3643>.
- Kiesel, A., Steinhauser, M., Wendt, M., Falkenstein, M., Jost, K., Philipp, A. M., et al. (2010). Control and interference in task switching—A review. *Psychological Bulletin*, *136*(5), 849–874. <http://dx.doi.org/10.1037/a0019842>.
- Leijten, M., & Van Waes, L. (2013). Keystroke logging in writing research: using inputlog to analyze and visualize writing processes. *Written Communication*, *30*(3), 358–392. <http://dx.doi.org/10.1177/0741088313491692>.
- Logan, G. D., & Crump, M. J. C. (2011). Hierarchical control of cognitive processes. vol. 54, In *Psychology of learning and motivation* (pp. 1–27). Elsevier, <http://dx.doi.org/10.1016/B978-0-12-385527-5.00001-2>.
- Lotze, M., Montoya, P., Erb, M., Hülsmann, E., Flor, H., Klose, U., et al. (1999). Activation of cortical and cerebellar motor areas during executed and imagined hand movements: An fMRI study. *Journal of Cognitive Neuroscience*, *11*(5), 491–501. <http://dx.doi.org/10.1162/089982999563553>.
- MacDonald, H. J., Coxon, J. P., Stinear, C. M., & Byblow, W. D. (2014). The fall and rise of corticomotor excitability with cancellation and reinitiation of prepared action. *Journal of Neurophysiology*, *112*(11), 2707–2717. <http://dx.doi.org/10.1152/jn.00366.2014>.
- MacDonald, H. J., McMorland, A. J. C., Stinear, C. M., Coxon, J. P., & Byblow, W. D. (2017). An activation threshold model for response inhibition. *PLOS ONE*, *12*(1), Article e0169320. <http://dx.doi.org/10.1371/journal.pone.0169320>.
- Monsell, S. (2003). Task switching. *Trends in Cognitive Sciences*, *7*(3), 134–140. [http://dx.doi.org/10.1016/s1364-6613\(03\)00028-7](http://dx.doi.org/10.1016/s1364-6613(03)00028-7).
- Mullen, K., Ardia, D., Gil, D., Windover, D., & Cline, J. (2011). DEoptim: An R package for global optimization by differential evolution. *Journal of Statistical Software*, *40*(6), <http://dx.doi.org/10.18637/jss.v040.i06>.
- Nalborczyk, L., Batailler, C., Løvenbruck, H., Vilain, A., & Bürkner, P.-C. (2019). An introduction to Bayesian multilevel models using brms: A case study of gender effects on vowel variability in standard Indonesian. *Journal of Speech Language and Hearing Research*, *62*(5), 1225–1242. http://dx.doi.org/10.1044/2018_JSLHR-S-18-0006.
- Nalborczyk, L., Debarnot, U., Longcamp, M., Guillot, A., & Alario, F.-X. (2022). The role of motor inhibition during covert speech production. *Frontiers in Human Neuroscience*, *16*, Article 804832. <http://dx.doi.org/10.3389/fnhum.2022.804832>.

- Nalborczyk, L., Longcamp, M., Gajdos, T., Servant, M., & Alario, F.-X. (2024). Towards formal models of inhibitory mechanisms involved in motor imagery: a commentary on Bach et al. *Psychological Research*, (2022), <http://dx.doi.org/10.1007/s00426-023-01915-8>.
- New, B., Pallier, C., Brysbaert, M., & Ferrand, L. (2004). Lexique 2 : A new French lexical database. *Behavior Research Methods, Instruments, & Computers*, 36(3), 516–524. <http://dx.doi.org/10.3758/BF03195598>.
- O'Shea, H., & Moran, A. (2017). Does motor simulation theory explain the cognitive mechanisms underlying motor imagery? A critical review. *Frontiers in Human Neuroscience*, 11, <http://dx.doi.org/10.3389/fnhum.2017.00072>.
- Peirce, J., Gray, J. R., Simpson, S., MacAskill, M., Höchenberger, R., Sogo, H., et al. (2019). PsychoPy2: Experiments in behavior made easy. *Behavior Research Methods*, 51(1), 195–203. <http://dx.doi.org/10.3758/s13428-018-01193-y>.
- Pereira, M., Perrin, D., & Faivre, N. (2022). A leaky evidence accumulation process for perceptual experience. *Trends in Cognitive Sciences*, 26(6), 451–461. <http://dx.doi.org/10.1016/j.tics.2022.03.003>.
- Pinet, S., Dell, G. S., & Alario, F.-X. (2019). Tracking keystroke sequences at the cortical level reveals the dynamics of serial order production. *Journal of Cognitive Neuroscience*, 31(7), 1030–1043. http://dx.doi.org/10.1162/jocn_a_01401.
- Pinet, S., Ziegler, J. C., & Alario, F.-X. (2016). Typing is writing: Linguistic properties modulate typing execution. *Psychonomic Bulletin & Review*, 23(6), 1898–1906. <http://dx.doi.org/10.3758/s13423-016-1044-3>.
- Pinet, S., Zielinski, C., Alario, F.-X., & Longcamp, M. (2022). Typing expertise in a large student population. *Cognitive Research: Principles and Implications*, 7(1), 77. <http://dx.doi.org/10.1186/s41235-022-00424-3>.
- R. Core Team (2017). *R: a language and environment for statistical computing*. R Foundation for Statistical Computing, <https://www.R-project.org/>.
- Ratcliff, R., & Smith, P. L. (2004). A comparison of sequential sampling models for two-choice reaction time. *Psychological Review*, 111(2), 333–367. <http://dx.doi.org/10.1037/0033-295X.111.2.333>.
- Rieger, M. (2012). Motor imagery in typing: Effects of typing style and action familiarity. *Psychonomic Bulletin & Review*, 19(1), 101–107. <http://dx.doi.org/10.3758/s13423-011-0178-6>.
- Rieger, M., Dahm, S. F., & Koch, I. (2017). Inhibition in motor imagery: A novel action mode switching paradigm. *Psychonomic Bulletin & Review*, 24(2), 459–466. <http://dx.doi.org/10.3758/s13423-016-1095-5>.
- Rieger, M., Martinez, F., & Wenke, D. (2011). Imagery of errors in typing. *Cognition*, 121(2), 163–175. <http://dx.doi.org/10.1016/j.cognition.2011.07.005>.
- Rumelhart, D. E., & Norman, D. A. (1982). Simulating a skilled typist: a study of skilled cognitive-motor performance. *Cognitive Science*, 6(1), 1–36. http://dx.doi.org/10.1207/s15516709cog0601_1.
- Scheil, J., & Liefvooghe, B. (2018). Motor command inhibition and the representation of response mode during motor imagery. *Acta Psychologica*, 186, 54–62. <http://dx.doi.org/10.1016/j.actpsy.2018.04.008>.
- Schmitz, F., & Voss, A. (2014). Components of task switching: A closer look at task switching and cue switching. *Acta Psychologica*, 151, 184–196. <http://dx.doi.org/10.1016/j.actpsy.2014.06.009>.
- Schneider, D. W., & Logan, G. D. (2011). Task-switching performance with 1:1 and 2:1 cue-task mappings: Not so different after all. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, 37(2), 405–415. <http://dx.doi.org/10.1037/a0021967>.
- Servant, M., Tillman, G., Schall, J. D., Logan, G. D., & Palmeri, T. J. (2019). Neurally constrained modeling of speed-accuracy tradeoff during visual search: Gated accumulation of modulated evidence. *Journal of Neurophysiology*, 121(4), 1300–1314. <http://dx.doi.org/10.1152/jn.00507.2018>.
- Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2012). A 21 word solution. *SSRN Electronic Journal*, <http://dx.doi.org/10.2139/ssrn.2160588>.
- Snyder, K. M., Logan, G. D., & Yamaguchi, M. (2014). Watch what you type: The role of visual feedback from the screen and hands in skilled typewriting. *Attention, Perception, & Psychophysics*, 77(1), 282–292. <http://dx.doi.org/10.3758/s13414-014-0756-6>.
- Storn, R., & Price, K. (1997). Differential evolution – A simple and efficient heuristic for global optimization over continuous spaces. *Journal of Global Optimization*, 11(4), 341–359. <http://dx.doi.org/10.1023/A:1008202821328>.
- Van Waes, L., Leijten, M., Pauwaert, T., & Van Horenbeeck, E. (2019). A multilingual copy task: measuring typing and motor skills in writing with inputlog. *Journal of Open Research Software*, 7(30), <http://dx.doi.org/10.5334/jors.234>.
- Williams, D. R., Mulder, J., Rouder, J. N., & Rast, P. (2021). Beneath the surface: Unearthing within-person variability and mean relations with Bayesian mixed models. *Psychological Methods*, 26(1), 74–89. <http://dx.doi.org/10.1037/met0000270>.
- Xie, Y. (2015). *Dynamic documents with R and knitr* (2nd ed.). Chapman; Hall/CRC, <https://yihui.org/knitr/>.
- Zimnik, A. J., & Churchland, M. M. (2021). Independent generation of sequence elements by motor cortex. *Nature Neuroscience*, 24(3), 412–424. <http://dx.doi.org/10.1038/s41593-021-00798-5>.