Probing for Intentions: The Early Readiness Potential Does Not Reflect Awareness of Motor Preparation

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Highlights:

1. We investigate the mechanisms underlying voluntary action initiation in a new probe paradigm.
2. Contrary to prior results, the readiness does not reflect reported awareness of motor preparation.
3. Computational modeling supports stochastic accumulation over linear ballistic accumulation and classic RP models.
4. Reported awareness of motor preparation may emerge from metacognitive access to stochastic accumulation.
5. Time-frequency analysis suggests reported awareness may also relate to pre-probe beta desynchronization.

Abstract

Voluntary actions are typically preceded by the Readiness Potential (RP), a negative midfrontal EEG deflection that begins ~2 seconds before movement. What cognitive and neural process the RP reflects and how it relates to conscious intention remain unclear due to conflicting findings. We investigated the neural basis and cognitive significance of the RP in a novel probe-based paradigm. Contrary to prior reports, we found that pre-probe RP buildups were not related to reported awareness of motor preparation. Computational modeling suggested that the best explanation for these results is via metacognitive access to stochastic accumulation. Reported preparation was also related to beta desynchronization over contralateral motor cortex shortly before probe onset. We conclude that the RP may be metacognitively accessible in response to external task demands, but does not reflect the onset of a conscious intention. We discuss implications of these findings for voluntary action initiation and intention awareness.

Introduction

Voluntary actions are typically preceded by a slow buildup of aggregate neural activity in midfrontal regions[1–5]. Single-unit activity in the supplementary motor area (SMA) and anterior cingulate cortex that ramped up or down in advance of movement onset was also demonstrated before voluntary action[6]. The most well-studied of these slow-ramping signals is the readiness potential (RP), an event-related potential that consists of a negative deflection in electroencephalography (EEG) that begins around 2 seconds before self-initiated movements[1,7]. Despite the decades that have passed since the

RP's discovery, the kind of process that this signal reflects, and its cognitive significance and role in action initiation remain contested.

Traditionally, the onset of the RP was thought to reflect a discrete neuro-cognitive event such as the beginning of motor preparation[1], or the onset of an unconscious decision to move[2,7,8]. In contrast, more recent work suggested that the RP may instead reflect an integration-to-bound process of autocorrelated noise, which then resembles a gradual deflection when aligned to threshold-crossing and back-averaged[9–14] (see[15] for review). The so-called Stochastic Accumulator model thus parsimoniously accounts for the early rise and for the shape of the RP as well as for the distribution of wait times in unconstrained self-initiated action. It has further made novel predictions that were empirically confirmed[9], and we recently demonstrated that a spiking neural network extension of stochastic accumulation can parsimoniously explain pre-movement activity at the single-neuro and network levels[16]. However, Bogler and colleagues[17] suggested that evidence specific for stochastic accumulation is still lacking, because other models can account for many of the same phenomena as stochastic accumulation. For instance, they note that linear ballistic accumulation—a process in which a monotonic linear buildup with a random slope triggers movement upon crossing a threshold[18]—can also account for the RP's shape and waiting-time distributions. Unlike the traditional model of the RP, the onset of ramping in stochastic accumulation and linear ballistic-accumulation models does not reflect a specific event that initiates the ramping. The three models entail different implications for the neural bases of spontaneous voluntary action, the implementation of conscious control, and the utility of the RP and similar signals for movement prediction such as for brain-computer interfaces. Distinguishing between them is therefore of paramount importance.

Efforts to establish what kind of process underlies the RP are further complicated by conflicting results concerning the RP's cognitive significance. Studies of self-initiated action often have participants report the onset of the conscious urge or intention to move (referred to as W-Time) using the position of a rotating clock[2,5,19]. Though several studies have found that the onset of the RP does not correlate with W-Time as reported using the clock method[5,20,21], recent studies employing an alternate method of assessing participants' subjective state found that the RP may indeed be related to RP onset[22,23] (though see[24] for a contrary report). For instance, Parés-Pujolràs and colleagues[22] utilized an online-reporting paradigm in which participants were randomly probed before they moved[25,26] and asked whether they had already begun preparing to move. Using this method, Parés-Pujolràs and colleagues found RP-like deflections specifically before probes when the participants reported having begun preparing to move. Those deflections were absent when the participants did not report preparing to move. Similarly, Schultze-Kraft and colleagues[23] used an online decoding algorithm based on the RP to deliver probes when the RP was present or absent. They found that reported awareness of preparation was more likely when their decoder indicated an RP was present compared to absent.

These results suggest that the RP may specifically relate to the conscious intention to move. Considering recent criticisms of the clock method[19,27–29], it may be the case that

probe methods, rather than clock methods, are the more appropriate avenue for investigating the onset of conscious intention. Nevertheless, it is unclear how these results influence the debate regarding what kind of process underlies the RP. Furthermore, probe methods inherently disrupt the movement-generation process, so they cannot determine when the probes are delivered in relation to RP onset or to the onset of the movement that would have taken place had the probe not been delivered. It is therefore unclear whether the apparent link between the RP and reported awareness of intention apply to the early RP or only to its latest stages. Furthermore, decreases in beta power (desynchronization) in contralateral motor cortex also occur prior to self-initiated actions and appear to reflect motor preparation[7,30,31]. It was further claimed that beta desynchronization—rather than the RP—is related to awareness of motor preparation[24], although evidence supporting that hypothesis remains tentative.

Here we developed a novel probe paradigm to investigate (1) whether the RP actually reflects the onset of conscious intention and (2) what neuronal processes the RP reflects. Participants were probed while they made self-paced movements and were instructed to inhibit their movement and report whether they were already preparing to move when the probe occurred. Importantly, our design enabled us to tease apart failures to inhibit, when motor commands were already ballistic and participants could no longer inhibit their movement, from earlier stages. If the early RP is related to conscious intentions, we would predict an RP-like buildup before probes on trials when participants successfully inhibit their movement and then report that they were indeed preparing to move. However, we found that pre-probe EEG amplitude did not co-vary with participants' subjective reports after controlling for failures-to-inhibit, suggesting that the early RP does not relate to conscious volition. Furthermore, we compared the ability of three computational models of action-initiation—a traditional RP model, stochastic accumulation, and linear ballistic accumulation—to account for our results, informing us which model is the most apt for describing the process underlying the RP. A combination of stochastic accumulation with dual-stage metacognition could explain our ERP results while all other models failed. Further time-frequency analysis demonstrated that pre-probe beta desynchronization may relate to reported preparation. Our results strongly support the hypothesis that RP onset does not relate to the onset of consciously-accessible motor preparation. But they also suggest that metacognitive access to stochastic accumulation or beta desynchronization could underlie awareness of motor preparation in probe paradigms.

Results

Participants carried out a self-paced movement task, in which they were sometimes interrupted by an auditory tone that was scheduled to be delivered at a random time in each trial (the probe; see Fig. 1 and the Paradigm subsection of the Methods). Participants were instructed to move whenever they felt like it after around 3 seconds had elapsed from trial onset, but to abstain from moving if the probe occurred. If they moved before 2.5 seconds had elapsed, they were given a warning and the trial was aborted and designated an *Error trial*. Alternatively, if they moved after 2.5 seconds

elapsed but before the probe went off, the trial was designated a *Movement trial* and participants immediately advanced to the next trial. Otherwise, the probe occurred before participants spontaneously moved. Despite being instructed not to move if the probe went off, participants sometimes pressed the button after probe onset. These presumably reflected failures to inhibit the movement (FTI) for those trials—i.e., trials where the participants could no longer inhibit the movement at probe onset (or, in other words, the movements were already ballistic). We designated trials where the button presses took place within 200 ms of probe onset as FTI trials because 200 milliseconds before movement marks the 'point of no return' at which action initiation processes become ballistic[32] (see the Data Retention section of the Methods). Finally, if no movement followed the probe, participants were asked whether they were preparing to move when the probe went off. They could respond Yes, in which case the trial was designated a *Preparation trial*; Unsure, in which case the trial was discarded; or No, in which case the trial was designated a *No-preparation trial*. The primary trials of interest were (1) Movement Trials (Move), (2) FTI trials, (3) Preparation (Prep) trials, and (4) No Preparation (No-Prep) trials. Other trials were not further analyzed.

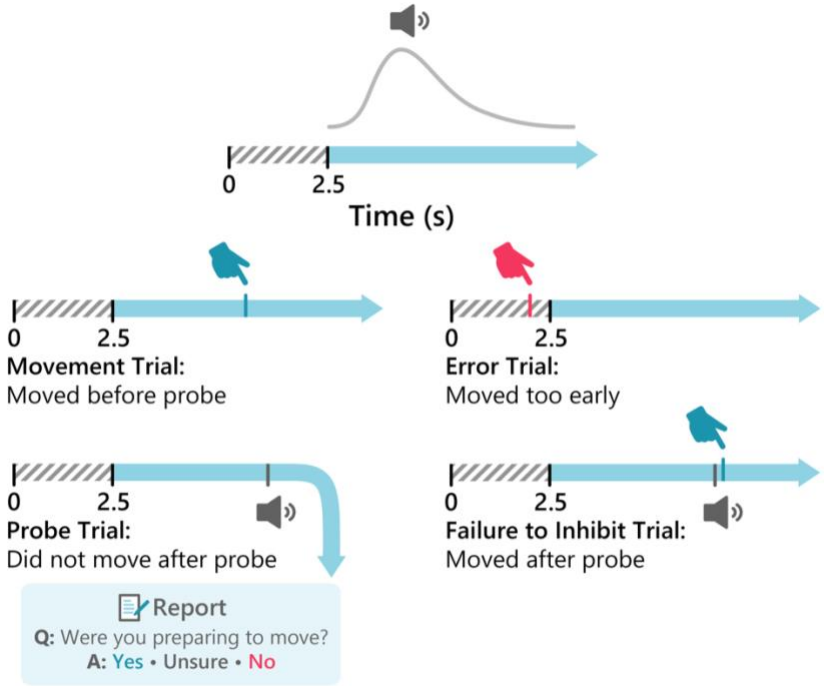

Figure 1: Paradigm. Participants were instructed to move whenever they felt like it after around 3 seconds had elapsed. At the beginning of each trial, the timing of an auditory probe was randomly generated according to a gamma distribution (top). Participants were instructed to inhibit movement following the probe and then indicate whether they were preparing to move at probe onset. These left four outcomes on each trial: movement trials, in which participants move before designated probe time; error trials, in which participants did not wait at least 2.5 seconds to move; probe trials, in which participants hear the probe and do not move following the probe; and failure-to-inhibit (FTI) trials, in which participants are unable to inhibit their movement following probe (presumably because the probe came too close to when they would have moved. Following the probe, participants were asked whether they were preparing to move. If they responded "yes", the trial was designated a Preparation (Prep) trial, and if they responded "no," the trial was designated a No Preparation (No-Prep) trial.

Behavioral results

On average (grand averaged across participant-specific averages), participants waited 3.98 seconds before moving (STD: 0.96, range: 3.38-5.91; see Fig. 2A for all waiting times pooled across participants) and were interrupted by probes on 39.2% of trials (STD: 18.2%, range: 14.0%-85.0%; see Fig. 2A insert for all probe delivery times). The heterogeneity across participants in the frequency of being probed is likely because some participants tended to move earlier (later) in the trial than others. Such movements were less (more) likely to encounter a probe before they moved. This also explains why the empirical distribution of probe delivery times was skewed earlier than the distribution used for probe scheduling (red line in Fig. 2A insert): later probes were more likely to be preempted by a participant's movement and hence less likely to go off.

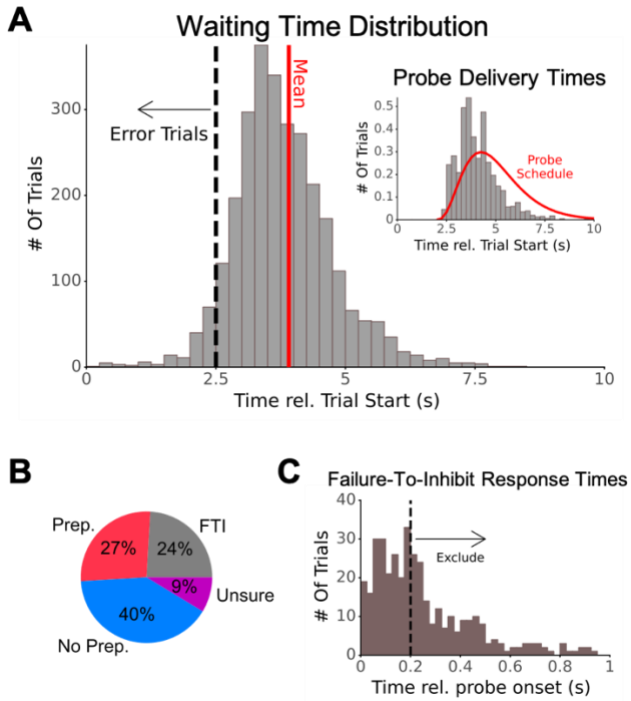

Figure 2: Behavioral results. A: Histogram of waiting times pooled across participants (for visualization. purposes only). Dotted line: 2.5 second cut-off for excluding responses from the analysis. Solid line: mean of waiting times (after excluding waiting times < 2.5 s). Inset: Histogram of probe delivery times (in gray; density; also pooled across participants) and the gamma distribution used for random probe delivery schedule (in red). **B:** Frequency of experimental conditions following the probe. Participants could answer the question about preparing to move with "Yes" coded as Preparation (Prep), "No" coded as No Preparation (No Prep), and "Unsure". Or, if they moved within 200 ms of probe onset, the trial was categorized as failure-to-inhibit (FTI; see Methods for more information). **C:** Histogram of button-press times when participants moved following the probe, pooled across all participants. About 65.4% of movements were within 250 milliseconds of the probe, suggesting actions were already ballistic and participants were not able to inhibit their movements (a uniform distribution across 1 s after probe onset would predict 25% rather than 65.4%). However, we retained only those button presses within 200 milliseconds of probe onset, as that this was found to be the point of no return[32].

Among probe trials, participants reported preparation in 26.9% of trials, no preparation in 40.4%, and being unsure in 8.7%; a further 24.1% of trials were FTI (Fig. 2B). Hence, in 88.5% of non-FTI trials participants were confident in their ability to report having prepared or not prepared to move. Overall, averaged across participants, 117.2 ± 35.4 (mean ± STD) of trials were Movement trials, 20.2 ± 17.2 were Prep trials, 33.3 ± 25.4 were No-prep trials, 7.0 ± 7.0 were trials where participants were unsure about preparing to move, and 15.7 ± 11.6 were FTI trials. Notably, most button presses following the probe occurred within 250 milliseconds of probe onset (65% compared to 25% at chance level assuming a uniform distribution across 1 second; Fig. 2C), suggesting that participants strove to follow instructions and inhibit movements after probe onset.

Removing FTI and unsure responses from probe trials, we found that the probability of reporting preparation significantly increased with time from trial onset ($\beta_{time} = 0.322$, $p = 0.001$; Logistic Mixed Effects). Similarly, Prep trials tended to have longer wait times than No-prep trials ($p=0.023$; Linear Mixed Effects). Similarly, among all probe trials, the probability a participant would fail to inhibit a movement also increased significantly with time from trial onset.

EEG and modeling results

The RP does not reflect awareness of motor intention

We investigated pre-probe EEG during Movement trials, FTI, Prep and No-prep trials. A clear RP was visible for Movement trials (Fig. 3A, in green; see individual participants in Fig. S1A). FTI trials were also preceded by a significant negative deflection compared to Prep and No-Prep trials, but we did not observe a difference between pre-probe EEG when comparing Prep and No-Prep trials. To investigate the significance of these results, we investigated single-trial amplitudes in the 250 milliseconds before probe onset (or button-press for movement trials) using linear mixed-effects models (LME; implemented in python using the pymer4 library[33]) and a Bayesian ANOVA (implemented in JASP[34] version 0.6.13). Critically, we found no difference between pre-probe EEG amplitude for Prep and No Prep trials, with Bayes factors providing strong evidence that the two trial types were equivalent (Fig. 3B; post-hoc tests from LME analysis: No Prep vs Prep: $t(3305.9) = 0.874$, $p_{tukey} = 0.004$, $BF_{10} = 0.091$; No Prep vs Movement: $t(2345.7) = 5.140$, $p_{tukey} < 0.001$, $BF_{10} = 815.4$; No Prep vs FTI: $t(3206.6) = 3.260$, $p_{tukey} = 0.006$, $BF_{10} = 21.0$; Prep vs Movement: $t(2903.4) = 2.948$, $p_{tukey} = 0.017$, $BF_{10} = 2.127$; Prep vs FTI: $t(2.994) = 2.059$, $p_{tukey} = 0.167$, $BF_{10} = 1.584$; Movement vs FTI: $t(3440.4) = -0.223$, $p_{tukey} = 0.996$, $BF_{10} = 0.072$).

To account for concerns that the choice of baseline can artificially introduce differences in amplitude, we also investigated the EEG slope in the second before movement, because slopes are not affected by the choice of baseline. To do so, we fit LME models to the EEG data in the second before probe onset/movement. Consistent with the above analysis, pre-probe EEG slope was more negative in FTI and Movement trials compared to Prep and No-Prep trials, whereas the slope for Prep and No-Prep trials was not significantly different (post-hoc tests from LME analysis: No Prep vs Prep: $Z= -0.572$, $p_{tukey} = 0.940$; No Prep vs Movement: $Z = 6.657$, $p_{tukey} < 0.001$ No Prep vs FTI: Z

= 3.260, $p_{tukey} < 0.001$; Prep vs Movement: Z = 2.948, $p_{tukey} < 0.001$; Prep vs FTI: Z = 2.059, $p_{tukey} < 0.001$; Movement vs FTI: Z = 0.704, $p_{tukey} = 0.896$). However, pre-probe slope was indeed slightly negative on both Prep and No-Prep trials (Prep: β_{slope} = -0.509 μV/s, 95% CI: [-0.935, -0.083]; No-Prep: β_{slope} = -0.661 μV/s, 95% CI: [-0.962, -0.361]). Notably, these findings were similar for more stringent exclusion criteria (see Table S1).

Furthermore, we hypothesized that mixing EEG signals from trials that include ballistic button presses (FTI trials) with EEG signals from trials that include presses stemming from actual metacognitive decisions (Prep trials) would lead to artificial differences between Prep + FTI trials and No-Prep trials. We tested this in our dataset and found these artificial differences (Fig. 3C).

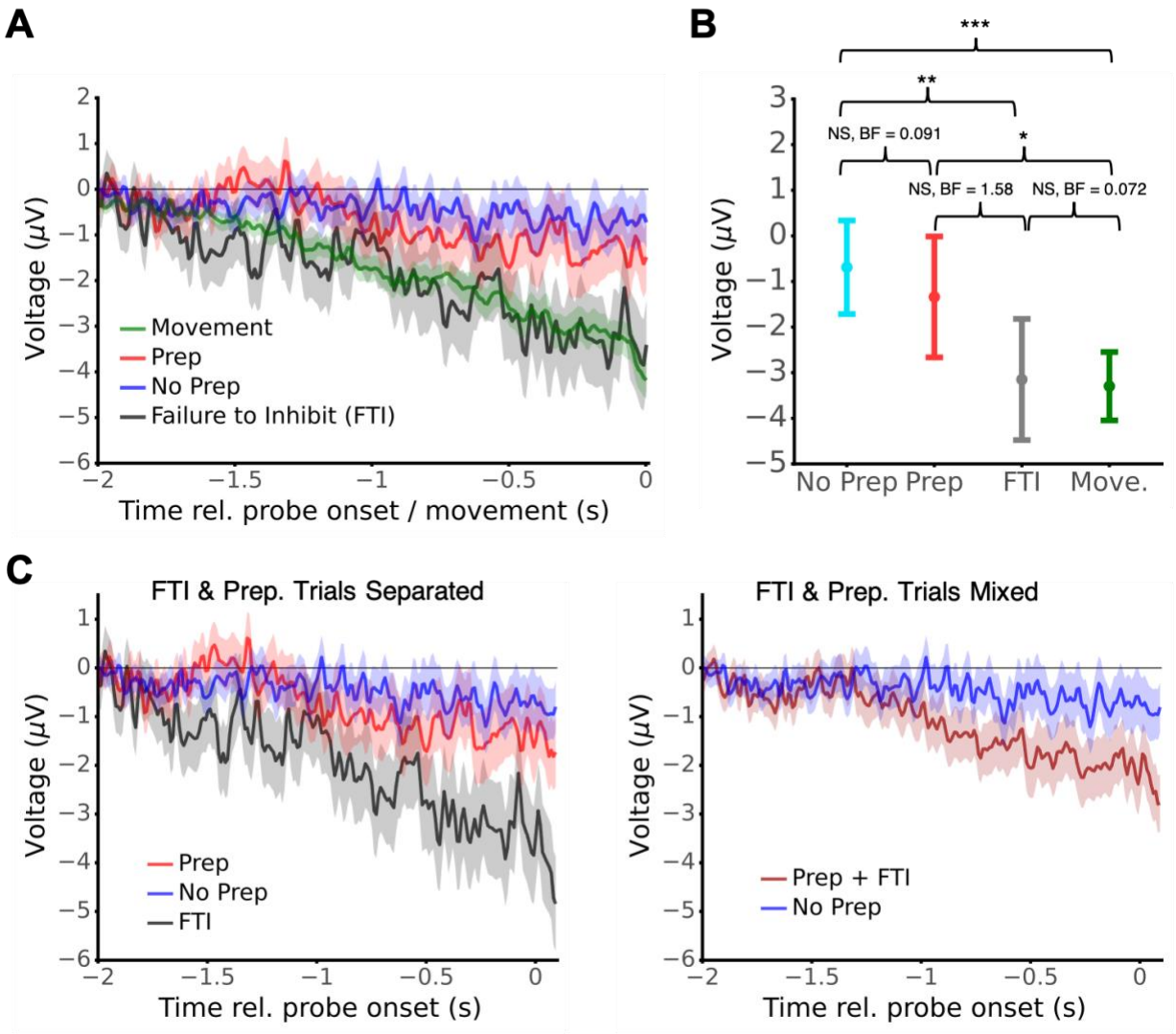

Figure 3: ERP Results: pre-probe RP amplitude is not associated with subjective reports of motor preparation. A: ERPs for Movement (green), Prep (red), No-prep (blue), and FTI (black) trials. The ERPs are aligned to button-press onset for the Movement trials and to probe onset for other conditions. Solid lines are means and shaded regions are standard error (obtained via Linear Mixed Effects; LME). **B:** RP amplitude (mean & 95% confidence interval; LME analysis) in the 250 milliseconds before probe onset

(Prep, No-Prep, FTI) or movement onset (Movement). Statistical results from LME analysis post-hoc comparison (FDR corrected) & Bayesian ANOVA shown. **C:** Zoom on pre-probe/movement period for probe trials (means & SE; LME analysis). Separating FTI and Prep trials results in negative deflection only on FTI trials (left). But mixing FTI and Prep trials creates a downward, RP-like, deflection on "prep" trials (right).

Metacognitive access to stochastic accumulation explains ERP results

Next, we used computational models of the putative neural mechanisms underlying action initiation to investigate what kind of process & reporting features might underlie the results reported above. First, we looked at the classic RP interpretation—that its deflection reflects motor preparation following an unconscious decision to move[8]. Under that interpretation, probing after (before) the onset of the RP will result in the reported presence (absence) of motor preparation[23,25]. We developed a simple computational model to capture the essential components of this interpretation. Briefly, activity fluctuates noisily (random walk) until the onset of an "implicit decision", after which a strong input drives activity up towards a threshold. Movement is initiated when that threshold is crossed. Although the RP usually has an exponential shape, we used a linear input for simplicity (see Classic RP model in the Computational Modeling section of the Methods; results are the same if we use an exponential buildup). In this model, if a randomly timed probe is delivered before (after) the implicit decision, the trial would be categorized as No-Prep (Prep) (Fig. 4A left). If the probe was delivered after threshold-crossing, the trial was designated a Movement trial (we did not model FTI trials for simplicity).

We simulated 10,000 trials under these conditions (Fig. 4A; see Classic RP Model section of the Supplementary Methods for details; see Fig. S2 top for example runs) and observed a flat ERP on No-Prep trials (blue), a slight negative pre-probe deflection in Prep trials (red), and a stronger negative deflection before the probe or movement on FTI and movement trials (black and green, respectively). Comparing the model's predictions to our empirical results (Fig. 3A) suggests that they are qualitatively not a good fit. In particular, the model predicts that there would be a difference between Prep and No-Prep trials that grows with time, which we did not observe in the empirical data. Hence, the classic RP model is incompatible with our empirical results.

We then tested the ability of stochastic accumulation[9,11] (Fig. 4B top left) and linear ballistic accumulation[17,18] (LBAc; Fig. 4B top right) to explain our results. In our stochastic accumulator model, movement is initiated when a noisy diffusion process crosses a threshold (see Computational Modeling in Methods for details). Critically, that process is not monotonic—it can rise and fall until threshold-crossing—and only resembles an exponential rise when each run is aligned to its threshold crossing and many trials are then back averaged. In our linear ballistic accumulator model, movement is initiated when a linear and monotonic signal crosses a threshold. The accumulator's slope is drawn from a half-normal distribution at the onset of the accumulation process, and the accumulation then proceeds linearly & monotonically with that slope (see Fig. S2 for individual model runs).

We combined these two action-initiation models with two models of the reporting process. In the first reporting model reports were based on the accumulator amplitude at the time of the probe: if the accumulator is relatively high (low) at probe onset—i.e., if the accumulator was closer to (farther from) the threshold—the trial was categorized as Prep (No-Prep) (Fig. 4B bottom left, where—schematically—the gray dashed line marks the threshold between preparing and not preparing; see Single-Stage Metacognitive Model in Methods for details). We termed this a single-stage reporting model. Notably, however, perceptual metacognition is sometimes better explained by dual-stage models, where reports are based on whether evidence continues to accumulate after crossing the decision threshold[35,36]. Hence, we also considered a second reporting model based on the *direction* of the post-probe accumulation. If the slope of the accumulator was relatively high (low) in the 200 milliseconds following probe onset, the trial was categorized as Prep (No-Prep) (Fig. 4B lower right). We termed this a dual-stage reporting model (see Single-Stage Reporting Model and Dual-Stage Reporting Model in Methods for details).

We therefore simulated two accumulation models, each with two reporting reporting, hence four models overall: (1) stochastic accumulation with single-stage reporting, (2) stochastic accumulation with dual-stage reporting, (3) linear ballistic accumulation with single-stage reporting, and (4) linear ballistic accumulation with dual-stage reporting. We simulated 10,000 runs of each model type and contrasted average traces before threshold-crossings and simulated probe onset. Both stochastic accumulation and linear ballistic accumulation recreated the shape of the RP in Movement trials (inverted to match the negative trajectory of EEG; Fig. 4C). Interestingly, model (2), stochastic accumulation with dual-stage reporting (bottom left in Fig. 4C), was the only model that was able to recreate our finding that pre-probe EEG traces were equivalent on Prep and No-Prep trials (Fig. 3 top). Intuitively, for us to observe no difference between pre-probe waveforms on Prep and No-Prep trials, yet for reports to be based on a feature of the RP or accumulation process, the feature used for reporting and the pre-probe accumulator activity must be statistically independent. Of the models we tested, only stochastic accumulation with dual-stage reporting satisfies this condition. Notably, the same model also predicted a slight negative slope in pre-probe EEG for both Prep and No-Prep trials, which was also observed in experimental data (Fig. 3).

It should be noted that there is another version of the stochastic accumulator model, which we term the pink-noise accumulator. In this model, the RP reflects an autocorrelated noisy *input* to stochastic accumulation, rather than the state of the accumulator itself[10]. Interestingly, this variant of the stochastic accumulator, based on pink noise accumulation, also generated predictions commensurable with our empirical data when combined with dual-state reporting. (Fig. S3A).

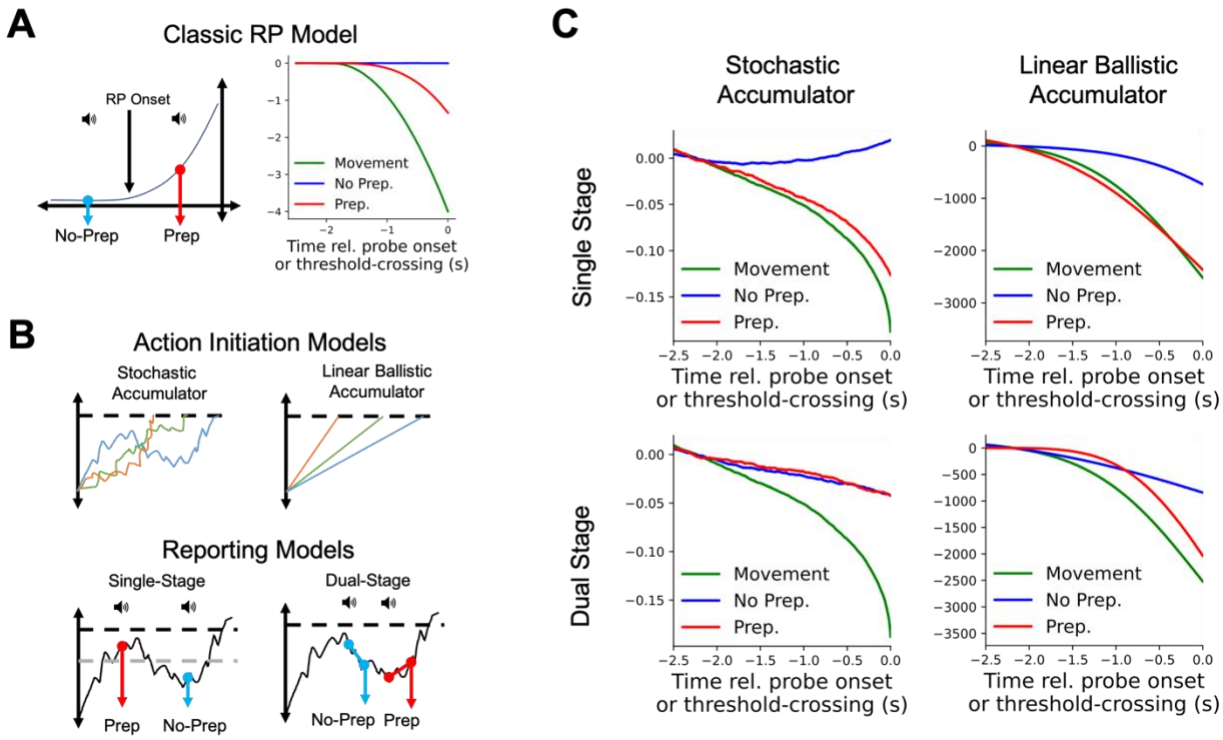

Figure 4: **Computational modeling results: dual-stage metacognitive access to stochastic accumulation can explain ERP results. A:** Classic model simulations. Left: model schematic. If the probe occurs before (after) an RP onset, the trial is categorized as a No-Prep (Prep) trial. Right: modeling results. Prep trials show moderate deflection while No-Prep trials do not. Move trials show stronger deflection. **B:** Modeling framework. Top: Schematic of two accumulator models; Left: stochastic accumulator: a noisy diffusion process triggers movement upon crossing a threshold (dashed line). Right: linear ballistic accumulator: linearly accumulating process triggers movement upon crossing the threshold. Bottom**:** Schematic of metacognitive reporting demonstrated on stochastic accumulator dynamics. Left: single-stage model, wherein reports are based on the magnitude of the accumulator process at the time of the probe (roughly, above or below the dashed gray threshold; see Methods). Right: dual-stage model, where participants' reports are based on the *slope* of the accumulator immediately after probing. **C:** Modeling results. We tested two types of underlying accumulation dynamics each with two types of reporting models. With single-stage metacognition, both stochastic and linear ballistic accumulation predict differences between Prep and No Prep trials. Only dual-stage metacognition with stochastic accumulator dynamics matches ERP results, and also recreates the slight negative deflection before both Prep and No Prep trials.

Pre-probe beta power may track reported state of preparation

We next investigated changes of beta power in contralateral motor cortex before movement & probe onset. We observed beta desynchronization on Movement and FTI trials (Fig. 5A). We also observed visibly less beta power prior to probe onset for Prep compared to No Prep trials. We next computed average beta power in the 250 milliseconds (as in our RP analysis) prior to probe onset / movement to investigate whether differences between conditions were significant. We separately analyzed low beta (12-20 Hz) and high beta (20-30 Hz) because pre-movement desynchronization was most prominent in the low beta band in our data (analyzing beta as a whole, 12-30 Hz, led to similar but weaker results as analyzing the low beta band). Furthermore, pre-movement desynchronization occurs at different times for low and high beta band

activity[7], suggesting separate analysis of these bands is appropriate. We fit LME models and conducted post-hoc tests to investigate differences and used a Bayesian ANOVA in JASP to estimate Bayes Factors. Pre-probe power in the low beta-band significantly differed across trial type (Fig. 5B upper; No Prep vs Prep: $t(3979.6) = 3.421$, $p_{tukey} = 0.004$, $BF_{10} = 0.711$; No Prep vs Movement: $t(3987.4) = 6.459$, $p_{tukey} < 0.001$, $BF_{10} > 1000$; No Prep vs FTI: $t(3974.6) = 5.591$, $p_{tukey} < 0.001$, $BF_{10} > 1000$; Prep vs Movement: $t(3982.4) = 1.467$, $p_{tukey} = 0.458$, $BF_{10} = 0.876$; Prep vs FTI: $t(3975.9) = 2.857$, $p_{tukey} = 0.022$, $BF_{10} = 60.2$; Movement vs FTI: $t(3972.8) = 2.287$, $p_{tukey} = 0.101$, $BF_{10} = 0.606$). However, we found no differences in pre-probe power in the high beta-band across conditions (Fig. 5B lower; No Prep vs Prep: $t(3974.3) = 1.987$, $p_{tukey} = 0.193$, $BF_{10} = 0.066$; No Prep vs Movement: $t(3978.0) = 1.003$, $p_{tukey} = 0.748$, $BF_{10} = 0.046$; No Prep vs FTI: $t(3972.3) = 1.233$, $p_{tukey} = 0.606$, $BF_{10} = 0.097$; Prep vs Movement: $t(3975.5) = -1.442$, $p_{tukey} = 0.473$, $BF_{10} = 0.057$; Prep vs FTI: $t(3972.8) = -0.222$, $p_{tukey} = 0.996$, $BF_{10} = 0.106$; Movement vs FTI: $t(3971.6) = 0.750$, $p_{tukey} = 0.877$, $BF_{10} = 0.180$).

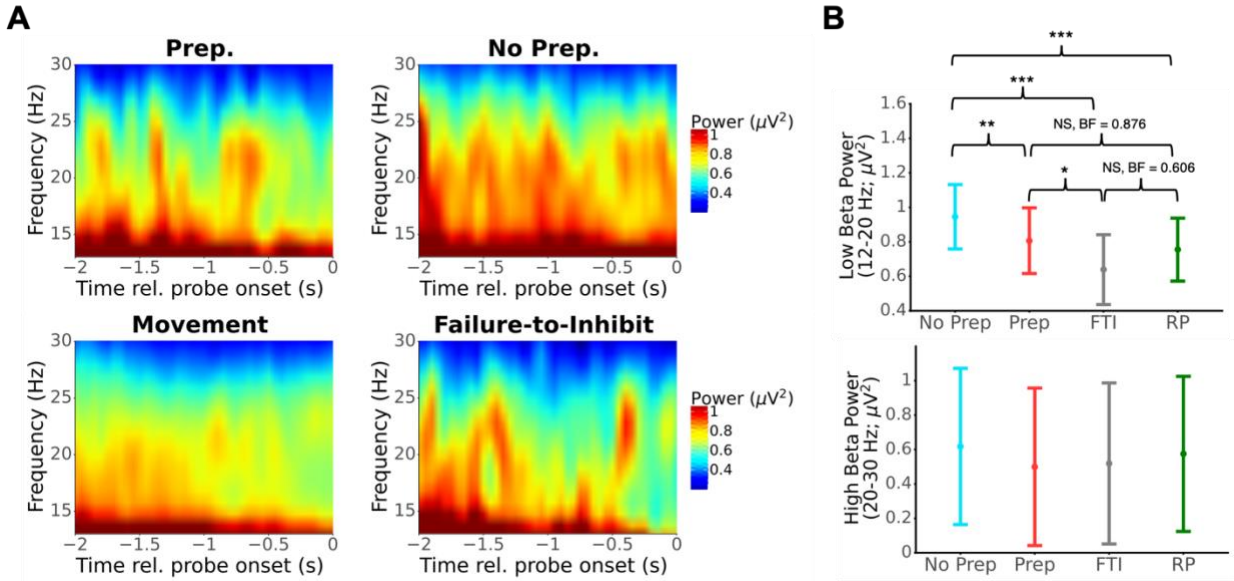

Figure 5: Analysis of pre-probe beta desynchronization. A. Spectrograms of beta-range activity (12-30 Hz) in the 2 seconds prior to probe onset (Prep, No Prep, Failure-to-Inhibit) or movement. Grand-average power estimates obtained by fitting a LME model at each time X frequency pair. **B.** Estimated beta power (mean & 95% CI, LME) in the 250 milliseconds before probe onset or movement for the low beta (12-20 Hz) and high beta (20-30 Hz) bands. No significant modulation was found in the high beta band, but condition significantly associated with pre-probe power in the low beta range. In particular, Prep trials were associated with lower pre-probe beta power than No Prep trials.

Exploratory analysis of what neural activity relates to reporting and report content

We next investigated other potential relations between neural activity and the reported awareness of motor preparation. In particular, we focused on electrodes above brain regions that have previously been associated with intention awareness—frontal (F1), central (Cz), contralateral motor (C3—as participants always moved their right hand), and parietal (P1) sites. We extracted power at different frequencies and times using a

Morelet wavelet decomposition[37] (see Time-Frequency Decomposition in Methods). We assessed whether spectral power depended on trial type by fitting a LME model to each time-frequency pair. Figure 5 shows the results of this exploratory analysis, with time-frequency pairs that had $p > 0.05$ (uncorrected) whited out. These analyses were exploratory and, in the latter case, likely confounded by factors such as auditory processing, yet we felt they may be of interest to the field and opted to include them.

To investigate what activity reflected the *content* of reports, we compared Prep to No Prep trials. Activity in several sites seemed to associate with report content (Fig. 5A). Notably, much of the modulation we found was present after probe onset. Most prominently, we found midfrontal delta (0.5-4 Hz) and theta (4-7 Hz) power was higher (red) on Prep than on No-Prep trials immediately after probe onset (Fig. 5A top left; peak modulation at 2.52 Hz, 350 ms after probe onset, $p = 3.44 \times 10^{-28}$ uncorrected). We also found a cluster of decreased (blue) parietal alpha (7-12 Hz) power (Fig. 5A top right; most extreme $p = 4.04 \times 10^{-8}$ at 9.6 Hz, 350 ms after probe onset).

To investigate what activity reflected the *metacognitive processes involved in reporting* we compared Prep and No Prep trials together to Movement trials. Once again, activity in several sites seemed to associate with the act of reporting (Fig. 6B), while modulations largely occurred after probe onset, excepting beta-band activity over contralateral motor cortex, which likely reflects the stronger beta desynchronization on movement trials compared to Prep and No Prep trials (hereafter just referred to as "Probe trials"). We found a cluster of broadly increased theta power following probe onset on Probe trials compared to Movement trials (Fig. 6B top left; peak modulation at 2.52 Hz, 350 ms after probe onset, $p = 3.44 \times 10^{-28}$ uncorrected), which may be an artifact of hearing the probe. We also found a cluster of decreased alpha power beginning several hundred milliseconds after probe onset, most prominently over Parietal sites (Fig. 6B bottom right; peak modulation at 13.67 Hz, 600 ms after probe onset, $p = 4.48 \times 10^{-23}$ uncorrected).

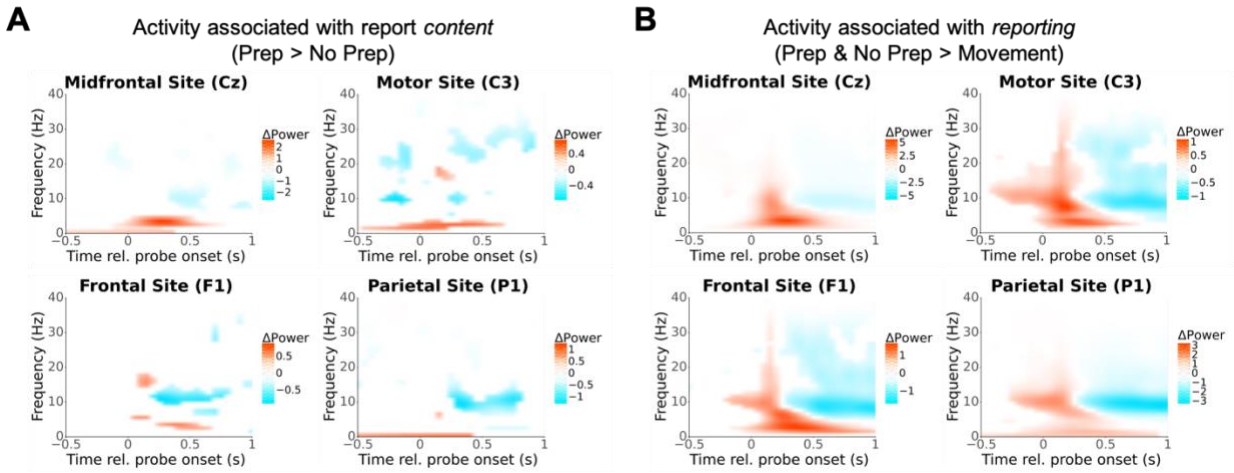

Figure 6: **Results from exploratory time-frequency analysis. A.** Time-frequency plots comparing report *content* at midfrontal, motor, frontal, and parietal sites (estimated difference in power between Prep vs No Prep trials estimated at each time X frequency pair using LME models). Red (blue) signifies greater

power on Prep (No Prep) trials. Time-frequency pairs resulting in non-significant modulation are whited out ($p > 0.05$ uncorrected, less conservative because this is an exploratory analysis). Notably, report content significantly varies with activity in the second following probe onset. **B.** Time-frequency activity associated with making probe reports compared to not (estimated difference in power on Prep & No Prep trials compared to movement trials). Analysis conducted as in A. Reporting is associated with broad changes in activity in theta & alpha bands following probe onset.

Discussion

We set out to investigate what process the readiness potential (RP) reflects and how it relates to the awareness of the preparation to move. We ran a variant of a self-initiated action task, where we sometimes interrupted participants before they moved with an auditory probe. We instructed participants to inhibit movement in response to the probe and only then report whether they were preparing to move when the probe arrived. This modification allowed us to separate cases of late-stage action initiation, when movement was already ballistic and participants failed to inhibit it, from earlier stages. Contrary to prior results[22,23], we found no relation between reported awareness of motor preparation and pre-probe RP-like buildups after controlling for trials where the participants failed to inhibit their movement. As we showed, such ballistic actions were preceded by an RP. This finding suggests that prior reports that pre-probe RP-like deflections were associated with reported awareness of motor preparation reflect the late but not early RP.

Our findings suggest that the early buildup of the RP does not reflect a phenomenal experience of motor preparation or of initiating an action. These results are therefore in line with findings that the timing of the RP's buildup does not relate to reported timing of the conscious intention to move timed using a clock[5,20,21]. Our results are also in line with another recent probe study which found similar results regarding the RP[24]. In the same vein, our findings also suggest that prior claims that the pre-probe RP amplitude relates to awareness of motor preparation are based on the inability of some probe paradigms to tease apart ballistic movements from trials where the participants report preparing to move. More specifically, Parés-Pujolràs and colleagues[22] found an RP before probes when participants reported they were preparing to move. However, in their paradigm, participants were instructed to move immediately if the probe occurred when they were already preparing to move (in contrast to our instruction to participants *not* to move in such cases). Hence, due to their experimental design, it was impossible for the authors to tease apart trials where the probe arrived when movement was already ballistic from trials where the participants moved in response to the probe to indicate they were preparing to move. Similarly, Schultze-Kraft and colleagues[23] found that participants were more likely to report having an intention upon being probed when an online, real-time, closed-loop decoding system determined that an RP was present. However, predicting when someone will make a spontaneous movement is notoriously difficult: for instance, Bai and colleagues[38] were able to predict an upcoming movement only around 0.62 seconds before its onset on average (with an average accuracy of 78% correct; other studies found similar results[39,40]). This is while RP onset occurs more than 1.5 seconds before the movement. Notably, those studies achieved their results by simultaneously analyzing tens of electrodes. Therefore, Schultze-Kraft and colleagues' finding that probes delivered when a BCI detected an RP were more likely to elicit

reported awareness of motor preparation were also likely based on the later stages of the RP.

Parés-Pujolràs and colleagues[24] recently ran another probe method study that controlled for ballistic button presses by having participants report whether they were preparing to move at probe delivery using the hand opposite the one used for the self-paced action task. With this change in task design, they found no difference in pre-probe RP amplitude when comparing trials in which participants reported preparing versus not preparing to move. They hypothesized that their prior results[22] were "confounded by some trials where self-paced action preparation was interrupted prior to awareness." Our results suggest that it was not just that action preparation was interrupted, but rather that participants were at the very latest stages of action initiation when the probe was delivered.

We next contrasted the ability of the classic RP model, stochastic accumulation, and linear ballistic accumulation to explain our RP results. Only stochastic accumulation, when combined with a dual-stage metacognition model, could successfully explain our EEG findings. Among other things, all other models predicted differences in pre-probe RP amplitude, contrary to our results. Critically, our ERP results directly contradict conceptual models wherein RP onset corresponds to a specific neurocognitive event, after which subjects (if probed) will report that they were preparing to move[22,23,25,26].

More generally, our computational-modeling results support the view that the RP reflects stochastic accumulation to a threshold that is aligned to and backward-averaged from threshold-crossings, and, furthermore, that subjective reports reflect dual-stage metacognitive access to this process. Only this combination of action-initiation and reporting models successfully explained our ERP results. Furthermore, our model also predicted the slight negative deflection in pre-probe ERP, which we observed on probe trials regardless of later reported awareness. Stochastic accumulation is a more recent yet influential model of self-initiated action and the RP[9–12]. Our results support stochastic accumulation over classic RP models[2,25] or linear ballistic accumulation[17]. Surprisingly, all the models that were based on single-stage reporting—i.e., on accumulator activity at the time of the probe—failed to recreate our empirical results. Instead, our results suggest that dual-stage reporting underlies reports of awareness of motor preparation. Hence the findings are in line with work on perceptual metacognition, which suggests that post-decision evidence accumulation drives confidence reports[35,36]. Dual-stage reporting could conceivably be implemented by a separate population of neurons that has the capacity to monitor the accumulator, but only does so when triggered by the probe.

Our study is limited by our assumption that responses to the probe are made based on a feature of the RP rather than another neural signal (a common assumption in probe paradigms[22,23,25,26]). Simulations show that if reports are independent of the RP it could lead to EEG results similar to those we observed (Fig. S3B). Recently, Parés-Pujolràs and colleagues[24] suggested that beta oscillations, rather than the RP, relate to subjective reports of motor preparation. In line with their results, we found that pre-

probe beta power over contralateral motor cortex was slightly higher for Prep trials compared to No Prep trials. Notably, our results are similar to those from more traditional stop-signal paradigms[41,42], in which participants are given a go-cue which is sometimes followed by a stop-signal, signifying they should cancel their movement. From that perspective, our study could be considered a stop-signal paradigm without a specifically-timed go-cue. In line with our results, stop-signal studies have found that beta-band activity is relevant for initiating and stopping actions[42–45], suggesting that the pre-probe differences in beta power we observed may indeed be related to initiation processes. Taken together, our results therefore raise three critical questions for future studies on volition: (1) are reports in probe paradigms made using a feature of the RP or beta desynchronization? (2) can beta desynchronization prior to self-initiated movement be explained by a stochastic accumulator-type process? And, (3) how does beta desynchronization in the motor cortex relate to the RP? Although many studies have been conducted on the RP and beta desynchronization, few look at them simultaneously. Furthermore, although they have different cortical sources[7], the motor cortex and SMA are strongly interconnected, and it is unlikely the two phenomena are completely independent.

We observed that post-probe oscillatory power in the theta and beta frequency bands was related to reported awareness of motor preparation. Interestingly, oscillations in those frequency bands have been observed during metacognition in other contexts[46–49]. But our paradigm differs from metacognition paradigms where participants reported confidence about a perceptual stimulus[35] or the quality of a value-based decision[50]. It is therefore unclear whether these oscillations relate to metacognition per se. Theta oscillations have also been associated with cognitive control[51–53], which may have been required to suppress movement when participants were already preparing to move—i.e., in Prep trials in our paradigm—leading to the increased theta power on Prep trials that we observed. Notably, it has been proposed that midfrontal theta oscillations broadcast a need for cognitive control[53], and then inter-region communication via beta-band synchrony underlies metacognition[49]. Our results are largely in line with these suggestions; although our study was not properly controlled to make inferences about what specific mechanisms these power modulations reflect. Future research on metacognition and motor preparation could use a modified version of our paradigm—for example by including a condition where probes are delivered but do not require metacognition—to investigate that hypothesis.

Our study was also limited in other ways. First, we required participants to inhibit their movement in response to the probe and only then report whether they were preparing to move. Hence, participants' reports in our paradigm relied on working memory, which was part of the impetus behind probe studies[22,25]. This design therefore may introduce memory-associated noise and biases to participants' reports, which were at least partially removed from fully online probe methods. However, importantly, even in such online probe studies, decisions about one's underlying state cannot be made immediately: at the very least, one must perceive the probe and then decide whether one was already preparing to move, thus introducing some delays and relying at least to some degree on working memory.

Taken together, our study parsimoniously resolves ongoing debates and conflicting findings regarding what kind of process underlies the RP and how that process relates to the conscious intention to move. Our ERP results suggest the RP is not directly related to the conscious experience of initiating action. But our computational modeling suggests that the neural process underlying the RP or beta desynchronization may nevertheless be accessible via metacognitive mechanisms. These results highlight the importance of investigating metacognitive mechanisms when studying conscious intentions. Consider that we are not constantly conscious of all our actions, decisions, and intentions when acting voluntarily—we can reach for a doorknob or pick up a cup of coffee without consciously representing, in advance or after the fact, all of the intentions that led to that action. Yet, we can introspectively access our intentions and report them if needed. We suggest that such metacognitive mechanisms are crucially involved in probe paradigms that target motor preparation, and may be involved in accessing intention-related information. The version of the probe method that we developed thus offers an opportunity to study conscious intentions more generally, which is a long-standing goal of volition neuroscience.

Methods

Participants:

Twenty-four participants were recruited from Chapman's student population (mean age 19.5, range: 18-22, 71% female, 92% right-handed). Written informed consent was obtained from participants before participated in the experiment. All methods were approved by the local ethics committee (Chapman IRB-20-122).

Paradigm

We opted for a trial-based paradigm in line with computational models of self-initiated action. In every trial, Participants were instructed to wait approximately 3 s and then press spacebar whenever they wanted. Participants always used their right hands regardless of handedness. Importantly, they were further instructed to fully inhibit their movement if they heard an auditory tone (the probe; 0.1 seconds at 500 Hz; randomly timed via a shifted gamma distribution (4, 0.75) that began after 2 seconds; these parameters were selected to result in roughly 50% probe trials). There were therefore 5 types of possible outcomes in every trial (Fig. 1). (1) If participants moved before 2.5 s had elapsed from trial onset, they were warned that they moved too quickly. These were designated *Error Trials*. (2) If participants moved before probe onset, the experiment would automatically advance to the next trial. These were designated *Movement Trials*. (3) If the probe went off before participants moved, they were asked whether they were already preparing to move when the probe occurred. If they answered "yes," these probe trials were designated *Prep Trials*. (4) If they answered "no," these were designated *No Prep Trials*. Finally, (5) if the participants pressed the button within 200 ms after probe onset, the trial was marked as 'failure to inhibit' (FTI; see Data retention section below)).

Regarding the movement, participants were instructed to press the spacebar with their right index finger spontaneously, without pre-planning, whenever they felt like it after waiting for around 3 seconds from the onset of the trial. However, they were further instructed not to count the seconds but to just estimate the time. For the first 40 trials we let the participant get used to the paradigm, so we did not include probes. Hence, participants just carried out self-initiated action, while fixating on a white cross on a gray screen. After those initial trials, participants completed 20 practice trials of the main experiment (Fig. 1). We specifically instructed the participants not to let the possibility of a probe change how they generated actions throughout the experiment. In probe and FTI trials, 1 s after probe onset, participants were presented with a new screen and asked, “Were you preparing to move when the tone occurred?” Participants responded by pressing 1 (no), 2 (unsure), or 3 (yes) with their left hand. Yes responses were counted as “preparation” trials, and No responses were counted as “no preparation” trials. Unsure trials were not included in further analyses. After practicing for 20 trials, participants were asked if they understood the experiment protocol, had the instructions repeated to them, and then they continued to the main experiment.

The actual experiment was broken into blocks of 20 trials each. And the participants were given a break between blocks. Our IRB approval set a limit of 2 h on our experimental session duration. Hence, after EEG setup and practice trials, we ran as many blocks as we could fit into the 2 h session. Participants completed between 8 and 10 blocks, and hence between 160 and 200 trials.

We were concerned that prior results linking the RP to access to consciousness were confounded by trials where participants were just about to move when the probe went off[22] and thus could no longer inhibit their action. To account for such cases, we instructed participants to *fully inhibit all actions upon hearing the probe.* Hence, trials where the motor process had become ballistic would result in button presses after probe onset, which we termed failures-to-inhibit (FTI). Using that method, we could tease apart probe trials that included ballistic button presses (before which RPs would be expected) from probe trials in which participants’ responses were based on metacognitive access to the underlying neural process.

EEG recording and preprocessing:

EEG was recorded online at 2048 Hz using a BioSemi 64-channel system and then read into MATLAB (MathWorks) R2019B and preprocessed using the FieldTrip software package. Data for each trial were epoched between 3.5 seconds before to 2 seconds after movement onset (movement trials) or tone onset (probe trials). First, all trials were visually inspected for artifacts, keeping the type of trial blind; trials containing artifacts were rejected (3.3±3.7% of all trials, range: 0-14%). Data were then downsampled to 200 Hz and bandpass filtered between 0.1 Hz and 35 Hz (filtered using Fieldtrip Defaults; Butterworth IIR filter). Using a 0.1 Hz high-pass filter has recently been suggested to reduce the impact of infra-slow oscillations (<0.1 Hz) when investigating the RP and other slow cortical potentials[54,55]. A non-filtered set of data was retained for

time-frequency analysis. Independent Components Analysis (RunICA algorithm; FieldTrip implementation) was then used to visually remove artifacts corresponding to blinks and eye movements. The ICA procedure results in an unmixing matrix, which was then also used to remove those components from the unfiltered data. Finally, we re-referenced the EEG data to the overall mean of the remaining electrodes. For ERP analysis, we baseline-corrected the data by subtracting average EEG amplitude 2.5 to 2 seconds before movement, as in Parés-Pujolràs et al. (2019).

Time-frequency decomposition:

Time-frequency analysis was conducted using custom scripts[37] in MATLAB. We decomposed the data into the time-frequency domain using complex Morelet wavelets, ranging from 0.5 to 40 Hz. Wavelets started at 4 cycles and increased to 13 cycles as the frequency increased. Power was taken as the squared absolute value of the resulting complex time-series. For power in specific frequency bands, the frequencies that fell within that band (delta: 0.5-4 Hz; theta: 4-7 Hz; alpha: 7-12 Hz; low beta: 12-20 Hz; high beta: 20-30 Hz; gamma: 30-40 Hz) were averaged together.

Data retention:

For EEG analyses, we omitted trials according to the following determined-in-advance criteria: (1) we removed probe trials on which the participants reported that they were ‘unsure’ whether they were preparing to move (3.6±3.5% of all trials, range: 0-11%), (2) we removed ‘error’ trials on which participants pressed the button less than 2.5 seconds after trial onset (3.4±2.9% of all trials, range: 0-11%), and (3) we removed ‘failure to inhibit’ trials on which participants pressed the button more than 200 milliseconds after probe onset (4.0±5.4% of all trials, range: 0-19%). 200 milliseconds before movement has been identified as the “point of no return” for self-initiated movements[32]. Therefore, movements following the probe by more than 200 milliseconds likely reflect lapses of attention rather than actual failures of inhibition. We used 200 ms as our cut-off to be conservative, even though the distribution of post-probe button presses in our analysis seemed to fall after about 250 milliseconds (see Fig. 2C). We retained the remaining data (besides those omitted from visualizing EEG; see EEG recording and preprocessing for details) for statistical analyses.

In addition, for our ERP analysis, we were specifically interested in the RP. Therefore, to account for differences in underlying brain morphologies, we inspected the obtained ERPs aligned to movement onset for movement trials at electrodes Cz, CPz, FCz, and Fz. For each participant, we used data from the electrode where the RP was maximal (using Cz for every participant reduced RP amplitude but did not meaningfully change our results). We omitted 4 participants (out of 24, 16.7%) who did not show a clear RP at any of these locations. Therefore, our main inclusion criteria had 20 participants, which is comparable to similar studies.

Statistical Analyses

The number of trials was not the same across participants (see Paradigm). Due to stochastic probe delivery and the dependency of reports on participants, our methods frequently result in different numbers of trials for different conditions (we split the probe-trial data into 4 cases; preparation reported, unsure, no preparation reported, and failure-to-inhibit). So, rather than traditional cluster-based ERP analysis, we opted to analyze single-trial data using mixed-effects models (LMEs, also called linear mixed-effects models). LMEs were implemented using the Pymer4 package in Python, which is a part of the commonly-used Lme4 package in R. This correction was not necessary for time-domain EEG. In some cases, we also wanted to assess how data affected a binary variable (e.g. response to a probe being a 'yes' or a 'no'). For these cases, we used a *logistic* mixed-effects model to assess the degree to which a given variable affects the log-odds of a binary outcome variable.

Behavioral Analysis

We also used logistic mixed-effects models to assess whether three binary outcome variables depended on how much time had elapsed since trial onset. Those three outcomes were whether the trial culminated in a probe or press, whether a probe resulted in a failure-to-inhibit, or whether participants responded 'yes' versus 'no' to the post-probe question and are respectively modeled by the following three regression equations with random slopes:

$$isprobe \sim time_{event} + (time_{event}|participant)$$
$$isfti \sim time_{probe} + (time_{probe}|participant)$$
$$isyes \sim time_{probe} + (time_{probe}|participant)$$

In figure 2E we present means and confidence intervals for the distribution of probe delivery times for 'No' and 'Yes' responses. Means and confidence intervals were assessed using the regression equation with random slopes:

$$time_{probe} \sim condition + (condition|participant)$$

Event-Related Potential Analysis

In Figure 3 we assessed the means of each ERP using mixed-effects models. For figure 3A we assessed grand-average amplitude at each time point using the below equation with random intercepts (to avoid singularities in fitting, we omitted random slopes):

$$amplitude(t) \sim condition + (1|participant)$$

The fitted values and their standard errors were used for Figure 3A and 3C left. Figure 3C right was obtained using the same equation except with 'FTI' trials re-coded as 'Yes' trials. Figure 3D was obtained using the same equation except with the EEG data baselined at (-0.2,0) instead of (-2.5,-2).

For assessing differences in pre-probe amplitude between No, Yes, and FTI trials, we averaged single-trial EEG amplitudes in the 250 milliseconds before movement and used the following equation with random intercepts to assess differences between conditions.

$$amplitude \sim condition + (1|participant)$$

For the analysis of slope mentioned in-text, we used a similar equation except we did not average amplitude, instead fitting on the preprocessed EEG. We also included a random effect of condition in order to account for the relatively lower number of Yes trials present in our data (model would not converge with a random effect of time or the interaction term):

$$amplitude \sim time + condition + time * condition + (condition|participant)$$

Time-frequency analysis

Power and phase were extracted using the aforementioned methods, which gave a power and a phase value for each time x frequency pair. For the analysis of power in the time-frequency domain in Figures 5A and 6, we fitted single-trial power data at every time-frequency pair using LMEs with a fixed effect of condition and random effect of participant (we did not use random slopes because of model fitting issues):

$$power_{freq,time} \sim condition + (1|participant)$$

Then, reported power in Figure 5A was taken as the marginal estimate of power for each condition. For Figure 6, we restricted the conditions to those specified and then conducted the same analysis, and reported estimated differences using post-hoc testing. In Figure 6 we omitted time-frequency pairs that had an uncorrected p-value greater than 0.05 because that analysis was exploratory. Because these analyses entailed 1200 tests (one for each time-frequency pair) for each of four channels of interest, there are likely some spurious findings.

For specific analysis of pre-movement and pre-probe beta power (Fig. 5B) we averaged beta power across the low (12-20 Hz) and high (20-30 Hz) beta bands in the 250 milliseconds before probe/movement to get single-trial beta power values. Then, we fit an LME to these data using the following equation, including condition as a fixed effect and a random effect of participant:

$$power \sim condition + (1|participant)$$

We established significance using post-hoc tests implemented in the pymer4 python library. For Bayesian analysis we ran a Bayesian ANOVA with the same structure in Jasp and reported Bayes factors obtained from post-hoc tests.

Computational modeling

We also conducted computational modeling of the action-generation and metacognitive process to explain the basis of our ERP results. Note that all units are arbitrary and inverted for plotting to match the ERPs. In some cases, model parameters are taken from prior studies (e.g. stochastic accumulation). In those cases, we note the source of parameters. In other cases, model parameters were tuned manually to simultaneously obtain an RP shape and response time distribution close to real data on movement trials (i.e. without investigating differences based on Prep or No-Prep trials).

Classic RP Model

The so-called 'classic' interpretation of the RP has not been given a formal model before, so we began by doing so. The interpretation posits that RP onset corresponds to an 'unconscious decision' followed by a monotonic rise in activity. We implemented this in an accumulator framework as a noisy fluctuation process that does not cross threshold itself. After some time has passed (modeled as a gamma distribution), a strong input turns on (reflecting an unconscious decision) that drives the accumulator to the threshold in roughly 1 second.

$$\dot{x} = I\ 1_A(t > t_{on})dt\ + \epsilon$$
$$t_{on} \sim Gamma(4,1)$$
$$\epsilon \sim N(0,0.005)$$
$$I \sim Unif(0.25,1.25$$

Where $1_A(u)$ is the indicator function for u (i.e., gives 1 if u is true, 0 if u is false), and t_{on} is a randomly generated time at which a strong input drives the accumulator to the threshold. In our simulations, the threshold is 4/3 and dt=0.001. Individual runs, threshold-crossing distribution, and threshold-locked averages are shown in Fig. S2. Probe delivery times were modeled as a shifted gamma function:

$$t_{probe} \sim Gamma(4,0.75)\ +\ 2$$

We first simulated 10,000 runs of 20 seconds, and then for each run calculated when t_{probe} occurred relative to t_{on}. If t_{probe} occurred before t_{on}, then the trial was categorized as a No-Prep. Otherwise, if t_{probe} occurred after t_{on} but before threshold crossing, the trial was categorized as a Prep. If t_{probe} occurred within 200 milliseconds of threshold crossing, the trial was categorized as a FTI. Otherwise, the trial was categorized as a Movement trial. Figure 5A bottom gives the average traces of these four conditions.

Stochastic Accumulator Model

In the stochastic accumulator model, movement is triggered upon autocorrelated fluctuations (implemented as drift-diffusion process) crossing a threshold. We implemented the model following Schurger et al., 2012, using the equation:

$$\dot{x} =\ (I - kx)dt\ +\ c\epsilon\sqrt{dt}$$
$$\epsilon \sim N(0,1)$$

Where I is the drift rate, k is the leak, x is the accumulator amplitude, and c is a noise scaling term. We used the parameters (I = 0.11, k = 0.5, c=0.1, dt = 0.001, and a threshold of 0.298, from Schurger and colleagues[9]). Individual runs, threshold-crossing distribution, and threshold-locked averages are shown in Fig. S2.

Linear Ballistic Accumulator Model

Recently, Bogler and colleagues[17] suggested that linear ballistic accumulation dynamics[18] could explain the early rise and shape of the RP. In linear ballistic accumulation, movement is triggered when a linearly increasing accumulator crosses a threshold. We therefore also simulated these dynamics to test whether our study's findings could distinguish between the two underlying processes. In order to more accurately recreate the shape of the RP, we included a fixed delay of 2500 ms, such that the LBAc would only begin 2500 milliseconds into the trial. Note that without this nonlinearity, the average trace of the LBA before a threshold crossing would be a straight line. Also note that we tested a variety of parameter combinations and they largely did not change our results. Our simulation was governed by the following equation (adapted from[17]):

$$\dot{x} = 1_A(t > 2500)I$$
$$I \sim N(1,2)$$
$$x_0 \sim Unif(0,4000)$$

Where I is the slope (normally distributed), and x_0 is the starting point of the accumulator. We used a normal distribution with mean = 2, standard deviation = 1 for slopes in our model whereas Bogler and colleagues[17] used a normal distribution with mean = 1, standard deviation = 2. We made this change because, in simulating the model runs, we found that using their distribution would sometimes result in very shallow or even negative slopes on some trials. This led to long waiting times and positive-trending pre-probe EEG on No Prep trials, so we modified parameters to better match behavioral and EEG data.

Pink-Noise Accumulator Model

Schurger (2018) hypothesized and found evidence that the RP might reflect a noisy autocorrelated *input* to an accumulator. This claim was evidenced by that RP amplitude being higher for trials that had shorter waiting times in comparison to longer waiting times. However, we did not find such a difference (Fg. S1B). Nevertheless, we included this model here as an alternative to the stochastic accumulator model. Briefly, we generated traces of pink noise with a 1/f slope of 1.5 using the "colorednoise" package in Python. If we let such traces be denoted P, our accumulators obeyed the following equation:

$$\dot{x} = (I - kx)dt + cP_t\sqrt{dt}$$

Where P_t denotes the tth entry in P. We used the same parameters as the stochastic accumulator above, except we used the noisy input P as the traces for further analyses.

Single-Stage Reporting Model

In our single-stage reporting model, whether a trial was designated Prep or No Prep was based on accumulator amplitude at the time of the probe. Probe delivery times were generated using the following distribution:

$$t_{probe} \sim Gamma(4, 0.75) + 2$$

We first simulated 10,000 runs of 20 seconds, and then for each run calculated when t_{probe} occurred relative to threshold-crossing. Trials where t_{probe} occurred before threshold crossing were counted as probe trials. Otherwise, the trial was counted as a regular press trial.

The amplitude at the time of the probe was then extracted for each probe trial and categorized following the percentages present in our behavioral data (using a median-split to define Prep versus No-Prep, or using an 40-20-40 split for Prep, Unsure, and No-Prep left results unchanged). The lowest 53.2% were categorized as No-Prep trials, the next 11.4% were counted as Unsure and discarded, and finally the highest remaining 35.4% were counted as Prep trials. Model runs were then grouped according to this classification and averaged for Figure 4C top row.

Dual-Stage Reporting Model

In our dual-stage reporting model, whether a trial was designated Prep or No Prep was based on accumulator slope immediately following the probe as opposed to amplitude at the time of probe delivery. This model was developed following post-decision metacognitive models in perceptual decision-making[35,36]. In such models, confidence reports are based on whether evidence continues to accumulate in the same direction after reaching a decision threshold—if the accumulation continues, the participant is confident, but if the evidence stops accumulating the participant is less confident (some variants include whether the post-decision accumulation hits a secondary, higher threshold). We used a simplified version of such models by taking the slope of the post-probe accumulation. Probe delivery times were generated using the same equation as the single-stage model, and the simulations followed the same protocol. For trials categorized as probe trials, we fit a linear regression on the 200 milliseconds following the probe using numpy's *polyfit* command in Python. Then, we categorized trials using the same percentiles as the single-stage model (i.e. highest post-probe slope percentile gets counted as Prep, lowest as No-Prep, and medium as Unsure). Model runs were then grouped according to this classification and back-averaged for Figure 4C bottom row.

Data and Code Availability

Data and code will be made available upon publication of the article.

Author Contributions

Jake Gavenas: conceptualization, methodology, software, formal analysis, investigation, visualization, writing – original draft; **Aaron Schurger:** methodology, resources, writing – review & editing, supervision; **Uri Maoz:** conceptualization, methodology, validation, resources, writing – review & editing, supervision, funding acquisition.

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Declaration of Competing Interests

The authors have no competing interests to report.

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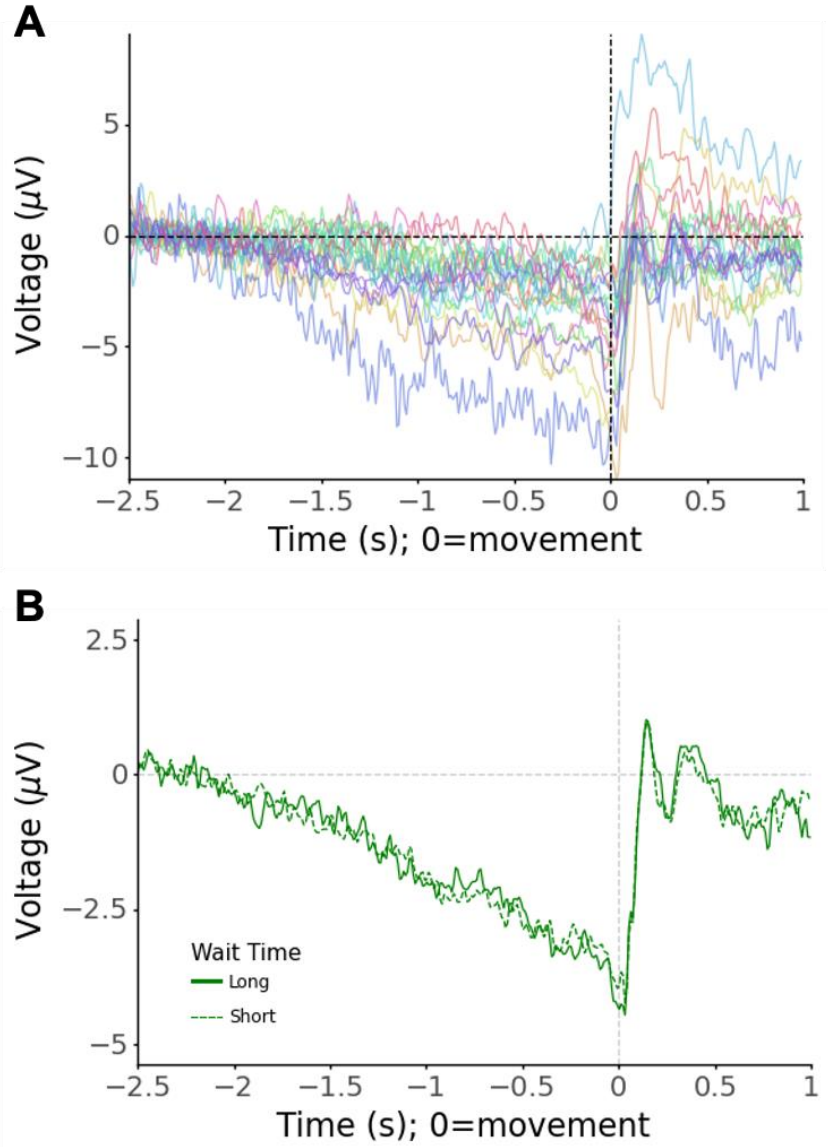
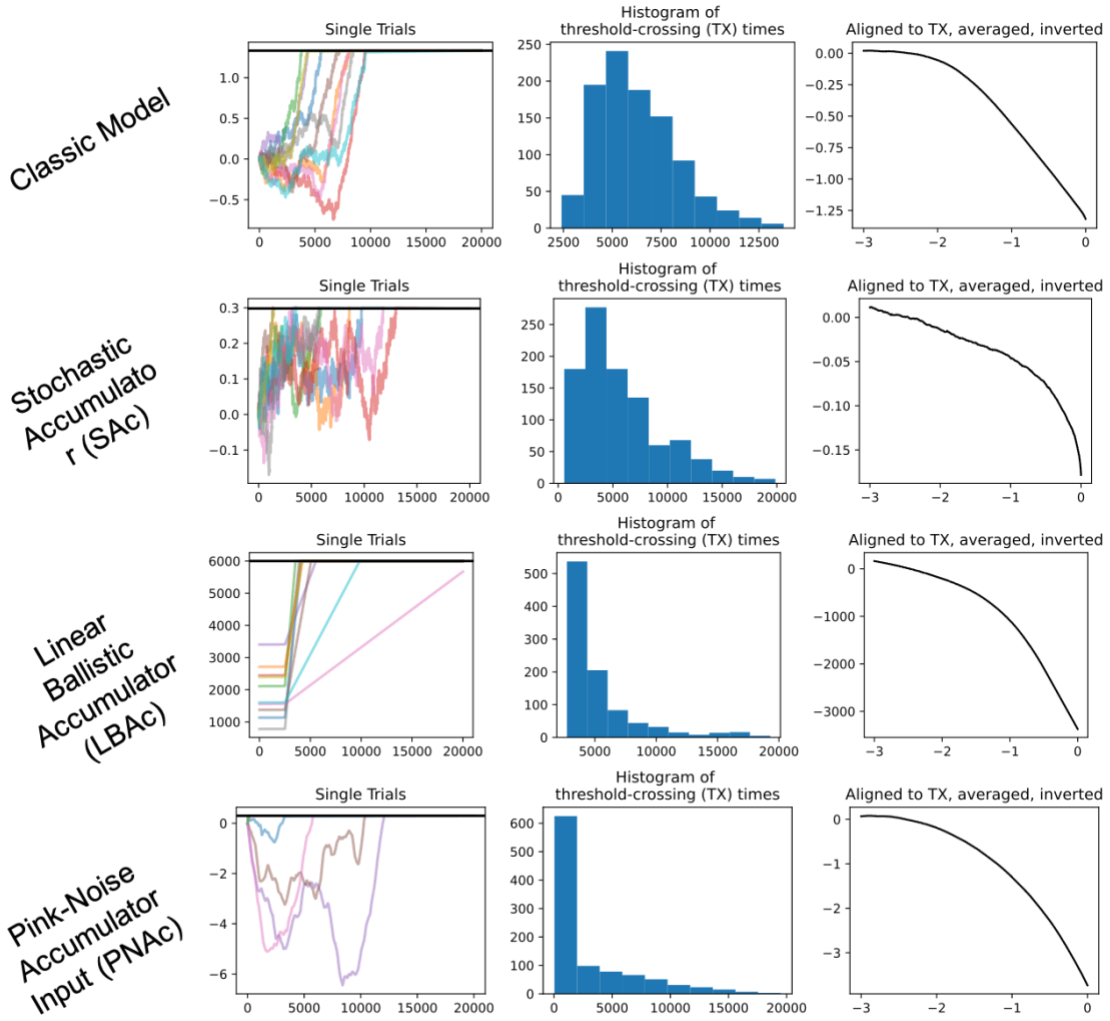
Supplementary Material



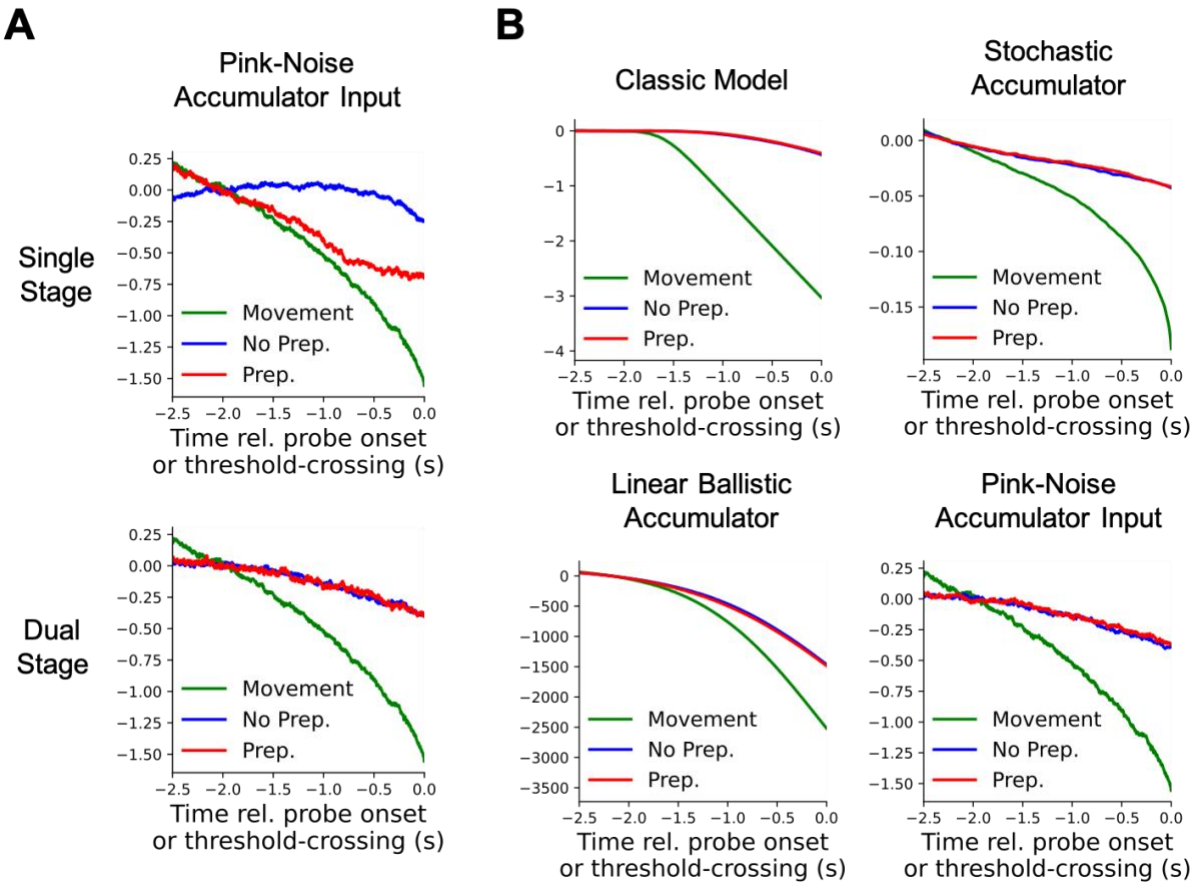
Supplementary Figure 1: Supplementary ERP findings. **A:** Individual participants' readiness potentials in Movement trials after selecting the electrode with maximal negativity (Cz n=9, FCz n=9, Fz n=2). **B:** Unlike Schurger (2018), we did not find a noticeable difference in RP amplitude for trials with relatively short or long waiting-times (by-participant median split after removing waiting times less than 2.5 seconds).

Inclusion criteria	Condition	Slope [-1s, 0s]	95% CI	Amplitude [-0.25s ,0s]	95% CI	BF_{10} vs Prep	BF_{10} vs No Prep.	BF_{10} vs FTI
Visible RP (n=20/24, main text)	Prep.	-0.509 mV/s	(-0.904, -0.115)	-1.102 mV	(-2.671, 0.466)	N/A	**0.091**	1.584
	No Prep.	-0.661 mV/s	(-0.939, -0.383)	-0.622 mV	(1.973, 0.729)	**0.091**	N/A	21.008
	FTI	-1.994 mV/s	(-2.394. -1.593)	-3.448 mV	(-5.019, -1.877)	1.584	21.008	N/A
+ At least 10 prep & no prep trials each (n=11/24)	Prep.	-0.582 mV/s	(-0.992, -0.172)	-0.461 mV	(-2.087, 1.166)	N/A	**0.105**	0.911
	No Prep.	-0.046 mV/s	(-0.395, 0.302)	-0.335 mV	(-1.868, 1.198)	**0.105**	N/A	3.719
	FTI	-1.125 mV/s	(-1.716, -0.535)	-3.549 mV	(-5.550, -1.548)	0.911	3.719	N/A
+ Frequency of being probed between 30% and 70% of trials (n=12/24)	Prep.	-0.663 mV/s	(-1.136, -0.191)	-0.430 mV	(-2.122, 1.262)	N/A	**0.108**	11.706
	No Prep.	-0.327 mV/s	(-0.665, 0.010)	-0.958 mV	(-2.387, 0.470)	**0.108**	N/A	14.823
	FTI	-2.054 mV/s	(-2.511, -1.597)	-3.263 mV	(-4.929, -1.597)	11.706	14.823	N/A

Supplementary Table 1: Summary of estimated pre-probe EEG slope [-1s, 0s] and amplitudes [-0.25 s, 0s] (times relative to probe onset, plus confidence intervals) for Prep, No Prep, and FTI conditions under different participant retention criteria. Also given are bayes factors (Bayesian ANOVA in JASP), comparing RP amplitude in [-0.25s, 0s] across conditions. All retention criteria tested resulted in Bayes factors below around or below 0.1 for the Prep vs No-Prep comparison (bolded), providing moderate to strong evidence that the EEG signals in the two conditions are the same.



Supplementary Figure 2: Some individual runs (left), the threshold-crossing distribution (middle), and threshold-aligned back-averages (right) of four different accumulator models. Classic model: noisy fluctuations occur until an 'unconscious decision' is made, after which a strong input drives activity towards the threshold. Stochastic accumulator: noisy fluctuations accumulate and trigger movement after crossing a threshold. Linear ballistic accumulator: after 2500 ms, a linear drive (drawn from a normal distribution, in addition to a starting value) pushes activity and triggers movement after crossing a threshold. Pink-Noise accumulator: autocorrelated noise (1/f exponent = 1.5) accumulates and triggers movement when crossing a threshold. All four model types recreated a long-tail distribution of threshold-crossing times (or wait times), and all recreated an early deflection as seen in the RP. However, only SAc and PNAc with dual-stage metacognition explained our EEG results (Fig. 4).



Supplementary Figure 3: Supplementary modeling results. A. Pink-noise accumulator model[10]. In this model, the RP reflects an autocorrelated noisy input to a drift-diffusion process rather than the process itself. Aligned to threshold-crossings, the noisy input will also show an early negative deflection akin to the RP. As in Figure 4C, we show modeling results where the decision to report 'Yes' or 'No' in response to the probe is based on the amplitude (single-stage) or slope (dual-stage) of the accumulator (not on the noisy input) at or immediately after the time of the probe. Like our findings for the stochastic accumulator model, dual-stage metacognition with this process can explain our ERP results. Furthermore, we did not find a difference between RPs on trials where participants waited a short versus long amount of time to move (Fig. S1B), which was the crucial difference that used to support this model over the standard stochastic accumulator model[10]. **B.** Model results if reports are based on unrelated brain activity *or* are pure guesses. We conducted similar analyses to Figure 4, except non-movement and non-FTI trials were randomly designated as Prep or No-Prep, as one would expect if intention awareness was independent of the process that generates the RP or if reports were mere guesses. Surprisingly, all four models were able to recreate our ERP results under these conditions (no difference between Prep and No-Prep, and a negative slope before probe onset in both of those conditions). However, random guesses are unlikely because our participants reported being unsure on a relatively small percentage of trials (Fig. 2). We therefore think the most likely case is that participants metacognitively access stochastic accumulation following probe onset (Fig. 4). Nevertheless, these results clarify that a classic or linear ballistic model underlying

the RP is mutually exclusive with reports of motor preparation being related to the RP at all—one cannot have it both ways.