Preparation and execution of voluntary action both contribute to awareness of intention

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Abstract

How and when motor intentions form has long been controversial. In particular, the extent to which motor preparation and action-related processes produce a conscious experience of intention remains unknown. Here, we used a brain-computer interface (BCI) while participants performed a self-paced movement task to trigger cues upon detection of a readiness potential (a well-characterised brain signal that precedes movement) or in its absence. The BCI-triggered cues instructed participants either to move or not to move. Following this instruction, participants reported whether they felt they were about to move at the time the cue was presented. Participants were more likely to report an intention a) when the cue was triggered by the presence of a readiness potential than when the same cue was triggered by its absence, and b) when they had just made an action, than when they had not. We further describe a time-dependent integration of these two factors: the probability of reporting an intention was maximal when cues were triggered in the presence of a readiness potential, and when participants also executed an action shortly afterwards. Our results provide a first systematic investigation of how prospective and retrospective components are integrated in forming a conscious intention to move.

1. Introduction

When we perform spontaneous, voluntary movements, our subjective experience contains a coherent flow of events, from forming the intention to act to executing the movement. In a similar vein, neurophysiological data show that the execution of voluntary movements is preceded by brain signals that indicate motor preparation (*1*,*2*). Conscious intention might simply be a readout of this neural preparation for action. Conversely, many psychological theories view intentions as a post-hoc inference triggered by body movements. Thus, the role of motor preparation in conscious intention remains unclear and controversial (*3*-*5*). We think three distinct features of voluntary actions must be integrated to resolve this controversy.

First, the classic interpretation of motor intention awareness suggests that people have some insight into their motor preparation processes before executing an action. People first feel an "urge" to move, and then they execute an action (*3*). In particular, it has been suggested that the readiness potential (RP), an increasing negativity over motor areas that consistently precede self-paced movements (*1*), may mediate awareness of intention (*3*,*6*-*8*). However, previous studies have investigated the relationship of the RP to intention awareness by locking the electroencephalogram (EEG) signal to the time of a spontaneous action (e.g. *3*), to a random probing time (*8*) or to general motor preparation signals such as the beta-band event-related desynchronization (ERD) (*9*), but they have not directly probed awareness by locking the EEG to the RP *itself*. Thus, it is unclear to what extent the presence (or absence) of an RP at any given time is *causally* relevant for subsequent experiences of intention. A particularly compelling way to investigate this question is to monitor the EEG in real-time and deliver awareness probes either upon detection or absence of an RP. Such an approach, which was once considered a mere thought experiment (*10*), can now be implemented by means of a brain-computer interface (BCI) technique that has been successfully used to predict self-paced movements on a single trial level by real-time detection of RPs using machine learning techniques (*11*). Here, we use it to directly investigate the relationship of the RP to intention awareness.

Second, the idea that a conscious experience of intention is accessible before action, and might therefore contribute to control of action, has been challenged (*12-14*). There is compelling evidence that intention reports are, at least partially, retrospectively reconstructed (*15,16*) and depend on neural activity after action execution (*17*). This opens another, more fundamental question: to what extent does the experience of intention depend on action execution itself? In other words, do we judge our intentions based on our subsequent actions (*14*)? Even if intentions are accessible before action execution, it may be the case that they are only consolidated if an action is executed. Because in most previous paradigms participants report their intentions only after an action has been executed, a retrospective process may always contribute to reports of intention (e.g. *3*). Indeed, it remains unclear whether "purely prospective" experiences of intention, reportable in the absence of actions, actually exist. Here, we aim to test this possibility. By combining a classic Go/No-Go task with a new method for probing intention based on real-time state of the brain, we obtained intention reports both after action execution (as in previous studies), but also in the absence of action – while controlling for the brain state. Thus, we were able to investigate the extent to which participants' intention reports depend on action execution.

Third, the existence of both prospective and retrospective effects on intentions is not incompatible. Rather awareness of intentions may extend over a period during which prospective and retrospective effects might be integrated (*17-19*). This view is in line with comparator models of action control which suggest that efferent copies of motor commands and post-action sensory feedback are integrated (*20*). We propose that a similar time-dependent integration mechanism might be in play for intention awareness, and we investigate it by studying, in one single paradigm, how motor preparation processes such as the RP and action execution interact over time to produce the experience of intention that accompanies voluntary movement.

In our study, participants performed a self-paced task during which they were instructed to press a footpedal at any time they wished after trial onset. Each trial was assigned in advance to one of four possible conditions of a 2-by-2 design. According to the condition, participants were interrupted while performing the self-paced task by either a green (*Go*) or a red (*No-Go*) cue, instructing them to press the pedal immediately or inhibit any movement, respectively. Importantly, these cues were triggered either at a random time when no readiness potential was detected (*RP-*), or as soon as an RP was detected (*RP+*) by a BCI that monitored participants' EEG in real-time. Thus, each trial was randomly assigned a combination of motor preparation state (*RP-*/*RP+*) and action execution instruction (*Go*/*No-Go*). When interrupted by a cue, participants were given time to respond accordingly (execute/inhibit a movement) and were additionally asked to verbally report (*"yes"*/*"no"*) whether they were preparing to move at the time the colored cue was presented. The green and red cues thus served two purposes at the same time: (i) Go/No-Go *cues*, and (ii) intention *probes*. The report was provided after the potential movement at the end of the trial.

Our experimental design thus allowed us to directly test (i) whether the presence of an RP directly influences intention reports, (ii) the extent to which intention reports depend on having executed an action, and (iii) how motor preparation and action execution interact over time to inform intention reports. In particular, we tested the following hypotheses. First, if people's intention reports depend on motor preparation processes happening before the movement (which we term prospection), participants should report an intention more often when probed in the presence of an RP than when probed in the absence of an RP. Second, if the action execution after an intention probe strongly contributes to intention reports (which we call retrospection), participants should be more likely to report having previously had an intention if an action is eventually executed than if it is not. Crucially, since the identity (Go or No-Go) of the cue is independent of the presence/absence of an RP, these two predictions are independent. Finally, a plausible integrative model proposes that intention judgements also depend on the integration of motor representations preceding action and on sensory feedback after action execution, and thus ultimately depend on the time delay between awareness probes and actions.

2. Materials and Methods

2.1. Participants

Based on the average sample size of several previous related studies (*8,11,18,25*), we aimed for a minimum sample size of 15 participants. Anticipating that some would have to be excluded, we tested a total of 23 participants. Following our *a priori* exclusion criteria (see below), 16 participants were included in the final sample (9 female, mean age 31, SD 5.0 years). All participants gave their informed oral and written consent, and were paid €10 per hour. Before initiating data analysis, we performed an *a priori* EEG-informed selection of participants. In this procedure we verified, for each participant individually, the effectiveness of the BCI in detecting the presence or absence of readiness potentials in the EEG and eliciting *RP+* and *RP-* cues accordingly. This BCI-based manipulation of the timings of *RP+* and *RP-* cues was a pivotal element of our experimental design. Based on this selection approach, which is presented in detail in the **electronic supplementary material**, we excluded 7 out of the 23 recorded participants and proceeded with the analysis of data from the remaining 16 participants.

2.2. Experimental setup

Participants were seated in a chair facing a computer screen at a distance of approximately 1 m with their hands on their lap and their right foot to the right of a 10 cm x 20 cm floor-mounted switch pedal (Marquardt Mechatronik GmbH, Rietheim-Weilheim, Germany). Throughout the experiment, EEG was recorded at 1 kHz with a 64-electrode Ag/AgCl cap (EasyCap, Brain Products GmbH, Gilching, Germany) mounted according to the 10-20 system and referenced to FCz and re-referenced offline to a common reference. EEG was recorded from the following 30 electrodes: F3, F1, Fz, F2, F4, FC5, FC3, FC1, FC2, FC4, FC6, C5, C3, C1, Cz, C2, C4, C6, CP5, CP3, CP1, CPz, CP2, CP4, CP6, P3, P1, Pz, P2, P4. Further, the right calf electromyogram (EMG) was recorded using surface Ag/AgCl electrodes in order to obtain the earliest measure of movement onset. The amplified signal (analog filters: 0.1, 250 Hz) was converted to digital (BrainAmp MR Plus and BrainAmp ExG, Brain Products GmbH, Gilching, Germany), saved for offline analysis, and simultaneously processed online by the Berlin Brain-Computer Interface Toolbox (BBCI, github.com/bbci/bbci_public). The Pythonic Feedback Framework (*21*) was used to generate visual feedback. Verbal reports in response to the prompting task (see below) were recorded by a microphone that was placed on the table and manually transcribed trial-by-trial after the experiment. Verbal reports were chosen over movement reports to disentangle the motor signal effects used in the main motor task (see below) from the intention reports.

2.3. Experimental design

The experiment was divided into three stages (Fig. 1). In a preparatory experimental stage I, participants performed a simple self-paced task. The data collected in stage I were used to train a classifier to monitor EEG activity in real-time during stage II. In stage II, the main experiment, participants performed the same self-paced task and a prompting task. In an additional stage III, participants performed a cued reaction task.

2.3.1. Stage I: Collection of training data for the classifier

During stage I, participants performed a simple self-paced task. The start of a trial was signaled by a traffic light display appearing on the screen with all three colored lights (green, yellow, red) turned off. Participants were instructed to wait for roughly 2 s, after which they could press the pedal at any time. They were asked to avoid preplanning the movement, avoid any obvious rhythm, and to press when they felt the spontaneous urge to move (*1*,*3*). When the pedal was pressed the yellow light was turned on for 1 s, after which the traffic light disappeared and was replaced by a fixation cross. The fixation cross remained onscreen for a 3 s intertrial period. Each participant performed a total of 100 trials in stage I, with the possibility of taking a break after each 25 trials.

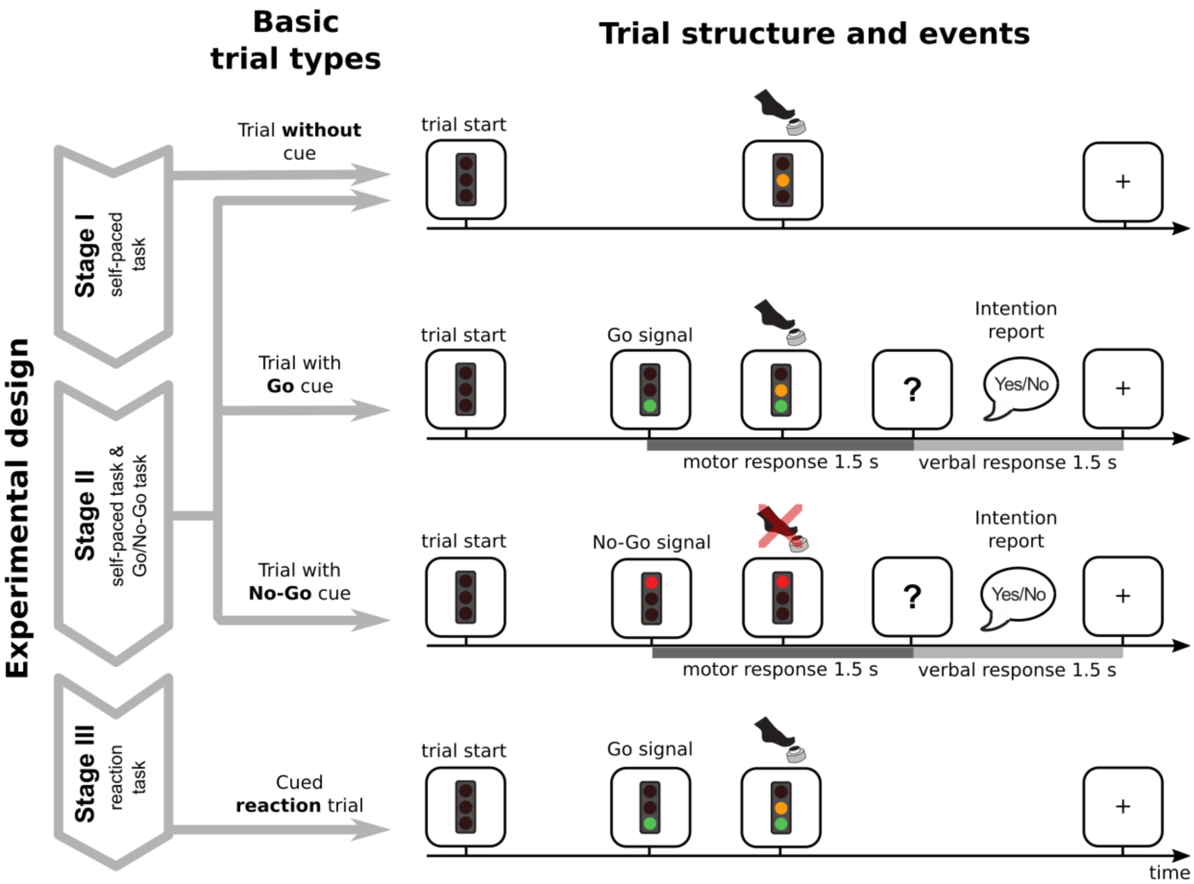

Fig. 1. Experimental design and trial types and events. During stage I, participants performed spontaneous, self-paced pedal presses. No green or red cues were elicited. During stage II, the main experiment, participants again performed self-paced pedal presses, but were occasionally interrupted by either the green or the red light turning on. If they pressed the pedal before either light was turned on, the trial ended as in stage I. If the green or the red light was turned on, participants had 1.5 s to follow the instruction, i.e. to press immediately after a green cue or not press / inhibit after a red cue. Subsequently, the question "Were you about to press?" appeared on screen for 1.5 s (indicated by a question mark) during which participants were asked to verbally respond "Yes" or "No". In stage III, participants performed a simple reaction task: In each trial, the green light would turn on after a random time, and participants were instructed to press the pedal as quickly as possible. In all three stages, once the pedal was pressed the yellow light turned on and served as a visual feedback for the completion of the movement.

2.3.2. Stage II: Main experiment

In stage II, participants performed the same self-paced task indicated above, but additionally they would sometimes be interrupted by either the green (*Go*) or red (*No-Go*) traffic light turning on for a duration of 1.5 s before the trial ended. Participants were instructed to press the pedal as quickly as possible in response to the green light, and to withhold from moving or to abort any potentially planned pedal press in response to the red light. They were given 1.5 s to respond to this Go/No-Go task. A *Go* trial was considered correct if the pedal was pressed while the green light was on. When participants pressed the pedal, the yellow traffic light turned on for 1 s. A *No-Go* trial was considered correct if the pedal was not pressed while the red light was on. If a trial was not executed correctly, it ended with a fixation cross and was discarded from further analysis. After correct trials, the question “Were you about to press?” appeared on screen for 1.5 s. Participants were instructed to verbally report (*”yes”/”no”*) whether they were preparing to move at the time the colored cue appeared on screen.

Each trial in stage II was randomly assigned to one of four conditions defined by a combination of two factors. The first factor was the Action execution instruction (*Go/No-Go*), while the second one was the motor preparation state that would be used to trigger the instruction (*RP+/RP-*). Thus, while the former determined *which* light would be turned on in the trial (green in *Go* trials and red in *No-Go* trials), the motor preparation state determined *when* the light would be turned on. Note that this assignment of trials was putative rather than absolute, because participants sometimes performed self-paced movements, as in stage I, before they were interrupted by any cue. Stage II had a total duration of 60 minutes, with the possibility to take a break every 15 minutes. The number of trials executed in stage II varied across subjects depending on the frequency of participants’ self-paced actions and the time at which the cues were presented.

2.3.3. Stage III: Supplementary task

In stage III, participants performed a simple, cued reaction task. At the beginning of a trial, a the traffic light with all lights off appeared on the screen. After a random time, chosen from a uniform distribution between 2 and 5 s, the green light would turn on for 1.5 s. Participants were instructed to respond as fast as possible to the green light with a pedal press. When they pressed the pedal, the yellow light was turned on for 1 s after which the traffic light disappeared and was replaced by a fixation cross. The fixation cross remained onscreen for a 3 s intertrial period. Each participant performed this task for a total time of 8 minutes, with the possibility to take a break after 4 minutes. The aim of this stage was to obtain measures of speeded reaction times in the absence of a self-paced task, and to compare them to the reaction times to *Go* cues obtained in stage II.

2.4. Real-time BCI

To elicit Go and No-Go cues during stage II, we trained a BCI on EEG data from the 100 trials recorded during stage I. The single steps of this procedure are detailed in the **electronic supplementary material**, and are summarized in the following. First, for higher temporal precision, we defined the onset of the movement of each trial based on the EMG rather than based on the final completion of the movement with the pedal press. Subsequently, we defined for each trial two periods as move and idle for the training of a classifier. The move periods were 1200 ms long segments preceding EMG onset, while the idle periods were 1200 ms long segments preceding the trial start cue. The EEG data in these segments were averaged across specific intervals, concatenated across all channels and used as features to train a regularized Linear Discriminant Analysis (LDA) classifier with automatic shrinkage (22). During stage II, the so-trained classifier was used to monitor the ongoing EEG in real-time. Therefore, every 10 ms a feature vector was constructed from the immediately preceding 1200 ms of EEG data, as outlined above, and used as input to the classifier, generating a classifier output value every 10 ms. This output variable was a continuous signal that probabilistically classified the current EEG segment either to the idle or to the move class. Finally, because the classifier output signal was likely to mirror the stochastic nature of the EEG, a conservative threshold was defined for each participant individually in order to avoid many cues to be prematurely triggered by noise. This threshold was chosen to minimize the number of false alarms, at the cost of potentially missing some actions.

2.5. Timing of cues during stage II

2.5.1. Timing of *RP*+ cues

During stage II, if a trial was assigned as an *RP+* trial, the BCI was inactive during the first 1500 ms after trial start. This ensured that an *RP+* cue was not elicited during the minimum self-paced waiting time of 2 s instructed to participants. After 1500 ms, the BCI was activated and either the green or the red light were turned on as soon as the classifier reached the specific threshold.

2.5.2. Timing of *RP*- cues

During stage II, if a trial was assigned as a *RP-* trial, a cue was elicited after a predefined random time that was chosen before trial start for each trial individually. In these trials, to ensure that the cue was displayed at a plausible time given behavioral characteristics of the participant, a random time was selected from a uniform distribution between the 15 and 85 percentiles of the waiting times (time from trial start to EMG onset) of the 100 trials in stage I. We further ensured that there was no EEG evidence for movement preparation at the randomly selected time points by eliciting *RP-* cues only if the classifier output indicated as being within the *idle* class.

2.6. Statistical analysis

We ran two logistic mixed-effects analyses using the *glmer* function in the lme4 package (*23*). In both analyses, we used a model comparison approach to select the optimal random effect structure, as suggested in (*24*). Exhaustive details of the step-by-step random effect selection process are available in the **electronic supplementary material**.

2.6.1. Prospective vs. retrospective contributions

The aim of the first analysis was to investigate whether intention reports are influenced by prospective (motor preparation) and retrospective (action execution) components. For this, we used all selected *Go* and *No-Go* trials and fit a logistic regression to predict the proportion of awareness reports based on the presence or absence of an RP (*RP+*/*RP-*), the execution or inhibition of an Action (*Go*/*No-Go*) and the interaction between both factors (RP x Action).

2.6.2. Dynamic integration of prospective and retrospective cues

The second analysis aimed to study whether retrospective reconstruction and motor preparation interact in a time-dependent manner. For this, we studied selected *Go* trials only, because integration of prospective motor preparation and action-related signals was only possible when participants executed an action. In *Go* trials, participants could execute an action at different times after cue presentation. We refer to this time delay as reaction time (RT), its characteristics are described in detail in the Results. For each participant, we excluded trials where the RT was above or below 3 SD from the individual mean. Then, we fit a logistic regression to predict the probability of reporting awareness given the presence or absence of an RP (*RP+*/*RP-*), the continuous reaction time (RT) and their interaction (RP x RT).

3. Results

3.1. Data description and selection

The number of trials in which participants were presented a cue, as well as the exact times when cues were presented, could not be precisely experimentally controlled. In case of *RP+* trials, this is because the BCI was calibrated so as to elicit cues preferably during the interval just before a movement, based on the detection of a readiness potential. In case of the *RP-* trials, because the time of interruption was random, and participants might move at any time. In order to test our hypotheses, our target trials were those in which cues were presented *before* EMG onset and in which participants successfully followed the cue instruction: In the *Go* condition, only trials where participants moved and successfully pressed the pedal after the green cue presentation were included for analysis. In the *No-Go* condition, only trials where no EMG onset was detected after the red cue presentation were included for analysis. The analysed trials included an average of 29 (SEM = 4) *RP+/Go* trials, 29 (SEM = 3) *RP-/Go* trials, 16 (SEM = 3) *RP+/ No-Go* trials and 23 (SEM = 3) *RP-/ No-Go* trials, per participant.

In the **electronic supplemental material**, we describe in detail all types of trials, including those that were rejected either because no cue was presented or because a movement occurred shortly before a cue was triggered (Fig. S5), and we provide a detailed description and interpretation of the behaviour and reaction times observed after cue presentation in all conditions (Figs. S6, S7).

3.2. Prospective and retrospective contributions to motor intention awareness

Traditional views on voluntary action suggest that people have conscious access to their motor preparatory processes before movement initiation, and it thus predicts affirmative intention judgements to be more likely in the *RP+* than in the *RP-* condition. In turn, retrospectivist theories have suggested that awareness of intention strongly depends on action execution, and thus predict that the execution of a movement (*Go* condition) will yield more awareness reports than the absence of an action (*No-Go* condition).

As shown in Fig. 2, participants were significantly more likely ($X^2_{(1)}$ = 20.74, p < 0.001) to report awareness in the *Go* (M = 35.2%, SEM = 6.4%) than in the *No-Go* condition (M = 16.0%, SEM = 4.7%). This suggests a strong effect of retrospection: the presence of an action strongly increased the probability of participants reporting an intention to move at the time of probing, compared to trials where no overt movement was present. Furthermore, participants were also significantly more likely ($X^2_{(1)}$ = 5.65, p = 0.017) to report awareness of an intention to move in the *RP+* (M = 32.7%, SEM = 6.1%) than in the *RP-* condition (M = 24.0%, SEM = 6.0%). That is, if neural signals of preparing to move were present when the probe appeared, they were more likely to report an intention than if these signals were not present. No significant interaction was found ($X^2_{(1)}$ = 1.79, p = 0.179).

We further controlled whether the time at which an *RP+* or *RP-* cue were presented (with respect to trial start) could explain the results. Including the time of cue presentation as a fixed effect in the model did not improve the fit. The statistical significance of the RP and Action effects remained unchanged, and no significant effects were found for the time of cue (see **electronic supplemental material**, Table S4). Finally, we checked that the observed retrospective effects were not merely related to the instruction to move (*Go*) or not move (*No-Go*), but rather the action execution itself. To do so, we compared the selected *No-Go* trials to those that were excluded because an EMG onset was present after cue presentation. Participants were significantly more likely to report awareness in trials where an EMG onset was present than in those where it was absent, further confirming that the strong retrospective effect was not due to the instructions but rather the presence of a movement (see **electronic supplemental material**, Fig. S8).

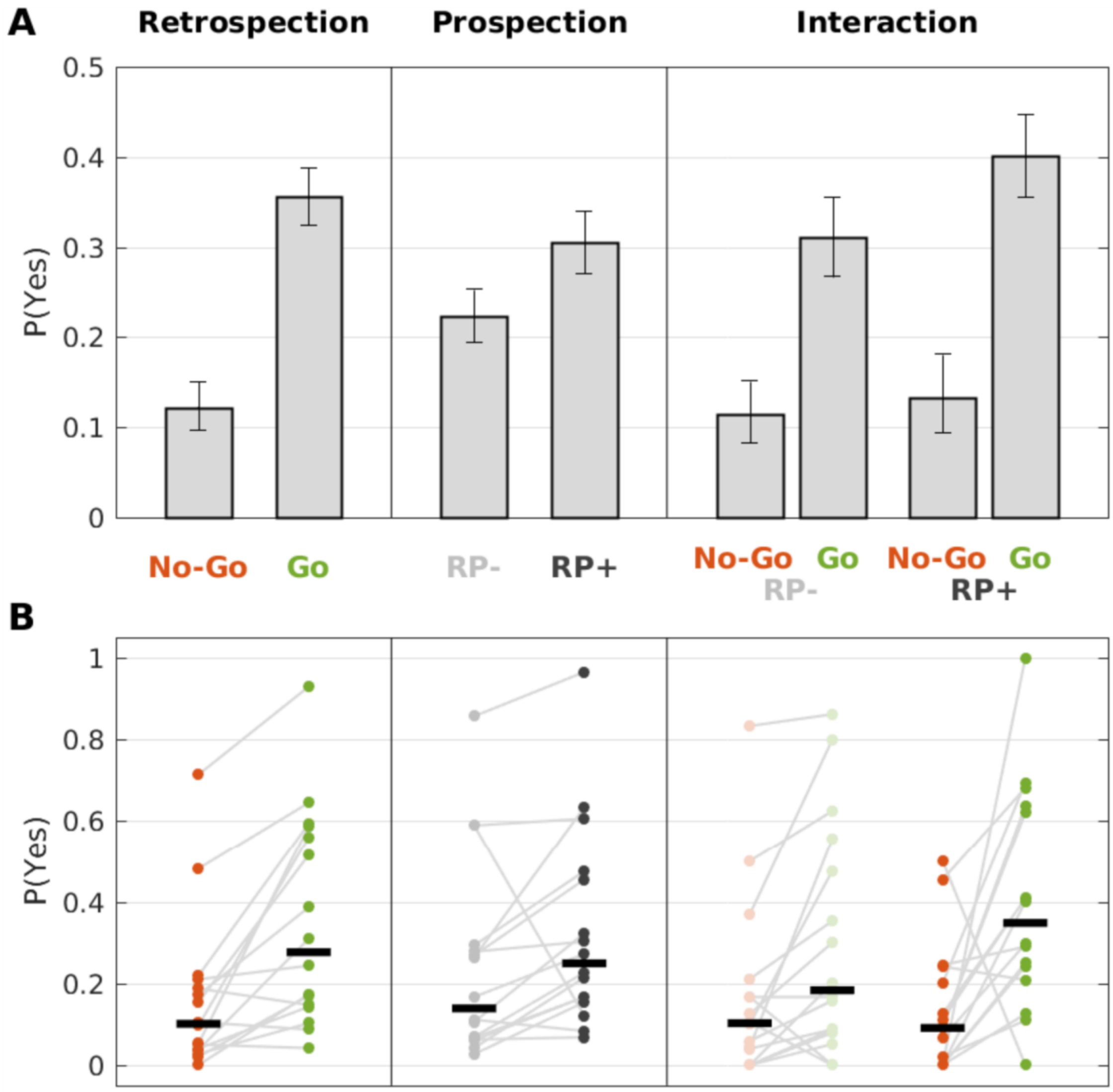

Fig. 2. Retrospective and prospective contributions to intention reports. (**A**) Probability of responding "yes" in *No-Go* and *Go* trials (left), in *RP-* and *RP+* trials (middle), and in their corresponding intersections (right). These comparisons reflect the retrospective and prospective contributions and their interaction to awareness judgements, respectively. Bars and antennas show probability estimates and 95% confidence intervals, respectively, calculated by pooling the response of the corresponding subset of trials across all participants. (**B**) Scatter plots show the paired probabilities of individual participants, solid black lines show the population median.

3.3. Dynamic integration of prospective and retrospective information

We next investigated whether prospective and retrospective cues are dynamically integrated in intention awareness judgements. A plausible account suggests that prospective motor preparation and retrospective factors related to action execution are integrated over time to shape the experience of intention. Because *No-Go* trials lacked any movement and thus a measureable reaction time, we restricted this analysis to *Go* trials only. Fig. 3A shows the distribution of reaction times with respect to the time of the *Go* cue presentation.

This analysis allowed us to test whether the RT modulates the retrospective reconstruction of intention. Second, it allowed us to investigate whether the effect of the motor preparation state triggering the cue (*RP+*/*RP-*) is dependent on the RT. If awareness of intention follows a mechanism similar to comparator models of motor control (*20*), we predict that prospective information about motor preparation is only available for integration with retrospective feedback for a short time. Thus, we expect intention judgments to be modulated by the time delay between the time elapsed between the motor preparation state triggering the cue and the execution of a movement.

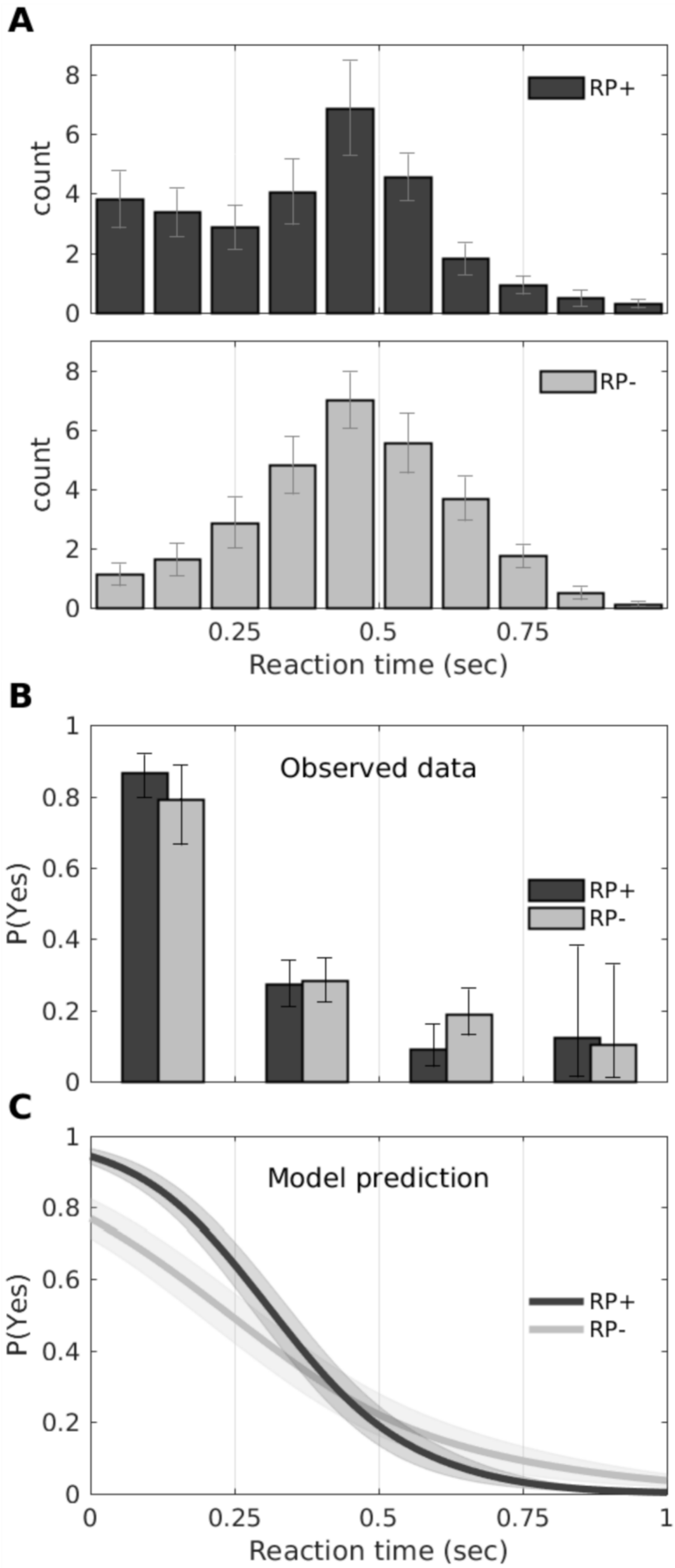

Fig. 3. Time-dependent integration of prospective and retrospective contributions to intention reports. (A) Reaction time distribution (EMG onset) with respect to the time of

cue presentation in *RP+* (top) and *RP-* (bottom) trials. Bars show the grand averages and SEMs of trial counts in 100 ms bins, respectively. The distributions for individual participants are shown in Fig. S9 of the **electronic supplemental material**. (**B**) Probability of responding *yes (intention present)* after *Go* cues for *RP+* and *RP-* trials individually (color coded) and for different reaction times. Probability estimates and 95% confidence intervals are calculated by pooling data across participants and are reported according to reaction times in 4 bins of 250 ms. (**C**) Model predictions are generated for a continuous reaction time variable. Shown are the grand averages across participants (SEM shown as shaded area). The probabilities estimated for individual participants are shown in Fig. S10 of the **electronic supplemental material**.

As described in Fig. 3, we found that the probability of reporting awareness decreased over time ($X^2_{(1)} = 68.66$, $p < 0.001$). Participants were very likely to report awareness of intention if they initiated a movement shortly after a cue, but very unlikely to report awareness if they were slow. This was the case both in the *RP+* and the *RP-* condition. Furthermore, the interaction between the RT and the RP ($X^2_{(1)} = 11.87$, $p < 0.001$) indicated that the presence of an RP significantly increased the probability of reporting awareness, but *only if* an action was executed within approximately 250 ms after cue presentation. At a hypothetical RT of 0 s, for example, the probability of reporting awareness predicted by the model is 0.944 in the *RP+* condition, while it is only 0.788 in the *RP-* condition. Both the time-dependency of the retrospective reconstruction and the interaction between motor preparation and time could be seen in individual participants' data (see **electronic supplemental material**, Fig. S10).

As in the previous analysis, we controlled whether the time of the cue contribute to these effects. Including the time of cue as a fixed effect in the model did not improve the fit. The statistical significance of the RP, RT and their interaction remained unchanged, and no significant effects were found for time of cue presentation (see **electronic supplemental material**, Table S5).

4. Discussion

We conducted an EEG study of intention awareness using a BCI technique which allowed us to monitor motor preparation processes in real-time. Participants performed a self-paced movement task and were occasionally interrupted by a cue which instructed them to either execute or inhibit an action. They were then asked to report whether they had or had not been intending to move at the time the cue appeared. The time of presentation of the green and red cues was determined by a BCI trained to detect the presence or absence of an RP. This experimental design allowed us to investigate how awareness of intention depends on (i) the presence/absence of motor preparation (i.e. the RP), (ii) the execution/inhibition of an action, and (iii) the potential time lag between the two. Our results provide new insight into the elements contributing to the experience of intention.

Our first finding was a strong effect of retrospection. Participants were overall more likely to report having had an intention to move at the time of the probe when an action was subsequently executed (*Go* condition) compared to when no overt movement was made (*No-Go* condition) (Fig. 2). This retrospective effect is in line with previous findings showing that intention judgements are (at least partly) reconstructed using information about action execution (*15-17*). Further, the probability of reporting awareness was significantly higher for probes preceded by an RP, compared to those where no RP was present. This suggests that motor preparation processes prior to the probe also influence motor intention judgements. To our knowledge, ours is the first study to demonstrate this point: while there is some evidence that motor preparation states are accessible before action execution (*8*) and that the absence of an RP preceding action correlates with abnormal time of intention judgements (*7*), the extent to which RP activity may inform subsequent judgements of intention remained an open question. It is worth noting, however, that although we did not find the interaction between prospective and retrospective factors to be significant, the effect of prospection was numerically less in the *No-Go* than in the *Go* condition. Given the limited number of prospective *No-Go* trials in our dataset, our failure to find any interaction could reflect lack of power rather than absence of an effect. Thus, while the current data suggest that the RP also has an effect in the absence of an action, and thus supports the possibility of "pure prospection", pure prospection effects appear small relative to retrospective effects triggered by action execution.

With our second model, we explored the temporal dynamics of the prospective-retrospective interaction by taking into account the time at which actions were executed with respect to *Go* signals. First, this analysis showed that the retrospective reconstruction of intention found in the first model is time-dependent. Participants were very likely to report awareness when they responded fast to a *Go* signal, but this probability decreased sharply as elapsed time between the *Go* signal and movement initiation increased (Fig. 3). These temporal dynamics were observed in both *RP+* and *RP-* trials. Even in the absence of movement preparation (*RP-*) a fast reaction to the cue (RT < 250 ms) was sufficient to produce a high percentage of intention reports (M = 72.8%, SEM = 9.5). Importantly, however, equally fast trials preceded by movement preparation in the *RP+* condition resulted in a still higher rate of subsequent intention judgements (M = 86.1%, SEM = 5.1). Thus, the model revealed a time-dependent effect of prospection: when a movement was executed, the presence of a preceding RP increased the probability of awareness reports if the movement was executed within approximately 250 ms after a *Go* cue. Because the cues were locked to the presence or absence of an RP, the result can also be phrased as follows: in the Go condition the RP only made awareness reports more likely when an action took place shortly after movement preparation was detected. This suggests that information about motor preparation is available to interact with subsequent action-related signals for a limited period of time. This time-constraint is consistent with everyday experience. Normal self-paced actions are executed immediately after an RP is present, and not otherwise. Therefore, it makes sense that only events (i.e. actions) happening at a physiologically plausible time after presence of a motor preparation brain signal are integrated with that brain state and perceived as its consequence. The time-dependency of the retrospective effect explains the fact that participants only reported awareness of an intention to act on 40% of trials (see Fig. 2), even when they were probed in the presence of an RP *and* when they executed an action in response to the *Go* cue. Since fast (< 250 ms) responses to *Go* cues were less frequent than slow responses (Fig. 3), the low average percentage of intention reports is mostly driven by trials with longer RTs to the *Go* cue. Intention reports were less frequent when cue and action occurred further away in time, even if an RP had triggered the cue.

A few considerations are worth noting before the final conclusions. First, this experiment used delayed reports of intention awareness. Because we were interested in studying both the prospective and retrospective contributions to motor intention awareness, participants provided their intention judgement after the allowed motor response time window of 1.5 s. Thus, although we asked participants about their intention at the time of the cue, our results clearly show that the report does not veridically reflect the experience of intention participants had at the time the probe was presented, simply because it is influenced by subsequent events (i.e. the action). The RP is a transient signal, and it decays over time. It seems plausible that the information it may contain regarding motor intention could become likewise less accessible to consciousness as time elapses (despite having an effect at the time of the intention report). Thus, while the effect of the RP on intention awareness observed in the first analysis was small, the possibility remains that the effect of prospection could be higher if reports were obtained closer to the time of action.

Second, participants might have been able to complete our task successfully without awareness of intention. Their main goal was to respond to the *Go* and *No-Go* cues correctly, and they required to report intentions only afterwards. This contrasts with other awareness report methods, where action execution is contingent on the conscious experience (e.g. *8*,*25*) and which thus focus on the prospective component of motor awareness. Further research is required to evaluate to what extent purely prospective cues are accessible to guide action using paradigms where task performance is dependent on awareness.

The findings in this study thus contribute to understanding the mechanisms underlying awareness of motor intention (AOI). Here, we propose a tentative model to explain the subjective intention reports and to integrate them with the previous literature (Fig. 4). At the end of the trial participants are asked to tell whether they had an intention to move at the time of the intention probe. Our data show that this report is somewhat influenced by the state of motor preparation prior to the movement (Fig. 2A, "prospection"). Participants more frequently report having had an intention at the time of the probe if an RP was present prior to the probe, i.e. when their motor preparation was more advanced. This is compatible with previous reports of prospective contributions to AOI. Some studies (*8,25)* have suggested that motor preparation may be initiated unconsciously (stage 1 in Fig. 4) and only becomes accessible to consciousness after it crosses a latent awareness threshold at some later point (stage 2). This latent awareness threshold could occur around 1.4 s before movement execution (*25*). While the results in our study are silent as to precisely *when* people may be aware of an intention to move if probed, our results are compatible with the idea that people may have some awareness of intention prior to action execution (stage 3). In principle, prospective signals for reporting intention could be present from the beginning of stage 2 onwards. When people are asked after the movement about their experience of an "urge" to move, their reports indicate that this is present around 200 ms before movement execution (*3*). Please note that such Libet-style *(3)* designs involve reports made after movements, so it has remained unclear whether the movement itself might have contributed to the judgement of awareness.

Our study allows us to address this question. Participants are instructed to report at the end of the trial whether they were aware of an intention at the time of the probe. Our results clearly show that the awareness reports not only reflect the motor preparation happening before the probe, but are also influenced by events happening between probe and report. Specifically, the execution of the action itself has the largest effect on the AOI report (Fig. 2A, "retrospection"), even stronger than the prospective effect. Please note that our design does not reveal *which aspect of the action* is relevant for the retrospective modification of the awareness report. It could be either the efferent execution signal, or sensory feedback, for example haptic signals that occur during the movement.

Interestingly, our data demonstrate the presence of a third contribution to the AOI report. In those trials where participants execute a movement, the probability of AOI is also further increased if there is a close temporal proximity between motor preparation and the action (Fig. 3). This contribution might be explained by similar comparator models that have been proposed for motor control (e.g. *20*). A crucial aspect of comparator models is the temporal proximity of the participating signals (*26*). Prospective information about intentions is available before movement, whereas signals related to movement execution are only available after movement. Thus, these fundamentally asynchronous signals must be brought together by some process of temporal integration in order to be compared. Several computational models explicitly recognise that comparator models additionally require a temporal integration process (*27*).

Thus, our results show that the probability of reporting awareness is maximal (i) when motor preparation (indexed by the readiness potential) is present before the movement, (ii) when an action is executed and (iii) when motor preparation and action occur in close temporal proximity during a narrow time window of approximately 250 ms (stage 4). We designate this window as *I-window* (integration window). For more delayed actions (stage 5), or when no motor preparation is present (*RP-*, stages 4 and 5), intention reports are driven only by the time-dependent retrospective reconstruction. As a result, the probability of reporting an intention is reduced compared to probes occurring during the I-window. Temporal contiguity is an essential component of causal inference (*28*), and delays in expected action outcomes have been shown to delay the reported times of intention in Libet type judgements (*29*). We suggest that retrospective reconstruction involves such a type of causal inference strongly relying on temporal contiguity, independent of motor preparation.

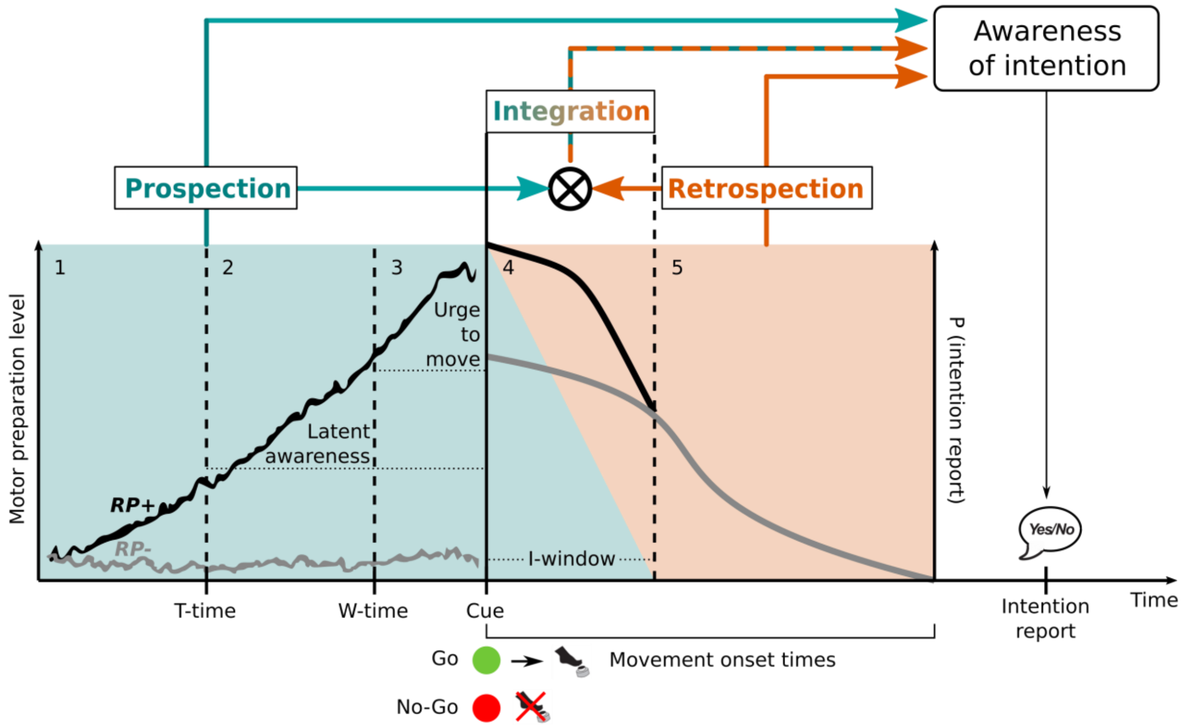

Fig. 4. Schematic model of motor intention awareness formation. The shaded areas and coloured arrows indicate prospective (blue) or retrospective (orange) information contributing to the experience of intention that is provided late in the trial. Left side: Black and grey traces represent the level of motor preparation, according to whether an RP is (RP+) or is not (RP-) present. This reflects influences on AOI judgements from time periods prior to the intention probe (cue). Right side: AOI ratings are also influenced by processes happening after the intention probe. The curves show the effect of executing an action and additionally how this effect is additionally modulated by whether motor preparation was present or not. Dashed vertical lines indicate critical events in the generation of intention. We propose the following time line: Motor preparation processes are initially inaccessible to consciousness (1). Once preparation has reached a certain "latent awareness" level, people may have conscious access if probed (2, T-time). When motor preparation approaches an action-triggering threshold, people start feeling an "urge" to move (3, W-time). This is to account for effects of previous studies (*3,8,25*). These prospective factors contribute to the subsequent AOI report. However, the report is also influenced retrospectively by events after the probe. In our experiment, a BCI was trained to prompt people with Go/No-Go cues at the time of maximal motor preparation when an RP was present (*RP+*), or when no preparation was visible (*RP-*). The results in Go trials allowed us to identify a critical time window (*I-window*) during which intention reports are influenced by the temporal coincidence between

motor preparation and action (4). Beyond that critical time window, there are no more contributions of motor preparation to the subsequent AOI report (5).

5. Conclusions

We have shown that both prospective and retrospective cues influence delayed motor intention judgements, and that they are additionally integrated in a time-dependent fashion. The presence of a motor preparation signal increases the probability of reporting an intention, and reports of intention are more likely after executing an action than in the absence of overt movement. Further, the retrospective effect is modulated by response time, i.e. the probability of reporting awareness decreases as the reaction time to the cue increases. Further, prospective information is integrated with action execution feedback during a critical time window of approximately 250 ms. Specifically, if an action occurs within 250 ms of an RP, reports of awareness are more likely than if no RP is present in the 250 ms before action.

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Preparation and execution of voluntary action both contribute to awareness of intention

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Electronic Supplementary Material

1. EEG-informed selection of participants

The readiness potential was the target brain signal that we aimed to use in order to manipulate prospective information about motor preparation. Therefore, we investigated whether such BCI-based manipulation was effective in each individual participant.

A qualitative assessment of EEG data from stage I used to train the classifier (Fig. S1A) shows that for most participants the signals look as expected, with EEG signals preceding self-paced movements in average displaying the typical negative trend of a readiness potential ("Move" class), while EEG signals preceding trial start cues do not show any particular trend ("Idle" class). However, while the RP is a potentially informative feature that the BCI may use for classification, it is not guaranteed a priori that the EEG features extracted by the classifier to separate the "Move" and "Idle" classes were based on the presence and absence of an RP over central channels.

A visual inspection of stage II data (Fig. S1B) suggests that for most participants *RP+* cues were effectively preceded by an RP-like negativity, while *RP-* cues were not (with some conspicuous exceptions). Note that here we only consider *RP+* and *RP-* cues that were elicited *before* any movement onset, thus excluding EEG data that would otherwise be contaminated with signals related to movement execution. In order to test whether we could rely on the BCI-triggered cues during stage II to discriminate *RP+* from *RP-* activity in each individual participant, we performed the following analysis. Channel Cz was chosen for analysis because readiness potentials preceding foot movements are typically most distinct over that channel (Brunia et al., 1985). For each trial individually, we subtracted the average

EEG signal in the time interval -200ms to 0ms from the average EEG signal in the time interval -1200ms to -1000ms, with respect to the time of cue presentation. These values represent the relative change in amplitude in channel Cz during the 1.2 seconds before cue presentation. If the BCI relied on the readiness potential for classification, EEG signals over central channels preceding *RP+* cues should be on average more negative than signals preceding *RP-* cues. To test this hypothesis, we ran a two-sample one-sided t-test, for each participant separately. The box plots in Fig. S1C show, for each participant and for *RP+* and *RP-* cues individually, the distributions of amplitude changes, with participants ordered by the t-statistics of the t-test from largest (left) to smallest (right). For the first 16 participants the t-test showed that signals preceding *RP+* cues became significantly more negative during the 1.2 sec interval than signals preceding *RP-* cues. For the remaining 7 participants this was not the case, suggesting that the classifier did not made interruptions based on the presence or absence of RP-like events in the EEG. Consequently, these participants are excluded from all subsequent analyses. Fig. S1D shows individual and grand average EEG signals preceding *RP+* and *RP-* cues of the 16 participants selected for the final sample.

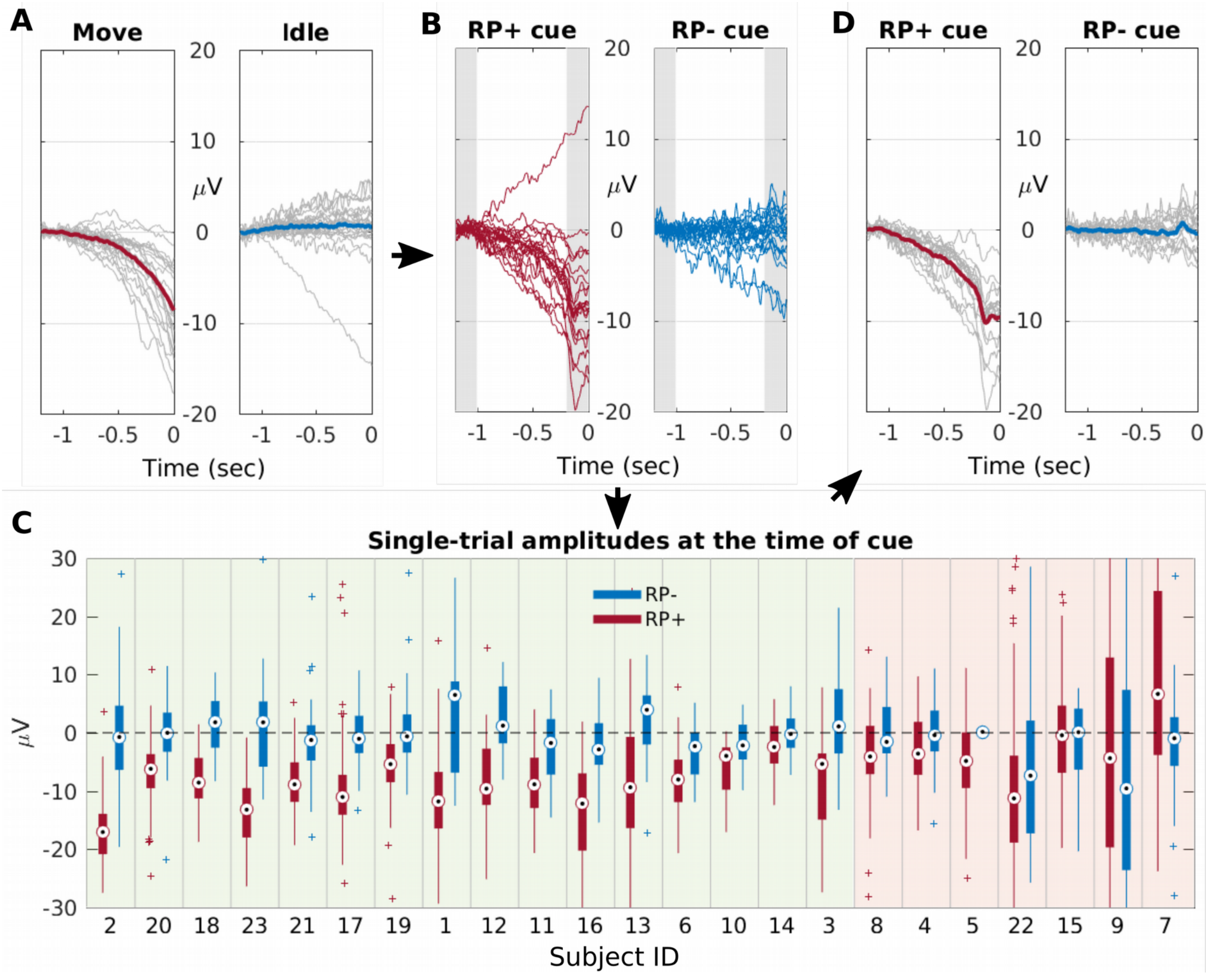

Fig. S1. Selection of participants based on EEG signals of channel Cz. (**A**) Event-related potentials (ERPs) of EEG signals recorded during stage I, time-locked to self-paced EMG onsets (left, "Move") and time-locked to trial start cues (right, "Idle"). ERPs are baseline corrected in the interval -1200 to -1000 ms, and shown for individual participants (grey) and as grand average (colored). (**B**) ERPs of EEG signals recorded in stage II, time-locked to *RP+* cues (left) and time-locked to *RP-* cues (right). ERPs are baseline corrected in the interval -1200 to -1000 ms and shown for individual participants. (**C**) For each participant (ID on x-axis) and for *RP+* and *RP-* cues individually (color coded), the box plots show the distribution of EEG signal amplitude changes between the time interval -1200 to -1000 ms and -200 to 0 ms with respect to cue onset (indicated by gray areas in panel B). Participants are ordered in ascending order by the t-statistic of a two-sample one-sided t-test that tests whether the mean change in *RP+* trials was more negative than in *RP-* trials. Participants for which $p<.01$ are highlighted in green, otherwise in red. (**D**) As in B, but only for the selected N=16 participants (gray) and the corresponding grand average (colored).

2. Setup of Real-time BCI

For the BCI predictor used in stage II, a linear classifier was trained on EEG data from the 100 pedal presses recorded during stage I.

2.1. EMG onset detection

For each trial, we assessed the movement onset. For higher temporal precision, we defined the onset of the movement based on the EMG rather than based on the final completion of the movement with the pedal press. To obtain EMG onset we high-pass filtered the EMG signal at 20 Hz. Then the standard deviation of the signal during the first 1000 ms after each trial start cue was determined as an *idle* baseline. For each trial individually, the standard deviation of subsequent, overlapping 50 ms windows was computed and EMG onset identified as the end of the first 50 ms window where the standard deviation exceeded idle baseline by a factor of 3.5.

2.2. Class specification

Based on these movement onsets, two periods were defined as *move* and *idle* for the training of the classifier. The *move* periods were 1200 ms long segments preceding EMG onset, while the *idle* periods were 1200 ms long segments preceding the trial start cue (i.e. the onset of the traffic light).

2.3. Feature extraction and classifier training (Stage I)

EEG data from those segments were baseline corrected to the mean signal in the time interval between -50 and 0 ms locked to EMG onset or trial start cue, respectively. These were then averaged over time windows defined by the time points -1200, -900, -650, -450, -300, -200, -100 and -50 ms locked to EMG onset or trial start cue, respectively. The choice of the baseline correction interval being locked to the end of the EEG segment (as opposed to the traditional choice of being locked to the beginning of the segment) and the choice of unequal time intervals were both based on a piloting analysis on previous data (Schultze-Kraft et al., 2016) that showed improved classification accuracy with these parameters. The resulting values were concatenated and used as features to train a regularized Linear Discriminant Analysis (LDA) classifier with automatic shrinkage (Blankertz et al., 2011). Classification accuracy (obtained from a 10-fold cross-validation on stage I data) averaged 81.8% (SEM = 2.1%) across participants. In Table S1 we report classification accuracies of single participants. Fig. S2 shows, for channel Cz exemplarily, the single-trial EEG waveforms of the *move* periods used to train the classifier.

Participant	1	2	3	6	10	11	12	13
Accuracy	**86.9%**	**91.4%**	**89.6%**	**88.8%**	**82.0%**	**91.7%**	**75.5%**	**78.1%**
Participant	14	16	17	18	19	20	21	23
Accuracy	**71.1%**	**86.1%**	**86.7%**	**81.3%**	**79.9%**	**69.0%**	**88.4%**	**62.9%**

Tab. S1. Cross-validated classification accuracies of single participants. Classification accuracies were computed on the 100 trials from stage 1 in a leave-one-out cross-validation. Mean accuracy was 81.8% (SEM=2.1).

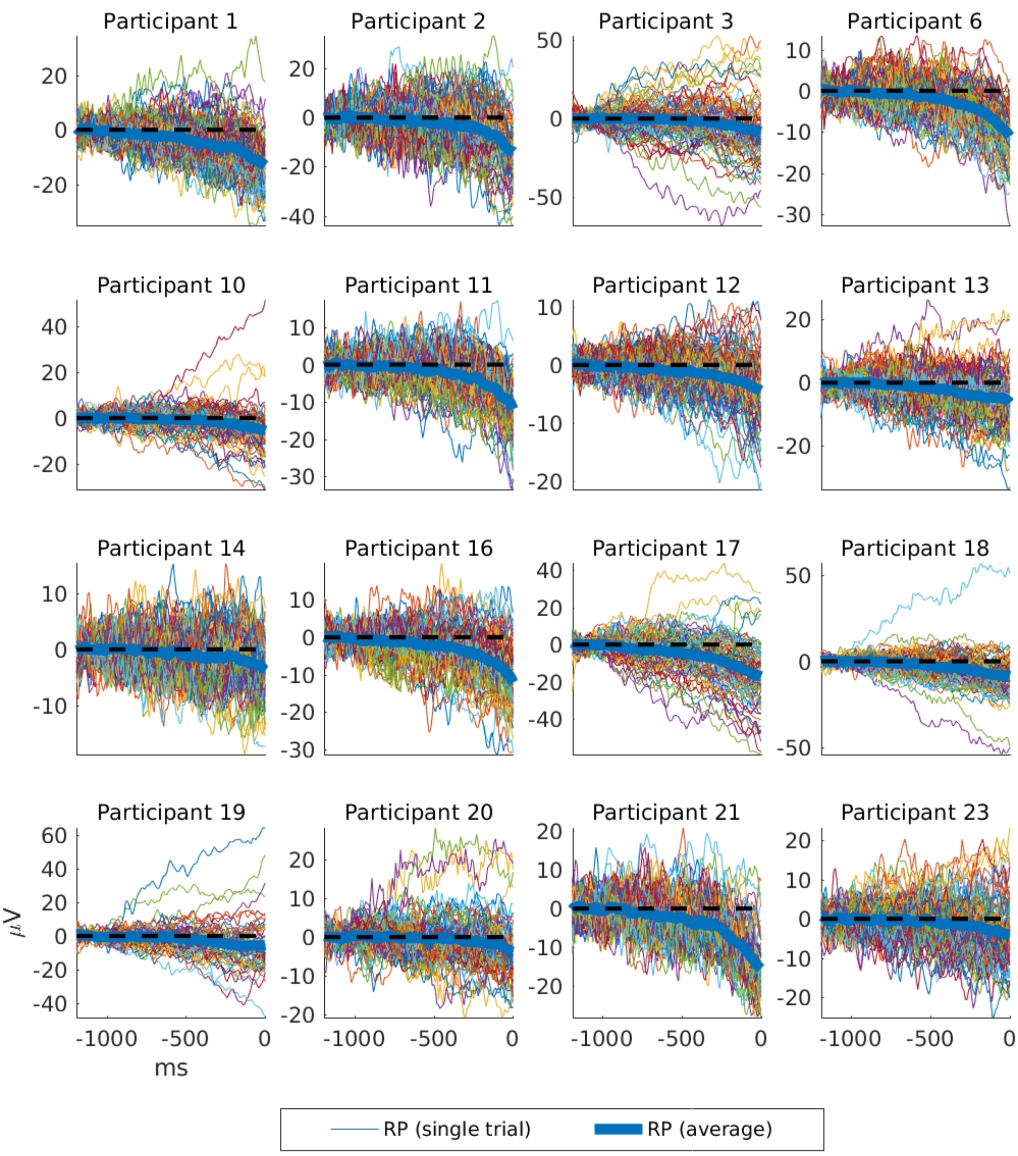

Fig. S2. Single-trial EEG waveforms of RPs in stage I. Panels show, for each participant individually, single-trial EEG waveforms in channel Cz recorded in stage I. These are time-locked to movement onset and thus constitute single-trial RPs. Baseline corrected in the interval [-1200 -1000] ms. Average is shown as a thick blue trace. Axes are as specified in the lower left panel.

2.4. Real-time application of classifier (Stage II)

During stage II, the so-trained classifier was used to monitor the ongoing EEG in real-time. Therefore, every 10 ms a feature vector was constructed from the immediately preceding 1200 ms of EEG data, as outlined above, and used as input to the classifier, generating a classifier output value every 10 ms. This output variable was a continuous signal that probabilistically classified the current EEG segment either to the *idle* or to the *move* class.

2.5. Threshold setting

A classifier threshold was set for each participant individually. Because the classifier output signal was likely to mirror the stochastic nature of the EEG, a conservative threshold was defined in order to avoid many cues to be prematurely triggered by noise. For this, we trained the classifier on 99 trials from stage I and applied it to each consecutive and overlapping 1200 ms feature window in the left out trial, thereby mimicking the real-time application during stage II. This was done for each of the 100 trials in a leave-one-out crossvalidation scheme. For each of these continuous classifier output vectors the time of first threshold crossing after trial start was computed. Let us refer to the time of first threshold crossing in a trial as a "prediction" event. Now, we define predictions occurring somewhere between trials start and up to 600 ms before movement onset as false alarms (FA), predictions occurring between 600 ms before movement onset and the time of movement onset as Hits, and predictions occurring after movement onset or not occurring at all as Misses. From this the F-measure (Powers, 2011) $F_\beta(\theta)=\frac{(1+\beta^2)\,Hit(\theta)}{(1+\beta^2)\,Hit(\theta)+\beta^2\,Miss(\theta)+FA(\theta)}$ was computed for different threshold values θ. The largest F thus corresponds to the threshold θ were the Hit rate is maximal, while at the same time the FA and Miss rates are minimal. Moreover, by choosing β=0.5, we aimed at giving the minimization of FAs more weight than minimizing Miss rate. We prioritized minimizing the number of false alarms, at the cost of potentially missing some actions. The resulting F-values were smoothed and the threshold with the highest F-value chosen.

Fig. S3 shows single-trial EEG waveforms time-locked to *RP+* cues in (stage II) that were elicited when the specified threshold was reached before participants initiated a movement. In Fig. S4 we compare the distribution of amplitudes of the waveforms shown in Fig. S2 and S3, respectively.

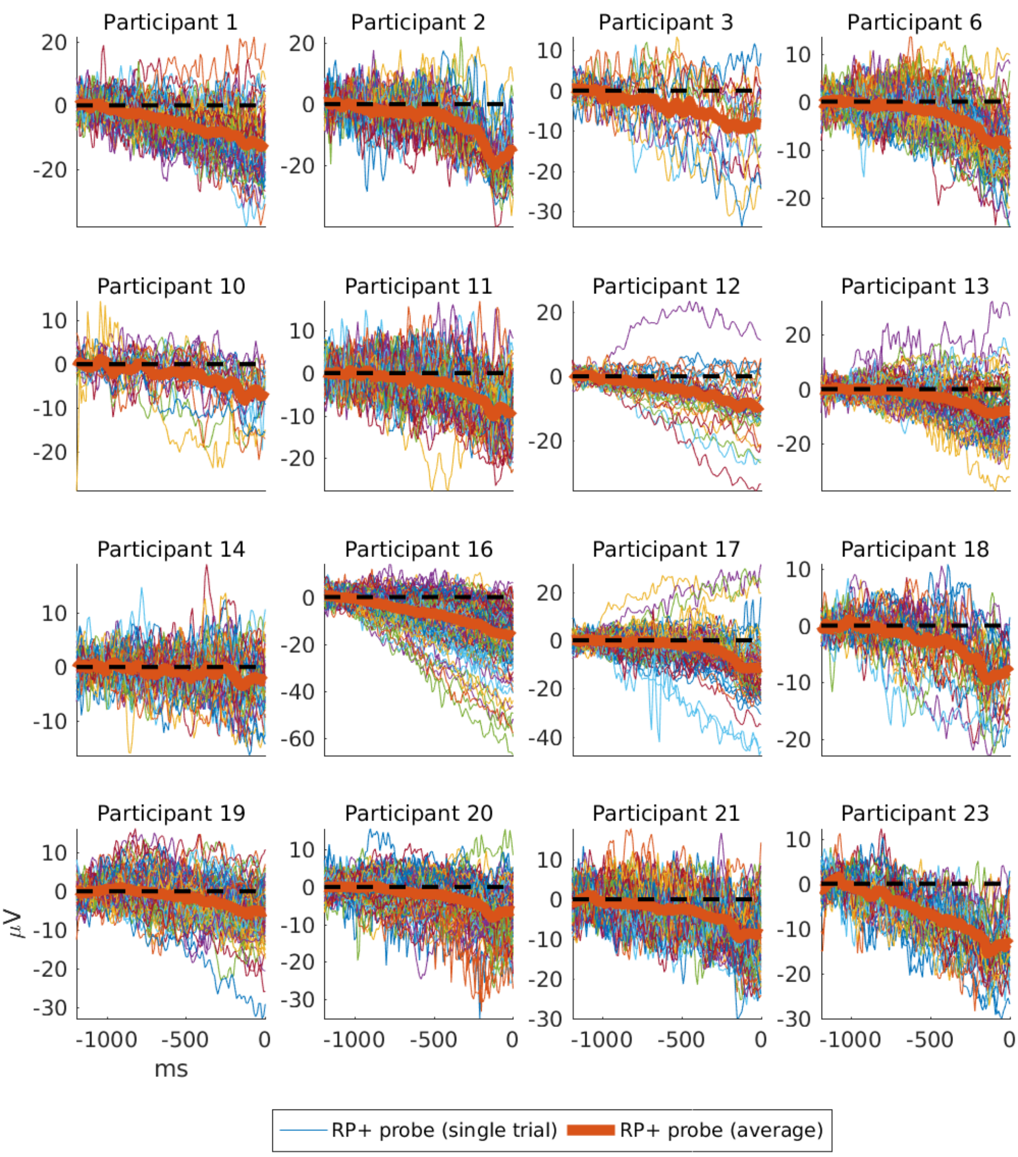

Fig. S3. Single-trial EEG waveforms of *RP*+ cues in stage II. As in Fig. S2, but here EEG waveforms are time-locked to *RP*+ cues elicited by the BCI during stage II. Average is shown in thick red traces. Axes are as specified in the lower left panel.

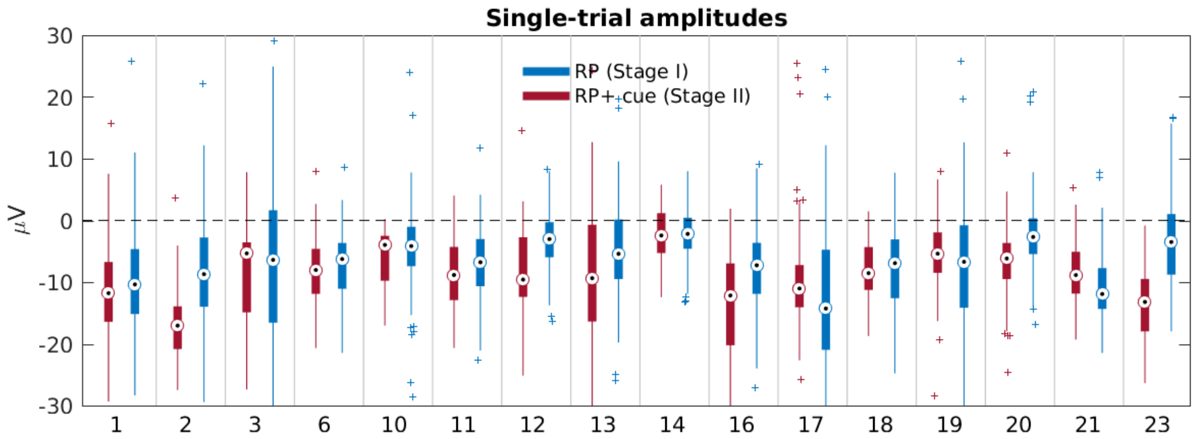

Fig. S4. Distribution of single-trial amplitudes. For each participant (ID on x-axis), the box plots show the distribution of EEG signal amplitude changes between the time interval -1200 to -1000 ms and -200 to 0 ms, with respect to movement onsets in stage I (blue), and with respect to *RP*+ cues (stage II). The former thus represent single-trial amplitudes of the RP used to train the BCI.

3. Model selection procedure and statistical details

As described in the Statistical Analysis section of the methods, we used linear mixed-effects models to test the effects of our explanatory variables on the probability of participants reporting awareness. To select the model that best explained our observed results, we followed the random effect selection procedure suggested in (Matuschek at al. 2017).

In all models, a random intercept was included to account for the variability in the dependent variable across participants. Further, we included those random effects that significantly improved the model fit. To determine the optimal random effects structure, we fit a baseline model which included all explanatory variables and all possible interactions as fixed terms. We then iteratively compared this baseline models against models with one additional random slope using a chi-squared test. If the inclusion of a random slope significantly improved the model fit, the random slope was included in the final model. This approach has been suggested as a better option than including random slopes for all fixed effects, as it decreases the probability of Type II errors while maintaining the same power against type I errors, and has previously been used in the literature (e.g. Steinemann et al., 2018). All models were fit using the *glmer* function in the homonymous R package (Bates et al., 2015).

Tables S2 and S3 provide the detailed results of the random effect selection procedure for both main analyses and the final inference statistics reported in the main text.

Supplementary Table 2: model 1 random effects selection			
Test individual random effects	**Baseline model:** yes ~ 1 + RP + Action + RP:Action + (1+|sub)		
	X^2	**DF**	**p-value**
yes ~ 1 + RP + Action + RP:Action + (1+RP|sub)	10.939	2	0.0042 **
yes ~ 1 + RP + Action + RP:Action + (1+Action|sub)	17.07	2	<0.001***

Tab. S2. Model 1 selection steps and statistical results of model comparison. Random slopes for both RP and Action significantly improved the fit of the baseline model and were therefore included in the model.

Supplementary Table 3: model 2 random effects selection			
Test individual random effects	**Baseline model:** yes ~ 1 + RP + RT + RP:RT + (1+|sub)		
	X^2	**DF**	**p-value**
yes ~ 1 + RP + RT + RP:RT + (1+RP|sub)	0.2518	2	0.881
yes ~ 1 + RP + RT + RP:RT + (1+RT|sub)	7.1686	2	0.027*

Tab. S3. Model 2 random effect selection steps and statistical results of model comparison. Only the RT random slope significantly improved the fit of the baseline model and was therefore the only random effect included in the model.

4. Data description and trial selection procedure

The number of trials in which participants were presented a cue, as well as the exact times when cues were presented, could not be precisely experimentally controlled. In case of *RP+* trials, this is because the BCI was calibrated so as to elicit cues preferably during the interval just before a movement, based on the detection of a readiness potential. However, the detection of transient events in the EEG in real-time by means of an asynchronous BCI is only possible with a limited accuracy, bound by the noisy nature of EEG signals. Further, to test our hypothesis we required participants to correctly follow the instructions

Fig. S5 illustrates the types of trials that occurred during the task and highlights the ones that were included for analysis.

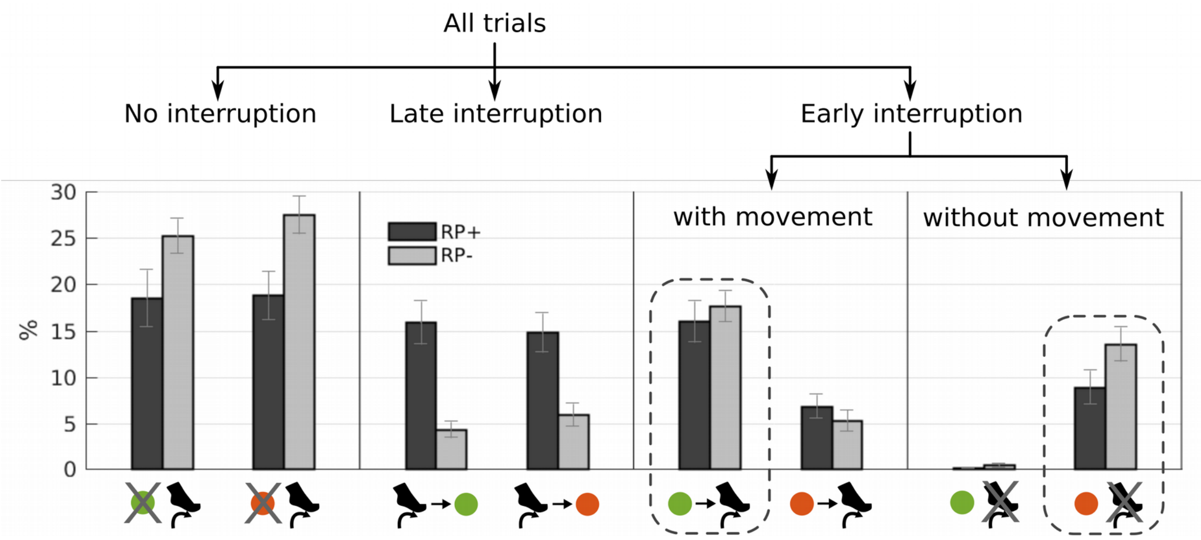

Fig. S5. Types of observed trials and selection procedure. Bar graphs represent the grand-averaged percentage (+ SEM) of trials within each category, for *Go* (green cues) and *No-Go* (red cues) trials, and in the *RP+* (dark grey) and *RP-* condition (light grey). Percentages are calculated in *RP+* and *RP-* conditions separately, i.e. dark grey and light grey bars sum up to 100, respectively. The pictograms below the bar graphs indicate the temporal relation between cue presentation and movement onset. *No interruption* trials: In some trials, participants executed a movement and no cue was presented at all. In these trials, no awareness report was collected and no further analysis was conducted. *Late interruption* trials: In some trials, cues came "too late", shortly after participants had already started moving. All these trials were discarded from further analysis. *Early interruption* trials: Cues were shown before any EMG onset was detected. In the *Go* condition, only trials where participants moved after the green cue presentation were included for analysis (left dashed box). In the *No-Go* condition, only trials where no EMG onset was detected after the red cue presentation were included for analysis (right dashed box).

4.1. Characterization of trial types

In some cases, participants pressed the pedal *without* a cue being elicited (*No interruption* trials). In the *RP+* condition, these represent instances where the BCI failed to detect a readiness potential (*RP+/Go*: M = 18.5%, SEM = 3.1%; *RP+/No-Go:* M = 18.8%, SEM = 2.6%). In *RP-* trials, these represent instances where participants pressed the pedal before the random predetermined time of the cue (*RP-/Go:* M = 25.3%, SEM = 1.9%; *RP-/No-Go:* M = 27.5%, SEM = 2.0%). In all these cases, since no cue was presented, no awareness report was collected. Thus these trials are excluded from further analysis.

In another subset of trials, a cue was presented *after* EMG onset (*Late interruption* trials). In some *RP+* trials, a readiness potential was presumably correctly detected by the BCI, but a cue was presented after participants had already started moving (*RP+/Go:* M = 15.9%, SEM = 2.3; *RP+/No-Go:* M = 14.8%, SEM = 2.1). In turn, the *RP-* trials where a cue was presented after participants' movement reflect rare instances where the predetermined probing time by chance coincided with the self-paced time of movement (*RP-/Go*: M = 4.3%, SEM = 0.9; *RP-/No-Go:* M = 5.9%, SEM = 1.2). For our purposes, these cues came too late and the corresponding awareness reports are thus excluded from further analysis.

In another subset of trials, the cue was presented *before* EMG onset. In the *Go* condition (*Early interruption* trials *with movement*), these trials fulfil our prerequisite that *Go* cues must be followed by a movement, and thus the corresponding awareness reports are used in the main analysis (*RP+/Go:* M = 16.0%, SEM = 2.2; *RP-/Go:* M = 17.7%, SEM = 1.7). In the *No-Go* condition, participants sometimes initiated a movement after a cue was presented (*RP+/No-Go:* M = 6.9%, SEM = 1.3; *RP-/No-Go:* M = 5.3%, SEM = 1.1). Although they were often able to abort a movement before fully pressing the pedal in some of these trials, the very initiation of a movement - even though aborted - might suffice for participants to reconstruct an awareness of intention in the awareness probes that followed those cues. Thus, these trials were excluded from further analysis.

Finally, in some trials a cue was elicited before any EMG onset but no movement was produced after it (*Early interruption* trials *without movement*). In the *Go* condition, these very rare occurrences reflect trials where participants failed to respond with a pedal press to a green cue (*RP+/Go*: M = 0.15%, SEM = 0.06; *RP-/Go*: M = 0.4%, SEM = 0.2). In contrast, as expected, in the *No-Go* condition this occurred more frequently (*RP+/No-Go:* M = 8.9%, SEM = 1.8; *RP-/No-Go:* M = 13.6%, SEM = 1.8). In these trials, participants successfully followed the instruction to withhold any movement after a red cue. Because they fulfil our prerequisite that *No-Go* cues must not be followed by a movement, the corresponding awareness reports are used in the main analysis.

4.2. Time relation between movements and cues

A closer look into the distributions of time differences between EMG onsets and cues provides further insight into the way in which our experimental design resulted in the observed proportions of trials (Fig. S6).

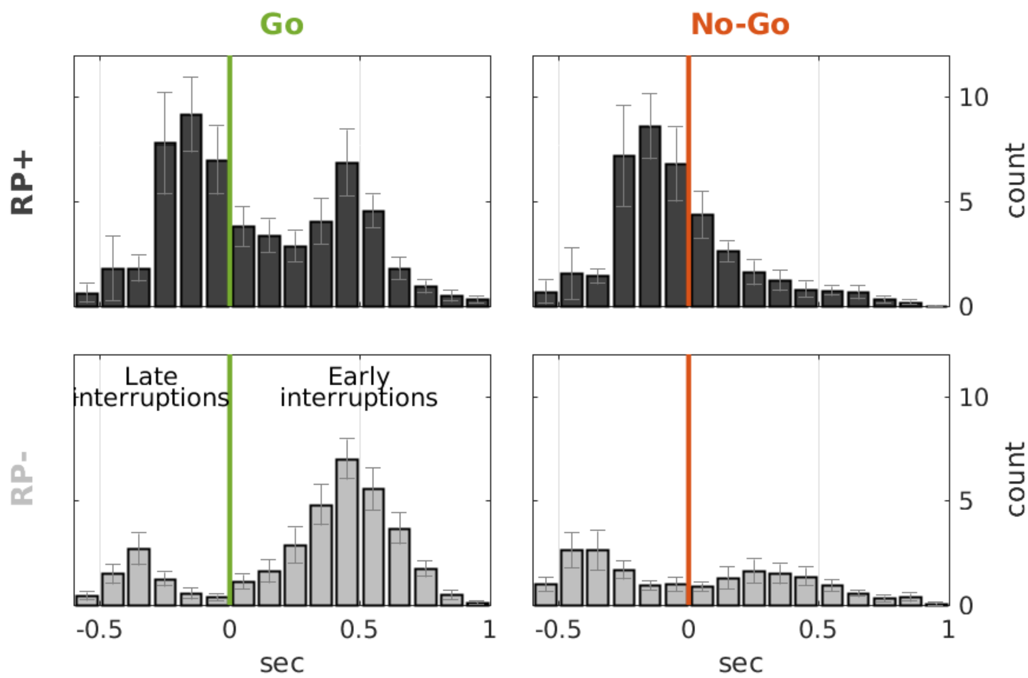

Fig. S6. Reaction times in trials with cues and movements. Shown are the time histograms of EMG onset time with respect to the time of cue presentation in *Go* (left) and *No-Go* (right) trials, in the *RP+* (top) and *RP-* condition (bottom). Negative times correspond to EMG onsets in *Late interruption* trials, in which the cue was presented after participants started moving. Positive times correspond to the distribution of EMG onsets in *Early interruption* trials (i.e. classic reaction times), where a cue was presented and a movement was initiated shortly afterwards. Bars and antennas show the grand averages and SEMs of trial counts in 100 ms bins, respectively.

Go and *No-Go* signals were often triggered *after* participants had started moving in the *RP+* conditions, while this was rarely the case in *RP-* condition. In the *RP+* condition, these *Late interruption* trials correspond to the distribution centered before cue presentation. These are instances of motor preparation states that were successfully detected by the BCI, but too late. Trials falling on the right tail of this distribution were instead instances where motor preparation was successfully interrupted early by the BCI. These trials can be interpreted as interruptions after the point of no return (Schultze-Kraft et al., 2016). That is, trials in which participants would have moved *anyway* if a cue had not been presented. In fact, in a number of *No-Go* trials participants failed to inhibit a movement and an EMG onset was detected after the red cue. In turn, in the *Go* condition, the effect of these intercepted self-paced actions is visible in the higher count of trials with very fast responses (RT < 200 ms) in the *RP+/Go* condition compared to the *RP-/Go* condition. In sum, in the *RP+/Go* condition, very fast trials (<200 ms) include both self-paced movements that happened to occur just after the green *Go* signal (right tail of the *Late interruption* distribution, Fig. S5), and also reactions to the *Go* signal (left tail of the *Early interruption* distribution). In turn, in the *RP-/Go* condition, movements produced very fast after the cue presentation were only reactions.

We checked that these very fast responses in the left tail of the *Early interruption* distribution could physiologically be fast reactions rather than self-paced actions that the classifier did not predict, by looking at the RT distribution during a simple cued reaction time task. These RTs were recorded in a final stage of the experiment, where no self-paced actions were being performed and participants were only reacting to *Go* cues presented at random times (Fig. S7). Here, we also observed some very fast reaction times (<200 ms) comparable to the ones found in the *RP-* condition.

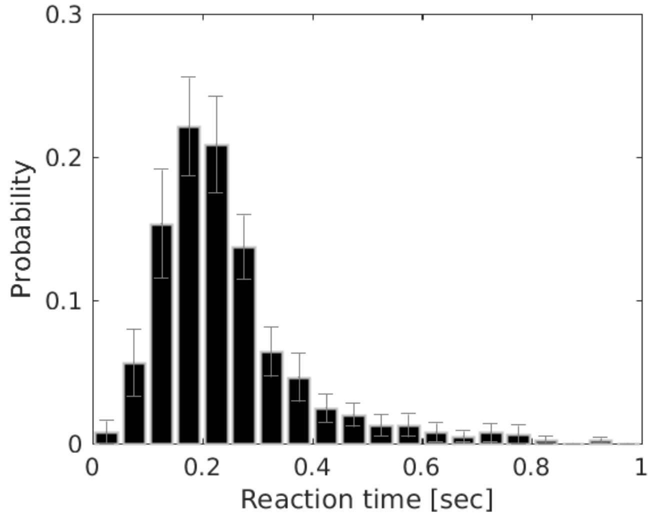

Fig. S7. Distribution of reaction times in a simple cued reaction task. The histogram shows, in discrete 50 ms bins, the probability (± SEM) of observing EMG onsets after presentation of the Go cue.

5. Control of instruction effects in model 1

To check that the observed retrospective effects were not merely driven by the instructions rather than the action execution, we ran a mixed-model predicting the probability of reporting awareness based on the presence or absence of the RP (*RP+*/*RP-*) and on whether participants moved (EMG+) or did not move (EMG-) after the *No-Go* cue was presented (Fig. S8). A similar analysis was not performed in the *Go* condition because participants extremely rarely failed to execute an action following the instruction to press the pedal after the green light. Intention reports were significantly more likely after a movement than in its absence within the *No-Go* condition (X^2 = 200.23, p < 0.001). This suggests that participants' reports were not merely driven by the instruction to move or not move.

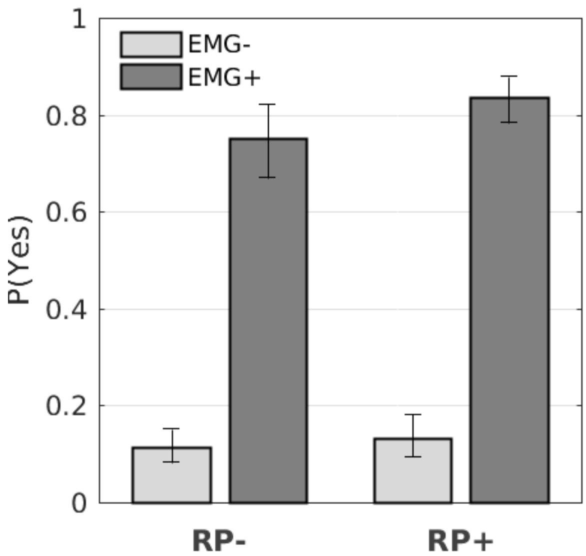

Fig. S8. Retrospective effects are not driven by instruction. Bars represent responses in trials where a *No-Go* cue was not followed by an EMG onset (EMG-, included in main analysis) or was followed by an EMG onset (EMG+, excluded from the main analysis), for *RP-* (left) and *RP+* (right) conditions separately. Participants were significantly more likely to report an intention to move after an EMG onset than in the absence of it within the *No-Go* condition. Bars and antennas show probability estimates and 95% confidence intervals, respectively, calculated by pooling the responses of the corresponding subset of trials across all participants.

6. Testing for effect of time of cue in models 1 and 2

Supplementary Table 4: model comparison including cue presentation time			
(A) Model comparison	**Original model** P(yes) ~ 1 + RP + Action + RP:Action + (1+Action + RP|sub)		
	X^2	**DF**	**p-value**
Control model yes ~ 1 + RP + Action + CT + RP:CT + RP:Action + RP:Action + RP:Action:CT + (1+Action + RP|sub)	3.95	4	0.4127
(B) Control model output	X^2	**DF**	**p-value**
RP	9.53	1	0.002**
Action	19.89	1	<0.001***
CT	2.63	1	0.104
RP:Action	2.10	1	0.1467
RP:CT	1.31	1	0.2507
Action:CT	0.09	1	0.7546
RP:Action:CT	0.21	1	0.6402

Tab. S4. To control whether the effects observed in model 1 could be accounted for by the time at which the *RP+*/*RP-* cue were presented, we included the Cue Time (CT) as a fixed effect in the model, together with its interaction with RP and Action. The inclusion of this variable did not significantly improve the model fit (A), and the statistical significance of the Action and RP effects remained unchanged (B).

Supplementary Table 5: model comparison including cue presentation time			
(A) Model comparison	**Original model** P(yes) ~ 1 + RP + RT + RP:RT + (1+ RT |sub)		
	X^2	**DF**	**p-value**
Control model yes ~ 1 + RP + RT + CT + RP:CT + RP:RT + RT:CT + RP:RT:CT + (1+RT |sub)	6.09	4	0.1919
(B) Control model output	**X^2**	**DF**	**p-value**
RP	1.08	1	0.29
RT	65.29	1	<0.001***
CT	1.44	1	0.23
RP:RT	8.33	1	0.003**
RP:CT	1.31	1	0.25
RT:CT	0.95	1	0.32
RP:RT:CT	1.88	1	0.1688

Tab. S5. To control whether the effects observed in model 2 could be accounted for by the time at which the *RP+*/*RP-* cue were presented, we included the Cue Time (CT) as a fixed effect in the model, together with its interaction with RP and RT. The inclusion of this variable did not significantly improve the model fit (A), and the statistical significance of the RT and RP effects remained unchanged (B).

7. Single subject reaction times and response probabilities in *Go* trials

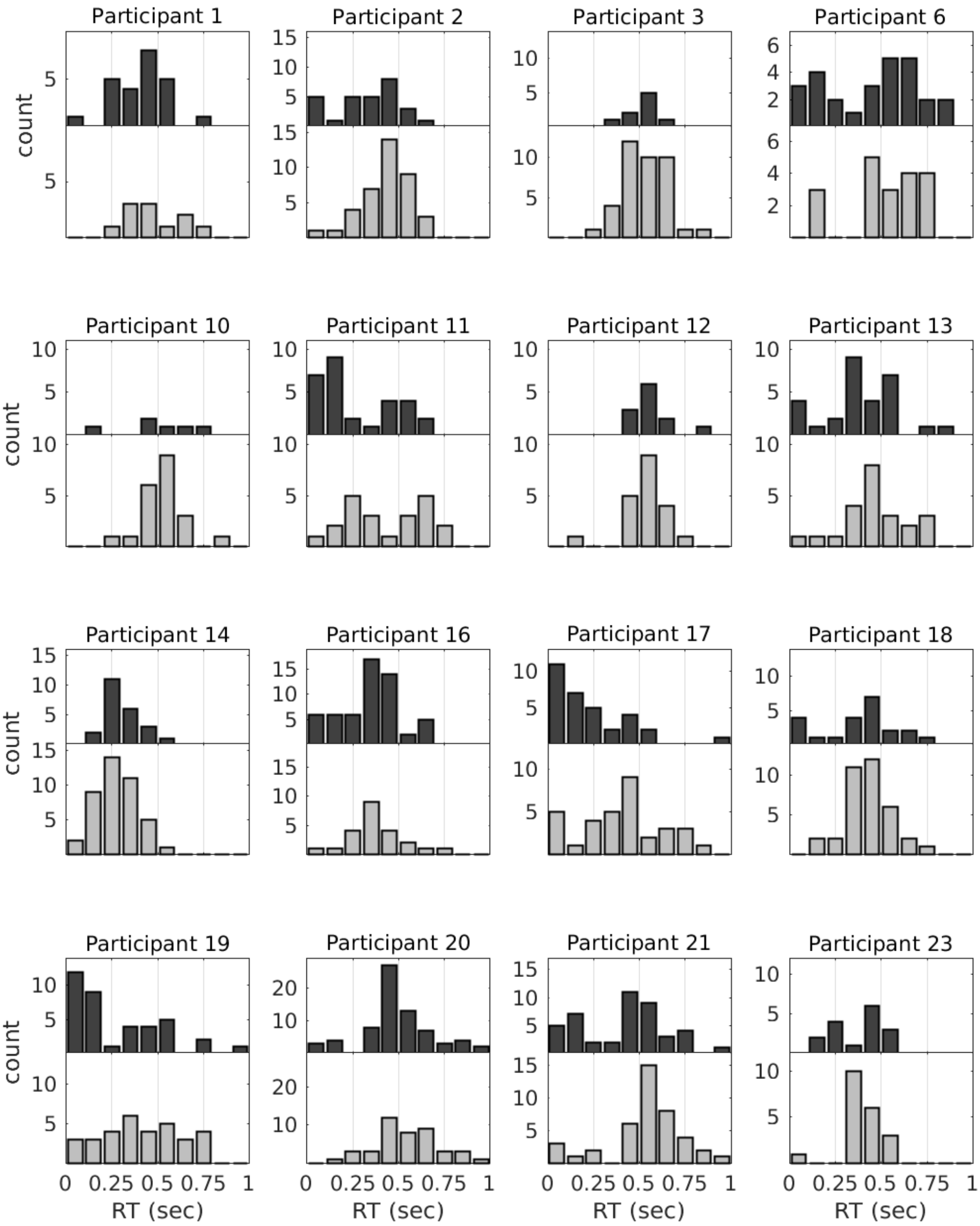

Fig. S9. Reaction time distribution in *Go* trials for each individual participant in the *RP+* (black) and *RP-* (gray) conditions.

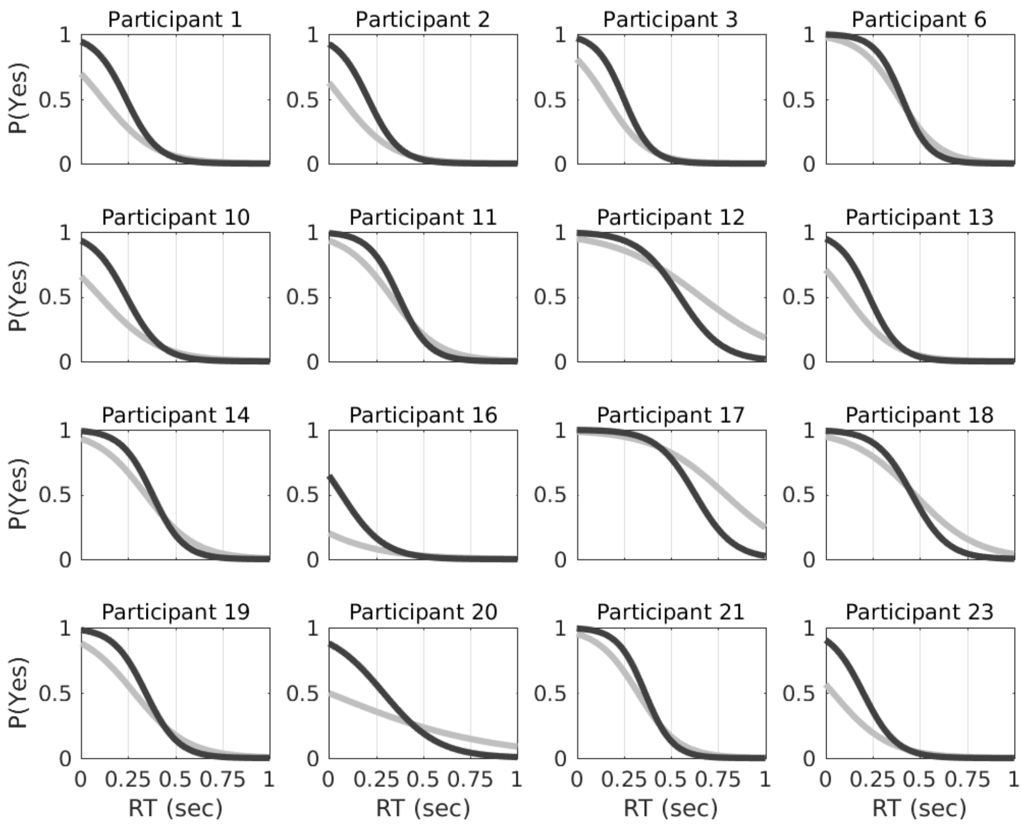

Fig. S10. Probability of responding ‘yes’ in *Go* trials as predicted from a regression model fitted to each individual participant in the *RP*+ (black) and *RP*- (gray) conditions.

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