CORTEX 196 (2026) 117–136

Available online at www.sciencedirect.com

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Journal homepage: www.elsevier.com/locate/cortex

Research Report

How prior motor states can shape perceptual decision bias: Insights from sensorimotor beta oscillations

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ARTICLE INFO

Article history:
Received 5 August 2025
Revised 9 January 2026
Accepted 9 January 2026
Action editor Thomas Schenk
Published online 16 January 2026

Keywords:
Perceptual decision making
Embodied cognition
Sensorimotor cortex
Beta oscillations
Decision bias

ABSTRACT

Emerging evidence suggests that decision making is not a purely cognitive process preceding motor output but rather an embodied phenomenon in which the sensorimotor system actively shapes choice selection. Beta oscillations (13–30 Hz) over sensorimotor cortex are known to encode movement-related activity and have recently been shown to influence behaviour in perceptual decision-making tasks through lateralization of the post-movement rebound following response execution, biasing subsequent decisions toward the alternative response hand. This study investigated whether sensorimotor beta oscillations elicited by an isolated choice-unrelated motor action influence a subsequent perceptual decision. Twenty-nine healthy adults completed a two-stage task while 64-channel EEG was recorded. Each trial began with a left or right thumb button press, followed after a variable delay (.5, 1.2, or 3 sec) by a briefly presented visual grating requiring a decision response on its orientation via a second button press. Beta activity following the initial movement was related to subsequent decision bias at both the between-subject and the within-subject single-trial level: participants with stronger beta power lateralization during decision stimulus presentation exhibited stronger alternation bias, and stronger lateralized beta power in individual trials was associated with higher alternation probability, independent of the delay between the initial movement and the decision stimulus. These results suggest that beta activity may index individual susceptibility to decision bias, while also acting as a momentary neural signal influencing alternation behaviour. Within the framework of embodied decision-making, these findings support the influence of sensorimotor beta oscillations on the choice process.

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https://doi.org/10.1016/j.cortex.2026.01.003

1. Introduction

Perceptual decision making describes the process by which sensory information from the environment is transformed into goal-directed actions in both humans and animals (Cisek & Pastor-Bernier, 2014; Gold & Shadlen, 2007; Heekeren et al., 2008). It is commonly investigated using paradigms such as motion discrimination (e.g., Hanks et al., 2006; Huk & Shadlen, 2005) and orientation judgment tasks (e.g., Assarioti et al., 2025; Zhang et al., 2019), where participants make binary choices by selecting motor responses that reflect stimulus-related decisions. Traditionally, perceptual decision making has been characterized as a serial process (Lepora & Pezzulo, 2015). This process starts with sensory evidence being encoded in the corresponding sensory cortex (Britten et al., 1996; Newsome & Pare, 1988). The evidence is then integrated in association regions such as posterior parietal and prefrontal cortex (Huk & Shadlen, 2005; Zhou & Freedman, 2019). Finally, the resulting decision signals are transmitted to sensorimotor areas such as the premotor cortex for action execution (Cisek & Kalaska, 2005). This framework suggests a functional dissociation between cognitive processing circuits (i.e., posterior parietal and prefrontal cortex) where decisions are thought to be formed, and the sensorimotor system which is considered solely as the final output stage. However, accumulating neurophysiological evidence challenges this view by showing that competing choice-related action plans are concurrently activated within sensorimotor areas even prior to the final commitment of a choice in higher-order cognitive regions (Cisek & Kalaska, 2005, 2010; Pastor-Bernier & Cisek, 2011). These findings support a parallel processing model, where choice formation and action specification unfold simultaneously and are dynamically intertwined (Lepora & Pezzulo, 2015).

In contrast to traditional lab-based experiments, decision making in real-word scenarios often occurs in dynamically changing environments where costs and affordances of possible actions actively shape the process of choice formation (Cisek, 2007). This idea has led to the embodied decision-making framework (Cisek & Pastor-Bernier, 2014; Lepora & Pezzulo, 2015), which posits that the sensorimotor system is not merely a passive implementer of decisions but is actively involved in and even capable of influencing the decision making itself. For instance, in a predator–prey interaction scenario, a lion choosing between two moving preys may continuously adjust its preference based on fluctuating factors such as movement trajectory and distance, demonstrating how motor affordances shape choice commitments over time. A growing body of behavioural evidence has indicated that motor-related factors influence the choice formation. For example, using computational modelling, Lepora and Pezzulo (2015) found that incorporating a "commitment" parameter that captures a bias toward an initially selected option, even as accumulating evidence starts to favour the alternative, provides a better fit to empirical data. This indicates that the dynamics of an unfolding action can bias the ultimate choice. Additional evidence comes from observations demonstrating that an increased motor effort of the response, such as elevated physical resistance (Burk et al., 2014; Hagura et al., 2017) or greater reaching distance (Assarioti et al., 2025; Marcos et al., 2015) biases choice behaviour toward the less effortful option.

The embodied decision-making framework also offers a different perspective on the phenomenon that current choices are not only determined by ongoing sensory input but also biased by previous choices. Inherently, previous choices are accompanied by a motor response to indicate the selected choice, which leaves the possibility that it might be the motor response per se, rather than the choice itself, that influences subsequent decisions. Behavioural studies examining how previous motor responses affect choice bias have yielded mixed findings. Some studies found no significant contribution of motor history (Akaishi et al., 2014; Braun et al., 2018; Fernberger, 1920) while others reported clear motor-history effects (Pape et al., 2017; Urai et al., 2017; Zhang & Alais, 2020). These inconsistencies may be attributed to differences in task design, such as the presence or absence of feedback (Fründ et al., 2014), or the use of variable delays between motor response and decision cues. Most studies adopted a varied choice-response mapping paradigm, as in the study by Zhang and Alais (2020) where identical perceptual choices were randomly assigned to different motor responses, explicitly dissociating the contribution of motor history from that of perceptual choice. They found an alternating motor bias, where participants were inclined to alternate motor responses, regardless of the associated perceptual choice. Similarly, Pape et al. (2017) showed that a choice-unrelated motor action preceding a decision task reduced choice repetition, further suggesting the direct influence of prior motor responses on subsequent decisions.

Neurophysiologically, a motor history bias might arise through the temporal dynamics of sensorimotor beta oscillations that occur around each movement. Beta oscillations refer to rhythmic activity in the 12–30 Hz frequency range and are widely considered as a neural index of motor preparation and execution (Jurkiewicz et al., 2006; Kilavik et al., 2013; Pfurtscheller & Da Silva, 1999; van Wijk et al., 2012). During brief movements, a reduction in beta power (i.e., beta desynchronization) is typically observed starting around .5 sec before movement onset and continuing throughout movement execution (Leocani et al., 2001; Takemi et al., 2013). This is followed by a rapid increase in beta power (i.e., beta rebound), beginning approximately .5 sec after movement offset and lasting up to 4–5 sec in some cases (Bailey & Bardouille, 2025; Houdayer et al., 2006). Beta desynchronization is thought to reflect active motor preparation, whereas the subsequent beta rebound has been linked to processes that inhibit motor output (Jurkiewicz et al., 2006; Pfurtscheller et al., 1996; van Wijk et al., 2009). This is supported by findings of slower responses when actions are initiated during the rebound phase (Muralidharan & Aron, 2021; Zhang et al., 2024) and reduced corticospinal excitability during this period (Chen et al., 1998). Crucially, the beta rebound is typically stronger in the sensorimotor areas contralateral to the moving hand compared to the ipsilateral side (Jurkiewicz et al., 2006;

Pfurtscheller et al., 1996). This lateralization can hypothetically lead to a bias in subsequent decisions, especially when new stimulus information is presented while the beta rebound triggered by the previous motor response is still ongoing.

Two MEG studies have directly examined motor history effects in perceptual decision making through the lens of sensorimotor beta oscillations (Pape & Siegel, 2016; Urai & Donner, 2022). Pape and Siegel (2016) used a random dot motion task with a varying choice-response mapping paradigm that allowed them to dissociate the influence of previous responses from choices. Their results indicated that a stronger lateralized beta rebound was associated with a higher likelihood of choice alternation, both at the single trial level and across participants. By contrast, Urai and Donner's (2022) study did not indicate a difference in sensorimotor beta lateralization during stimulus presentation between participants who had a tendency to repeat their previous motor response and those who tended to alternate. Yet, using drift-diffusion modelling, the authors found that the degree of beta power lateralization internally biased the starting point of evidence accumulation toward alternation, hence still indicating an influence on the decision-making process. Some studies (de Lange et al., 2013; Donner et al., 2009), although not explicitly testing motor history effects, employed a fixed stimulus-response mapping and found that spontaneous fluctuations in beta lateralization could partially explain subsequent choices, suggesting a potential top-down regulatory role of the motor cortex in decision-making.

Studies examining motor-history effects on decision-making (Pape & Siegel, 2016; Zhang & Alais, 2020) have typically employed relatively complex paradigms in which motor actions are embedded within varying choice-response mappings which may introduce additional cognitive demands or strategic processes that confound the genuine motor-history effects. Other studies deliberately manipulating motor contingencies by varying motor cost or effort (Assarioti et al., 2025; Burk et al., 2014; Hagura et al., 2017; Marcos et al., 2015), inherently involve choice-related variables such as action cost. To date, no study has directly provided neural evidence on whether the state of the motor system itself, induced by an isolated and choice-unrelated motor action, can influence a subsequent perceptual decision. To address this gap, we adopted a simple paradigm similar to Pape et al. (2017) in which a perceptual decision-making task was embedded immediately following an initial choice-unrelated movement. This design allowed us to test whether motor beta activity triggered by the initial movement could influence subsequent perceptual choices. To ensure that this movement did not trigger additional cognitive processing, its direction was held constant within each block rather than being determined by a choice-response mapping. To probe how the evolving lateralized beta rebound shapes decision bias, we introduced three stimulus onset delays after movement termination: short (.5 sec), medium (1.2 sec), and long (3 sec). These time points were selected to roughly capture distinct phases of the beta rebound, with the short delay corresponding to its onset, the medium delay approximating the expected peak, and the long delay approaching a return to baseline, based on previous studies (Jurkiewicz et al., 2006; Pfurtscheller & Lopes da Silva, 1999). Considering that rebound timing varies across individuals (Cheyne et al., 2003; Jurkiewicz et al., 2006), we treated these delays as exploratory sampling points for beta dynamics. We hypothesized that sensorimotor beta power lateralization during the presentation of the decision stimulus reflects an inhibitory influence on actions performed with the hand that just executed the choice-unrelated movement and would therefore drive subsequent decisions towards alternation. Accordingly, we predicted that participants with stronger average beta lateralization would exhibit a stronger alternation bias, and that stronger trial-level beta lateralization would be associated with a higher probability of alternation on a given trial. Additionally, we expected that within each participant, delays that evoke stronger beta lateralization would exhibit stronger alternation bias.

2. Methods

2.1. Participants

Twenty-nine healthy adults were recruited via the university's online subject pool for participation in the study. All participants had normal or corrected-to-normal vision, reported no history or current diagnosis of neurological, psychiatric, or musculoskeletal disorders, and did not use sleep-inducing medications, sedatives such as benzodiazepines, or anticonvulsants such as carbamazepine. Six participants were excluded from further analyses based on visual inspection of their individual psychometric curves (see Section 2.5.1). The final sample comprised 23 participants (17 females; median age = 20.5 years, age range = 18–28 years), of whom 21 were right-handed and 2 were left-handed. All participants provided written informed consent prior to participation and were compensated with course credits. The study protocol was approved by the Scientific and Ethical Review Board of the Faculty of Behavioural and Movement Sciences at Vrije Universiteit Amsterdam. The sample size was determined in accordance with a commonly used rule of thumb for within-subject EEG studies (25–30 participants), and all inclusion and exclusion criteria were established prior to data analysis.

2.2. Stimuli

The experiment was programmed in MATLAB R2023b (The MathWorks, Natick, Massachusetts). Stimuli were generated and presented using the Psychophysics Toolbox Version 3.0.14 (Brainard, 1997; Kleiner et al., 2007; Pelli, 1997). All stimuli were presented on a mid-grey background (RGB: [127, 127, 127]) using an ASUS ROG Strix XG248Q monitor (23.8″ diagonal, 1920 × 1080 resolution, 240 Hz refresh rate; physical dimensions: 526 mm × 296 mm), centrally positioned for stimulus display. A fixation cross (25 pixels in size, 8 pixels in thickness), letter cues ("L" or "R"; 40-pixel font size, Times font), and task instructions presented at the beginning of each block (40-pixel font size, Times font) were all displayed centrally in white (RGB: [255, 255, 255]).

Orientation grating stimuli (Fig. 1A) were generated using a 400 × 400 pixel sinusoidal grating. The grating had a

Michelson contrast of .8, a spatial frequency of .1 cycles per pixel, and a phase of 0°, and was rendered with alpha blending and the smooth step smoothing method to ensure gradual transitions at the aperture boundary. To increase perceptual difficulty, the grating was overlaid with a Gaussian noise texture, generated by sampling pixel intensity values from a zero-mean Gaussian distribution and applying a spatial Gaussian filter with a standard deviation of 80 pixels. The noise texture was spatially constrained by a circular alpha mask (radius = 200 pixels) to match the size of the grating aperture. A central grey annulus (radius = 40 pixels) was superimposed on the grating, allowing the fixation cross to remain visible at the centre to maintain spatial consistency throughout each trial. The orientation of the grating differed between trials.

2.3. *Experimental procedure and design*

The experiment was conducted in a quiet room with dim, constant artificial lighting. The experimenter was present in a separate room next door. Participants were seated in an adjustable chair behind a table with a computer monitor at a viewing distance of approximately 80 cm, wearing an EEG cap (Fig. 1B). They were instructed to hold a response box with their left and right thumbs resting on the corresponding buttons while their forearms were positioned comfortably on the table, and to respond by pressing the appropriate button according to the task requirements. The chair height was adjustable to ensure physical comfort and optimal visibility of the display. The full experimental session lasted approximately 90 min, comprising roughly 45 min of preparation time

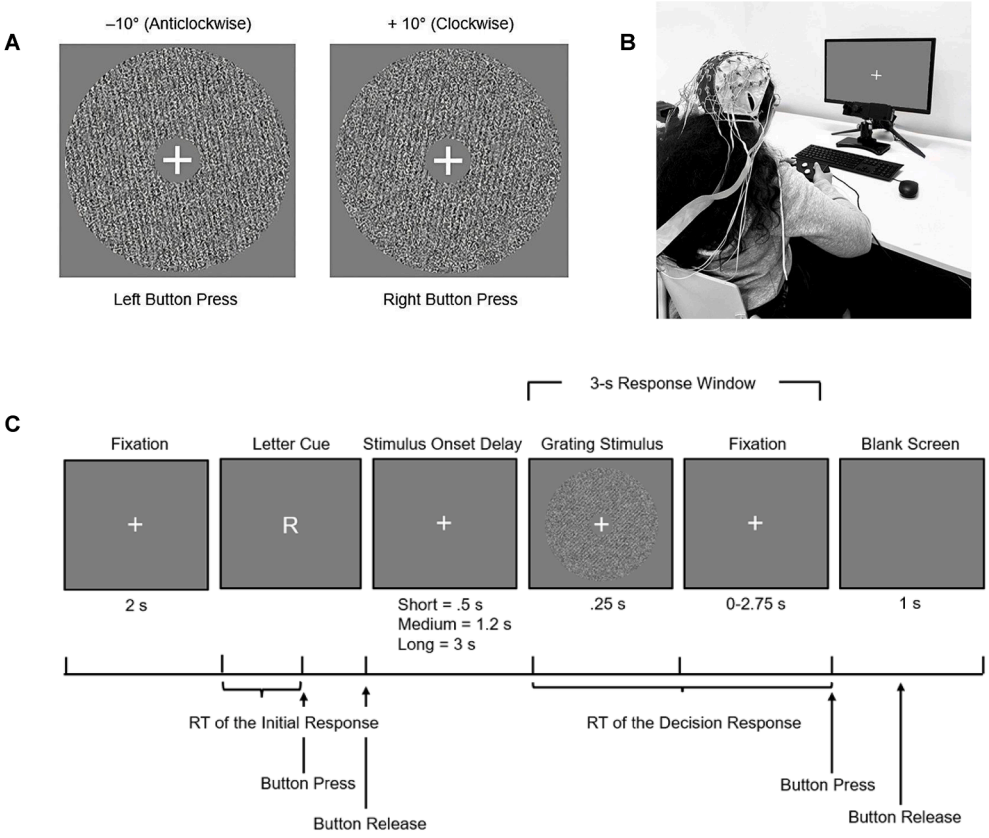

Fig. 1 – (A) Two example orientation grating stimuli. The stimuli shown correspond to the initial orientations used in the staircase: −10° (anticlockwise, left panel), and +10° (clockwise, right panel). Below each stimulus, the correct button press is indicated. (B) Experimental Setup. Participants were seated comfortably in front of a monitor while wearing an EEG cap. They held a response box with their left and right thumbs positioned on the corresponding buttons. (C) Trial sequence of the experiment. Each trial began with the presentation of a central white fixation cross displayed for 2 sec, followed by a letter cue ("L" or "R") prompting a left or right button press (i.e., initial response) (*In the illustrated example, the required response is a right-button press.*) RT of the initial response refers to the reaction time between the onset of the letter cue and the participant's button press. Upon release of the button, the fixation cross reappeared for one of three possible delays (0.5, 1.2, or 3 sec), followed by a .25-sec decision grating stimulus. Participants responded based on perceived orientation (anticlockwise = left, clockwise = right). RT of the decision response refers to the reaction time between the onset of the decision grating stimulus and the decision-related button press. The total response window was 3 sec. See main text for further details.

(including instructions and EEG setup) and 45 min of task execution, with short breaks provided between blocks to minimise fatigue.

Each experimental trial consisted of two sequential stimuli: a letter cue "L" or "R" that prompted the participant to press the corresponding button with their left or right thumb, followed by an orientation grating stimulus pointing either anti-clockwise or clockwise. We will refer to the first button press as "initial response", which merely served to induce a post-movement beta rebound in sensorimotor cortices that would still persist at the time of the grating stimulus presentation. The cue for the initial response was always the same within a block of 120 trials, so it did not require a decision. To reinforce this structure, participants received an on-screen instruction before each block indicating the required initial response (e.g., "*Within this block, you will see a letter "L" at the beginning of each trial, so please press the LEFT button to start the trial.*"). The second button press, hereafter referred to as the "decision response", indicated the participant's judgment of the orientation of the grating stimulus. Participants were instructed to press the left button if they perceived the grating to be tilted anticlockwise, and the right button if it was tilted clockwise (see Fig. 1A for example stimuli).

As illustrated in Fig. 1C, each trial began with the presentation of a central fixation cross displayed for 2 sec, followed by a letter cue ("L" or "R") shown at the centre of the screen. Participants were instructed to press the corresponding button (left or right) as quickly as possible. Upon release of the button, a fixation cross reappeared at the centre of the screen for one of three possible stimulus onset delays (short = .5 sec, medium = 1.2 sec, or long = 3 sec), which served to ensure between-trial variability in the degree of beta rebound lateralization. Following this delay, an oriented grating appeared around the fixation cross for .25 sec. Participants were instructed to make their decision response as quickly and accurately as possible. After the grating offset, the fixation cross remained visible for up to 2.75 sec, yielding a maximum response window of 3 sec. The fixation cross disappeared immediately after a response was registered, followed by a 1-sec blank screen. If participants responded before the grating disappeared, the response was recorded, but the grating remained on-screen for the full .25 sec. In this case, the trial transitioned directly to a 1-sec blank screen. If no response was made within the 3-sec window, the trial was recorded as a non-decision response, followed by the same 1-sec blank screen. Participants completed a total of 480 trials, divided into four blocks of 120 trials each, with block order fully randomized across participants. Two blocks required left-hand initiation (i.e., the letter cue "L" presented on every trial), and two blocks required right-hand initiation (letter cue "R" presented). This resulted in a 2 (initial response: left/right) × 3 (stimulus onset delay: short/medium/long) factorial design.

To maintain task difficulty, a staircase procedure (Cornsweet, 1962) was implemented within each block to determine the orientation of the grating. Each of the three stimulus onset delays (short, medium, long) had two staircases, one in which the grating was initially tilted +10° (clockwise) and one in which it was initially tilted −10° (anticlockwise) relative to vertical, resulting in a total of six independent staircase sequences per block (2 initial orientation × 3 stimulus onset delays). The six staircases were randomly assigned and equally distributed (40 trials per delay) within each block. Each staircase followed a 1-up-1-down rule based on participants' decision responses. If a participant made a left decision response on a given trial, the orientation for the next trial in that staircase increased by 1°, shifting further in the right (clockwise) direction. In contrast, a right decision response resulted in a 1° decrease in the angle, shifting the orientation towards the left (anticlockwise) direction. For example, following a right response to a +10° (clockwise) stimulus, the next stimulus in that staircase sequence would be presented at +9°. If the response had instead been left, the next stimulus would be presented at +11°. All orientations were theoretically constrained within a range of −45° to +45° to prevent excessive deviation from vertical. In practice, orientations used in the task varied only between −12° and +12°.

Before the main experiment began, participants completed a practice block to familiarise themselves with the task. The practice block consisted of 20 trials, with the initial letter cue ("L" or "R") constant, randomly assigned at the beginning of the block. Grating orientations followed a fixed sequence: ±45°, ±40°, ±35°, ±30°, ±25°, ±20°, ±15°, ±10°, ±5°, ±1°, with positive or negative signs randomly assigned on each trial. For the practice block only, participants received immediate visual feedback at the centre of the screen following each decision response: a green "*Correct!*" for accurate responses, a red "*Incorrect!*" for errors, and a white "*Too slow!*" if no response was made within the maximum 3-sec response window. Participants were instructed to respond as quickly as possible, to attend to the variable delay between the initial response and stimulus onset, and to withhold their decision response until the grating appeared. Participants were also instructed to sit still, focus on the fixation cross, and blink only during the blank screen periods.

2.4. *EEG acquisition*

Electroencephalography (EEG) data were recorded using a 64-channel BioSemi ActiveTwo system (BioSemi, Amsterdam, The Netherlands) at a sampling rate of 2048 Hz. Electrodes were positioned according to the international 10–10 system, covering the entire scalp. During EEG acquisition, signals were referenced to the common mode sense (CMS) and driven right leg (DRL) electrodes, with scalp electrode-skin impedances kept below 10 kΩ. Offline, EEG data were re-referenced to the average signal across all electrodes. Additionally, eight external electromyographic electrodes were used to record hand muscle activity for potential validation of motor onset timing but these signals were not analysed for the current study. Event synchronization was achieved via digital triggers sent from the stimulus computer to the EEG recording system to mark trial events.

2.5. *Data analysis*

2.5.1. *Behavioural analysis*

All behavioural analyses were conducted using MATLAB R2023b and R (version 4.4.1; R Core Team). Parametric or non-parametric tests were applied depending on the normality of the data. Reaction time (RT) of the initial response refers to the

reaction time between the onset of the letter cue and the participant's button press; RT of the decision response refers to the reaction time between the onset of the decision stimulus (i.e., the grating stimulus) and the decision-related button press (see also in Fig. 1C). Prior to all data analyses, we excluded trials based on the following criteria: (1) an incorrect initial response (i.e., a right-button press following the cue "L" or a left-button press following "R"); (2) an RT of the initial response exceeding 1.5 sec; or (3) no registered decision response within the 3-sec response window; to maintain consistency with the EEG preprocessing pipeline (see Section 2.5.2.1) and to ensure proper task engagement. A total of 161 trials (1.5% of all trials) were excluded based on these criteria, with a mean of 7 trials per participant (SD = 6.2).

Next, we fitted psychometric curves using *psignifit* version 4.0, a MATLAB toolbox for psychometric function estimation that fits a parametric, unidimensional sigmoid to binary responses to estimate the probability of a particular response as a function of stimulus intensity (Fründ et al., 2011; Wichmann & Hill, 2001). Psychometric curves were fitted separately for each combination of initial response (left/right) and delay (short/medium/long) within each participant, modelling the proportion of rightward choices as a function of the grating's orientation. Each psychometric function was modelled as a cumulative Gaussian, with all decision responses equally weighted. From each fit, we extracted four parameters: (1) the threshold, representing the orientation at which 50% of responses were rightward; (2) the width, defined as the distance between the 5th and 95th percentiles of the unscaled cumulative Gaussian, reflecting the participant's sensitivity to changes in orientation; (3) the lapse rate, representing the proportion of stimulus-independent responses and corresponding to the upper and lower asymptotes of the fitted curve; (4) the slope, representing the change in response probability per degree of orientation at the midpoint of the psychometric function. Parameter values for each combination of initial response (left/right) and delay (short/medium/long), averaged across participants, are provided in Supplementary Table S1. We excluded participants with poor task engagement and unreliable perceptual performance. Specifically, participants were excluded if their mean lapse rate across all six combinations exceeded 7%, or if any individual psychometric curve exhibited a lapse rate greater than 15%. Additionally, we carefully inspected each psychometric fit to ensure that the data points did not show any considerable deviations from the fitted curve. Based on these criteria, six participants were excluded, resulting in a final sample of 23 participants included in subsequent analyses (See Fig. 2 for examples of good and poor task performance).

To determine whether decision responses showed an alternation bias relative to initial responses across the three stimulus onset delays, we compared the estimated threshold parameter (i.e., the orientation at which participants responded "right" 50% of the time) of the psychometric curve that was fitted for trials beginning with a left initial response and those with a right initial response. This method was adopted since the initial response was held constant within each block, making alternation probability an unsuitable measure for quantifying decision bias. For the fitted psychometric curves, a negative threshold indicates a rightward bias (less clockwise tilt required to choose "right"), while a positive threshold reflects a leftward bias (more clockwise tilt needed). For left-initial trials, an alternation bias would lead to a negative threshold whereas a repetition bias would lead to a positive threshold. The opposite pattern holds for right-initial trials: a negative threshold reflects repetition; a positive threshold reflects alternation. To obtain a single, hand-independent index of decision bias, we subtracted the right-initial threshold from the left-initial threshold values. Thus, negative decision bias indicates an alternation bias (a tendency to make the decision response opposite the initial response), while positive decision bias indicates repetition bias. We computed this decision bias value for each participant and delay and tested it against zero using Wilcoxon signed-rank tests for each delay. Finally, we used the Friedman test to determine whether decision bias varied systematically across the three stimulus onset delays.

To characterize overall patterns in participants' decision-making performance, we examined the RTs of the decision response. We divided the data into twelve combinations defined by initial response (left/right), decision response (left/right), and stimulus onset delay (short, medium, long). For visualisation, we first computed each participant's median RT within each of the twelve combinations and at each orientation, then averaged these medians across participants to yield group-level RT estimates. To formally test the RT differences related to initial response and stimulus onset delays while preserving trial-by-trial variability, we conducted an exploratory analysis using a linear mixed-effects model on trial-level RTs. The model included initial response, decision response, stimulus onset delay, and absolute orientation as fixed effects, with participants modelled as random intercepts.

2.5.2. *EEG analysis*

2.5.2.1. EEG PREPROCESSING. Raw EEG data underwent preprocessing using the open-source toolbox FieldTrip (version 2024-07-04; Oostenveld et al., 2011) in MATLAB R2023b. To facilitate artifact rejection and ensure consistent independent component analysis (ICA), EEG data were initially segmented into long stimulus-locked epochs from −3 sec to 8 sec relative to the onset of the letter cue. As we were primarily interested in beta oscillations during the post-initial movement period and the decision-making phase, we subsequently time-locked the time series of each trial to the decision stimulus onset. A baseline interval was defined from −1.5 sec to 0 sec relative to the onset of the letter cue and was inferred from sample indices stored during the initial segmentation.

Epoched time series were first band-pass filtered between .1 and 70 Hz using a second-order bidirectional Butterworth filter, and a notch filter (49–51 Hz) was used to remove line noise. Artifact rejection was conducted in two stages. A first round of artifact rejection was performed based on visual inspection prior to ICA to eliminate prominent artifacts such as head movements that could impair ICA decomposition. Bad channels exhibiting excessive noise were identified and excluded during this step, which were then replaced with the average of their neighbouring channels. On average, 1.4 channels per participant were removed and replaced. Next, the epoched data were re-referenced to the common average. ICA was then implemented to identify and remove ocular (e.g., blinks,

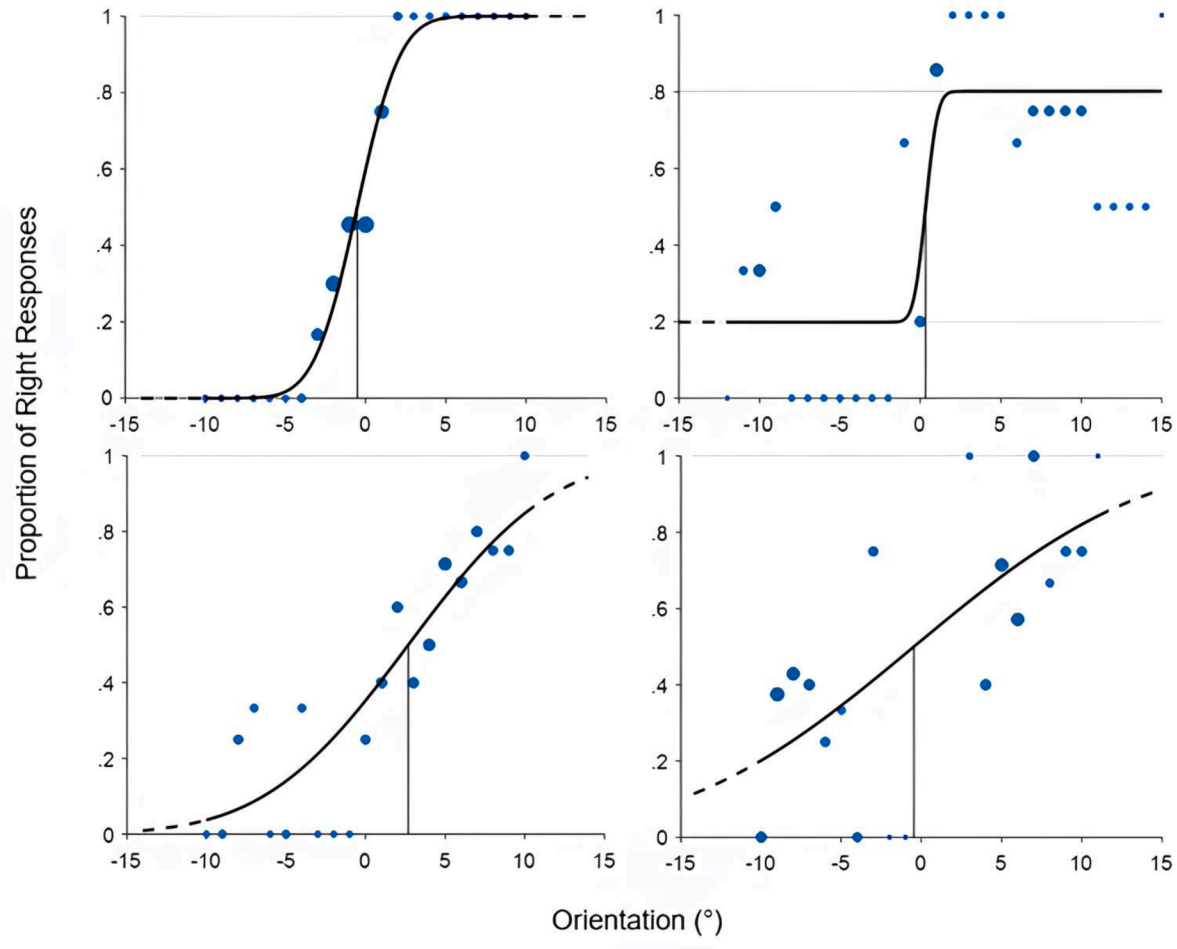

Fig. 2 – Examples of psychometric curves for good and poor task performance. The vertical lines represent the fitted thresholds, indicating the orientation perceived as vertical. Thin horizontal grey lines indicate the fitted lapse rates, which capture deviations from perfect performance at the extreme ends of the stimulus range. Blue dots show the proportion of right choices at each orientation, with dot area proportional to the square root of the number of trials at that angle. The transition from solid to dashed in the black curve corresponds to the range of the presented orientation values. The left panels show examples of acceptable fits: the top-left shows good performance with a steep slope and minimal lapse rate, and the bottom-left shows small deviations around negative to mid-range angles but no major misfits. Participants with these fits were included in the analysis. The right panels show poor fits: the top-right shows a high lapse rate (19.9%), and the bottom-right shows considerable deviations from the fitted curve across orientations. Participants with these fits were excluded.

saccades) and muscle artifacts while preserving beta-band features. On average, 21 components were rejected per participant (range: 9–27). A second round of visual inspection was then conducted to reject any residual artifacts. Prior to the second round of artifact rejection, the data were re-segmented for two stimulus-locked analyses: (1) epochs spanning −3.5 sec to 3 sec relative to the onset of the decision stimulus for event-related time-frequency analysis, and (2) epochs from −2.5 sec to 1 sec relative to the letter cue for baseline normalization. To ensure complete event capture and exclude abnormally slow initial responses to the letter cue, trials with initial response RTs exceeding 1.5 sec were removed. Consistent with the behavioural analysis, trials were also excluded if the initial response was incorrect, or if no decision response occurred within the 3-sec response window.

2.5.2.2. Scalp-level time–frequency analysis. To inform source localization and virtual channel construction, we first computed scalp-level time–frequency representations (TFRs) to identify beta-band desynchronization and rebound following initial responses. A sliding-window multi-taper Fourier transform was applied to two time-locked epochs: from −3.5 to 3 sec relative to the decision stimulus onset, and from −2.5 to 1 sec relative to the letter cue. Spectral power was estimated across frequencies from 5 to 40 Hz in 1 Hz steps, using 50 msec time steps and a frequency smoothing of 40% of the centre frequency (i.e., $\pm.4 \times f$). Analyses were performed separately for each participant, initial response (left/right), decision response (left/right), and delay (short/medium/long). TFRs time-locked to the decision stimulus onset were baseline-corrected using the −2.0 to 0 sec window relative to

the letter cue. Specifically, for each channel and frequency, power at each time point was expressed as a percentage change from the mean baseline power, computed by subtracting and then dividing by the baseline mean, and then multiplying by 100%. Grand-averaged, baseline-normalized beta-band activity (13–30 Hz) were used to define delay-specific time windows for subsequent source-level analyses: −.75 to −.25 sec (desynchronization) and −.25 to .25 sec (rebound) for short delay; −1.5 to −1.0 sec and −1.0 to −.5 sec for medium delay; and −3.0 to −2.75 sec and −2.75 to −2.25 sec for long delay, each relative to the decision stimulus onset. These windows corresponded to periods of strongest beta desynchronization and rebound induced by the initial response.

2.5.2.3. Beamforming source localisation and seed extraction. The selected time windows were used to identify the source locations with the largest contrast between beta synchronization and desynchronization. For this, cross-spectral density matrices were calculated at 22 Hz with a spectral smoothing of ±8 Hz for each delay, initial response, and participant. A standard three-shell volume conduction model and a 1 cm resolution source grid in MNI space were used to construct forward models and compute lead field matrices. Frequency-domain beamforming was performed using the Dynamic Imaging of Coherent Sources (DICS) method (Gross et al., 2001). A common spatial filter was computed from the combined time windows and then applied separately to each window to estimate source-level power. Beta band power was computed as the normalised difference between the rebound and desynchronization windows, by dividing their power difference by the average power across the two windows. The resulting source-level beta activity maps were averaged across delays and initial responses. To identify motor-related regions, left hemisphere activity was examined using right initial-response trials, and right hemisphere activity using left initial-response trials. The motor-related anatomical regions were identified using the SPM Anatomy Toolbox (Eickhoff et al., 2005). Group-level peak coordinates were identified in each hemisphere, and individual peaks were selected within a 3 cm radius of these group-level maxima. These individual peak coordinates served as seed points for virtual channel extraction, referred to as the left motor cortex (LMC) and right motor cortex (RMC). Source-level time series were extracted using the linearly constrained minimum variance (LCMV) beamforming method based on covariance matrices that were computed for the entire −3.5 to 3 sec time window relative to decision stimulus onset and frequencies between 5 and 40 Hz. The resulting spatial filters were then applied to the scalp-level data to extract single-trial virtual channel time series for each seed. This procedure was repeated for the epoch from −2.5 to 1 sec time-locked to the letter cue.

2.5.2.4. Source-level time-frequency analyses and statistical testing. Source-level TFRs of the virtual channel time series were computed using a single-taper sliding-window Fourier transform with a Hanning taper (5–40 Hz range in 1 Hz steps, 50 msec timesteps, 5 cycles). TFRs were computed separately for LMC and RMC, initial response (left/right), decision response (left/right), and delay (short/medium/long). TFRs time-locked to the decision stimulus were baseline-corrected using the −2 to 0 sec interval from the letter cue-locked data, by calculating the percentage change from the mean baseline power for each frequency. The resulting grand-averaged, normalized TFRs were visualized across all combinations of motor cortex (LMC/RMC), initial and decision responses (left/right), and delay (short/medium/long), for each seed location. To investigate whether lateralized beta power at the onset of the decision period varied across stimulus onset delays, we extracted beta power (13–30 Hz) within the 0 to .25 sec window during which the decision stimulus was displayed. For each delay, beta power was computed separately for the motor cortex contralateral and ipsilateral to the initial motor response. We then calculated the difference between contralateral and ipsilateral beta power (hereafter referred to as contra–ipsi beta power), providing a measure of lateralized sensorimotor beta power. The values were averaged across the defined time and frequency window, and a one-way repeated-measures ANOVA was conducted to test for a significant effect of stimulus onset delay on contra–ipsi beta power. To examine beta dynamics at the single-trial level, we also extracted beta power for each trial, averaged over the 0 to .25 sec window relative to the decision stimulus onset. For each trial, beta power was baseline-corrected using the −2 to 0 sec interval from the letter cue–locked data, computed as the average across trials for each subject, delay, decision response, and initial response. We then calculated contra–ipsi beta power relative to the initial response and used this normalized index as a predictor in mixed-effects models of trial-level decision bias and RTs.

2.5.3. *Brain–behaviour relationships*

To test our hypothesis that stronger sensorimotor beta lateralization during decision stimulus presentation is associated with alternation bias, we conducted two linear mixed-effects analyses: (i) at the condition level where data were averaged across trials for each of the three stimulus onset delays, decision bias, quantified as the psychometric threshold shift between left- and right-initial response trials, was used as the dependent variable; (ii) at the trial level, alternation probability, coded as repeat (0) or alternate (1) depending on whether the decision response matched the initial response, was used as the dependent variable. We focused these analyses on the most difficult trials with orientation values constrained between −5° and +5°, as choice history biases are known to be strongest when perceptual evidence is weak. Prior work (Fründ et al., 2014) showed that up to 32% of decision variance on difficult trials (55–75% accuracy) is attributable to prior choices, whereas on easier trials (>75% accuracy), behaviour is almost entirely stimulus-driven. For the condition-level analysis, decision bias was modelled across all subjects and delays, using averaged contra–ipsi beta power as the main predictor. The model included between-subject contra-ipsi beta power (each participant's mean across the three delays) and within-subject beta deviation (contra-ipsi beta power values for each delay minus the participant's mean) as fixed effects, and a random intercept for subject. This approach allowed us to examine both between-subject variability, reflecting whether participants with stronger beta lateralization also exhibited stronger alternation bias,

and within-subject variability reflecting whether beta lateralization was associated with decision bias across delays within participants (Enders & Tofighi, 2007; Rights & Sterba, 2019). For the trial-level analysis, we fitted a logistic mixed-effects model predicting whether the decision response alternated (1) or repeated (0) the initial response on a given trial. Trial-level contra–ipsi beta power during decision stimulus presentation and stimulus onset delay (as a categorical effect: short, medium, long) were included as fixed effects, together with a random intercept for subject. This analysis examined whether moment-to-moment fluctuations in beta power were associated with decision bias at the single trial level.

For exploratory purposes, we further examined whether sensorimotor beta lateralization was associated with decision speed. Two analogous linear mixed-effects models were conducted for RTs, matching the condition-level and trial-level structure of the decision-bias analyses: (i) at the condition level where mean RTs, computed as the average of median RTs for each combination of initial response (left/right) and decision response (left/right) within each delay, were used as the dependent variable; (ii) at the trial level, using trial-wise RTs as dependent variable. At the condition level, the model included both between-subject contra–ipsi beta power (each participant's mean across the three delays) and within-subject beta deviation (contra-ipsi beta power values for each delay minus the participant's mean) as fixed effects, with a random intercept for subject. At the trial level, the model included trial-level contra–ipsi beta power and stimulus onset delay (categorical: short, medium, long) as fixed effects, and a random intercept for subject.

3. Results

3.1. Behavioural results

We firstly characterised the overall behavioural pattern in participants' decision-making performance using the median RTs across combinations of initial response (left/right), decision response (left/right) and stimulus onset delay (short/medium/long). Median RTs were computed per participant for each combination and orientation and then averaged across participants. As shown in Fig. 3A, RTs exhibited a consistent trend: responses were slower for grating stimuli near the vertical axis, in line with increased task difficulty at more vertical orientations. Notably, across all three stimulus onset delays, participants appeared to respond consistently faster following right initial responses compared to left initial responses. This observation was supported by an exploratory trial-level linear mixed-effects analysis, which revealed that trials with right initial responses (median = .55 sec, IQR = [.44, .69] sec) were significantly faster than those with left initial responses (median = .57 sec, IQR = [.46, .73] s), $\beta = -.05$ sec, SE = .004 sec, $t = -11.66$, $p < .001$. Additionally, trials with right decision responses (median = .55 sec, IQR = [.45, .70] sec) were significantly faster than those with left decision responses (median = .57 sec, IQR = [.45, .72] sec), $\beta = -.02$ sec, SE = 0 .004 sec, $t = -4.11$, $p < .001$. RTs were also influenced by stimulus onset delays: the short delay (median = .58 sec, IQR = [.47, .73] sec) resulted in significantly slower responses compared to the medium (median = .54 sec, IQR = [.44, .69] sec) and long delay (median = .55 sec, IQR = [.45, .70] sec). Longer delays significantly accelerated decision speed relative to the short delay (medium: $\beta = -.04$ sec, SE = .01 sec, $t = -7.41$, $p < .001$; long: $\beta = -.03$ sec, SE = .01 sec, $t = -5.62$, $p < .001$), as illustrated in Fig. 3B.

To examine whether the initial response biased subsequent decisions towards alternation, we fitted individual psychometric functions for trials beginning with a left versus a right initial response at each stimulus onset delay. We quantified decision bias as the difference in decision thresholds (i.e., the orientation at which participants responded "right" 50% of the time) between left-initial and right-initial trials. Negative decision bias indicates an alternation bias (i.e., a tendency to make a decision opposite to the initial response), while positive bias reflects a repetition bias. As shown in Fig. 3C, a positive mean decision bias was observed in the short delay (.11°, 95% CI = [−.40°, .62°]), indicating that the threshold for left-initial trials (Mean = −.19°, SD = 1.02°) was higher than that for right-initial trials (Mean = −.25°, SD = .85°). This result suggested a tendency toward repetition through a higher likelihood of making a decision consistent with the initial response. However, the effect was not statistically significant, as revealed by a Wilcoxon signed-rank test (Mdn = .11°, W = 156, z = .55, $p = .584$). In contrast to the short delay, negative decision biases were observed in both the medium (Mean = −.01°, 95% CI = [−.47°, .45°]) and long delay (Mean = −.16°, 95% CI = [−.60°, .27°]). In the medium delay, thresholds were slightly lower following left-initial responses (Mean = −.30°, SD = 1.01°) than right-initial responses (Mean = −.29°, SD = .84°), suggesting a weak alternation bias. A similar pattern emerged in the long delay, where thresholds following left-initial responses (M = −.16°, SD = 1.06°) were lower than those following right-initial responses (Mean = .00°, SD = .72°). However, neither effect reached statistical significance (medium: Mdn = −.14°, W = 87, z = −1.55, $p = .121$; long: Mdn = −.26°, W = 112, z = −.79, $p = .429$). These findings suggest that initial motor responses do not exert a systematic bias on subsequent perceptual decisions at a group level. Moreover, decision bias did not significantly differ between the three stimulus onset delays, as indicated by a Friedman test, $\chi^2(2, N = 23) = 1.04$, $p = .594$, Kendall's W = .02. The absence of a significant difference may be attributed to substantial individual variability (consistent across the three delays), with some participants exhibiting alternation biases and others showing repetition biases.

3.2. EEG results

We identified the source locations with the largest contrast between beta synchronization and desynchronization induced by the initial response in order to extract source-level time series. Beamformer source images were computed for each participant, type of initial response and stimulus onset delay, and subsequently grand-averaged separately for left and right initial responses. Results reveal prominent beta activity in the hemisphere contralateral to the initial response

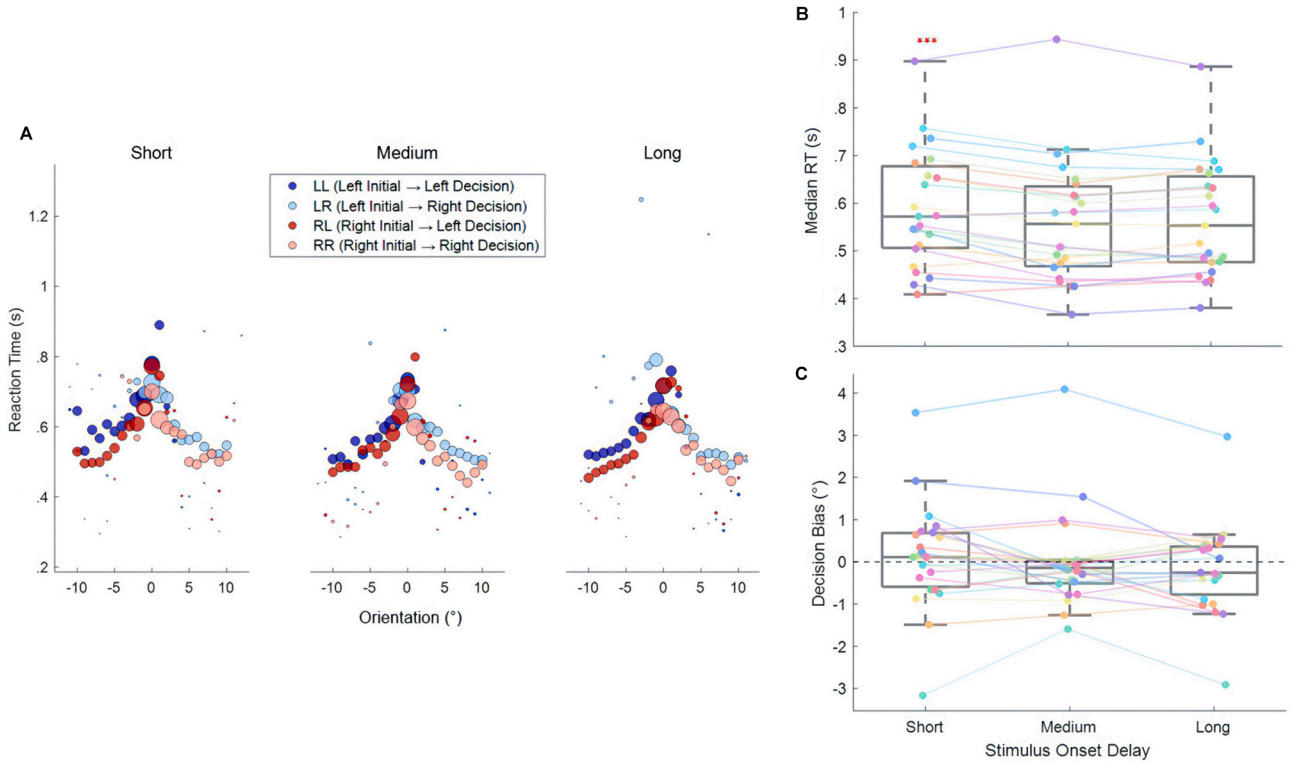

Fig. 3 – (A) Group-level median RTs as a function of stimulus orientation. Each subplot combines initial (left/right) and decision (left/right) response types and displays data per stimulus onset delay (short, medium, long). Positive orientation values represent clockwise stimuli, while negative values indicate anticlockwise stimuli. Task difficulty increases as orientation approaches 0°, corresponding to vertical. The area of each data point represents the proportion of trials associated with each orientation and combination. (B) Individual participants' median reaction times across stimulus onset delays. In each boxplot, the central line represents the median, while the upper and lower edges indicate the 75th and 25th percentiles, respectively. Whiskers indicate the most extreme values within 1.5 times the interquartile range. Individual data points are connected by coloured lines to illustrate within-subject trajectories across the three delays. Three red asterisks indicate $p < .001$, suggesting a significant slower RTs observed in the short delay compared to the medium and long delay. (C) Decision bias computed as the threshold difference between left- and right-initial response trials, plotted across the three stimulus onset delays. Negative values indicate an alternation bias (i.e., a tendency to make a decision opposite to the initial response), while positive values reflect a repetition bias. Boxplots follow the same format as in (B), with coloured lines connecting each participant's data across delays.

hand (Fig. 4). Group-level peak coordinates were identified in each hemisphere. In the left hemisphere (based on right initial-response trials), peak beta activity was localized at MNI coordinates [−40, 0, 60] mm, corresponding to the left premotor and middle frontal gyrus. In the right hemisphere (based on left initial-response trials), the peak was observed at [40, −20, 70] mm, localizing to the right primary motor cortex. We refer to these locations as LMC and RMC in the remainder of the manuscript.

Grand-averaged, baseline-corrected source-level TFRs for LMC and RMC across all combinations of initial response (left/right) and decision response (left/right), for the short, medium, and long stimulus onset delays are shown in Figs. 5–7. Across all onset delays, beta power was still decreased for approximately 250 msec following the termination of the initial response, followed by a prominent beta rebound in the hemisphere contralateral to the responding hand, lasting approximately 500 msec. Following the onset of the decision stimulus, a second beta decrease emerged rapidly, lasting until approximately 250 msec after the initiation of the decision response. This was again followed by a robust beta rebound lasting for approximately 1 sec. The second beta rebound was stronger contralateral to the decision response hand in trials with left initial responses, as expected. However, in trials beginning with right initial responses, the rebound remained consistently stronger over the LMC, regardless of the expected lateralization.

To better visualize and compare the temporal dynamics of lateralized beta power during the decision task across the three delays, we computed contra–ipsi beta power time series relative to the initial response hand for each delay, as shown in Fig. 8A. Contra–ipsi beta power was clearly elevated at the time of decision stimulus onset in the short delay, partially persisted in the medium delay, and returned more fully to baseline in the long delay. This pattern reflects a significant main effect of delay, as revealed by a repeated-measures

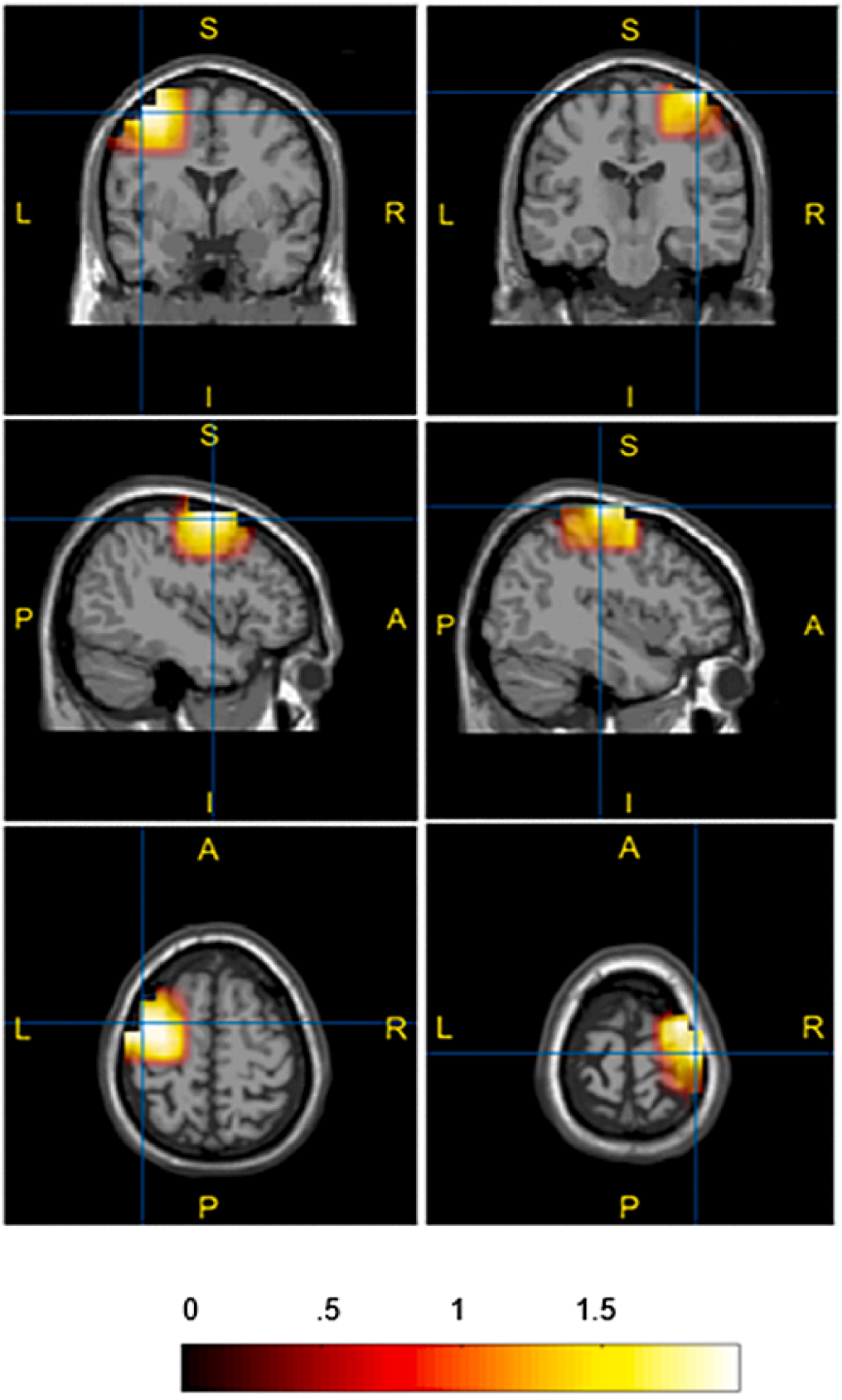

Fig. 4 – Grand-averaged source maps of the contrast between beta-band rebound and desynchronization induced by the initial response. In the left panels (right initial-response trials, assessing left–hemisphere activity), the peak beta activity was localized at MNI coordinates [–40, 0, 60] mm, consistent with the left premotor and middle frontal gyrus. In the right

ANOVA on contra–ipsi beta power averaged across 13–30 Hz and the 0 to 250 msec window of decision stimulus presentation (Fig. 8B). Mean contra–ipsi beta power was highest in the short delay (Mean = .24, SD = .23), lower in the medium delay (Mean = .15, SD = .09), and lowest in the long delay (Mean = .09, SD = .11), $F(2, 44) = 6.72$, $p = .003$, $\eta^2_p = .23$ (Greenhouse–Geisser corrected $p = .011$). Bonferroni-adjusted post hoc comparisons revealed significantly lower contra–ipsi beta power in the long delay compared to both the medium delay (mean difference = −.06, SE = .02, $p = .021$) and short delay (mean difference = −.16, SE = .05, $p = .024$). The difference between the short and medium delay was not statistically significant (mean difference = −.09, SE = .05, $p = .17$).

3.3. *Brain–behaviour relationships*

To examine whether stronger sensorimotor beta lateralization during decision stimulus presentation are associated with alternation bias, we conducted two linear mixed-effects analyses: (i) at the condition level where data were averaged across trials for each of the three stimulus onset delays, decision bias, quantified as the psychometric threshold shift between left- and right-initial response trials, was used as the dependent variable; (ii) at the trial level, using alternation probability, coded as repeat (0) or alternate (1) depending on whether the decision response matched the initial response on a given trial, as the dependent variable.

For the condition-level analysis, the model included between-subject contra-ipsi beta power (participant mean across the three delays) and within-subject beta deviation (contra-ipsi beta power for each delay minus the participant's mean) as fixed effects, allowing us to assess whether participants with stronger beta lateralization exhibited greater alternation bias and whether this relationship also existed within-participants across delays. Consistent with our hypotheses, the between-subject beta component negatively predicted decision bias ($\beta = -3.44$, SE = 1.63, $t = -2.11$, $p = .019$, one-tailed; Fig. 8C, upper panel), suggesting that participants with stronger beta lateralization during decision stimulus presentation exhibited a greater tendency to alternate. In contrast, there was no significant effect of within-subject beta deviation on decision bias ($\beta = -.35$, SE = .41, $t = -.87$, $p = .194$, one-tailed), suggesting that variations in beta lateralization across stimulus onset delays within participants did not contribute to alternation bias.

For the trial-level analysis, we fitted a logistic mixed-effects model predicting the probability of alternation from trial-level contra–ipsi beta power, with stimulus onset delay included as a categorical covariate and subject as a random intercept. This analysis tested whether moment-to-moment fluctuations in beta power were associated with decision bias at the single-trial level. Consistent with our hypothesis, single-trial contra–ipsi beta power significantly predicted a higher probability of alternation ($\beta = .05$, SE = .03, $z = 1.82$, $p = .034$, one-tailed; Fig. 8C, lower panel), whereas delay factors showed no significant effect (p values > .40), suggesting that the relationship between beta lateralization and decision bias also persists at the single-trial level.

Taken together, these results suggest that beta lateralization during decision stimulus presentation is associated with alternation bias both as a stable individual tendency and as a momentary trial-level neural signal, and this beta-bias link was not tied to specific temporal delays between initial motor responses and subsequent decision stimulus presentation.

For exploratory purposes, two analogous linear mixed-effects models were conducted for RTs, matching the condition-level and trial-level structure of the decision-bias analyses: (i) at the condition level where mean RTs, computed as the average of median RTs for each combination of initial response (left/right) and decision response (left/right) within each delay, were used as the dependent variable; (ii) at the trial level, using trial-wise RTs as dependent variable. Similar as for the condition-level model for decision-bias, the condition-level model for RT included between-subject contra-ipsi beta power (participant mean across the three delays) and within-subject beta deviation (contra-ipsi beta power for each delay minus the participant's mean) as fixed effects, as well as subject as a random intercept. This allowed us to test whether participants with stronger beta lateralization exhibited slower or faster decision speed and whether this relationship also existed within participants across delays. Neither the between-subject beta component ($\beta = .30$, SE = .25, $t = 1.18$, $p = .243$) nor the within-subject beta deviation ($\beta = .006$, SE = .03, $t = .25$, $p = .807$) significantly predicted RTs. Consistent with this, single-trial analysis using a linear mixed-effects model as a function of RTs with trial-level contralateral–ipsilateral beta power and stimulus-onset delay as predictors also failed to reveal a significant relationship between trial-wise beta power and RT ($\beta = .004$, SE = .004, $t = 1.16$, $p = .247$). These results suggest that beta lateralization was not associated with decision speed in our data.

4. Discussion

The aim of the present study was to investigate whether prior motor states can bias subsequent perceptual decisions through the lens of sensorimotor beta oscillations. We designed a perceptual decision-making task in which participants judged whether a briefly presented orientation grating was tilted clockwise or anticlockwise by responding with a left- or right-hand button press. Each decision was preceded by an initial, choice-unrelated motor action, cued by letters

panels (left initial-response trials, assessing right–hemisphere activity), the peak was observed at [40, −20, 70] mm, within the right primary motor cortex. The colour bar reflects the magnitude of the normalised beta power difference, with positive values indicating higher power during the rebound compared to the desynchronization period. Individualized peak coordinates were identified within a 3 cm radius of the group-level peaks and served as the LMC and RMC seed locations for subsequent virtual channel extraction.

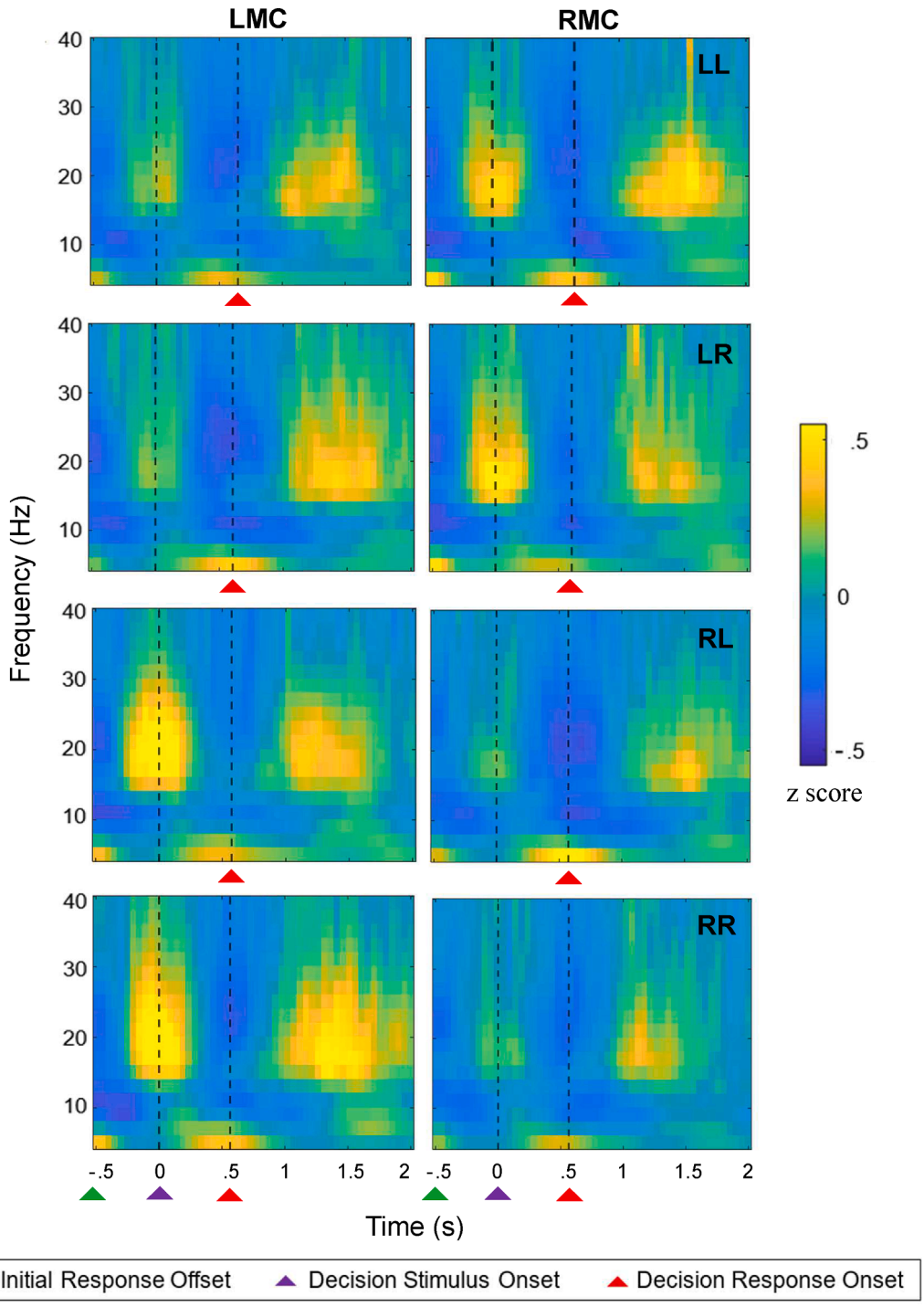

Fig. 5 – Grand-averaged time-frequency representations for the LMC and RMC across all combinations of initial response (left/right) and decision response (left/right) for the short onset delay. Power spectra are time-locked to the onset of the decision stimulus and baseline-corrected using the −2 to 0 sec interval relative to the letter cue. Each horizontal pair of panels represents one initial–decision response combination (e.g., "LL" = left initial response and left decision response), with LMC activity shown on the left and RMC activity on the right. The green triangles indicate the termination of the initial response. The purple triangles indicate the onset of the decision stimulus presentation. The red triangles indicate the median RT of the decision response.

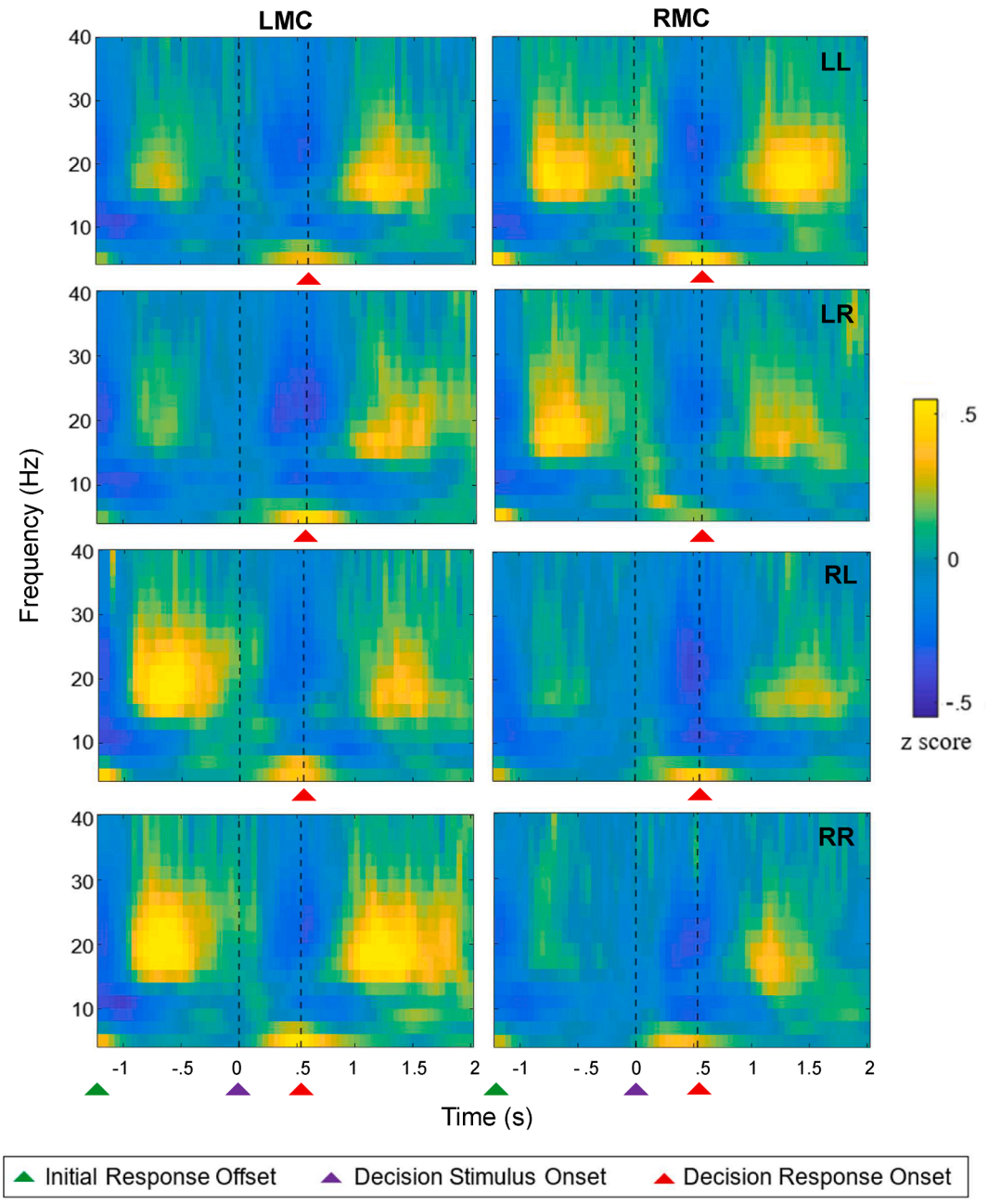

Fig. 6 – Grand-averaged time-frequency representations for the LMC and RMC across all combinations of initial response (left/right) and decision response (left/right) for the medium onset delay. Additional details are provided in Fig. 5.

and requiring a left- or right-hand button press, with three variable delays separating this initial motor response and decision stimulus presentation. The results revealed that beta power, extracted from sources in left and right motor cortex, following the initial movement was associated with subsequent decision bias: Participants exhibiting stronger post-movement beta power lateralization during decision stimulus presentation showed a greater alternation bias, and higher beta power lateralization also related to increased alternation probability at the single-trial level, independent of the delay between the initial motor response and the decision stimulus. These findings suggest that beta activity may both index individual susceptibility to decision bias and act as a transient neural signal shaping alternation behaviour.

Behaviourally, we found no systematic decision bias as a function of the initial motor response, indicated by the lack of a significant difference in threshold for the psychometric functions fitted separately to trials following left versus right initial responses. Before discussing the differences with other studies, we should emphasize that our psychometric-function approach provides a robust and widely established methodology for quantifying perceptual bias. By modelling how

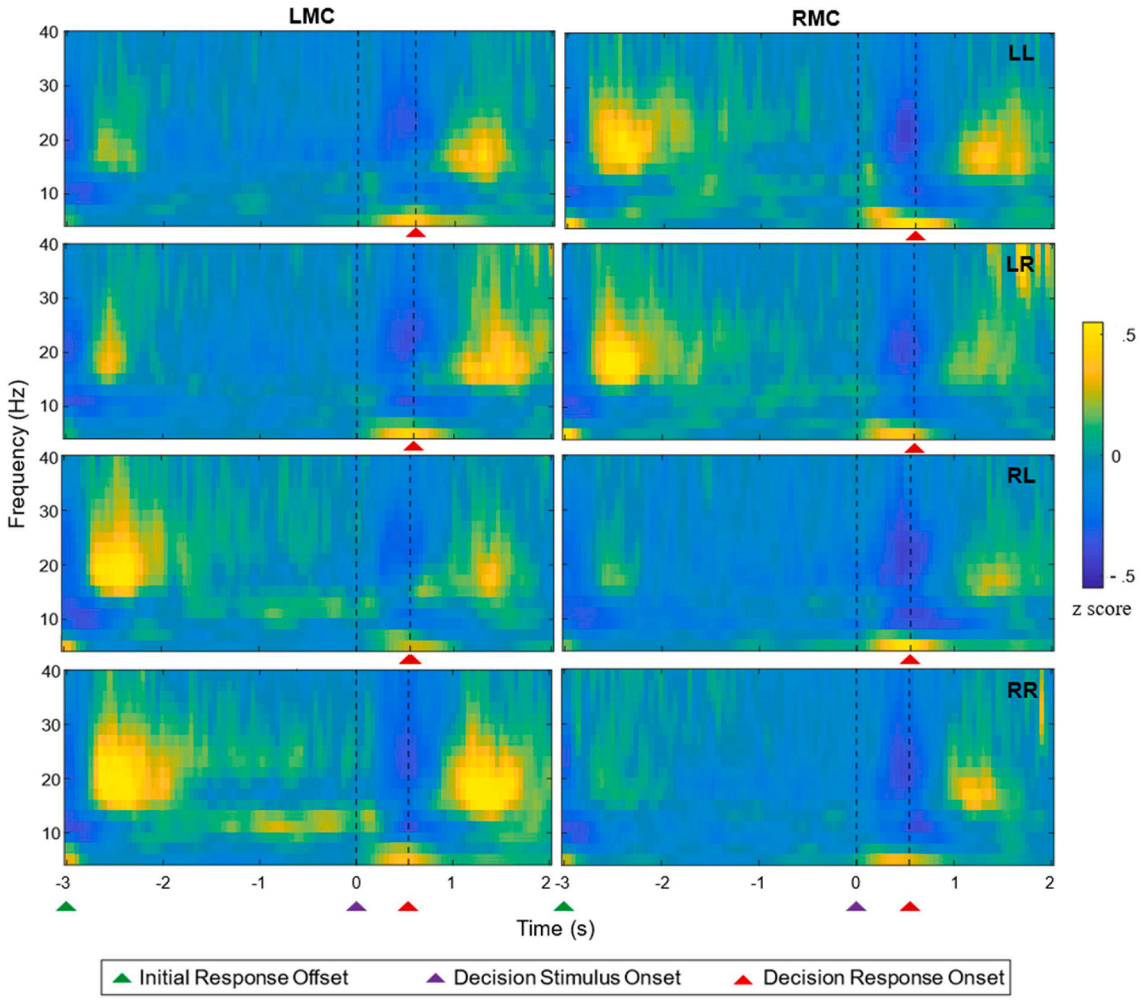

Fig. 7 – Grand-averaged time-frequency representations for the LMC and RMC across all combinations of initial response (left/right) and decision response (left/right) for the long onset delay. Additional details are provided in Fig. 5.

response probability changes with stimulus evidence, it integrates all trial-level data while reducing random noise, an approach broadly adopted in perceptual decision-making studies (e.g., Hagura et al., 2017; Linares et al., 2019; Urai & Donner, 2022). The lack of a systematic decision bias suggests that the prior motor action did not influence subsequent perceptual decisions at the behavioural group level. Such an absence of overt behavioural bias is not surprising, as the initial motor response in our task was entirely choice-unrelated and did not convey any decision-related information, and thus might not engage higher-order cognitive computations. The task manipulation differs from those used in previous studies (Assarioti et al., 2025; Burk et al., 2014; Hagura et al., 2017; Marcos et al., 2015), which found that a decision bias could result from a manipulation of motor effort during decision execution, an inherently choice-dependent variable that is naturally integrated into the decision-making process. The lack of a motor history effect on the behavioural level in our results is consistent with the findings of Akaishi et al. (2014) and Braun et al. (2018), both of whom used variable stimulus-response mappings and unpredictable delays, and found that sequential dependencies in behaviour were attributed primarily to previous choices, rather than to motor history. By contrast, Pape et al. (2017) and Zhang and Alais (2020) reported clear motor history effects. Zhang and Alais (2020) observed a motor alternation bias under variable stimulus-response mappings, indicating that motor history can influence decisions independently of perceptual choice history. Pape et al. (2017), using a similar paradigm to ours with a choice-unrelated motor action and variable response mappings, found an increased tendency to alternate choices.

These discrepancies in results may reflect differences in task structure, as also observed by Fründ et al. (2014). For example, our use of extended stimulus-onset delays, similar to those employed by Akaishi et al. (2014) and Braun et al. (2018), may have reduced sensitivity to subtle motor-history effects at the behavioural level. Previous studies have shown that choice-history biases are most pronounced following fast responses, when the subsequent decision occurs shortly after the preceding movement (Bonaiuto et al., 2016; Leite & Ratcliff, 2011; Rustichini and Padoa-Schioppa, 2015; Urai et al., 2019; White & Poldrack, 2014). Moreover, the presence or absence

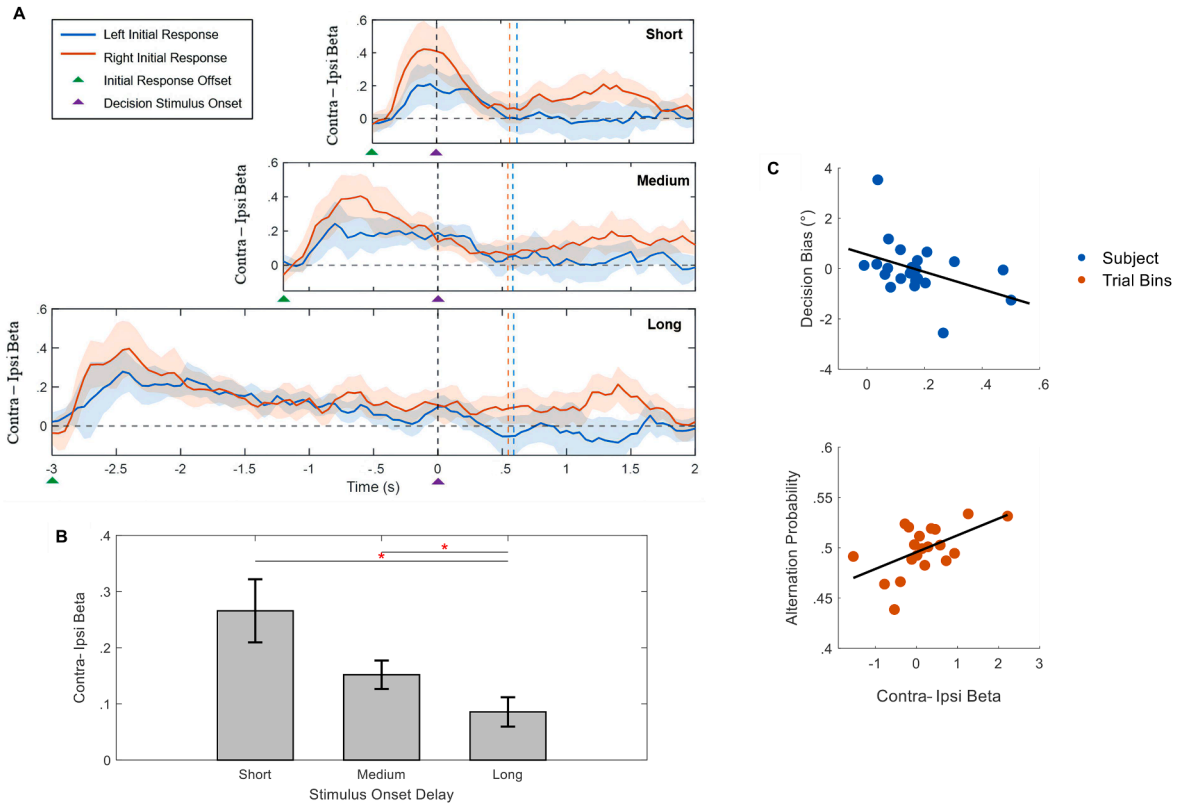

Fig. 8 – (A) Lateralized beta power time series relative to the initial response hand across short, medium, and long delay (top to bottom panels), time-locked to the onset of the decision stimulus and baseline-corrected using the −2 to 0 sec interval relative to the letter cue. The blue solid line shows lateralized beta power for left initial-response trials, computed as RMC minus LMC; the blue dashed vertical line indicates the median RT for the decision response in these trials. The red solid line shows laterlized beta power for right initial-response trials, calculated as LMC minus RMC; the red dashed vertical line marks the median RT for the decision response in these trials. The shaded areas indicate the 95% confidence interval of the mean lateralized beta time course. (B) Lateralized beta power averaged across the 13–30 Hz beta frequency range and the 0 to 250 msec window of decision stimulus presentation, shown for the short, medium, and long delay. Bar heights represent the mean value across participants, and whiskers indicate the standard error of the mean (SEM). Contra–ipsi beta power decreased progressively with increasing delay duration. Significant differences were observed between the short and long delay ($p = .024$), as well as between the medium and long delay ($p = .021$), as determined by repeated-measures ANOVA with Bonferroni-adjusted post hoc tests. The red asterisk indicates $p < .05$. (C) Upper panel: negative relation between mean contra–ipsi beta power (averaged per subject) and decision bias, estimated using the linear mixed-effects model ($\beta = -3.44$, $p = .019$, one-tailed). This indicates that stronger beta lateralization was associated with a larger alternation bias. For visualization, a regression line was fitted to subject-wise means of decision bias and contralateral–ipsilateral beta power, both averaged across delays. Lower panel: positive relation between trial-level contra–ipsi beta power and alternation probability, showing that trials with greater beta lateralization were more likely to result in an alternated response ($\beta = .05$, $p = .034$, one-tailed). For visualization, single-trial beta power values were divided into 20 quantile bins for each participant, then averaged over trials and participants within each bin. A regression line was subsequently fitted to the mean beta power and corresponding alternation probability across bins. Note that despite a different sign in slope, results in both panels point at an increased tendency to alternate the decision compared to the initial response with stronger beta lateralization.

of feedback can impact decision strategies, such that feedback may prompt participants to shift their decision criterion following errors (Fründ et al., 2014; Pape et al., 2017). Task difficulty is another factor: choice-history biases are often more pronounced in difficult trials when stimulus evidence is weak, and decisions rely more on internal priors (Fründ et al., 2014). In addition, decision uncertainty has been shown to modulate history biases, either dampening or amplifying them depending on context (Braun et al., 2018; Koizumi et al., 2015; Urai et al., 2017).

Another possibility for the absence of a behavioural decision bias is that susceptibility to decision bias might reflect individual differences, with some participants showing alternation tendencies and others showing repetition, potentially

cancelling out any group-level effect (Fründ et al., 2014; Urai & Donner, 2022; Urai et al., 2019). Such inter-individual differences are reflected in our neurophysiological data: participants with stronger beta power lateralization during decision stimulus presentation exhibited a greater tendency to alternate their decision compared to the initial response. These findings suggest that beta lateralization may serve as a sensitive marker of motor cortex involvement in decision making, revealing individual differences in decision strategies that are not necessarily captured by group-mean behaviour under the current experimental conditions. Consistent with this, Pape and Siegel (2016) also reported between-subject associations between beta lateralization and response alternation. Additionally, we found that beta lateralization on a single-trial basis was a significant predictor of alternation probability, indicating that beta activity not only reflects a stable individual predisposition but also acts as a moment-to-moment neural signal shaping choice behaviour. This pattern again aligns with Pape and Siegel (2016), who observed trial-by-trial correlations, and with Urai and Donner (2022), who used single-trial modelling to show that motor-history signals shift the starting point of the decision process toward alternation.

This alternation effect is likely driven by the inhibitory role of beta oscillations (Jurkiewicz et al., 2006; Pfurtscheller et al., 1996; Van Wijk et al., 2009, 2012), which may suppress the repetition of recently executed actions. In principle, various neuronal mechanisms could underlie such an inhibitory effect, e.g., increased inhibitory interneuron activity, a reduced excitability of corticospinal neurons, or post-movement recovery dynamics of neuronal activity, which we are unable to distinguish with our data. Interestingly, this relationship between beta lateralization and decision bias was not linked to specific temporal delays between the initial motor response and decision-stimulus presentation, suggesting that delay-specific fluctuations in beta power did not systematically relate to changes in decision bias within individuals. Such insensitivity to timing may reflect the highly dynamic and transient nature of motor-beta oscillations on a trial-by-trial basis (Little et al., 2019). At the same time, the absence of temporal modulation supports the notion that the beta-bias link represents a more stable motor-decision coupling, rather than a transient timing-driven phenomenon.

Our exploratory analyses also examined how prior motor states influence subsequent decision speed. Behaviourally, we found that executing right-hand responses, regardless of whether they occurred during the initial action or decision phase, consistently led to faster reaction times. Given that the majority of our participants were right-handed, this finding aligns with previous studies reporting a response speed advantage for the dominant hand (Dexheimer et al., 2022; Kerr et al., 1963). This dominant-hand advantage is possibly due to the larger motor representation for the dominant limb (Triggs et al., 1994, 1999) and lower thresholds for motor cortical excitability in the left hemisphere (Macdonell et al., 1991; Triggs et al., 1994). Beyond faster motor preparation, this advantage might also reflect the dynamics of the decision process itself that the brain can favour right-hand responses even before sensory evidence is accumulated.

At the neurophysiological level, we found no evidence of an association between beta lateralization and decision speed at the between-subject, within-subject, or trial level, suggesting that beta power during decision stimulus presentation did not drive decision speed in our data. This contrasts with previous findings showing that increased post-movement beta rebound relates to longer preparation times for subsequent motor actions (Muralidharan & Aron, 2021), likely due to differences in task demands: the subsequent action in their study did not involve perceptual decision-making and thus reflected purely motor reconfiguration. Another possibility is that RT within each participant in our data varied only minimally across delays, and that controlling for individual baseline RTs in our mixed-effects model may have reduced sensitivity to detect beta-related effects, even though we observed a significant between-subject correlation between mean beta power and mean RT ($\rho = .48$, $p = .021$, Spearman's correlation). The finding that beta lateralization is associated with decision bias but not decision speed suggests that beta activity in the motor system may influence the decision-making process by shifting the starting point of evidence accumulation and biasing the system toward alternation, rather than modulating the rate of evidence accumulation itself, consistent with the drift-diffusion modelling results of Urai and Donner (2022).

Another interesting observation is that the beta rebound around the decision phase appeared more bilateral compared to the rebound following the initial motor response (see Figs. 5–7). Bilateral beta rebound has been previously reported in both voluntary movement (Heinrichs-Graham et al., 2017; Jurkiewicz et al., 2006) and decision-making tasks (Donner et al., 2009; Pape & Siegel, 2016). This pattern could arise either from a carryover effect of the initial motor response especially when the time delay is short, or from the broader integration of associative regions during decision-making, which engages bilateral cortical networks more than simple motor execution. Furthermore, on trials that began with right-hand responses, the beta rebound remained consistently stronger over the left motor cortex, likely because the rebound threshold is lower in the contralateral (left) motor cortex for right-handed subjects, which allows left-hemispheric beta to dominate even during the subsequent decision phase.

Several limitations of the present study should be noted. To isolate motor-induced decision bias, we fixed the initial motor response cue within each block, ensuring voluntary movement without decision demands. While this design ensures a clean manipulation of motor-state readiness, it may have induced a specific motor configuration rather than neural processes that are computed at the cognitive decision-making stage. Our sample consisted primarily of right-handed participants, and asymmetries in decision speed were clearly present. Although beta power was computed as contralateral minus ipsilateral activity, such lateralization effects may still be influenced by handedness. Future research should therefore explicitly account for handedness when examining motor-decision interactions. Moreover, emerging work suggests that transient beta bursts, rather than sustained oscillations, play a critical role in motor control (Little et al., 2019). Future research should therefore examine how specific features of beta bursts, such as burst duration, amplitude, or waveform shape (Szul et al., 2023) contribute to perceptual decision-making processes. To some extent, our single-trial

analysis is conceptually similar to a burst-based approach, in that it captures between-trial variability in burst occurrence (including duration and amplitude), although it does not allow us to distinguish specific features of individual bursts. Finally, our findings also invite exploration of oscillatory markers in the motor cortex beyond beta activity. Prior studies have highlighted that sensorimotor alpha-band oscillations can build up prior to a response and may encode error decisions (Urai & Donner, 2022) or contribute to decision biases (Zhang et al., 2019). Whether this alpha modulation reflects top-down regulation of decision formation or simply motor preparation remains future investigation.

In summary, we investigated how prior motor states influence subsequent decision bias by embedding an initial left- or right-hand movement with variable delays before a perceptual decision-making task. We found that beta power elicited by the initial movement was associated with subsequent decision bias at both the between-subject and single-trial level: participants with stronger beta lateralization during decision stimulus presentation exhibited stronger alternation bias, and stronger beta lateralization related to higher alternation probability at the single-trial level, independent of the delay between the initial motor response and the decision stimulus. These results suggest that beta activity may both index individual susceptibility to decision bias and as a momentary neural signal influencing alternation behaviour. Within the framework of embodied decision-making, these findings provide support for the influence of motor cortex activity on the choice process.

CRediT authorship contribution statement

Ningjing Cui: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Robert J. van Beers:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Jeroen B.J. Smeets:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Bernadette C.M. van Wijk:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Data availability

Behavioural data, processed EEG data, and code are available on OSF (https://osf.io/rkxwz/). The raw EEG data are available from the corresponding author upon reasonable request.

Scientific transparency statement

DATA: Some raw and processed data supporting this research are publicly available, while some are subject to restrictions: https://osf.io/rkxwz.

CODE: All analysis code supporting this research is publicly available: https://osf.io/rkxwz.

MATERIALS: All study materials supporting this research are publicly available: https://osf.io/rkxwz.

DESIGN: This article reports, for all studies, how the author(s) determined all sample sizes, all data exclusions, all data inclusion and exclusion criteria, and whether inclusion and exclusion criteria were established prior to data analysis.

PRE-REGISTRATION: No part of the study procedures was pre-registered in a time-stamped, institutional registry prior to the research being conducted. No part of the analysis plans was pre-registered in a time-stamped, institutional registry prior to the research being conducted.

For full details, see the *Scientific Transparency Report* in the supplementary data to the online version of this article.

Funding

This project is funded by starter grant S/000038 awarded to B.C.M. van Wijk by the Vrije Universiteit Amsterdam.

Declaration of competing interest

The authors declare no competing interests.

Acknowledgements

The authors thank Prof. Andreas Daffertshofer for his valuable feedback and insights during the early stages of the experiment.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cortex.2026.01.003.

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