

Jointly modeling behavioral and EEG measures of proactive control in task switching

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Abstract

In this study, we implement joint modeling of behavioral and single-trial electroencephalography (EEG) data derived from a cued-trials task-switching paradigm to test the hypothesis that trial-by-trial adjustment of response criterion can be linked to changes in the event-related potentials (ERPs) elicited during the cue-target interval (CTI). Specifically, we assess whether ERP components associated with preparation to switch task and preparation of the relevant task are linked to a response criterion parameter derived from a simple diffusion decision model (DDM). Joint modeling frameworks characterize the brain-behavior link by simultaneously modeling behavioral and neural data and implementing a linking function to bind these two submodels. We examined three joint models: The first characterized the core link between EEG and criterion, the second added a switch preparation input parameter and the third also added a task preparation input parameter. The criterion-EEG link was strongest just before target onset. Inclusion of switch and task preparation parameters did not improve the performance of the criterion-EEG link but was necessary to accurately model the ERP waveform morphology. While we successfully jointly modeled latent model parameters and EEG data from a task-switching paradigm, these findings show that customized cognitive models are needed that are tailored to the multiple cognitive control processes underlying task-switching performance. This is the first paper to implement joint modeling of behavioral measures and single-trial electroencephalography (EEG) data derived from the cue-target interval in a cued-trials task-switching paradigm. Model hyperparameters showed a strong link between response criterion and the pre-target negativity amplitude. Additional parameters (switch preparation, task preparation) were necessary to model the cue-locked ERP waveform morphology. This is consistent with multiple cognitive control processes underlying proactive control and points to the need for more nuanced models of task-switching performance.

A subset of these findings were presented as a poster at the 2019 Australian Chapter of the Organization of Human Brain Mapping (OHBM), Callaghan, Australia.

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KEYWORDS

EEG, ERPs, evidence accumulation, hierarchical Bayesian estimation, joint modeling, task switching

1 | INTRODUCTION

Cognitive control refers to a set of processes that fine-tune behavior to achieve current goals and flexibly adapt goals depending on changes in context (Gratton et al., 2018). Event-related potentials (ERPs) have provided evidence for multiple neural components associated with proactive and reactive of cognitive control processes, and formal models of cognition have identified distinct latent parameters linked to decision-making in task-switching. However, current modeling approaches can only loosely map neural and behavioral parameters of cognitive control (de Hollander et al., 2016). In this study, we implement for the first time joint modeling of behavioral and neural measures derived from a cued-trials task-switching paradigm to characterize proactive cognitive control processes involved in maintaining or updating task goals.

Cued-trials task switching paradigms tap into core cognitive control processes that select, shift, and implement task goals and protect them from interference (Jamadar et al., 2015; Vandierendonck et al., 2010). Participants are presented with cues that are mapped to different tasks and must use these cues to prepare to respond to the relevant target dimension. For example, if the cue is associated with a Letter Task, they can prepare to classify the letter in the upcoming target as vowel or consonant. The following trial is a repeat trial if the next cue is also mapped to the Letter task. Alternatively, on switch trials, the following cue is mapped to the alternative task, e.g., a Number task, and the participant must update the task-set and classify the number in the upcoming target as odd or even.

Task switch trials are associated with poorer performance than task repeat trials. This “switch cost” is smaller when the cue provides valid information that the task will change and the cue-target interval is sufficiently long to upload the new task rules before target onset (e.g., Meiran, 2000; Nicholson et al., 2005). Event-related potentials (ERPs) recorded during the cue-target interval show temporally distinct components associated with proactive control processes (Braver, 2012) involved in preparing to switch or repeat a task (Jost et al., 2008; Karayanidis et al., 2010; Lavric et al., 2008; Periañez & Barceló, 2009). A large parietal switch-positivity¹ is elicited by cues that

reliably index an upcoming switch trial (Barceló et al., 2006; Finke et al., 2012; Jost et al., 2008). The amplitude of the switch-positivity is inversely related with trial by trial variability in the behavioral switch cost (Karayanidis, Provost, et al., 2011) and directly associated with switch-related BOLD signal activation in the posterior parietal cortex (Jamadar et al., 2010). The amplitude of the later pre-target negativity is larger for partially informative cues, that is, cues for which the identity of the task to be performed is revealed only at target onset (Karayanidis et al., 2009), and is inversely related with trial by trial variability in the behavioral switch cost (Karayanidis, Provost, et al., 2011).

Decision making behavior in many contexts, including cued-trials task switching, can be understood from the perspective of the accumulation of decision-relevant evidence to a response threshold or criterion (Forstmann et al., 2016; Ratcliff et al., 2016). The response criterion is a latent construct that can be estimated from evidence accumulation models, such as the diffusion decision model (DDM; Ratcliff, 1978). It represents the level of caution or the amount of information required when selecting one of two decisions (e.g., is the number odd or even). In cued-trials paradigms, the response criterion is larger for switch than repeat trials (Karayanidis et al., 2009; Karayanidis, Provost, et al., 2011; Schmitz & Voss, 2012), indicating that the level of response caution can be readjusted for each trial depending on whether the cue indicates that the task will repeat or switch. Higher response criterion for switch trials is associated with a smaller cue-locked switch-positivity, suggesting that less efficient preparation to switch task results in more cautious decision making (Karayanidis et al., 2009). A higher response criterion for switch trials is also associated with smaller BOLD signal activation in the pre-supplementary motor area and greater activation in the subthalamic nucleus (Mansfield et al., 2011), consistent with more cautious responding under less prepared conditions. These findings suggest that the information provided by the cue is used to prepare to switch or repeat task for the upcoming target and to set response criterion accordingly. The association between response criterion setting and amplitude of the cue-locked switch-positivity further suggests that the latter represents or triggers the adjustment of response criterion.

However, these modeling approaches can only loosely characterize the links between brain and behavior because the two data sources are modeled independently

¹There is considerable discussion in the field about whether this represents an increased P300 component or a distinct ERP component, e.g., Periañez and Barceló (2009). We discuss this at length in Karayanidis and McKewen (2021) and justify our reason for preferring the use of the term “switch-positivity” over enlarged P300.

and their relationship is examined using simple regression approaches (de Hollander et al., 2016).

The model-based cognitive neuroscience framework (Forstmann et al., 2011) provides a novel approach for characterizing the coupling between neural and cognitive mechanisms that underlie the dynamics of cognitive control by linking latent parameters derived from formal models of cognition with functional neural measures. This approach has been used to link distinct latent cognitive processes to time-sensitive event-related potential (ERP) components elicited by task stimuli (Palestro et al., 2018). The joint modeling framework directly characterizes the brain-behavior link by simultaneously modeling behavioral and neural data, and implementing a linking function to bind these two sub-models (Turner et al., 2017, 2019). This joint model approach simultaneously determines latent variables to best account for the combined behavioral and neural data.

Therefore, the neural data can affect the estimation of the parameters of the behavioral model and vice versa (Turner et al., 2013, 2019). Van Ravenzwaaij et al. (2017) illustrated the strength of this approach by jointly modeling behavioral and target-locked EEG data from a mental rotation task using a linear ballistic accumulator (LBA) model. Drift rate (i.e., a latent parameter that characterizes the rate at which evidence is accumulated towards a decision) was a stronger linking parameter than non-decision time (i.e., the perceptual and response processes that are unrelated to the decision but affect response time) and explained rotation angle effects in both the behavioral data and the target-locked rotation-related negativity. This study demonstrated the strength of the joint modeling approach in directly linking EEG and behavioral data associated with reactive cognitive control. Specifically, EEG data associated with mentally rotating the representation of the task-relevant target stimulus were directly associated with decision model parameters that characterize the efficiency of the evidence accumulation process (i.e., drift rate).

The present study for the first time uses this joint modeling approach to establish the computational link between cue-locked EEG activity that represents proactive control processes involved in maintaining or updating task goals and the response criterion parameter of a behavioral model that is based on principles of evidence accumulation using the DDM approach. We implement joint modeling of single-trial behavioral measures and cue-locked EEG data derived from a cued-trials task switching paradigm to link trial-by-trial adjustment of response criterion to event-related potentials (ERP) elicited in preparation to switch or repeat a task. We use the to/away task switching paradigm (Karayanidis et al., 2009) in which four cues differ in the information they provide

about whether to switch task or repeat the same task and which task to perform on the upcoming target. Typically, all cue-locked ERP waveforms show a large parietal positive deflection that resolves into a negative shift just before target onset. When cues validly indicate that the task will change, they also elicit a switch-positivity, even if they do not specify which task will be performed on the upcoming target. Cues that identify the relevant task for the upcoming target, regardless of whether the task is the same as the previous trial or will change, elicit a smaller pre-target negativity. Thus, the switch-positivity varies with the need for switch preparation, whereas the pre-target negativity varies with level of task preparation. In this study, we examine the parameters arising from the behavioral-neural joint model to test whether the function that links response criterion and EEG is sufficient to characterize variability in cue-locked ERPs as a function of cue type. Based on earlier evidence for a relationship between the switch-positivity and response criterion, we predict that the linking parameters will be stronger within the time range of the switch-positivity (400–600 msec post-cue). Given evidence from cue-locked ERPs for multiple proactive control processes, we then examine whether joint models that also characterize switch preparation and/or task preparation processes provide better estimation of behavioral and neural data.

2 | METHOD

2.1 | Participants

We conducted secondary analysis of data from 45 undergraduate students (31 female, right handed) who completed one of two studies for course credit (Karayanidis et al., 2009; Mansfield et al., 2011). We combined these two data-sets that used an identical task-switching paradigm.

2.2 | Task and stimuli

A gray circle (5° of visual angle) was continuously presented and divided into six wedges. Pairs of adjacent wedges were marked with thicker lines denoting three task sections: letter, digit and color (see Figure 1a). The target was a pair of characters (i.e., combinations of a letter, a digit or a non-alphanumeric symbol) and was presented either in gray or in one of four “hot” or “cold” colors. Each target (e.g., gray A4) consisted of three dimensions: one relevant to the currently cued task (e.g., the letter A mapped to a left hand response), one selected randomly from one of the two alternative tasks and incongruently mapped with the relevant task (e.g., the digit 4

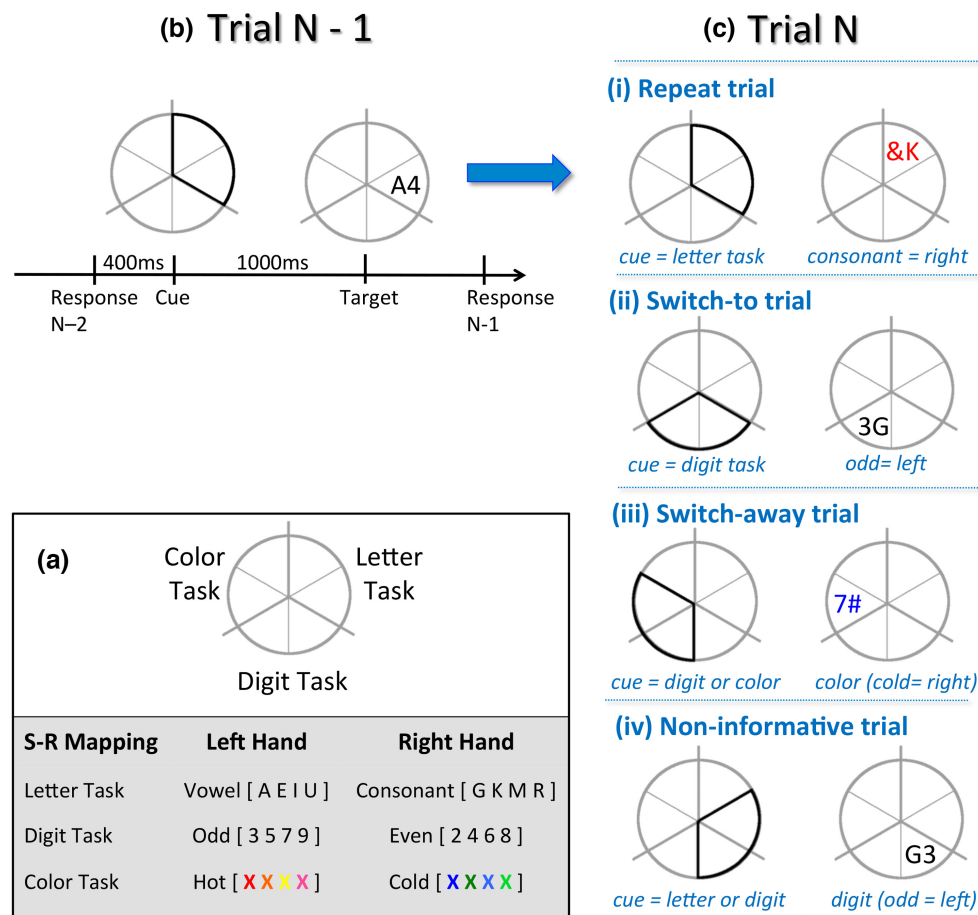


FIGURE 1 The to/away task switching paradigm (Karayanidis et al., 2009). (a) Two adjoining segments of the gray circle are associated with one of three classification tasks. The table shows the stimuli used for each task and an example of stimulus–response mappings. (b) each trial comprised of a cue–target pair. (c) the position of the cue presented on trial N relative to that on trial $N - 1$ defined the trial type.

mapped to a right hand response) and one that was neutral (e.g., letter and digit presented in gray—a color that was not mapped to any response). Participants responded with a button press using their left or right index finger. The hand assigned to each response was counterbalanced across participants. The same target could not appear on consecutive trials. The targets remained on screen until response or for 5000 ms.

Each trial consisted of a cue–target sequence with a 1000 ms cue–target interval and a 400 ms response–cue interval (Figure 1b). Four trial types were defined by the location of the cue on the circle and were presented with equal probability in a pseudo-random sequence so that the same trial type was not repeated on more than four consecutive trials. Targets were always presented in one of the two cued segments. Trial type was defined by the location of the cue on trial N relative to trial $N - 1$ (Figure 1c). On repeat trials (25%), the cue highlighted the two segments associated with the same task as that completed on the preceding trial, indicating the task would be repeated. On switch-to trials (25%), the

cue highlighted segments associated with one of the two tasks that were irrelevant on the previous trial, indicating that the task will switch and identifying the relevant task. On switch-away trials (25%), the cue highlighted a segment from each of the two tasks that were irrelevant on the previous trial, indicating that the task will change but not specifying which of the other two tasks is relevant for the upcoming target. Finally, on non-informative trials (25%), the cue highlighted one segment associated with the task completed on the preceding trial and an adjacent segment associated with one of the other two tasks, indicating that the task is equally likely to repeat or switch. Non-informative cues were not entirely uninformative as this would introduce a confound. Like switch-away trials, they indicated which two of the three tasks were likely to be relevant for the upcoming target. For switch-away and non-informative trials, the relevant task was identified by the position of the target. For non-informative cues, targets were equally likely to require a task repeat and a task switch. These four cue types offered different opportunities to engage in

proactive control during the cue-target interval. Repeat cues allowed the relevant task-set to be maintained and switch-to cues allowed the new task-set to be uploaded before target onset (Prepare Task, i.e., maintain or update task-set). For switch-away and non-informative cues, task-set identification and uploading could only occur after target onset. Switch-away trials were partly informative, in that they indicated that the task will definitely change. So, during the cue-target interval, for both switch-to and switch-away cues, participants could deactivate the previously relevant task-set and prepare to change task (Prepare Switch).

Participants were instructed to respond as quickly and as accurately as possible. Incorrect responses were followed by an auditory feedback tone. Average accuracy and response time (RT) for each block were presented to participants so they could monitor their performance. Each block was followed by a short break and a longer break was offered mid-way through testing.

2.3 | Procedure and EEG recording

Participants completed two training sessions (approximately 30 min, maximum 14 days apart, total 1464 practice trials) to establish strong cue-target and target-response associations for each task. Each training session included practice on each task alone (single-task blocks) and on switching between tasks (mixed-task blocks). After the second training session, the EEG cap was fitted and the test session administered. The test session included nine mixed-task blocks (96 + 5 warm-up trials/block, total 909 trials, approximately 1 h with rest periods). Warm-up trials were excluded from further processing.

EEG was recorded continuously using an ActiveTwo Biosemi EEG system (2048 Hz, bandpass filter of DC-400 Hz) from 64 scalp electrodes (extended 10–20 system) plus bilateral mastoid, bilateral outer canthi, and both supra-orbital and infraorbital ocular sites. The Biosemi system uses active electrodes with common mode sense and driven right leg electrodes providing a reference relative to the amplifier reference voltage.

2.3.1 | EEG preprocessing

EEG data were processed using a MATLAB (2016) pipeline that included Fieldtrip (Oostenveld et al., 2011), CSD Toolbox (Kayser & Tenke, 2006) and in-house functions. Preprocessing was performed using Fieldtrip as follows. EEG data were re-referenced off-line to electrode Cz, down-sampled from 2048 Hz to 512 Hz using a zero-phase

anti-aliasing filter with a low-pass cut off frequency of 245 Hz. High pass and notch filtering were applied to remove line noise and low-frequency drift (high pass: 0.1 Hz, forward phase; 50 Hz notch: zero phase). Excessively noisy channels were identified with visual inspection and excluded (on average $7.62 \pm 5.52SD$ electrode channels were removed per participant). For each cue type (repeat, switch-to, switch-away, non-informative), EEG epochs were extracted from 1000 ms before to 3500 ms after cue onset. While non-informative cues led to either a task switch or a task repeat trial (depending on target location), this was not predictable during the cue-target interval, so we do not differentiate non-informative switch and non-informative repeat epochs. To remove blink and vertical eye-movement artifact, independent components analysis (ICA) was performed using the fastICA algorithm (Hyvärinen & Oja, 2000). This produces a set of components (one less than the amount of available electrodes). On average, $1.76 \pm 0.96SD$ components corresponding to ocular artifact were identified by visual inspection and deleted. The remaining components were projected back into sensor (electrode) space. The data were low pass filtered (30 Hz, zero-phase) to remove high frequency noise including muscular artifacts. EEG epochs that contained residual artifact larger than $120 \mu V$ were deleted. On average, $185.4 \pm 19.0SD$ Repeat, $184.5 \pm 18.6SD$ Switch-to, $184.9 \pm 17.5SD$ Switch-away, and $185.0 \pm 16.9SD$ Non-informative trials per participant were included for further analysis.

After preprocessing, EEG data were re-referenced using *average mastoids* (i.e., the algebraic average of the mastoids). Based on Karayanidis et al. (2009) and Wong et al. (2018), analyses were conducted on electrode POz. Mean amplitude was extracted for each 100 ms time window from cue onset (0 ms) to target onset (1000 ms) as input for joint modeling. Grand average ERPs for each cue type were derived by averaging all single-trial EEG epoched data for that cue type for each participant, and then taking the average ERP waveform across all participants.

2.4 | Joint model of behavioral and neural data

The joint models have two independent sub-models (behavioral and neural) that are structurally linked to form a model with similar properties to the sub-models. The linking process allows the model to dynamically adjust itself and its constituents through proposed linking parameters that add constraints to the estimation process. Below we describe the behavioral and neural sub-models and the linking structure that binds them.

2.4.1 | Behavioral sub-model

The task switching paradigm generated two behavioral data points on each trial: response choice, which was coded as correct or incorrect response (based on whether a left or right hand response was required for that particular stimulus code), and response time for each response. We refer to this as the choice-response time pair. We assume the choice-response time pairs were generated from a simple diffusion decision model (DDM) with four parameters: z , the starting point of evidence accumulation, ν , the drift rate (i.e., rate of evidence accumulation), α , the response criterion (i.e., the amount of evidence required to trigger a response), and τ , non-decision time (i.e., the time required for processes outside of the decision process, such as stimulus encoding and response execution).

With the set of 4 model parameters that could be estimated in each of the 3 tasks \times 4 cue types = 12 cells of the design, one could freely estimate $4 \times 12 = 48$ model parameters. To simplify the model, we reduced the number of freely estimated parameters to eight by imposing four plausible constraints on the model parameters across task and trial type (outlined below). We used a hierarchical approach to determine the group level distributions, from which we sampled a parameter vector for each participant $s \in \{1, 2, \dots, S\}$, where $S = 45$ participants, to model the choice-response time pairs.

First, we assumed that only task type [$t \in \{\text{color, letter, digit}\}$] determined the drift rate, ν_t . It is plausible that drift rate varied with task difficulty, but not cue type, given that drift rates are driven by post-target stimulus features. Second, we assumed that only cue type [$c \in \{\text{repeat, switch-to, switch-away, non-informative}\}$] determined the response criterion, α_c . That is, we assumed that some cue types led to higher response criterion than others, but that criterion was independent of task. This is also plausible because it is generally accepted that response criterion does not vary as a function of post-target stimulus features. Third, we assumed that both task and cue type had negligible effects on non-decision time, so there was a single value across conditions, τ_s . Fourth, we assumed that there was no bias in favor of a left or right hand response [$z_c = .5\alpha_c$ for any tasks, cue types and participants]. Finally, we assumed that the choice-response time pair for trial i , cue type c , task t and subject s , RT_{icts} , was distributed as

$$RT_{icts} \sim \text{DDM}(\nu_{t|is}, \alpha_{c|is}, z_{c|is}, \tau_s) \quad (1)$$

where t_{is} and c_{is} , respectively, represent the task and cue type presented on trial i to participant s . The conditioning on cue and task for trial i of subject s holds in all cases that

follow, so to simplify notation we henceforth suppress the explicit conditioning (i.e., $\cdot|is$) and simply write ν_{ts} , z_{cs} , and α_{cs} . Appendix S1 outlines the model structure and the associated prior distributions.

2.4.2 | Neural sub-model

The neural data were extracted from single trial cue-locked EEG epochs by splitting the 1000 ms cue-target interval into ten 100 ms time bins. For every trial, we averaged across consecutive values within each time bin to obtain the mean amplitude for the bin (for similar approaches, see also Turner et al., 2017; Van Ravenzwaaij et al., 2017). We then used all single-trial EEG epochs for each cue type at a single electrode (POz) to model the ERP data. We assumed the vector of mean amplitudes ERP_{is} of the ERP for all time bins $k \in \{1, 2, \dots, 10\}$ of trial i for subject s was multivariate normal distributed with mean vector $\mu_{c|is}$ and covariance matrix Σ

$$ERP_{is} \sim \text{MN}(\mu_{c|is}, \Sigma) \quad (2)$$

where MN is the multivariate normal distribution and Σ is a $k \times k$ matrix; we again suppress the explicit conditioning on trial and subject (i.e., $\cdot|is$) and simply write the mean vector as μ_{cs} . Since functional brain activity and associated networks show dynamic temporal and spatial variation, we freely estimated the covariance between each time-bin pair $\{k_1, k_2\}$ for $k_1, k_2 \in \{1, 2, \dots, 10\}$. Appendix S1 details the prior distributions.

2.4.3 | Linking the behavioral and neural sub-models

To provide a targeted test of the brain-behavior relationship, we focused on a hypothesized link between the response criterion of the behavioral sub-model (α) and the mean EEG amplitude of the neural sub-model (μ). We elaborated this link to generate three joint models of increasing complexity that we subsequently tested against the behavioral and neural data.

2.4.3.1 | Joint model 1: Linking ERP amplitude with response criterion

The behavioral and neural sub-models were linked via a linear function such that the mean ERP amplitude in time bin k for cue type c of subject s , μ_{kcs} , was related to the response criterion for cue type c of subject s , α_{cs} ,

$$\mu_{kcs} \sim N(\beta_{0,s} + (\beta_{\alpha,ks} \cdot \alpha_{cs}), \sigma) \quad (3)$$

where $N(a, b)$ is the normal distribution with mean a and standard deviation b . The linking function imposes the constraint that the mean vector generating the cue type and subject-specific ERP data ($\mu_{cs} = \{\mu_{1cs}, \mu_{2cs}, \dots, \mu_{10cs}\}$) is linearly related to the response criterion (α), with participant-specific intercept ($\beta_{0,s}$) and slope ($\beta_{a,ks}$) parameters. To simplify the model, we assumed the variance parameter σ was common across participants.

The linking function implies that conditions with higher response criterion are associated with larger mean ERP amplitude, where the sign of the slope parameter determines the direction of the ERP deflections. Importantly, the association is not causal: larger ERP deflections may lead to higher estimates of response criterion or vice versa. By estimating independent slope parameters for each time bin, we can identify the time course of the link between response criterion and ERP amplitude during the cue-target interval.

2.4.3.2 | Joint model 2: Linking ERP amplitude with response criterion and switch preparation

We extended joint model 1 to incorporate that, in the to/away paradigm, some cue types indicate with certainty that the task will change for the upcoming target. Cue-locked ERPs indicate that participants use this information to activate neural processes associated with preparing to switch task (Karayanidis et al., 2009). To operationalize “switch preparation”, we grouped together trials where the cue validly indicates that the task will change (switch-to and switch-away) as participants can activate neural processes to prepare to switch task (e.g., disengage the now irrelevant task rules), even if they do not know which of the other two tasks to activate (i.e., on switch-away trials). We also grouped together trials where the cue validly indicates that the task will repeat (repeat trials) and trials where the cue indicates that the task may repeat (non-informative trials). In the former, the participant knows they will not need to switch task and in the latter they do not know whether they will need to switch task, so they do not need to prepare to switch in either trial type. Switch preparation was coded as a binary indicator variable, P_{switch} , such that

$$P_{switch} := \begin{cases} 0 & \text{if cue = repeat/non-informative} \\ 1 & \text{if cue = switch-to/switch-away} \end{cases} \quad (4)$$

which we used to extend the linking function of joint model 1:

$$\mu_{kcs} \sim N\left(\beta_{0,s} + (\beta_{a,ks} \cdot \alpha_{cs}) + (\beta_{P_{switch,k}} \cdot P_{switch})\right) \sigma \quad (5)$$

That is, the linking function in Equation (5) allows “switch preparation” cues to differentially modulate

cue-locked ERPs according to whether they provide certainty that the task will change, consistent with previously reported data (Karayanidis et al., 2009).

2.4.3.3 | Joint model 3: Linking ERP amplitude EEG with response criterion, switch preparation and task preparation

In the to-away paradigm, some cue types identify the task to be performed on the upcoming target (repeat and switch-to). For other cues (switch-away and non-informative), the identity of the relevant task is not available until target onset. Joint model 3 incorporated the notion that some cue types allow preparation for a specific task, and not just a change of task as in joint model 2. We again motivate this model extension on the theoretical foundations of the to/away paradigm as well as cue-locked ERP evidence that participants actively upload the task when the cue allows (Karayanidis et al., 2009). We refer to this as “task preparation” and operationalize it as whether the cue provided valid information about the specific task that would be completed on the upcoming target.

Repeat cues validly indicate that the task completed on trial $i - 1$ will be repeated on trial i , so participants can actively maintain the currently activated task rules. Switch-to cues not only indicate that the task will change, but also validly identify the task that will be performed on the upcoming target. So, during the cue-target interval, participant can prepare in anticipation of target onset by maintaining the old task rules for repeat cues and uploading the new task rules for switch-to cues. In contrast, for both switch-away and non-informative cues, the participant must wait until target onset to identify the relevant task and upload the new task rules, if needed. Collectively we code this information as a binary indicator variable, P_{task} , where

$$P_{task} := \begin{cases} 1 & \text{if cue = repeat/switch-to} \\ 0 & \text{if cue = non-informative/switch-away} \end{cases} \quad (6)$$

We incorporate the task preparation variable in joint model 3 such that

$$\mu_{kcs} \sim N\left(\beta_{0,s} + (\beta_{a,ks} \cdot \alpha_{cs}) + (\beta_{P_{switch,k}} \cdot P_{switch}) + (\beta_{P_{task,k}} \cdot P_{task})\right) \sigma \quad (7)$$

All four models—behavioral-only, and joint models 1, 2 and 3—were estimated in a hierarchical Bayesian framework via Markov Chain Monte Carlo. Supporting information Appendix S1 outlines the prior distributions for the parameters of the behavioral and neural models, including the linking functions, and all parameter estimation details.

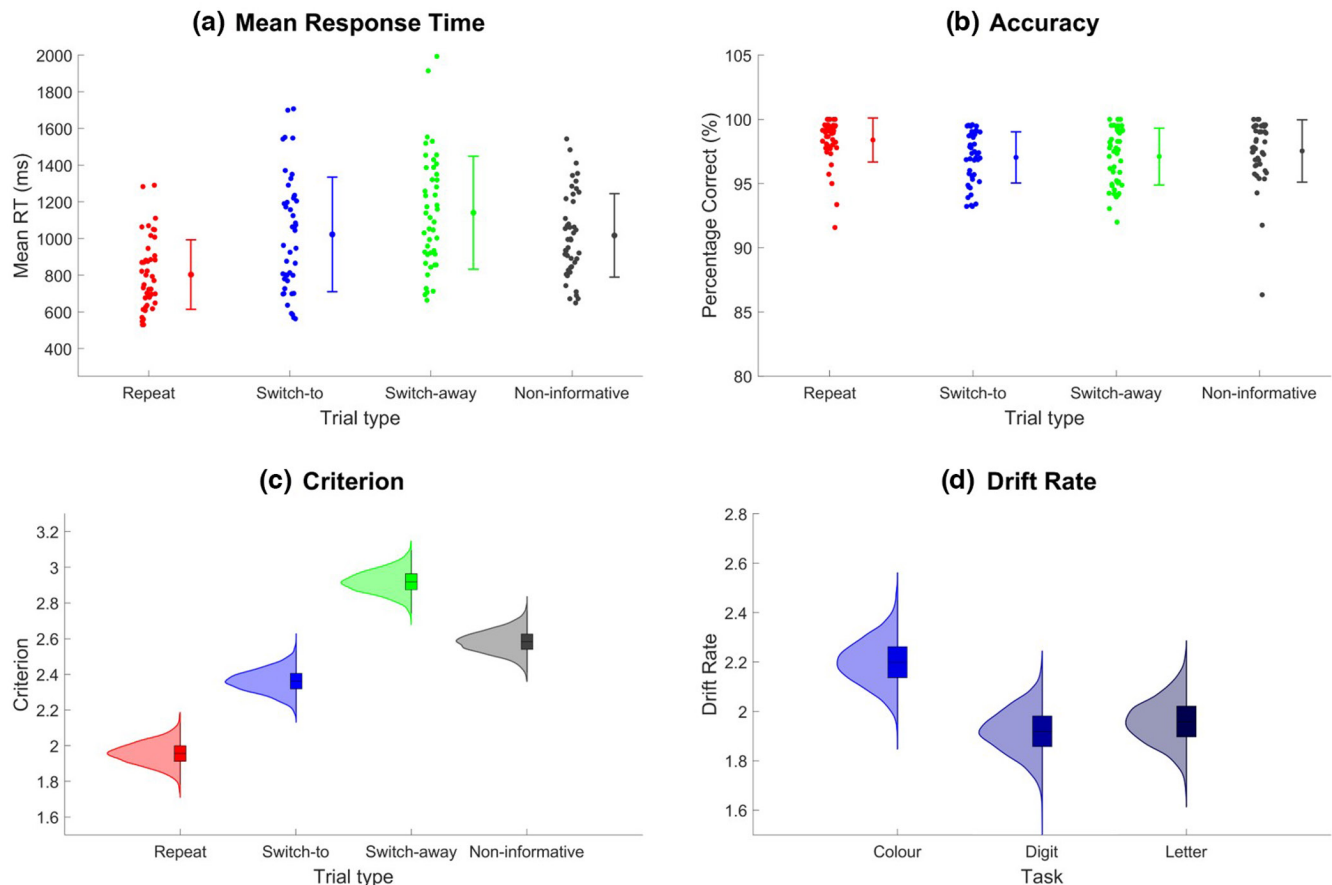


FIGURE 2 Mean response time for correct responses (a) and accuracy (b) as a function of cue type. Posterior distributions of the group-level mean parameters from the behavioral sub-model are shown for the response criterion as a function of cue type (c) and for drift rate as a function of task type (d). In panels a and b, individual participant data are presented as dots and uncertainty bars display the mean and standard deviation across participants. In panels c and d, half violin plots display the posterior distribution and boxplots display the median and lower and upper quartiles.

3 | RESULTS

3.1 | Behavioral data

Figure 2 shows mean RTs for correct responses (A) and mean accuracy rate (B) for each cue type.² These highly practiced participants were both very accurate and fast. As shown previously, repeat cues resulted in faster and more accurate performance than the other cue types. In addition, switch-to cues, which provided information that could be used to prepare to switch task and to upload the new task-set before target onset, resulted in faster and more accurate performance than switch-away

² Note that, for the non-informative cues, behavioral results are averaged across targets that prescribed a repeat vs a switch in task. Our behavioral model focuses on response criterion which is assumed to be set before target onset and hence before knowing whether the task will change. Therefore, we estimated a single response criterion for non-informative cues, regardless whether they ended up in a task switch or repeat.

cues, which only supported preparation to switch task. Figure 2 also shows the response criterion (C) and drift rate (D) estimates for the behavioral-only model. As shown previously with this task using a similar diffusion decision model in Karayanidis et al. (2009), response criterion was lowest for repeat cues and progressively increased for switch-to and switch-away cues, which required more evidence before committing to a decision. Drift rate was higher for the color task relative to both letter and digit tasks.

Figure 3 depicts observed and posterior predictive RT for correct responses and accuracy for individual participants for the behavioral model (column 1) and each joint model (columns 2-4). All four models provided a good explanation of the behavioral data. There was little difference between the behavioral-only model and the three joint models either qualitatively or quantitatively as indicated by the root mean square error. In all cases, median RT was explained very well, with only minor underprediction of the fastest (10th percentile) and slowest (90th percentile)

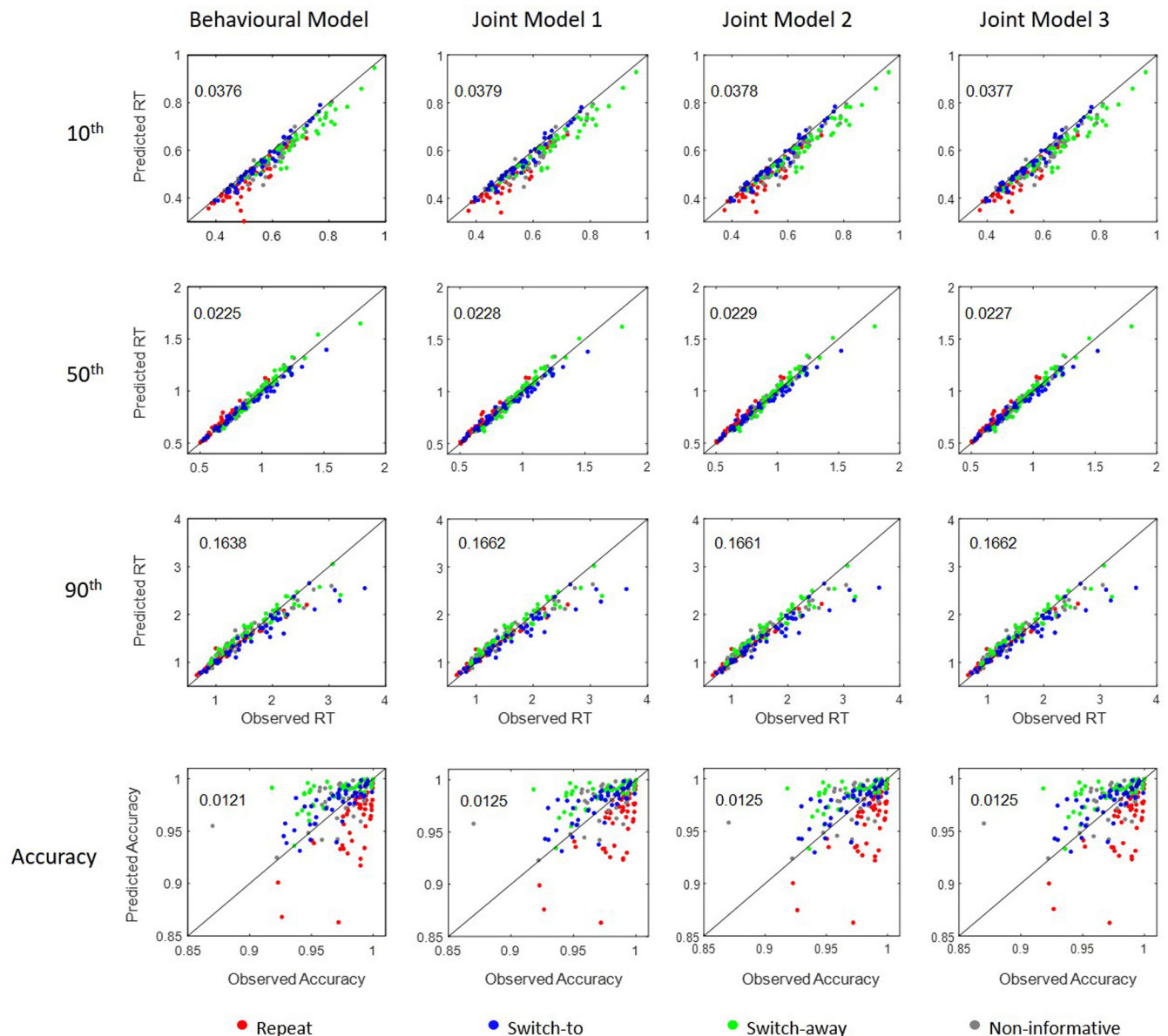


FIGURE 3 Observed (x-axes) versus mean posterior predictive (y-axes) data for individual participants. The first column represents the behavioral model and columns 2–4 represent joint models 1–3, respectively. The top three rows depict the 10th, 50th and 90th percentiles of the correct RT distribution, respectively, and the bottom row shows mean accuracy. Each dot represents a single participant in a single cue type condition. Color represents cue types. The root mean square error is shown in the upper left of each panel.

responses. Accuracy was also fairly well described, although there was some variability across participants and cue types owing to very high overall accuracy rates. So, the behavioral model characterized the data quite well across all four cue types, and the additional parameters from the joint models did not result in further improvement.

3.2 | ERP waveforms

ERPs for each cue type were obtained by averaging all EEG epochs for that cue type (including correct and error trials). These observed ERP waveforms were compared to

the waveforms derived from each joint model that were sampled from the posterior predictive distribution of each model. Figure 4a shows the grand average of observed cue-locked ERP waveforms and are largely consistent with previous findings with this paradigm (Karayanidis et al., 2009; Wong et al., 2018). Within the cue-target interval, all four cue types showed a broad large positive deflection followed by a negative shift peaking just before target onset. In addition, there were two superimposed components. The switch-positivity peaked approximately 400 ms after cue onset for the two cue types which provided certainty that a different task will be performed on the upcoming target, i.e., switch-to and switch-away (Figure 4a).

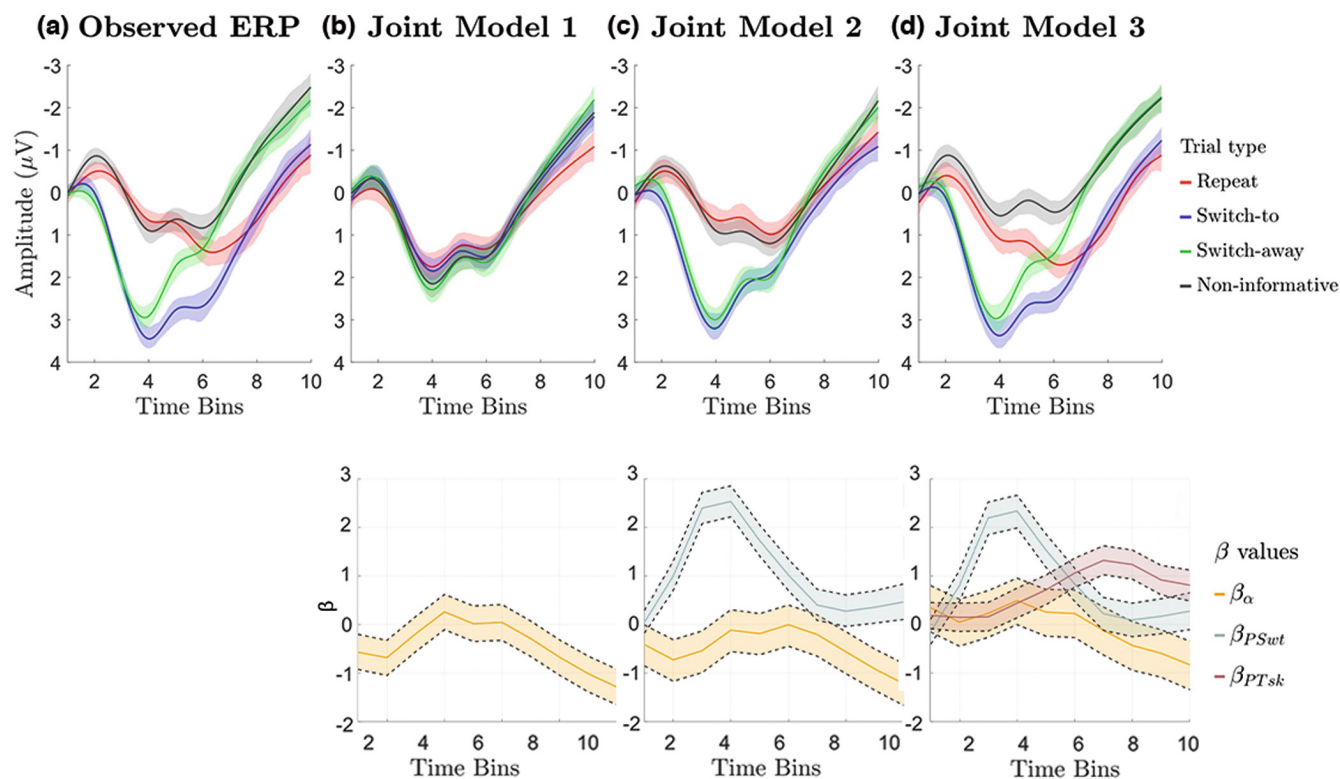


FIGURE 4 Grand average ERP waveforms for observed data and posterior predictive data for each joint model (top). (a) Observed ERP, (b) joint model 1 with response criterion only (β_α), (c) joint model 2 with added switch preparation parameter ($\beta_{P_{switch}}$), and (d) joint model 3 with added task preparation parameter ($\beta_{P_{task}}$). The lower panels show the 95% credible interval of the hyper parameters for each joint model: β_α for scaling the response criterion α (orange), $\beta_{P_{switch}}$ for scaling the prepare switch variable P_{switch} (gray), $\beta_{P_{task}}$ for scaling prepare task variable P_{task} (red).

From around 600 ms post-cue, the pre-target negativity emerged for all four cue-locked ERP waveforms but was larger for the switch-away and the non-informative cues, for which task identity was not available until target onset. These two components are consistent with the to/away paradigm's manipulation of preparation to switch tasks and preparation to implement the task, which are represented in the switch preparation variable added to joint models 2 and 3, and the task preparation variable added to joint model 3.

3.2.1 | Joint model 1

Joint Model 1 contained only the core link between mean EEG amplitude and response criterion. Figure 4b (upper) shows that the predicted ERP waveforms are consistent with the overall morphology of the grand average ERP waveform: a broad positivity over 200–700 ms followed by a sharp negative deflection. Figure 4b (lower) shows the 95% credible interval of the criterion-EEG scaling parameter (β_α) for each time bin. The criterion-EEG link values over the 10 time bins showed a pattern similar to the deflections in the posterior predictive data: an early peak

around 200 ms followed by a sustained dip over the time-frame of the ERP positivity, and a second larger peak at time bin 10 (900–1000 ms) similar to the pre-target negativity. This indicates that response criterion is weakly related to EEG amplitude shortly after cue onset (200 ms) and more strongly just before target onset. The predicted ERP waveforms did not differ across the four cue types, indicating that the criterion-EEG linking function influenced the general trends in the observed ERP but it did not differentiate the information provided by the four cue types.

3.2.2 | Joint model 2

In Joint Model 2, we incorporated a variable representing switch preparation to inform the model whether the cue provided reliable information that the task will change for the upcoming target. As shown in Figure 4c (upper), the ERP waveforms predicted by Joint Model 2 showed a substantial improvement compared with Joint Model 1. The switch-positivity clearly emerged for both switch-to and switch-away cues and showed a similar timeline and amplitude as the observed ERPs.

Figure 4c (lower) shows that the morphology of the criterion-EEG linking parameter estimates were very similar in Joint Models 1 and 2, i.e., for both joint models, response criterion was weakly related to EEG amplitude shortly after cue onset (200ms) and more strongly just before target onset. The switch preparation parameter ($\beta_{P\text{switch}}$) was strongly linked to EEG amplitude in the first half of the cue-target interval, showing a rapid rise that peaked over 300–500ms (Figure 4c, lower). The morphology of the beta values for the switch preparation parameter across the cue-target interval corresponds with the morphology of the cue-locked switch-positivity, which also peaks around 400 ms.

A shortcoming of Joint Model 2 is that—unlike the observed data—the posterior predicted ERP amplitude did not differentiate between switch-to and switch-away cue types, and there was little differentiation between cue types in the latter part of the ERP waveform leading up to target onset.

3.2.3 | Joint model 3

We extended Joint Model 2 with the addition of a variable representing task preparation to inform the model whether the cue reliably identified the task to be performed on the upcoming target. Figure 4d (upper) shows that Joint Model 3 predicted not only the overall morphology of the ERP waveform and the switch-positivity, but also the later reorganization of ERP waveforms across cue types. Specifically, it captured the smaller pre-target negativity for cues that allowed the task to be fully uploaded before target onset (i.e., repeat, switch-to) compared to cues where task identity was only available upon target onset (i.e., switch-away, non-informative). Thus, Joint Model 3 very closely predicted the temporal dynamics of the observed cue-locked ERP waveforms (Figure 4a). Figure 4d (lower) shows that adding the task preparation parameter to Joint Model 3 had a minor effect on the morphology of the criterion-EEG and the switch-EEG beta values, reducing the magnitude of both estimates compared to Joint Model 2. The beta values for the link between task preparation and EEG showed a slow increase from 300–400 ms, peaked at 600–700 ms, and slowly decayed thereafter. The maximal beta values corresponded to the period during which the ERP waveforms crossover to produce a larger pre-target negativity for those cues where the target carried important information about task identity, compared to cues where the identity of the task had already been provided.

3.2.4 | ERP covariance across time

We also freely estimated the covariance matrix that supported the behavior-EEG linking function. Figure 5

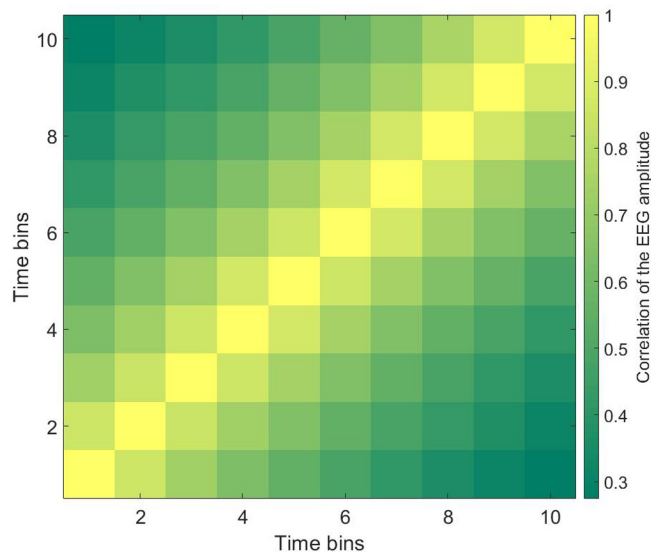


FIGURE 5 Estimated correlation of the EEG amplitude across time bins from joint model 1; joint models 2 and 3 produced similar trends.

displays the 10×10 correlation matrix implied by the estimated covariance matrix. The off-diagonal entries show the temporal correlation of the ERP signal between all time-bin pairs. This was greatest in neighboring bins (lighter colors) and decreased with increasing distance (darker colors). The estimated patterns of correlation in Joint Model 1 (Figure 5) were similar for Joint Models 2 and 3 (not shown). This result highlights the very high degree of temporal autocorrelation in the EEG signal, serving as an important reminder of the importance in explicitly modeling temporal covariation in neural data. Without such an explicit model of temporal covariation, the EEG data in each time bin would be treated independently and would thus exert too much influence in a joint model. Our covariance estimation approach decreases the influence of each time bin in proportion to the amount of independent information contained within that bin.

4 | DISCUSSION

This paper joint modeled behavioral and EEG measures of proactive cognitive control from a cued-trials task switching paradigm in order to provide direct evidence for a link between cue-locked ERP activity and response criterion setting. This aim can be broken down into two sub-questions. First, are response criterion estimates derived from a joint model (and therefore informed by both behavioral and neural data) more informative than those derived from the behavioral model alone? Second, is the computational link between response criterion and cue-locked ERP activity sufficient to model ERP components

associated with switch preparation and task preparation processes (i.e., switch-positivity and pre-target negativity)?

Joint Model 1, which modeled behavioral and EEG data, resulted in essentially identical response criterion estimates and pattern of response criterion differences across cue types as the behavioral model alone. Adding parameters to model switch preparation (Joint Model 2) and task preparation (Joint Model 3) did not further change response criterion estimates. So, in response to the first question, jointly modeling behavioral and cue-locked ERP data reproduced, but did not further constrain the estimates of response criterion derived from a behavioral model alone.

Of our three joint models, Joint Model 3 most precisely captured the trends in behavioral *and* ERP data. There was evidence of a trade-off between task preparation and response criterion, but not switch preparation parameters. In Joint Model 3, only the late link between response criterion and EEG, within the timeframe of the pre-target negativity, were reliable. Yet, ERP waveforms derived from Joint Model 3 most closely replicated the pattern of the observed ERP waveforms, including the differentiation between switch-to and switch-away waveforms, as well as between repeat and non-informative cue types. This is consistent with models proposing trial-by-trial variation in both switch preparation and task repetition benefit (De Jong, 2000), and previous findings that the amplitude of the switch-positivity varies with level of switch preparation (Karayanidis, Provost, et al., 2011) and may even emerge on repeat trials when participants unnecessarily prepare task-set (Karayanidis, Whitson, et al., 2011).

Therefore, although response criterion setting was associated with ERP activity during the preparation interval, it alone was not sufficient to account for ERP differences as a function of cue information. Rather, at least two more parameters were required to model ERP findings: switch preparation and task preparation. The addition of these two binary parameters resulted in high fidelity of estimation of the cue-locked ERP waveforms. It also modulated the pattern of impact of the response criterion parameter across the cue-target interval—that is, the estimation of response criterion setting varied according to whether the cue provided the opportunity to undertake switch and/or task preparation.

Interestingly, while more complex models were necessary to accurately model the ERP waveforms, jointly modeling behavioral and neural data did not change response criterion estimates. In fact, all models were equally adequate in reproducing the response criterion estimates derived from the behavioral data alone. This indicates that more complex models may be necessary to capture proactive control processes. Specifically, we interpret our joint modeling results to mean that latent constructs relating to

switch preparation and task preparation are “targets” for future theoretical development—with the view to developing a more complete cognitive model of cued-trials task switching.

5 | CONCLUSIONS AND CAVEATS

This is the first direct confirmation that response criterion is associated with proactive control processes. It is temporally linked to neural processes elicited proactively after cue onset and adjusted trial-by-trial in the interval leading up to target onset. However, while we expected the link between response criterion and cue-locked ERP activity to be maximal in the timeline of the switch-positivity, it was instead temporally linked to the pre-target negativity. Although this suggests that response criterion setting occurs after the switch-positivity resolves, temporal overlap between ERP and behavioral (or latent) parameters is neither necessary nor sufficient to indicate a functional relationship between behavioral and neural processes (Luck, 2014). In fact, it is possible that response criterion is set earlier but impacts later task preparation.

Importantly, modeling response criterion alone was not sufficient to fully characterize variability in the neural signal across cue conditions. Therefore, the simple behavioral-neural model does not accurately represent the response criterion-EEG link. Switch preparation and task preparation parameters were necessary to estimate the ERP waveforms more accurately. Including both these parameters (Joint Model 3) modified the timeline of the response criterion linking estimates, with only the large late peak that coincided with the pre-target negativity remaining reliable.

In this study, switch and task preparation parameters were entered as categorical scores (present vs. absent) and successfully modeled the grand average ERP waveform. However, there is ample evidence that the level of both switch preparation and task preparation can vary from trial-to-trial, with task practice, and across individuals (De Jong, 2000; Karayanidis, Whitson, et al., 2011; Provost et al., 2018; Steyvers et al., 2019). Future variations of the model would need to consider such variation in preparation.

These findings are consistent with ERP evidence that preparation to switch tasks involves multiple proactive control processes that are differentially activated depending on the information provided by the cue (Karayanidis & Jamadar, 2014). Response criterion setting is one mechanism by which we can flexibly adjust control depending on the difficulty of the upcoming decision. On trials where the cue validly signaled that the task-set will change (switch-to, switch-away), response

criterion was set higher compared to repeat cues. As all targets included incongruent mapping between the task-relevant dimension (e.g., letter) and one of the two irrelevant tasks (i.e., either color or number), a higher criterion on these switch trials can protect against carry over interference from the recently activated (now irrelevant) task-set. Response criterion was also set higher on trials where the cue did not specify the task-set for the upcoming target (switch-away, non-informative), and this information was provided by the target itself. A higher response criterion on these trials can also increase post-target interference control, as task activation will be weaker compared to trials where the task-set was either repeated or could be uploaded before target onset. Overall, these findings are consistent with recent models suggesting that response criterion is flexibly adjusted to regulate speed-accuracy tradeoff and optimize performance (Karayanidis et al., 2009).

Thus, these findings are consistent with previous evidence that flexible adjustment of response criterion plays a key role in proactive control processes that regulate task-switching performance. It is important to note that the version of the DDM model used here only allowed response criterion to vary across cue type. Drift rate was only allowed to vary across tasks (letter, number, color) as it represents post-target processes that were not examined here, whereas non-decision time was held constant across both cue type and task. We reran the analyses using a model that allowed both response criterion and non-decision time to vary and this produced largely identical pattern of differences in response criterion and little variability in non-decision time.

We have previously argued that, in task-switching paradigms, DDM model parameters are not sufficient to represent task activation processes, such as selection and uploading of task-set parameters (Karayanidis et al., 2009). These processes may be completed proactively or reactively, depending on whether the paradigm provides advance information regarding task identity, requires advance uploading of the relevant task-set or enforces task uploading after target onset. For instance, on trials where there is insufficient time or information to upload the correct task-set before target onset, task activation may need to be completed after target onset, delaying the onset of evidence accumulation. Similarly, failure-to-engage models argue that task preparation may fail on a proportion of trials even when the cue provides the time and information needed to prepare in advance (De Jong, 2000). ERP studies show that inter-trial variability of both switch-positivity and pre-target negativity amplitude is associated with RT (Karayanidis, Provost, et al., 2011), consistent with trial-by-trial variability in the efficiency of switch and task preparation (see also Cooper et al., 2017).

This is likely to impact task activation and to load on non-decision time. In a switch-stay paradigm without advance preparation (Steyvers et al., 2019), after each switch trial, task activation was dynamically adjusted over subsequent repeat trials and the efficiency of this task activation process varied with task practice and age. Therefore, while there is substantial evidence that response criterion is an important contributing variable to proactive control in task-switching, the role of other processes such as task activation need to be further examined. For future modeling directions, it will be important to not only investigate alternative ways of joining behavioral and neural data within the DDM modeling framework but also explore modeling approaches other than DDM.

It is puzzling that, although estimates from all three joint models closely resembled the estimates obtained from the behavioral model alone, the addition of neural measures did not produce any discernible change in response criterion estimates or model fits. One reason that the neural data provided little additional value may be that we only modeled a very limited representation of neural data. Cue-locked EEG epochs were summarized in 10×100 msec epochs from a single posterior parietal electrode (POz) which typically produces the largest cue-locked ERP effects in task-switching paradigms. This ERP signal is derived by averaging across multiple EEG epochs and represents averaged activity that has been conducted to this specific electrode from multiple neural generators (Luck, 2014). Using techniques that extract latent components of the EEG signal across multiple scalp electrodes (e.g., independent component analyses or cluster analysis) may provide alternative neural measures that more accurately represent underlying component processes.

In conclusion, we provide the first direct evidence for a link between cue-locked ERP activity and response criterion setting in a task-switching paradigm. However, response criterion was not sufficient to model proactive control processes involved in preparing to switch or repeat trial that are seen in the neural data. This may be partly due to the fact that only a small sample of neural data were modeled and/or to the simplicity of the behavioral model. While DDM models have a strong history of successfully modeling choice decision tasks, the component processes may not sufficiently explain performance in more complex task switching paradigms. There is a definite need for customized computational models of cued-trials task switching paradigms that will differentiate between processes involved in task selection and switch preparation from processes involved in the decision itself. Such models need to consider variations in performance and ERP components as a function of implementing proactive versus reactive control. Manipulations of cue informativeness, time to

prepare and task practice may impact the efficiency of proactive control engagement, and, by extension, the need for reactive control after target onset (Jamadar et al., 2015). While the DDM can provide the foundation for modeling choice-RT for each component task in a task-switching paradigm, these findings suggest that we need to design tailored models to account for the additional layers of cognitive control required in cued-trials task-switching.

AUTHOR CONTRIBUTIONS

Frini Karayanidis: Conceptualization; data curation; formal analysis; funding acquisition; investigation; methodology; project administration; supervision; visualization; writing – original draft; writing – review and editing. **Guy E. Hawkins:** Data curation; formal analysis; investigation; methodology; software; supervision; visualization; writing – original draft; writing – review and editing. **Aaron S. W. Wong:** Data curation; formal analysis; methodology; software; supervision; visualization; writing – original draft; writing – review and editing. **Fayeem Aziz:** Data curation; formal analysis; methodology; software; visualization; writing – review and editing. **Montana Hunter:** Methodology; visualization; writing – review and editing. **Mark Steyvers:** Conceptualization; formal analysis; methodology; supervision; writing – review and editing.

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CONFLICT OF INTEREST

We have no conflicts of interest to disclose.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Appendix S1: Supporting Information

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