Continuous and Discrete Transitions during Task-Switching

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Abstract

Decades of research have established that while people's performance suffers when they need to quickly switch between tasks, they can reduce these performance costs the more time they have to prepare. Two major theories have attempted to explain how people actively prepare for tasks over time, debating whether these task state transitions are discrete or gradual. We attempted to bring clarity to this debate by developing new statistical methods for single-trial modeling of task state transitions, which we use in a task that combines the strengths of cued and predictable task-switching. We found that participants' behavior was best explained as a hybrid between discrete and gradual transitions. Over the preparation period, participants discretely transitioned from an unprepared state into a dynamic, increasingly prepared state. These findings provide a new account of cognitive flexibility, paving the way for mechanistic models of task-switching.

Keywords: task-switching, cognitive control, attention

Introduction

It is obvious to anyone with a busy life how difficult it can be to switch between multiple tasks. Foundational research has confirmed that people perform more poorly when they need to change tasks (Jersild, 1927; Spector & Biederman, 1976; Allport, Styles, & Hsieh, 1994; Monsell, 2003; Koch, Poljac, Müller, & Kiesel, 2018). These 'switch costs' can be reduced, though not completely eliminated, if participants are given more time to prepare (Rogers & Monsell, 1995; Meiran, 1996). This cognitive flexibility is fundamental to goal-directed behavior, with research identifying task switching as a core factor structuring individual differences in executive functioning (Friedman & Miyake, 2017). While substantial progress has been made in developing qualitative theories of switch costs, progress has been slower on developing mechanistically explicit and quantitatively precise process models of how people reconfigure task processing.

There have been two major proposals that explain how people switch between 'task sets', the stimulus-response mapping appropriate for each task (Rogers & Monsell, 1995). The first approach proposes that people make continuous adjustments, gradually transitioning from one task set to the other. This approach is supported by how switch costs parametrically change over preparation time (Rogers & Monsell, 1995), leading to dynamical systems model of reconfiguration (Gilbert & Shallice, 2002; Yeung, Nystrom, Aronson, & Cohen, 2006; Ueltzhöffer, Armbruster-Genç, & Fiebach, 2015; Musslick, Jang, Shvartsman, Shenhav, & Cohen, 2018; Steyvers, Hawkins, Karayanidis, & Brown, 2019; Jaffe, Poldrack, Schafer, & Bissett, 2022). The second approach has proposed that people make discrete adjustments, with all-or-none transitions from one task set to the other. This has been influenced by distributional analyses showing that switch costs differ for faster and slower RTs (De Jong, 2000; Nieuwenhuis & Monsell, 2002), leading to theories that emphasize the successful recollection of task sets from memory (Mayr & Kliegl, 2000; Monsell, 2003). These proposals have neglected a third, hybrid option, in which people discretely transition between different continuous processes. In dynamical systems theory, this classes of processes are known as 'switching dynamical systems' (Ackerson & Fu, 1970), which have recently started to gain popularity as models of neural dynamics (Linderman, Nichols, Blei, Zimmer, & Paninski, 2019; Glaser, Whiteway, Cunningham, Paninski, & Linderman, 2020).

Here, we report an experiment that aimed to compare these different accounts of task set reconfiguration. First, we develop a novel task designed to maximize our ability to measure time-varying changes in task preparation, while minimizing the influence of confounds arising from associative learning (Logan & Bundesen, 2003; Arrington, Logan, & Schneider, 2007; Koch & Allport, 2006). Second, we develop a novel trial-level analysis of continuous and discrete reconfiguration to quantify the predictions made by these different accounts. Consistent with the hybrid theory, we find that participants showed evidence for both continuous and discrete dynamics during task set reconfiguration.

Methods

Task Design

We developed our task to facilitate a number of specific objectives. First, we wanted to maximize task differences, potentially increasing reconfiguration costs and facilitating future neuroimaging analyses. To this end, we used a cross-modal design, in which participants switched between visual and auditory tasks.
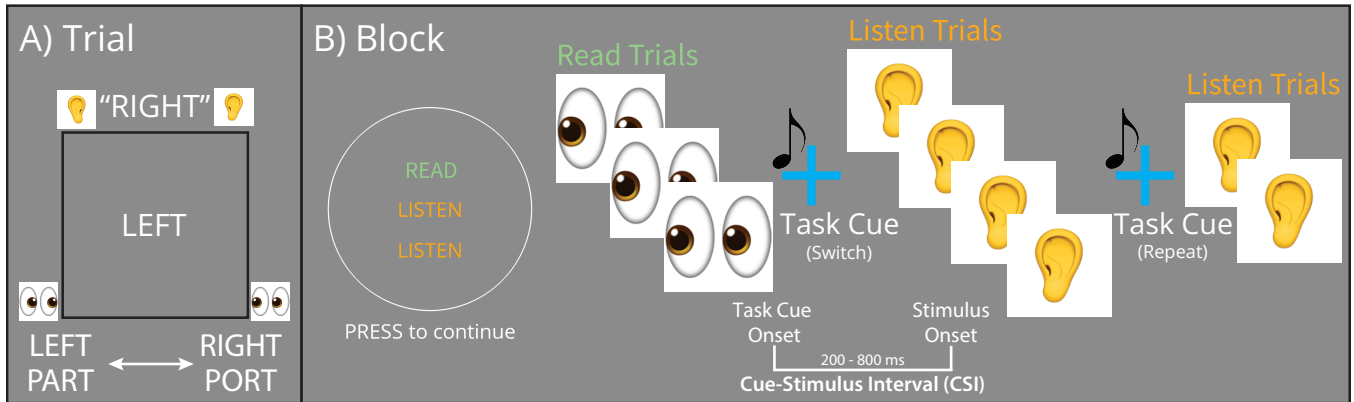
Figure 1: Task design. A) In each trial, participants simultaneously saw a word and heard a word, responding to the relevant dimension. B) At the beginning of each block, participants read a task list, instructing the order in which to perform the reading and listening tasks. They then performed each task over the course of a random-duration mini-block, switching to the next task on the list when they received a generic Task Cue. The preparation time for the next task randomly varied across task transitions (most common range: 200 - 800 ms, see Task Design in Methods).

On every trial, participants saw a word on the screen and heard a word over headphones (Figure 1A). The words were (*Left*, *Right*, *Part*, *Port*), and were randomly selected for each dimension on each trial. Participants had to attend to either the visual or the auditory dimension (see below), responding on a button box with a left keypress to (*Left* or *Part*) and a right keypress to (*Right* or *Port*). This task Incorporated both stimulus-response conflict (i.e., with *Left* and *Right* having strong response affordances) and stimulus-stimulus conflict (i.e., with *Part* and *Port* having greater perceptual similarity; Kornblum, Hasbroucq, & Osman, 1990; Egner, 2008). Both forms of conflict should encourage participants to focus their attention on the instructed task. Participants had 2 seconds (N=47) or 5 seconds (N=12) to respond, and between each trial there was a short ITI (250 - 350 ms).

Another objective of this task was to maximize task-switching requirements, while avoiding cue-priming. Previous experiments have suggested that cued task-switching may be driven by associative learning between the task cue and task set, rather than an endogenous control process (Logan & Bundesen, 2003; Kiesel et al., 2010). This concern can similarly disrupt neuroimaging analysis (i.e., confounding task and cue decoding). To avoid such cue-priming, we used a generic cue for all tasks (Figure 1B).

Participants performed 128 blocks over the experiment, each broken up into three mini-blocks. At the beginning of each block, participants were given a list of three tasks to perform in order (e.g., *READ*, *LISTEN*, *LISTEN*). This list always had one switch (e.g., *READ* to *LISTEN*) and one repeat (e.g., *LISTEN* to *LISTEN*). Participants self-initiated the first mini-block, performing the first task on the list (e.g., *READ*). Each mini-block had a random number of trials, with a Poisson distributed length (rate = 0.5) after a minimum of 2 trials (i.e., average length of 2.5 trials). Multiple trials in a

mini-block should encourage participants to commit to each task (Musslick, Bizyaeva, Agaron, Leonard, & Cohen, 2019; Yeung et al., 2006), and random mini-block lengths should discourage preparation for the next mini-block (though see below).

After the mini-block, participants received a generic Task Cue instructing them to perform the next task, without explicitly indicating the task itself (i.e., requiring participants to remember it from the initially presented list). Across task versions, the Task Cue was either a blue fixation cross (N=18) or a blue cross paired with an auditory tone (N=41). The block ended after participants performed all three mini-blocks. Each mini-block had one task switch and one task repeat, producing 128 well-matched trials of each.

The third objective of this task was to measure participants' reconfiguration dynamics from their behavior. We did so using a standard approach of manipulating the amount of preparation time available between tasks, varying the cue-stimulus interval (CSI; Rogers & Monsell, 1995; Meiran, 1996; De Jong, 2000). The CSI is measured from the onset of the Task Cue to the onset of the first trial in the mini-block, and we uniformly varied the CSI across trials (250 - 750 ms in N=18; 200 - 800 ms in N = 41). The final 100 ms contained an alerting cue to minimize onset uncertainty (the blue fixation cross turned white).

We collected three variants of the task over the course of piloting, which differed in their trial duration and/or cue stimulus. While we expect that these variants influenced performance, the data are underpowered to detect differences between task versions, and thus we have aggregated them for all analyses, using hierarchical analyses in order to minimize the influence of participant or task-version outliers.

Participants Fifty-nine participants performed the experiment at Princeton University (mean age = 19.4; 53% female gender). We removed 3 participants for unusually poor performance (less than 70% accuracy across all trials), leaving a sample of 56 participants. All participants provided informed consent, and the experiment was fully in accordance with the Princeton Institutional Review Board.

Results

Conflict depends on target and distractor prepotency On each trial, stimuli were either congruent (e.g., *Left* and *Left*) or incongruent (e.g., *Left* and *Right*). The target and distractor dimensions also had low or high prepotency (e.g., responding to *Left* affords a response, whereas responding to *Part* is a recently-learned arbitrary mapping). We used mixed effects regression (MixedModels.jl) to analyze accuracy and log RT on correct trials (removing post-error trials and RTs < 200 ms; *Performance = Congruence * (TargetPrepotency + DistractorPrepotency)*). We found that participants were faster and more accurate when the task was congruent (logRT: $t = -11.3, p < 10^{-28}$; Accuracy: $t = -12.9, p < 10^{-37}$) and the target was easy (logRT: $t = -15.6, p < 10^{-54}$; Accuracy: $t = -11.9, p < 10^{-31}$). Looking more closely at how prepotency interacted with congruence, we found that conflict depended on both targets and distractors. Target ease always improved performance, but had a stronger effect when the task was incongruent (Figure 2A; *Congruence × TargetPrepotency*, logRT: $t = 2.45, p = .0142$; Accuracy: $t = 4.04, p < 10^{-4}$). In contrast, distractor ease helped when the task was congruent, but hurt when the task was incongruent (Figure 2B; *Congruence × DistractorPrepotency*, logRT: $t = -5.09, p < 10^{-6}$; Accuracy: $t = 4.73, p < 10^{-5}$). These analyses provide evidence of conflict between the tasks, necessitating selective attention for good performance (Posner & Snyder, 1975; Cohen, Dunbar, & McClelland, 1990).

Task-switching improves with preparation time Given the evidence for the between-task competition that necessitates cognitive control, we next investigated how people switch between tasks. We used Mixed Effects Regression to quantify how performance on the first trial of a mini-block depends on task-switching and preparation time (*Performance = Switch * CSI*). Participants' key behavioral trends were largely consistent with previous work (Figure 3A; Rogers & Monsell, 1995). Participants performed worse on switch trials than repeat trials (logRT: $t = -13.2, p < 10^{-39}$; Accuracy: $t = -5.75, p < 10^{-8}$), and switch costs were were reduced with more preparation time (logRT: $t = 6.67, p < 10^{-10}$; Accuracy: $t = 1.86, p = .0628$). Preparation effects were stronger for RT than Accuracy, as has been observed previously (Nieuwenhuis & Monsell, 2002).

Previous work has found that conflict sensitivity is higher after switching tasks (Rogers & Monsell, 1995; Goschke, 2000; Wylie & Allport, 2000), though some have reported
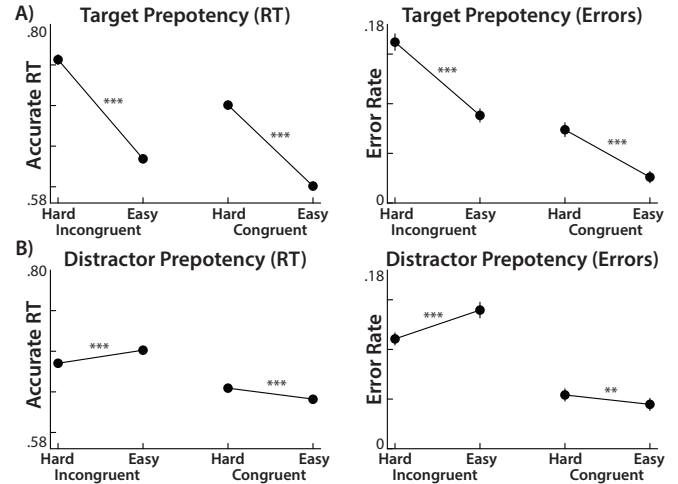

Figure 2: Conflict and feature prepotency. A) Participants performed better when the target was easy and the distractor was congruent. Target prepotency had a larger effect on incongruent trials than congruent trials. B) Distractor prepotency disrupted performance when the distractor was incongruent and helped performance when the distractor was congruent. Pairwise contrasts: $**p < .01; ***p < .001$.

inconsistent findings (Jongkees, Todd, Lloyd, Dayan, & Cohen, 2023; Fagot, 1994). This has been used as an index of how sensitive participants are to the previously performed task. However, we did not find strong evidence for increased conflict costs on switch trials (one-tailed test of the *Switch × Congruence* interaction: logRT: $p = .071$, Accuracy $p = .072$), and no modulation by CSI. Since most tasks do not vary target prepotency, our task can extend this account by also measuring changes in target processing. While we did not see an interaction between task-switching and target difficulty in RT ($p = .33$), in Accuracy we found that target prepotency had a weaker influence on switch trials ($p = .021$), consistent with reduced sensitivity to target information after switching. Together, we found that participants were less sensitive to targets after switching tasks, but that there was weaker evidence for switch-dependent task interference, potentially more consistent with reconfiguration than theories of 'task set inertia' (Allport et al., 1994).

Participants switch between tasks both discretely and continuously A classic challenge to dynamical models of task-switching suggests that the relationship between CSI and switch costs is an artifact of averaging over trials. Instead, each trial is due to either an 'unprepared' or a 'prepared' state, with participants discretely switching from unprepared to prepared over the course of the CSI (De Jong, 2000; Nieuwenhuis & Monsell, 2002). Consistent with this hypothesis, the distributions of participants' reaction times appeared to have two modes (Figure 3B).

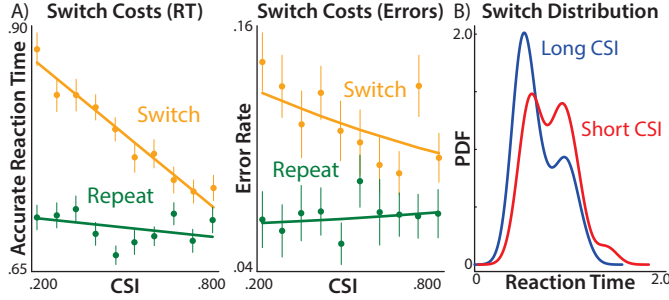Discrete task-switching models are often assessed using

Figure 3: Performance linearly improves with preparation time. A) Longer cue-stimulus intervals (CSI) reduced participants' switch costs. On switch trials (orange), participants were faster (left) and made fewer errors (right) with longer CSIs, whereas CSI had a much weaker influence on repeat trials. CSI is binned for visualization. Error bars reflect within-subject standard error; trend lines are predictions from mixed effects regression. B) Post-switch reaction time distributions from an example participant. 'Long CSI' are the longest 25% of CSIs (> 600 ms), 'Short CSI' are the shortest 25% of CSIs (< 334 ms).

a group-averaged measure of RT quantiles, which are not amenable to hierarchical analyses that can capture individual differences and trial-to-trial changes. To provide a rigorous comparison between the continuous and discrete switching hypothesis, we constructed trial-level statistical models representing each hypothesis, and then systematically compared how well they fit participants' behavior. We fit different models using hierarchical expectation maximization (EM.jl), which alternates between estimating participants' best-fitting parameters under the group prior (E-Step) and updating group-level prior (M-Step). To adjudicate between models, we compared the leave-one-subject-out cross-validated likelihood (LikCV, with smaller values reflecting a better fit).

The two historic classes of task-switching hypotheses make very different predictions for how task sets change over the CSI (Figure 4A). The Dynamic models test the continuous hypothesis, with participants' average performance changing over the course of the CSI. We estimated the linear effect of CSI on reaction time, with an intercept and slope for switch trials and just an intercept for repeat trials (reflecting the clear trends from our Mixed Effects Regression).

$$\mu_{\text{switch}} = \beta_0 + \beta_1 \text{CSI}$$
$$\mu_{\text{repeat}} = \beta_R \tag{1}$$
$$L = N(\log\text{RT}|\mu, \sigma)$$

where $L = N(.|\mu, \sigma)$ represents a Gaussian likelihood function parameterized by a mean (μ) and variance (σ).

The Mixture models test the discrete hypothesis, with performance coming from two different distributions.

Specifically, the likelihood on each trial was the weighted mixture of two Gaussian likelihoods (corresponding to the prepared and unprepared states), and this mixture weight changed as a function of the CSI. Unlike the Dynamic model, the means of these Gaussian distributions are static (do not depend on CSI). For convenience, we refer to each Gaussian as a 'task state', without committing to the underlying representation. These mixture models had the form:

$$L_{\text{switch}} = \pi N(\log\text{RT}|\mu_1, \sigma_1) + (1 - \pi)N(\log\text{RT}|\mu_2, \sigma_2)$$
$$\pi = \text{logistic}(\beta_0 + \beta_1\text{CSI}); \beta_1 < 0 \tag{2}$$

The first Mixture model we tested was a version of the original De Jong discrete switching model (De Jong, 2000). In this model, the late 'prepared' state is the same for switching and repeating (i.e., the likelihood on repeat trials was $L_{\text{repeat}} = N(\log\text{RT}|\mu_2, \sigma_2)$). Compared to the Dynamic model, we found that the De Jong Mixture model dramatically improved the model fit (ΔLikCV = 120; Table 1), consistent with the involvement of a discrete switching process.

We next tested De Jong's assumption that switch trials converge on the same state as repeat trials. We fit the Static Mixture model, which estimated separate states for late switch and repeat trials (i.e., the likelihood on repeat trials was now $L_{\text{repeat}} = N(\log\text{RT}|\mu_R, \sigma_R)$). This model further improved the fit over the De Jong model (ΔLikCV = 199), consistent with evidence for persistent differences between switch and repeat trials, even at long CSIs (i.e., a residual switch cost; Rogers & Monsell, 1995; Meiran, 1996; Wylie & Allport, 2000).

While these Mixture models are consistent with a discrete change in task state, they do not rule out more complex models of dynamics. In particular, it could be the case that participants are not switching between two static states (i.e., Guassians with means that don't depend on CSI), but instead switching between discrete states that themselves have dynamics (Ackerson & Fu, 1970). We explore this possibility in a class of Hybrid models that extended the Static Mixture model to include changes in the Gaussian means over time. In the Static-Dynamic Hybrid, participants switched from a static process to a dynamic process:

$$L_{\text{switch}} = \pi N(\log\text{RT}|\mu_1, \sigma_1) + (1 - \pi)N(\log\text{RT}|\mu_2, \sigma_2)$$
$$\pi = \text{logistic}(\beta_0 + \beta_1\text{CSI}); \beta_1 < 0$$
$$\mu_1 = \alpha_1 \tag{3}$$
$$\mu_2 = \alpha_2^0 + \alpha_2^1\text{CSI}$$

In the Dynamic Hybrid model, both μ_1 and μ_2 had CSI-dependent dynamics. We found that the Static-Dynamic Hybrid model fit behavior the best, better than the Static Mixture model (ΔLikCV = 13) or the Dynamic Hybrid model (ΔLikCV = 70). Group-level Bayesian model selection estimated that 77% of the population will be best fit by

the Static-Dynamic Hybrid (Posterior Model Probability; Stephan, Penny, Daunizeau, Moran, & Friston, 2009), and that there was >99% chance that Static-Dynamic Hybrid was the most prevalent winning model (Protected Exceedance Probability; Rigoux & Guigon, 2012). The Static-Dynamic Hybrid estimated that participants transitioned from an early state that was time-invariant to a late state in which performance improved over time (late CSI dynamics (α_2^1): group-level Cohen's $d = -1.0, p = 0.0026$). This same differentiation between early and late states was also supported by the Dynamic Hybrid model, which estimated non-significant CSI dynamics for early states ($d = 0.015, p = 0.95$) and significant improvements over the CSI for late states ($d = -0.99, p = 2.2 \times 10^{-7}$).

Model Name	N	ΔLikCV	P(Model)	PXP
Dynamic	4	331	0.0355	0
De Jong Mixture	7	212	0.0271	0
Static Mixture	8	13.1	0.134	0
Static-Dynamic Hybrid	**9**	**0**	**0.768**	**1**
Dynamic Hybrid	10	70.2	0.0348	0

Table 1: Comparison between Dynamic, Mixture, and Hybrid models. **N**: number of fixed-effects parameters. **ΔLikCV**: cross-validated log-likelihood, relative to the best-fitting model. **P(Model)**: Posterior Model Probability. **PXP**: Protected Exceedance Probability.

We validated that our models captured important trends in the data through posterior predictive checks (Figure 4C). We plotted single-subject RT distributions for trials within the shortest and longest CSI quartiles, finding compelling signatures of bimodality that were captured by our mixture models. When we simulated behavior from our best-fitting model, we found that it captures the major trends in the data, such as the bimodality (a property of the mixture model) and the leftward shift in the faster mode's mean (a property of the dynamic model; see also Figure 3B). Together, these results are consistent with a mixture of both discrete and dynamic reconfiguration during task-switching.

Finally, we confirmed these models were identifiable by our model fitting and model selection processes by performing model recovery (Figure 4C). We generated a synthetic dataset from each model, fit each model to these synthetic datasets, and then tested whether the model that generated the data was the one with the higher posterior model probability. We found accurate recovery of the data-generating models, suggesting that these models make discriminable predictions in this dataset.

Participants prepare for switching before the task cue
The durations of the mini-blocks were unpredictable: after the second trial, there was always a 50% chance of transitioning to the Task Cue. However, since participants
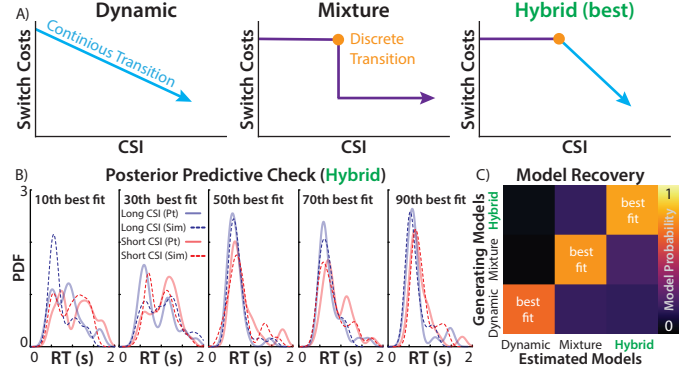

Figure 4: Model-based analysis of switching dynamics. A) There were three classes of models: models with continuous transitions ('Dynamic'), models with discrete transitions ('Mixture'), and models with both continuous and discrete transitions ('Hybrid'; best-fitting). Note that the discrete transition onset is random across trials. B) Behavior simulated from the best-fitting Static-Dynamic Hybrid model approximated participants' RT distributions. Participants are sorted according to their average model likelihood (left to right, worst to best fitting). Simulations reflect a single draw from the model to avoid over-smoothing. B) Model recovery demonstrated that the ground-truth model could be selected by our fitting and comparison procedures. Specific models are 'Dynamic', 'Static Mixture', and 'Static-Dynamic Hybrid'. Model fits are posterior model probabilities on cross-validated likelihoods.

knew the order of the tasks, they may have nevertheless anticipated upcoming switch demands, and prepared for them over the course of the mini-block as the expectation of a transition increased. Accordingly, we found that participants responded more slowly on the trial before switches than the trial before repeats, even though the Task Cue had not yet appeared (logRT: $t = 3.09, p = .0020$; Figure 5A). Critically, this slowing appeared to be strategic: it was associated with lower RT switch costs on the first trial of the next mini-block, controlling for baseline autocorrelation (Switch $\times$ PreviousRT: $t = -6.43, p < 10^{-9}$; Figure 5B). This suggests that slowing was associated with task preparation prior to, but presumably in anticipation of, the Task Cue. This effect of pre-cue slowing on switch costs did not further interact with CSI ($p = .313$), suggesting earlier progress towards the reconfigured state and not faster switching dynamics.

To assess how pre-cue slowing influenced the discrete and continuous dynamics modeled above, we included pre-switch RT as an additional covariate in the best-fitting Static-Dynamic Hybrid model. We compared distinct versions of how participants might have prepared for the upcoming task. In the Transition Preparation model, we included pre-switch RT in the discrete switching dynamics ($\pi = \text{logistic}(\beta_0 + \beta_1\text{CSI} + \beta_2\text{RT}_{t-1})$). In the State

Preparation model, pre-switch RT influenced the late task state ($\mu_2 = \alpha_2^0 + \alpha_2^1\text{CSI} + \alpha_2^2\text{RT}_{t-1}$). Finally, in the Combined Preparation model, pre-switch RTs influenced both the transition probability and the late state. We controlled for baseline autocorrelation by estimating the influence of the previous RT across all switch and repeat trials ($\text{RT}_t^* = \text{RT}_t - \gamma\text{RT}_{t-1}$).
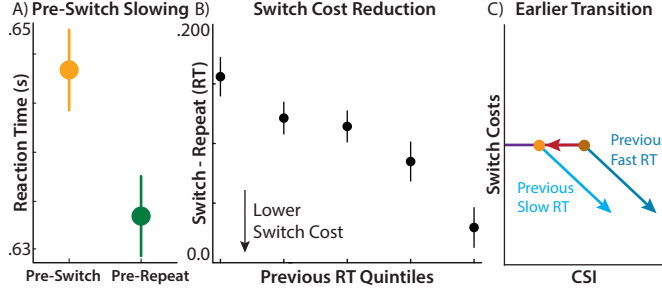

Figure 5: Pre-cue preparation. A) Participants responded more slowly on trials leading up to a switch cue. B) The slower participants respond before a task cue, the lower their switch costs. C) Model comparison found that pre-cue preparation was best explained as an earlier transition from the static task state to the dynamic task state.

We found that the Transition Preparation model fit participants' data better than State Preparation (ΔLikCV = 49; Table 2) or Combined Preparation (ΔLikCV = 16), albeit with a moderate exceedance probability (75%). The model fit suggested that slower pre-switch RTs increased the probability of switching from the static state to the dynamic state, though this effect was not significant ($d = -0.45, p = .12$; Figure 5C). This selective influence of preparation on discrete state transitions provides further evidence that discrete and continuous dynamics are dissociable constructs, but more research is needed to confirm these trends.

Model Name	N	ΔLikCV	P(Model)	PXP
Transition Preparation	**11**	**0**	**0.608**	**0.749**
State Preparation	11	49.0	0.160	0.125
Combined Preparation	12	16.0	0.233	0.126

Table 2: Comparison between pre-cue preparation models. **N**: number of fixed-effects parameters. **ΔLikCV**: cross-validated log-likelihood, relative to the best-fitting model. **P(Model)**: Posterior Model Probability. **PXP**: Protected Exceedance Probability.

Discussion

Researchers have debated for decades whether task set reconfiguration is a continuous or discrete process (De Jong, Berendsen, & Cools, 1999; De Jong, 2000; Nieuwenhuis & Monsell, 2002; Brown, Lehmann, & Poboka, 2006; Gilbert & Shallice, 2002; Kiesel et al., 2010). We approached this debate using an experimental paradigm that combines the strengths of cued and predictable task-switching designs, while minimizing associative learning confounds. Using a novel single-trial analysis of continuous and discrete switch dynamics, we found that task preparation exhibited characteristics of both hypotheses: people appear to transition from an unprepared static task state into a task state that continuously improved performance over the CSI. Moreover, we found that participants appear to strategically prepare for upcoming switch demands, which increases the probability that they will transition into a dynamic state. Our results provide a new, model-based approach to quantifying how people switch between tasks, which we used to test existing hypotheses concerning task set reconfiguration. These models should be seen as descriptive models, rather than mechanistic models, but they inform the behavioral patterns that a process model must capture.

Previous work has suggested that discrete transitions between task sets may arise due to the success or failure of recalling the correct task set (Mayr & Keele, 2000; Monsell, 2003). Speculatively, this may correspond to the early static task state, with the transition from this state to the dynamic state reflecting the successful episodic recall of the upcoming tasks. Perhaps then this transition reflects an evidence accumulation process (Ratcliff, 1978), sampling episodic memory to recall the task identity. While this process may have been emphasized in our task moreso than in previous experiments, it reflects an important component of many real-life uses of cognitive flexibility.

Once the goal has been recalled, the second, dynamic task state may reflect the reconfiguration process hypothesized by dynamic models of task-switching (Gilbert & Shallice, 2002; Ueltzhöffer et al., 2015; Steyvers et al., 2019; Musslick et al., 2019; Ritz, Leng, & Shenhav, 2022). While state dynamics appeared to be linear in time, longer CSIs may have revealed that switch-trial performance saturates at or above repeat-trial performance, as has been consistently observed in previous experiments (Rogers & Monsell, 1995; Meiran, 1996).

Using similar methods of state identification, future experiments should attempt to further dissociate the early and late task states, such as in terms of their sensitivity to proactive interference or memory aids as signatures of episodic recall. Our future research aims to use this task to investigate the neural correlates of task-set reconfiguration, providing further insight into the latent processes that govern our cognitive flexibility (Yeung et al., 2006; Esterman, Chiu, Tamber-Rosenau, & Yantis, 2009; Qiao, Zhang, Chen, & Egner, 2017; Hubbard, Kikumoto, & Mayr, 2017; Karayanidis et al., 2023).

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