COGNITIVE PROCESSES IN VOLUNTARY TASK SWITCHING

A Dissertation

by

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ABSTRACT

Voluntary task switching (VTS) paradigms are often used to assess cognitive flexibility in experimental settings. Here, the cognitive processes related to switching tasks and behavioral changes over time in VTS paradigms are assessed. In Chapter 2, a drift diffusion model was applied to two versions of a VTS paradigm in separate samples; results indicate that more proactive preparation was associated with task switches, and that requiring participants to overtly indicate their task choice affected the timing of task set preparation. In Chapter 3, improvements in reaction time and/or accuracy consistent with practice effects were identified across three different VTS paradigms. In two of the three paradigms, group-level declines in switch rates over time were also present, consistent with hypotheses that supported reduction in cognitive effort throughout the task and compensatory behavioral changes to combat early fatigue effects. Changes in switch rates over time were related to individual differences in approach/avoidance behavior in the third paradigm despite the lack of significant change at a group level. Chapter 4 examined the relationship between changes in switch rates over time and changes in EEG measures over time thought to index cognitive effort expenditure and fatigue. Chapter 4 replicated declines in switch rate over time at a group level identified in Chapter 3. However, the degree of change in switch rate was not related to change in any EEG measure examined, and no support for either proposed mechanism (effort avoidance or fatigue) was found. The series of experiments establishes replicable patterns in voluntary task switching performance related to preparation timing and changes in switch rates that should be explored further in future work.

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NOMENCLATURE

WCST	Wisconsin Card Sorting Test
VTS	Voluntary Task Switching
CSI	Cue-Stimulus Interval
RSI	Response-Stimulus Interval
RCI	Response-Cue Interval
RT	Reaction Time
CRSI	Cue Response-Stimulus Interval
DDM	Drift Diffusion Model
CI	Credible Interval
EEG	Electroencephalography
BIS/BAS	Behavioral Inhibition System/Behavioral Activation System
ERSP	Event-related Spectral Perturbations

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1. INTRODUCTION

1.1. Measuring Cognitive Flexibility in Experimental Settings

Cognitive flexibility is considered a core aspect of executive function (Diamond, 2013) and is implicated in a number of disorders (Geurts et al., 2009; Meiran et al., 2011; Nolan et al., 2004). However, there is a great deal of variability in how cognitive flexibility is measured in a lab setting. Reversal learning paradigms are sometimes used, in which the ability to adapt to a switch in optimal choices is considered the primary measure of flexibility (Clatworthy et al., 2009; Jocham et al., 2009; Kehagia et al., 2010; Murray et al., 2008). One advantage of reversal learning paradigms is that they are easily applicable to animal models (Castañé Anna et al., 2010; Johnson & Wilbrecht, 2011; Schrijver et al., 2004). The Wisconsin Card Sorting Test (WCST) is also commonly considered a measure of cognitive flexibility as participants must learn to adapt to changing rule sets (Barnett et al., 2007; Morice & Frost, 1993; Tchanturia et al., 2012), although this paradigm might capture more than simply cognitive flexibility due to its complexity (Barceló, 2001; Nyhus & Barceló, 2009).

Perhaps the most common methods of measuring cognitive flexibility in humans are variations of task switching paradigms (Kiesel et al., 2010; Koch et al., 2010), which involve switching between two simple task sets (i.e. classification of a digit as odd or even) often performed on bivalent stimuli that can be applied to either task. Unlike reversal learning paradigms and the WCST, which require participants to adapt to a task rule change after it has already occurred, task switching paradigms can allow for participants to prepare for a new task rule prior to performing the new task. Further, the degree to which participants can prepare can be manipulated, allowing for more specific conclusions than other flexibility paradigms. For example, some task switching paradigms present both the task stimuli and task set simultaneously (Demanet et al., 2013), providing no time for a participant to prepare for a new task set in advance. Other paradigms involve a task cue presented prior to the presentation of task stimuli, allowing for a manipulation of the preparation interval between task cue and task stimuli (Mayr, 2011). Still other paradigms might use a set task order such that participants can potentially prepare for a task switch a number of trials in advance once the task order is learned (Koch, 2005). This flexibility in manipulating the degree of task preparation has allowed task switching paradigms to yield well defined theories about the cognitive processes involved in adapting to a new task set.

1.2. Voluntary Task Switching

More recently, researchers have also begun employing voluntary task switching (VTS) paradigms. VTS paradigms allow participants to choose which task to perform on an upcoming trial. In contrast to cued choice paradigms, VTS paradigms are often considered to have greater ecological validity (Arrington & Logan, 2004, 2005; Demanet et al., 2011) and have the advantage of yielding additional information about participants' task choices.

However, VTS paradigms also vary in design. First, VTS paradigms can be split into single-registrant and double-registrant categories. Single-registrant designs only require a single response from the participant within each trial, which simultaneously indicates both task choice and task response. These designs are most similar to classical cued paradigms, which only require a single response per trial (a response to the task stimuli). Single-registrant designs often involve a cue prior to task performance that indicates participants should choose which task to perform. However, in a purely voluntary (no intermixed cued trials) single-registrant design, it's possible for participants to ignore this cue entirely.

Double-registrant designs aim to rectify this by requiring participants to respond twice within each trial – they first respond to a choice cue indicating which task they chose, then respond to the task stimulus to perform the chosen task. Double-registrant designs allow for a greater separation of task choice and task performance, allowing for greater resolution in examining each individually.

Additionally, the conditions under which participants can choose tasks varies across paradigms. Most often, participants are told to choose tasks randomly, such that they choose each task equally often and switch/repeat tasks equally often (Arrington & Logan, 2004, 2005; Fröber & Dreisbach, 2017; Orr et al., 2012). However, some designs allow participants to choose tasks entirely freely, with researchers arguing that constraining task choices harms ecological validity (Wickens et al., 2015) and adds complexity (Fröber et al., 2019). Nonetheless, the alternatives to task choice constraints have their own drawbacks. Some solutions involve devising much more complex paradigms, sometimes involving four or five tasks being performed simultaneously (Gutzwiller et al., 2019), to achieve greater ecological validity. This added complexity limits the ability to compare results to cued task switching paradigms, employ manipulations similar to those used in cued paradigms, and draw parsimonious conclusions regarding cognitive mechanisms occurring during task performance. However, maintaining the simple structure of a standard VTS paradigm but simply removing the constraint to choose tasks randomly generally results in participants choosing to repeat tasks on a very large percentage (or all) of trials (Arrington & Logan, 2004; Fröber et al., 2019), limiting statistical power to draw conclusions about the act of switching tasks.

1.3. Common Measures of Interest

In voluntary task switching paradigms, the rate at which participants choose to switch tasks (switch rate) is a frequently used measure of interest. Notably, this measure does not exist in cued task switching paradigms, making the ability to examine voluntary switch rate is a major strength of voluntary designs. Previous work has generally considered switch rates to index reward sensitivity, cognitive flexibility and control, and effort exertion (Braem, 2017b; Fröber & Dreisbach, 2017; Mittelstädt, Dignath, et al., 2018; Yeung, 2010).

Additionally, task switching studies consistently produce the finding of a reaction time switch cost, or worse reaction times on task switch trials compared to task repeat trials (Monsell, 2003; Schneider & Logan, 2009; Wylie & Allport, 2000). Accuracy switch costs, or a reduction in accuracy on switch trials compared to repeat trials, are also often present, although less reliably so. Because the finding of a reaction time switch cost is reliable across both voluntary and cued task switching paradigms, it provides the easiest avenue by which to explore whether theories regarding cognitive processes in cued task switching translate to voluntary contexts.

1.4. Goals of Current Research

1.4.1. Decomposing Switch Costs in VTS Paradigms

An extensive body of work has examined the cognitive processes that contribute to reaction time switch costs in cued task switching paradigms (Allport & Wylie, 1999; Grange, 2016; Grange & Cross, 2015; Koch & Allport, 2006; Meiran et al., 2000a; Monsell et al., 2000; Sohn & Carlson, 2000). Generally speaking, this work relies on manipulations of the time between task cue and task stimulus (CSI; cue-stimulus interval) and the time between task response and next task stimulus (RSI; response-stimulus interval) to manipulate task set reconfiguration and task set inertia, respectively. However, similar work in VTS is more difficult to interpret, largely because participants are able to prepare for a task prior to task choice cue presentation in VTS paradigms. Further, the degree to which this is true might depend on whether a participant is required to engage with the choice cue (e.g. if the design is single- or double-registrant).

Previous work in cued task switching has indicated that the effects of these classical manipulations on cognitive processes contributing to switch costs in cued task switching can be independently measured using the parameters in a drift diffusion model. Chapter 2 of the current work leverages this strength of drift diffusion model parameters to examine how these classical interval manipulations affect each process, how each process contributes to switch costs in VTS paradigms in general, and the degree to which single- vs. double-registrant designs influence these factors.

1.4.2. Examining Changes in Flexibility Measures Throughout Task Performance

The work discussed thus far, and the vast majority of existing work, has focused solely on subject- or group-level averages of the switch cost and switch rate measures described here to index cognitive flexibility. However, an understanding of how these measures change (or remain constant) throughout task performance might provide additional information about cognitive processes that occur during task performance. Identifying processes that occur during VTS paradigms which influence changes in performance over time might help form more complete theories about cognitive flexibility and contribute to our understanding of individual differences in VTS performance.

Chapter 3 of the current work examines three different VTS paradigms using separate samples collected across different labs. The goal of analyses in Chapter 3 is to identify patterns of change throughout task performance that might inform us about cognitive processes and individual differences. After a decline in switch rates was identified as somewhat replicable at a group level and informative at an individual level, a follow-up study (Chapter 4) was conducted examining hypothesized neural correlates of this change in switch rate to help identify which cognitive processes the change might index.

2. COMPONENT PROCESSES UNDERLYING VOLUNTARY TASK SELECTION[1]

2.1. Introduction

While theories characterizing the cognitive processes underlying switch costs differ slightly, most agree that switch costs are composed primarily of two components: task set inertia and task set preparation (Koch et al., 2018; Meiran et al., 2000b; Vandierendonck et al., 2010).

2.1.1. Task Set Inertia and Task Set Preparation

The first support for the processes of task set inertia and task set preparation composing switch costs came from manipulations of the response-stimulus interval (RSI) and cue-stimulus interval (CSI) in explicit task switching. Researchers found that lengthening the RSI, or the time between response on trial n-1 and stimulus onset on trial n, reduced switch costs (Allport et al., 1994; Rogers & Monsell, 1995). It was thought that manipulating this interval reduced the proactive interference on task performance stemming from previous, now irrelevant, trials. This proactive interference is known as task set inertia. It should be noted, however, that because these studies used predictable task switches (e.g., alternating runs), task set preparation could begin during the RSI. They made the assumption that task set preparation could be completed prior to the

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stimulus onset with a sufficiently long RSI; therefore, any residual switch cost was only attributable to other factors like task set inertia.

Later, Meiran (1996) developed the task-cueing paradigm with unpredictable cues in which the intervals between task cue and task stimulus (cue-stimulus-interval, or CSI) and the response-cue-interval (RCI) were independently manipulated. In this design, the CSI and RCI together compose the RSI (response-stimulus-interval). By lengthening the RCI when the CSI was shortened and shortening the RCI when CSI was lengthened, Meiran manipulated the CSI (which should affect preparation) while holding RSI constant (theoretically not affecting inertia). This manipulation also yielded a decreased RT switch cost, supporting the idea that the contributions of preparation and inertia to switch cost are separable. Notably, more recent work has complicated this interpretation by demonstrating a relationship between better preparation prior to task performance and reduced inertia during task performance (Koch & Allport, 2006; Yeung & Monsell, 2003). Therefore, even when the RSI is held constant, the effect of CSI manipulations on preparation might additionally affect inertia, making the two processes difficult to separate.

Further, our understanding of the mechanism by which RSI length affects task set inertia has evolved over time. While the reduction in switch cost during cued paradigms was originally attributed to dissipation of previous task sets over time (Allport et al., 1994), more recent work has indicated the effect might be additionally (or alternatively) attributable to learned associations between stimuli on the current trial and previous task sets (Wylie & Allport, 2000) and/or temporal distinctiveness between current and previous task sets that depend upon previous trial RSI length (Grange, 2016; Grange & Cross, 2015; Horoufchin et al., 2011b, 2011a). Nonetheless, manipulations of the RSI, RCI and CSI have proven valuable tools in examining task set inertia and task set preparation in task switching.

2.1.2. Task Set Inertia and Task Set Preparation in Voluntary Task Switching

The contributions of inertia and preparation to task switching are even more challenging to dissociate in voluntary task switching paradigms. In contrast to cued task switching paradigms, voluntary task switching paradigms allow participants to choose which task to perform on a trial-by-trial basis, either at the time of stimulus presentation (i.e., single-registrant designs) or at the time of a choice cue (i.e., double-registrant-registrant designs). While previous work does indicate that manipulating the RSI reduces switch cost (Arrington & Logan, 2004), it is much more difficult to discern whether the reduction is due to facilitation of preparation, reduction of inertia, or both.

In both single- and double-registrant-registrant designs, participants can theoretically choose the task prior to stimulus/ cue presentation. Further complicating the matter, participants in double-registrant-registrant designs can theoretically prepare for an upcoming trial prior to cue presentation (during the RCI) and after cue presentation (the CSI). For this reason, some previous work has referred to the entire RSI as a 'preparation interval' in voluntary task switching (Arrington, 2008). While some work comparing the effects of RSI manipulations in voluntary paradigms to CSI manipulations in cued paradigms has concluded that RSI manipulations in voluntary paradigms primarily affect preparation (Yeung, 2010), this idea is difficult to test directly without assuming further similarities across different paradigms. Further, other work has indicated that RSI manipulations additionally affect bottom-up processing in voluntary task switching (Arrington, 2008), raising the possibility that both top-down preparation and bottom-up task set inertia are affected by the manipulation.

In addition, the degree to which cue timing within the RSI affects performance in voluntary task switching might depend upon the specifics of the paradigm. While single-registrant voluntary task switching paradigms do not require participants to actively engage with a task choice cue, double-registrant-registrant paradigms require a response to the choice cue to indicate which task was chosen.

Previous work has demonstrated that both changing the CSI while holding the RSI constant and changing the RSI while holding the CSI constant reduced RT switch costs in a double-registrant-registrant paradigm, suggesting that cue timing does affect performance when choice response is required (Demanet & Liefooghe, 2014); however, because participants in a purely voluntary paradigm (with no intermittent cued trials) can prepare prior to the cue, it again must be assumed whether these manipulations affect task set inertia, task set preparation, or both when relying purely on reaction time measures.

2.1.3. Drift Diffusion Modeling Measures Latent Variables

Drift diffusion modeling (Ratcliff, 1978) provides a way to independently quantify the contribution of task set inertia and task set preparation to RT switch costs. Drift diffusion models (DDMs) assume that decision making occurs by accumulating evidence from a stimulus and that decisions are made when accumulated evidence reaches a decision threshold. As such, the models yield a ‘decision threshold’ parameter, which quantifies the amount of evidence necessary for a response to be made. This is especially important for task switching, as this parameter captures speed-accuracy tradeoffs during switches (more evidence necessary for a decision represents a greater emphasis on accuracy and vice versa; Karayanidis et al., 2009; Schmitz & Voss, 2012, 2014), allowing for this tradeoff to be controlled for when examining switch cost.

More directly relevant to switch cost theories, drift diffusion models also assume that reaction times consist of a period during which evidence is not being collected, known as nondecision time. Nondecision time can quantify time spent loading relevant information for task performance, such as working memory load representations (Maldonado et al., 2019) – in a task-switching context, the parameter should then quantify the amount of time spent loading the relevant task set. Further, nondecision times are generally longer on switches compared to repeats, a difference which is thought to quantify the additional preparation necessary for switch trials (Karayanidis et al., 2009; Schmitz & Voss, 2012, 2014). Notably, nondecision time is also considered to capture motor processes contributing to response times. However, previous task switching work has argued that these processes should be consistent within a participant across conditions, simplifying interpretation of the effects of switching on the parameter to exclude motor processes (Schmitz & Voss, 2012).

Similarly, the rate at which evidence is collected during decision making, known as drift rate, is worse on switch trials compared to repeat trials. This difference is thought to capture a decrease in the signal-to-noise ratio during decision making, quantifying the contribution of task set inertia to switch costs (Schmitz & Voss, 2014). Crucially, these interpretations of model parameters are supported by the fact that CSI manipulations affect nondecision time (Karayanidis et al., 2009; Schmitz & Voss, 2012, 2014) and RSI manipulations affect drift rate (Schmitz & Voss, 2012), in line with predictions from previous work in cued task switching.

2.1.4. Drift Diffusion Modeling to Assess Preparation in Voluntary Task Switching

No previous work, however, has sought to apply drift diffusion modeling to voluntary task switching. Because it is generally difficult to dissociate task set preparation from task set inertia in voluntary paradigms, the ability of a drift diffusion model to quantify each might be especially valuable whereas analysis of switch cost RT alone would confound the two.

Examination of the nondecision time parameter might help quantify the degree to which the effect of switching tasks, as well as RSI length and cue timing, might affect the contribution of task set preparation to switch costs. For example, if cue timing affects preparation prior to stimulus presentation, manipulating the CSI while holding the RSI constant should affect the amount of preparation needed post-stimulus presentation (nondecision time). Similarly, if participants prepare prior to cue presentation in voluntary task switching paradigms, RSI manipulations would affect nondecision time whereas they do not in cued task switching.

Further, examining the effect of RSI manipulations on drift rate during voluntary task switching might help determine the degree to which the manipulations affect task set inertia's contribution to switch costs. Equally valuable is the fact that the model quantifies both processes during task performance with independent parameters; therefore, if manipulations that improve task set preparation have a downstream effect on task set inertia (as has been suggested in cued task switching work), one would expect to see changes in both parameters.

2.1.5. Paradigms

The current work seeks to examine the effects of concurrent CSI and RCI manipulations on switch cost and drift diffusion model parameters in two versions of voluntary task switching; one single-registrant version (Experiment 1), which does not require a participant response to the task cue, and one double-registrant-registrant version (Experiment 2), which does require a response to the task cue to indicate task choice.

Single-registrant paradigms allow for more precise manipulation of the CSI and RSI; because there is no response to the task cue, CSIs in single-registrant paradigms can be fixed at very short lengths. This is particularly important when examining the nondecision time parameter, as previous work in cued task switching has only consistently found longer nondecision times for task switches when CSIs were very short (Schmitz & Voss, 2012). However, because participants are not required to actively engage with the cue, it is possible that cue timing itself does not affect the way participants perform the task despite instructions to decide on the task for the upcoming trial upon cue presentation. In other words, without requiring an overt response to the task cue, participants are theoretically able to ignore the cue entirely and decide on a task at any point independent of the cue.

In contrast, double-registrant registrant paradigms require additional time within the CSI for the participant to respond to the cue; this additional time might obscure effects of switching on nondecision time. Further, because these response times naturally vary trial-to-trial, the CSI in a double-registrant registrant paradigm also varies trial-to-trial even when the interval between cue response and stimulus presentation (CRSI) is manipulated. Hence, these trial-level differences must be controlled for when examining the effects of CSI length. However, the additional engagement with the task cue might change the manner in which the timing of the cue affects preparation, supported by previous work which found an effect of CSI length on RT switch cost in a double-registrant registrant paradigm (Demanet & Liefooghe, 2014).

2.1.6. Hypotheses

We first aimed to examine the effects of switching on RT, drift rate and nondecision time within each interval combination - short RCI/short CSI (S/S), short RCI/long CSI (S/L), long RCI/short CSI (L/S), and long RCI/long CSI (L/L). Different combinations of RCI and CSI also enabled us to either change or hold constant the RSI (i.e., RCI + CSI). For example, the S/L and L/S combinations held RSI constant, while changing CSI. We were primarily interested in effects of RSI and CSI length, and it should be noted that some RSI conditions (S/S and L/L) contain only a single level of CSI condition; for this reason, we specified a-priori which interval pairs to compare directly rather than conduct a classical ANOVA.

For both paradigms, we predicted longer RTs in switch trials than repeat trials in all conditions. These analyses of switch effects were most important for the model parameters - because nondecision time only captures preparation that occurs after stimulus onset (during RTs), we hypothesized that longer intervals that allow for switch-specific preparation to occur entirely before stimulus onset might not yield a switch effect on nondecision time. Relatedly, we predicted a stronger effect of switching on nondecision time in the single-registrant paradigm, as the CSI was shorter due to the lack of task choice response time within it.

In line with previous work, we expected a switch cost on drift rate in all conditions such that switching would lead to worse (decreased) drift rates on switches compared to repeats; while this has been consistently reported in cued task switching (Karayanidis et al., 2009; Schmitz & Voss, 2012, 2014), the effect had never been previously examined in a voluntary paradigm.

We then aimed to examine how the effects of RSI manipulations (holding CSI constant) on preparation might affect preparation and inertia. We hypothesized that conditions with longer RSIs would yield decreased RT switch costs in both paradigms as well as a decreased effect of switching on nondecision time, quantifying preparation prior to cue presentation. We expected that this effect would be reduced in the double-registrant-registrant version, where more engagement with the cue would encourage more preparation post-cue presentation. We also expected that, given previous work indicating effects of RSI length on bottom-up processes in voluntary task switching (Arrington, 2008), RSI manipulations would additionally result in changes in the effect of switching on drift rate (quantifying task set inertia).

Importantly, there were two pairs of conditions for which RSI was manipulated and CSI was held constant. The first comparison, L/S vs. S/S, was hypothesized to yield the stronger effects of the two; the shorter CSIs meant less preparation, which should in turn mean greater inertia effects. We also examined the differences between the L/L and S/L conditions; here, we expected similar effects of longer RSIs on inertia and preparation, although we also expected that the increased preparation during the long CSI would reduce the magnitude of these effects (Koch & Allport, 2006). However, we chose to include the L/L condition in the experiment in order to make this comparison – if manipulating the RSI, even when the CSI is held long, affects nondecision time, it would lend further credence to the importance of the RCI for preparation independent of cue timing.

In sum, our experiments aim to examine the degree to which the processes of task set preparation and task set inertia account for switch costs in voluntary task switching. We also aimed to quantify the degree to which participants prepare for upcoming trials prior to cue presentation as well as the degree to which the timing of cue presentation affects preparation. Finally, we examined whether there were any differences in these effects across single- and double-registrant-registrant paradigms.

2.2. Experiment 1 (Single Registrant) Methods

2.2.1. Participants

The sample consisted of undergraduate students (*n* = 56) who completed the study online for course credit. Participants who switched tasks on greater than 80% of trials or less than 20% of trials were removed from analyses (*n* = 11). We imposed a

60% accuracy criterion over the course of the experiment, which all subjects met. Age and gender characteristics of the final sample are reported in Table 2.1. All study procedures were approved by the Texas A&M University Institutional Review Board.

	Experiment 1 (*n* = 45)	Experiment 2 (*n* = 76)
	Demographic Information	
Gender % (F/M)	66.67/33.33	65.79/34.21
Age	19.03 (1.09)	19.36 (1.57)
	Task Performance	
Accuracy (%)	94.50 (7.38)	94.78 (5.72)
Overall reaction time (ms)	882.28 (185.30)	863.64 (166.95)
Switch reaction time (ms)	943.32 (200.89)	950.06 (206.97)
Repeat reaction time (ms)	842.34 (181.33)	800.43 (144.13)
Switch rate (%)	42.69 (11.11)	45.66 (13.38)

Table 2.1. Demographics and Task Performance. Means and standard deviations are presented for age and each behavioral metric. Gender breakdown is presented as percentage females/percentage males. Behavioral data displayed are calculated after removal of reaction time outliers, post-error trials, and first trials in each block. Reprinted from Imburgio & Orr, 2021b.

2.2.2. Paradigm

The experiment was coded in PsychoPy v. 2020.2.4 (Peirce et al., 2019), converted to javascript and hosted with Pavlovia (https://pavlovia.org/). Participants performed a modified version of a number Stroop task composed of a task choice and task stimulus phase. Each trial was composed of a task choice stimulus phase followed by a task stimulus phase. Task design is displayed in Figure 2.1.

In the task choice phase, a ‘?’ was presented in the middle of the screen. Participants were instructed to decide which of two possible tasks they chose to perform upon presentation of the stimulus. Participants were instructed to choose tasks randomly, without following a pattern, such that each task was chosen equally often and that they chose to switch tasks and repeat tasks equally often. Participants were encouraged to pretend as though they were choosing tasks by flipping a coin in their head to reinforce the random nature of their choice. In the task stimulus phase, participants were presented with two numbers that differed in both numerical size and physical size, one number above the fixation cross and one below the fixation cross. Participants were to perform either a numerical comparison (choose the number that is numerically larger) or a physical comparison (choose the number that is physically larger). Participants indicated their response using the ‘f’, ‘v’, ‘j’ and ‘n’ keys on a keyboard, where ‘f’ or ‘j’ indicated the top number was chosen and ‘v’ or ‘n’ indicated the bottom number was chosen. The left-hand keys (‘f’ and ‘v’) were mapped to one task and the right-hand keys (‘j’ and ‘n’) were mapped to the other, with hand-to-task mappings counterbalanced across participants. If participants responded incorrectly, a message that said ‘Error’ was displayed on the screen. If participants responded correctly, no feedback was presented.

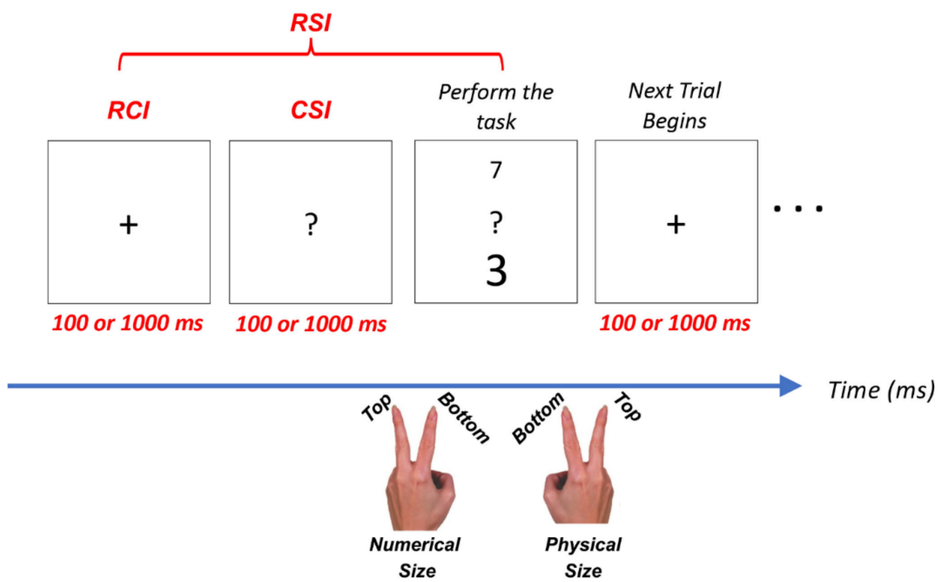

Figure 2.1. Depiction of Experiment 1 (single-registrant) paradigm. The response-cue interval (RCI) and cue-stimulus interval (CSI) compose the response-stimulus interval (RSI). Reprinted from Imburgio & Orr, 2021b.

In each trial, RCI (time between task response and cue stimulus on the next trial) and CSI (time between task choice cue and task stimulus) were either short (S; 100 ms) or long (L; 1000 ms). Each combination of RCI/CSI conditions (S/S, S/L, L/S, L/L) was equally likely - average and minimum trial numbers per participant for each condition are displayed in Table 2.2. Congruent trials (numerically larger number is also physically larger) and incongruent trials were also equally likely, although congruence effects were not analyzed. The full version of the task consisted of 6 blocks of 65 trials each. Participants completed practice versions of the task prior to the full version, beginning with single tasks of practice blocks, then a shortened version of the full task.

Paradigm	Switch/Repeat Condition	Interval Condition	Mean trials	Min. trials
Single - Registrant Paradigm (Experiment 1)	Switch	S/S	29.00	11
		L/S	38.82	20
		S/L	38.98	18
		L/L	41.89	21
	Repeat	S/S	59.62	18
		L/S	48.98	13
		S/L	48.82	10
		L/L	45.13	17
Double - Registrant Paradigm (Experiment 2)	Switch	S/S	39.02	11
		L/S	41.29	20
		S/L	29.14	14
		L/L	41.55	11
	Repeat	S/S	49.05	17
		L/S	47.57	17
		S/L	49.08	11
		L/L	46.96	18

Table 2.2. Average and minimum number of trials per participant by condition. Mean and minimum number of trials by condition for each experiment after removal of reaction time outliers, post-error trials, and first trials in each block. Interval conditions are listed as response-cue interval/cue-stimulus interval for Experiment 1 and response-cue interval/choice response-stimulus interval for Experiment 2. Min. = Minimum. Reprinted from Imburgio & Orr, 2021b.

If a participant failed to reach 60% accuracy on a given portion of practice, they were required to repeat that portion of practice until the accuracy criterion was reached. Participants were given feedback after the final practice phase that displayed their task accuracy, switch rate, and percent of trials where they chose each task. If participants switched tasks on less than 20% of trials or greater than 80% of trials, they were asked to repeat that portion of practice. Similarly, if participants chose one of the tasks more than 80% of the time, they had to repeat that portion of practice. Accuracies and RTs are presented along with demographic information in Table 2.1.

2.2.3. Data Preprocessing

The first trial of each block (neither a switch trial nor a repeat trial) was removed from analyses. Trials following errors were also removed from analyses to account for post-error slowing. Trials with task RTs less than 200 ms or greater than three standard deviations from the mean task RT were also removed. Finally, RTs were checked for normality visually, as a formal test of normality (such as a Shapiro-Wilk test) would be overpowered to detect small, inconsequential deviations from normality in the current sample of 34,000 trials (Ghasemi & Zahediasl, 2012). As RTs did not show a normal distribution, they were log transformed for all relevant analyses; the transformation yielded an adequately normal distribution.

2.2.4. Reaction Time Analyses

To mirror the Bayesian hierarchical approach used in the drift diffusion model analyses, we examined log-transformed RTs using Bayesian multilevel regression via the ‘brms’ R package (Bürkner, 2017) with a random intercept for each subject.

Convergence for all models was confirmed both by visually inspecting chains and by examination of $\hat{R}$ statistics (all $\hat{R}$'s ≤ 1.10). Regression coefficients were considered significant if their 95% credible interval (95% CI) did not contain zero, and coefficients representing the same effect across conditions were considered significantly different if their 95% CIs did not overlap.

2.2.5. Drift Diffusion Model Analyses

All drift diffusion model analyses were conducted using the HDDM Python module (Wiecki et al., 2013) in Python 2.7. Responses were accuracy-coded such that a correct response was coded as 1 and an incorrect response was coded as 0. As such, the inclusion of a bias parameter in the model would assume that participants had foreknowledge of a correct response, so this parameter was fixed at 0.5 (no bias) for all subjects and conditions.

We were primarily concerned with examining how interval manipulations influenced the effect of switching on drift rate (thought to quantify task set inertia) and the effect of switching on nondecision time (thought to quantify task set reconfiguration). To allow for these comparisons, we allowed drift rate and nondecision time to vary by levels of switch/repeat and interval combination (S/S, S/L, L/S, L/L). Because previous work indicated that switching can increase response boundary (Karayanidis et al., 2009; Schmitz & Voss, 2012), this parameter was also allowed to vary by levels of switch/repeat, although the effects of switching on this parameter were not of interest in this study. We did not allow the response boundary parameter to further vary by interval combination to avoid overfitting and because we did not have any clear hypotheses relating to possible effects of the interval conditions on this parameter.

The posterior probability that a parameter in one condition was greater than in another condition (P) was assessed by comparing the overlap of the posterior probability distributions of each parameter. Due to the one-tailed nature of these comparisons, a manipulation was considered significant when P was 97.5% or greater. However, previous work by the authors of the package (as well as the package documentation) has considered differences significant when P > 95% (Cavanagh et al., 2011; Cavanagh & Frank, 2014); Comparisons that would meet this previously established threshold, but not our more stringent threshold, are noted in the results section.

2.2.6. Examination of Switch Effects and Pairwise Interval Comparisons

Our pattern of analyses followed the same logic for analyses of RT and analyses of model parameters. We first examined the effect of switching on RT, nondecision time and drift rate within all interval combinations in both task versions by comparing log RT, nondecision time and drift rate in switch vs. repeat trials. These analyses were meant to 1) confirm the existence of RT switch costs in all interval conditions and 2) examine the degree to which the previously established differences in model parameters between switches and repeats were present in double-registrant registrant and voluntary paradigms. Then, we examined how RT and each parameter were affected by changes in CSI and RSI by comparing the pairs of intervals outlined in the hypotheses section of the Introduction within switch and repeat trials separately. Finally, we examined how the effects of switching on RT, drift rate and nondecision time were affected by changes in CSI and RSI using the same interval pair comparisons.

To quantify the effects of switching on RT, we compared the CIs of the switch regression coefficients (representing the difference in log RT between switch and repeat, or RT switch cost) in each interval condition to determine which conditions yielded significantly different effects of RT switch cost. If the CIs of the switch coefficient did not overlap between two conditions, we concluded the difference was significant.

To examine the effect of switching on each parameter, we calculated the difference in the parameter's posterior probability distribution between switch trials and repeat trials (similar to RT switch cost). To remain consistent with RT switch cost literature, we calculated each such that a positive number always meant worse performance on switch trials relative to repeat trials. For nondecision time, this meant the effect of switching on nondecision time was switch nondecision time minus repeat nondecision time, as larger nondecision times mean worse preparation; for drift rate, the effect of switching was repeat drift rate minus switch drift rate, as smaller drift rates mean worse processing. Then, we examined the differences in the effects of switching on RT, nondecision time, and drift rate across the interval comparisons of interest.

2.3. Experiment 1 (Single-registrant) Results

2.3.1. Effects of Switching

The posterior probability distributions of the effect of switching on RT, drift rate, and nondecision time within each interval condition are depicted in Figure 2.2. Relevant statistics for each comparison are depicted in Tables 2.3 and 2.4. As expected, a significant RT switch cost was present in all interval combination conditions; log RT during switch trials was always larger than log RT during repeat trials.

Measure	Interval (RCI/CSI)	Estimate	95% CI of estimate
Switch Trial log Reaction Time	S/S	6.90	(6.84, 6.96)
	L/S	6.81	(6.64, 6.77)
	S/L	6.71	(6.65, 6.77)
	L/L	6.69	(6.63, 6.75)
Repeat Trial log Reaction Time	S/S	6.69	(6.63, 6.75)
	L/S	6.60	(6.54, 6.66)
	S/L	6.62	(6.56, 6.68)
	L/L	6.64	(6.58, 6.70)
RT Switch Cost (Switch – Repeat)	S/S	0.215	(0.190, 0.240)
	L/S	0.112	(0.084, 0.130)
	S/L	0.089	(0.065, 0.112)
	L/L	0.049	(0.026, 0.072)

Table 2.3. Reaction time measures within interval conditions for single-registrant task. Positive switch costs indicate longer reaction times for switch trials. RCI = response cue-interval, CSI = cue-response interval, S = short, L = long, CI = credible interval. Reprinted from Imburgio & Orr, 2021b.

There was a significant effect of switching on drift rate in the expected direction (drift rates were better on repeat trials than switch trials) in conditions with short CSIs; however, there was no significant difference between switch and repeat drift rates for the

L/L condition, and the difference in the S/L condition met the 95% significance threshold but not our a priori 97.5% threshold.

Parameter	Direction of Effect	Interval (RCI/CSI)	P of Switch Effect	Sig.
Nondecision Time	Sw > Rep	S/S	100%	*
	Rep > Sw	S/L	64.08%	
	Rep > Sw	L/S	98.86%	*
	Rep > Sw	L/L	99.31%	*
Drift Rate	Rep > Sw	S/S	99.98%	*
	Rep > Sw	S/L	90.53%	
	Rep > Sw	L/S	99.93%	*
	Rep > Sw	L/L	96.91%	#

Table 2.4. Switch effects on model parameters within interval conditions. Larger drift rates and smaller nondecision times indicate better performance. Most likely direction of effect is shown. RCI = response cue-interval, CSI = cue-response interval, S = short, L = long, CI = credible interval, Sig. = significance, * = significant at 97.5% threshold, # = significant at 95% threshold. Reprinted from Imburgio & Orr, 2021b.

We hypothesized that, in line with previous work in cued task switching, nondecision times would be worse (larger) for switch trials than for repeat trials. This was only the case in the S/S condition; for both interval conditions with long RCIs, nondecision times were significantly better for switches than for repeats, suggesting that participants used the RCI to prepare more effectively for switches than for repeats.

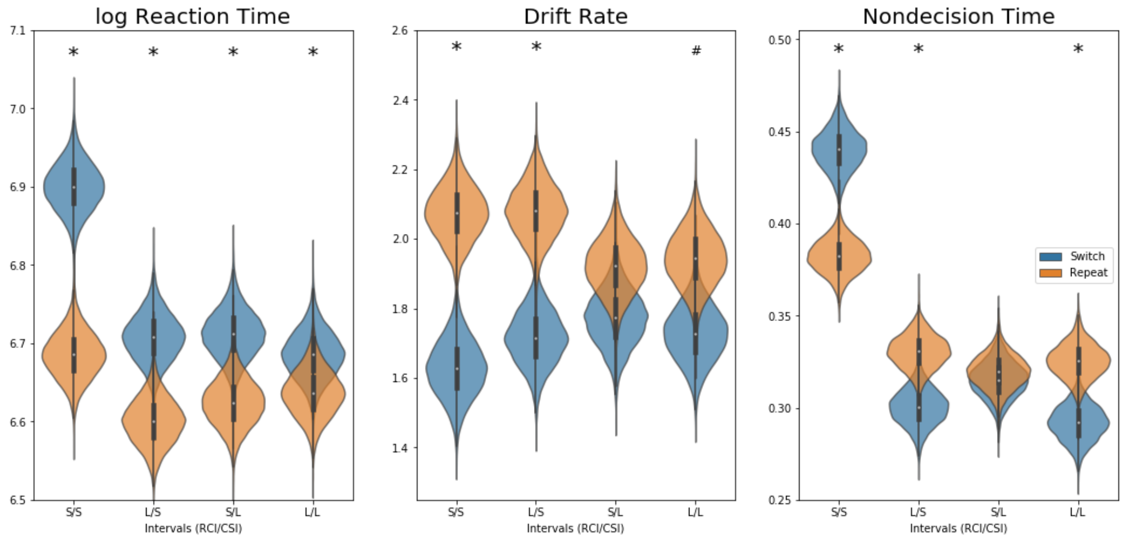

Figure 2.2. Violin plots of posterior probability distributions of single-registrant task performance and modeling parameters within each interval combination. An asterisk (*) denotes that the effect of switching was significant. RCI = response-cue interval, CSI = cue-stimulus interval. Reprinted from Imburgio & Orr, 2021b.

2.3.2. Effects of CSI Manipulation

Posterior probability distributions of RTs and model parameters across each pairwise interval comparison of interest are depicted in Figure 2.3. Statistics for relevant comparisons can be found in Table 2.3 (for RTs) and Tables 2.5 and 2.6 (for model parameters). Posterior probability distributions of RT, drift rate and nondecision time for switch and repeat trials separately are depicted in Figure 2.2 and can be found in Table 2.3 (for RTs) and Table 2.5 (for model parameters).

A comparison of conditions that represent different CSIs while RSI was held constant (S/L vs. L/S) revealed no effect on RT switch cost, nor any effects on RTs within switch or repeat trials individually. Further, there was no difference in either

DDM parameter of interest in switch or repeat trials individually, nor did the effect of switching on either DDM parameter differ across S/L and L/S trials.

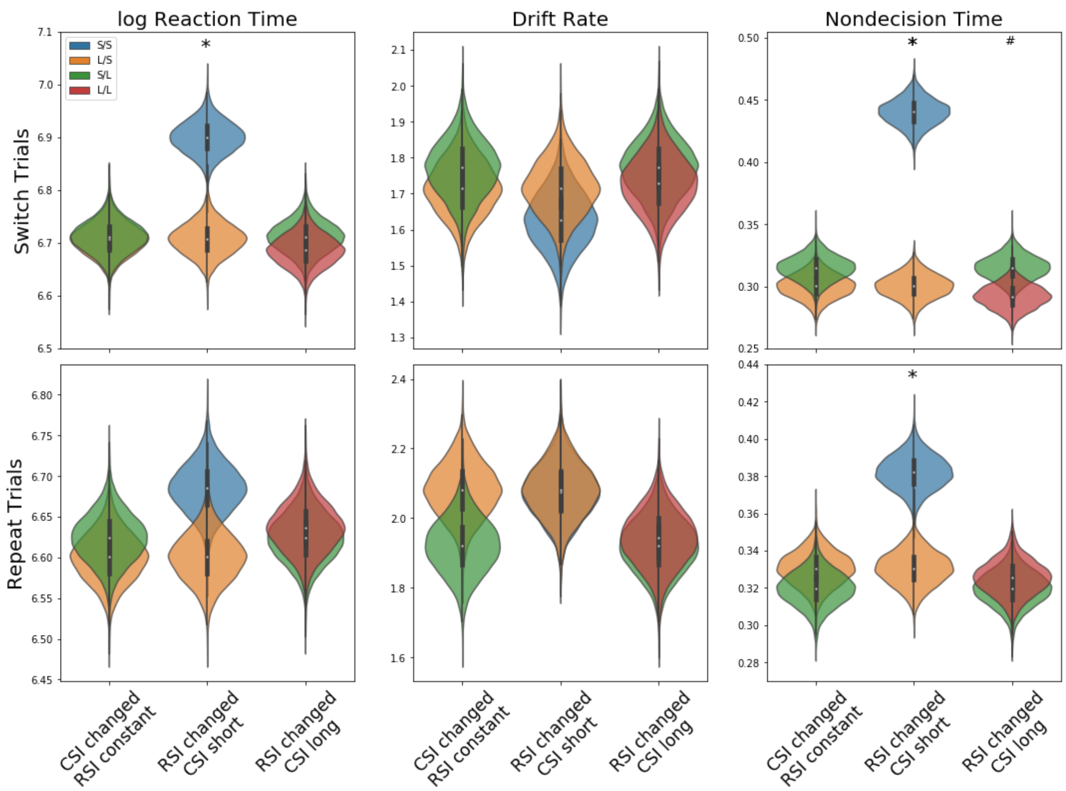

Figure 2.3. Violin plots of posterior probability distributions of single-registrant task performance and modeling parameters within switch and repeat trials across interval pairs of interest. The top row depicts switch trials, the bottom row depicts repeat trials. An asterisk (*) denotes that the effect of switching was significant. RCI = response-cue interval, CSI = cue-stimulus interval. Reprinted from Imburgio & Orr, 2021b.

2.3.3. Effects of RSI Manipulation, CSI Held Short

A comparison of interval conditions that represented changes in RSI length holding CSI short (L/S vs. S/S) revealed significantly larger RT switch costs when RSIs were shorter. An examination of RT within switch and repeat trials separately revealed the effect was attributable to better switch RTs for the L/S condition compared to the S/S condition; the difference in repeat RTs across the conditions was not significant.

Parameter	Trial Type	Interval Comparison (RCI/CSI)	*P* of Difference	Sig.
Nondecision Time	Switch Trials	S/L < L/S	13.14%	
		S/L < S/S	100%	*
		L/L < L/S	95.84%	#
	Repeat Trials	S/L < L/S	80.86%	
		S/L < S/S	100%	*
		L/L < L/S	32.03%	
Drift Rate	Switch Trials	S/L > L/S	69.14%	
		S/L > S/S	77.66%	
		L/L > L/S	34.54%	
	Repeat Trials	S/L > L/S	7.37%	
		S/L > S/S	51.96%	
		L/L > L/S	57.96%	

Table 2.5. Comparisons of single-registrant model parameters trial types across interval pairs of interest. Larger drift rates and smaller nondecision times indicate better performance. RCI = response cue-interval, CSI = cue-response interval, S = short, L = long, CI = credible interval, Sig. = significance, * = significant at 97.5% threshold, # = significant at 95% threshold. Reprinted from Imburgio & Orr, 2021b.

Further, DDM analyses revealed that this reduction was attributable to modulation of switch effects on preparation; the effect of switching on nondecision time was reduced in the L/S condition compared to the S/S condition, and nondecision times in switch and repeat trials individually were better for L/S trials compared to S/S trials. There was no difference across the two interval conditions for any drift rate-related effects.

To summarize, lengthening the RSI while holding the CSI short reduced RT switch cost by improving switch trial RTs. Modeling results revealed that this was attributable to a reduction in the difference in preparation across switch and repeat trials, but also that preparation for both trial types was facilitated by the longer RSIs.

Parameter	Direction of Switch Effect	Interval Comparison (RCI/CSI)	P of Difference	Sig.
Nondecision Time	Varies	S/L < L/S	7.86%	
		S/L < S/S	100%	*
		L/L < S/L	94.09%	
Drift Rate	Repeat > Switch	S/L < L/S	91.18%	
		S/L < S/S	70.76%	
		L/L < S/L	33.40 %	

Table 2.6. Comparisons of switch effects on single-registrant model parameters across interval pairs of interest. Nondecision times are larger (worse) for switches than repeats on S/S trials, but better than repeats for other interval combinations. RCI = response cue-interval, CSI = cue-response interval, S = short, L = long, CI = credible interval, Sig. = significance, * = significant at 97.5% threshold. Reprinted from Imburgio & Orr, 2021b.

2.3.4. Effects of RSI Manipulation, CSI Held Long

RT switch costs were unaffected when RSIs were changed but CSI was held long (L/L vs. S/L), as were RTs for switch and repeat trials individually. There was no significant difference in the effect of switching on drift rate or nondecision time between the two interval combinations, nor any differences in either parameter within repeat trials. Nondecision times were better for the L/L compared to S/L condition when the previously established 95% P criterion was used, although this difference did not reach significance at our more stringent 97.5% threshold.

2.4. Experiment 1 (Single-registrant) Discussion

In Experiment 1, we examined whether voluntary task switching affects DDM parameters, whether CSI and RSI length affects these parameters and RT measures, and whether the nature of these effects were comparable to previously reported effects in cued task switching.

We found effects of switching on the drift rate parameter only within conditions for which the CSI was short. This pattern is in contrast with work in cued task switching (Schmitz & Voss, 2012, 2014), which reports consistent effects of switching on drift rate across CSI. Further, while previous work in cued task switching consistently reports that RSI length moderates the difference in drift rate between switch and repeat trials (Schmitz & Voss, 2012, 2014), interval length manipulations had no effect on drift rate-related measures here.

Instead, lengthening RSIs while holding CSI short significantly reduced the effect of switching on the nondecision time parameter, as well as nondecision times for switch and repeat trials individually. This pattern suggests that, unlike in cued task switching, participants in voluntary task switching paradigms prepare for upcoming trials prior to cue presentation. Further, changing the CSI while holding the RSI constant did not affect any measures; together, these results suggest that manipulations of the RSI as a whole are important for modulation of task set preparation and task set reconfiguration in single-registrant VTS, independent of cue timing within the RSI, in line with some prior work (Yeung, 2010).

Previous work in cued task switching has reported worse nondecision times for switches than for repeats when CSIs are short, thought to index task set reconfiguration. We replicated this pattern for the shortest RSI condition (the S/S condition); however, in conditions for which the RCI was long, participants displayed better nondecision times for switches than for repeats. This pattern suggests that participants actively prepare for upcoming trials during the RCI more effectively when they choose to switch tasks compared to when they choose to repeat tasks, possibly indicative of a more proactive mindset on switch trials than repeat trials (Orr & Banich, 2014; Orr & Weissman, 2011).

In sum, our results from Experiment 1 suggest that in a single-registrant voluntary task switching paradigm: 1) participants prepare for the upcoming task throughout the entirety of the RSI rather than after cue presentation, 2) RSI manipulations primarily affect task set preparation rather than task set inertia, 3) the timing of cue presentation does not affect preparation, and 4) participants might choose to switch when they have prepared more effectively during the RCI.

In Experiment 2, we applied the same model to a double-registrant registrant paradigm. Here, we intended to test whether requiring a response indicating the task choice might change the way interval lengths interact with preparation when compared to a single-registrant paradigm, as the required response might change the manner in which participants prepare for upcoming trials with respect to cue presentation.

2.5. Experiment 2 (Double-registrant) Methods

2.5.1. Participants

The sample consisted of undergraduate students (n = 114) who completed the study in person for course credit. As in Experiment 1, participants who switched tasks on greater than 80% of trials or less than 20% of trials were removed from analyses (n = 14). Participants who did not reach an accuracy criterion of at least 60% were also excluded (n = 2). Further, some participants (n = 22) did not comply with task instructions and did not wait for the task choice cue to indicate their choice; because this made the cue-stimulus-interval for these participants qualitatively different from other participants, these early responder participants were removed from the sample. The process by which early responders were identified is outlined in the data preprocessing section of the Methods. Age and gender characteristics of the final sample are reported in Table 2.1. All study procedures were approved by the Texas A&M University Institutional Review Board.

2.5.2. Paradigm

Participants performed a modified version of a number Stroop task composed of a task choice and task stimulus phase as in Experiment 1. The experiment was coded in

PsychoPy 3.0.7 (Peirce et al., 2019) running on 21.5" iMac computers. Each trial was composed of a task choice stimulus phase followed by a task stimulus phase. Task design is displayed in Figure 2.4.

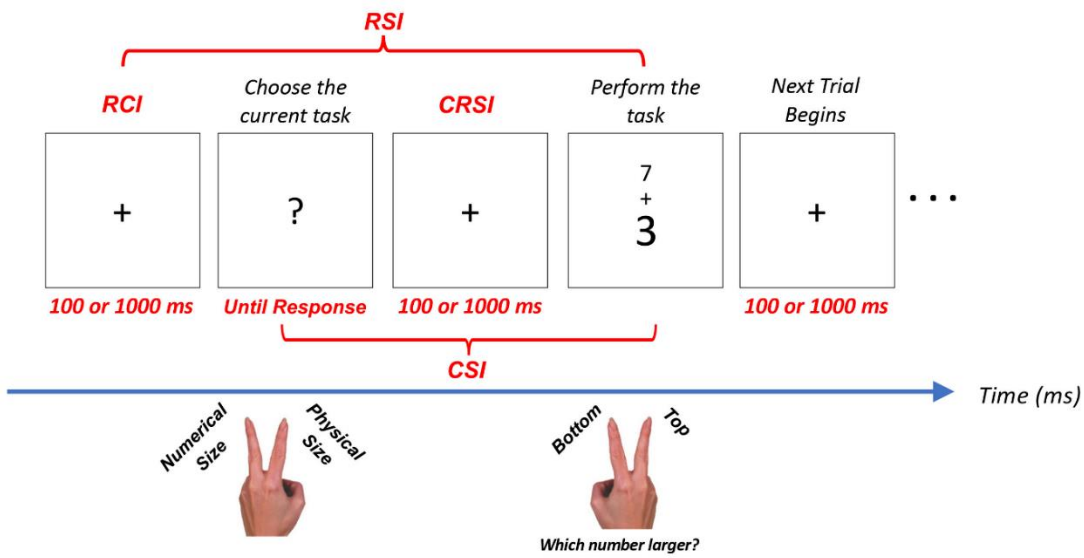

Figure 2.4. Depiction of Experiment 2 paradigm. The choice-response-stimulus interval (CSRI) and choice reaction time compose the cue-stimulus interval (CSI). The response-cue interval (RCI) and cue-stimulus interval (CSI) compose the response-stimulus interval (RSI). Reprinted from Imburgio & Orr, 2021b.

In the task choice phase, a '?' was presented in the middle of the screen. Upon seeing the stimulus, participants were to indicate whether they chose to perform a numerical comparison or a physical comparison by pressing the 'd' or 'f' keys (key mappings counterbalanced across participants). Participants were instructed to choose tasks randomly using the same instructions as in Experiment 1. In the task stimulus phase, participants were presented with two numbers that differed in both numerical size and physical size, one number above the fixation cross and one below the fixation cross.

Participants indicated their response using the ‘j’ and ‘n’ keys on a keyboard, where ‘j’ indicated the top number was chosen and ‘n’ indicated the bottom number was chosen. Error feedback, task practice, and task length were identical to the task in Experiment 1.

In each trial, RCI (time between task response and cue stimulus on the next trial) and CRSI (time between task choice response and task stimulus) were either short (S; 100 ms) or long (L; 1000 ms). Each combination of RCI/CRSI conditions (S/S, S/L, L/S, L/L) was equally likely – average and minimum trial numbers per participant for each condition are displayed in Table 2.2. Notably, this meant that the true CSI (time between cue stimulus presentation and task stimulus presentation; CSI) was dependent upon participants’ reaction time in response to the task choice cue. As in Experiment 1, congruent trials and incongruent trials were also equally likely.

2.5.3. Data Preprocessing and Calculation of CSI

Initial data preprocessing followed the same process as in Experiment 1. The first trial of each block (neither a switch trial nor a repeat trial) was removed from analyses. Trials following errors were also removed from analyses to account for post-error slowing. Trials with task RTs less than 200 ms or greater than three standard deviations from the mean task RT were also removed. Further, trials with choice RTs greater than 4000 ms were removed. RTs were log transformed for all relevant analyses; the transformation yielded an adequately normal distribution.

Inspection of the data revealed that some participants did not comply with task instructions and, rather than responding to the task choice cue to indicate their task choice, frequently responded prior to the task cue presentation (during the RCI) to indicate their task choice. For these participants, the RT to the task cue (choice RT) was recorded as zero, and the CSRI began immediately after the task cue was presented on the screen. Most of the participants that responded early did so frequently (13 participants responded early on greater than 20% of trials, 17 on greater than 10%). As such, the early responses would result in a qualitatively different interval manipulation throughout the course of the experiment when compared to non-early responders, as the CSI for the subjects that did comply with instructions would contain an additional period of time (the reaction time in response to the task cue, or choice RT). We then adopted a conservative threshold for subject exclusion due to early responses – participants that responded prior to the task choice cue on greater than 1% of trials were excluded from analyses (n = 22) – to ensure our manipulation was comparable across the entire sample.

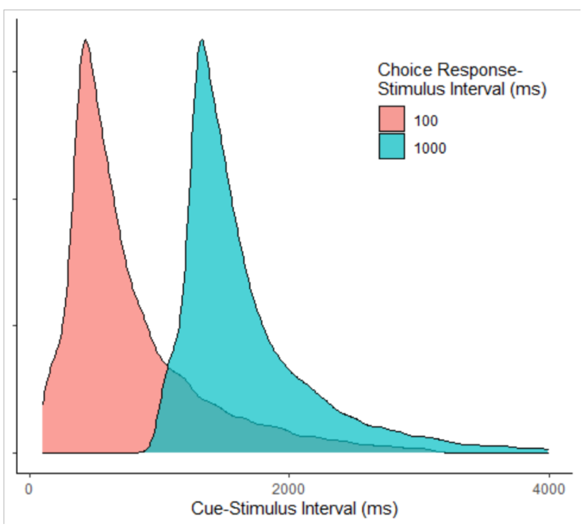

Figure 2.5. Density plots displaying distribution of cue-stimulus interval lengths (CSI) by choice response-stimulus interval condition (CRSI). Approximate peaks of each distribution were used as 'short' and 'long' values for CSI calculations. Reprinted from Imburgio & Orr, 2021b.

Unlike in the single-registrant paradigm, the CSI varied depending upon the choice RT during that trial. In order to account for this when analyzing the effect of RCI/CSI combinations on task RT, we calculated the CSI on each trial (the actual interval between task cue presentation and task stimulus presentation, including choice RT) and entered it as a continuous IV in regressions involving CSI-related effects. Then, we plotted the distribution of the CSI at each trial; we identified two clear peaks (see Figure 2.5) representing the most frequent 'true CSI' values within each level of the CRSI interval manipulation (CSI of 450 ms for the short CRSI manipulation, CSI of 1350 ms for the long CSRI manipulation). These values were used as 'short' and 'long' CSI values for all participants – this was accomplished by centering CSI at each of the two values in relevant regressions. This approach allowed us to account for trial-level differences in CSI length while also examining the longer and shorter CSIs resulting from the CRSI manipulation.

2.5.4. Reaction Time Analyses

As in Experiment 1, all RT analyses were conducted in R version 4.0.0 (R Core Team, 2020) using Bayesian multilevel regression via the brms R package (Bürkner, 2017) with a random intercept for each subject. Convergence for all models was confirmed both by visually inspecting chains and by examination of $\hat{R}$ statistics (all $\hat{R}$'s ≤ 1.10).

We first generated a regression where the DV was log-transformed task RT and IVs were CSI, RCI, switch/repeat and all possible interactions. This regression was meant to examine the effect of the RSI and CSI on RT switch cost and task RT within levels of switch/repeat. We then examined the estimated log RTs for each interval combination condition (using 450 ms and 1350 ms as values for long and short CSIs) within each level of switch/repeat, as well as the difference in switch RT and repeat RT at each interval combination.

Regression coefficients were considered significant if their 95% CI did not contain zero, and coefficients representing the same effect across conditions were considered significantly different if their 95% credible intervals did not overlap.

2.5.5. Drift Diffusion Model Analyses

All drift diffusion model analyses were conducted using the HDDM Python module (Wiecki et al., 2013) in Python 2.7. As in Experiment 1, responses were accuracy-coded such that a correct response was coded as 1 and an incorrect response was coded as 0, the bias parameter was fixed at 0.5 (no bias) for all subjects and conditions, and response boundaries were allowed to vary by switching condition but not by other IVs.

Following the same logic as in the RT analyses, we ran a hierarchical regression involving CSI, RCI, and switch/repeat along with all possible interactions as IVs; we then examined parameter estimates at each combination of RCI, CSI (using 450 ms and 1350 ms as short and long conditions), switch/repeat, and the difference between switch and repeat trials at each interval combination. Following the same logic as in Experiment 1, an effect was considered significant when P was 97.5% or greater, but effects that met a previously established threshold of P > 95% (Cavanagh et al., 2011, 2014) are noted in the results section

2.6. Experiment 2 (Double-registrant) Results

2.6.1. Effects of Switching

The posterior probability distributions of the effect of switching on RT, drift rate, and nondecision time within each interval condition are depicted in Figure 2.6. Relevant statistics for each comparison are depicted in Tables 2.7 and 2.8.

Measure	Interval (RCI/CSI)	Estimate	95% CI of estimate
Switch Trial log reaction time	S/S	6.77	(6.72, 6.81)
	L/S	6.77	(6.72, 6.81)
	S/L	6.75	(6.70, 6.79)
	L/L	6.73	(6.69, 6.78)
Repeat Trial log Reaction Time	S/S	6.53	(6.49, 6.58)
	L/S	6.61	(6.56, 6.65)
	S/L	6.58	(6.53, 6.62)
	L/L	6.62	(6.57, 6.66)
RT Switch Cost (Switch – Repeat)	S/S	0.231	(0.209, 0.253)
	L/S	0.156	(0.139, 0.174)
	S/L	0.168	(0.155, 0.181)
	L/L	0.119	(0.105, 0.134)

Table 2.7. Reaction time measures within interval conditions for double-registrant-registrant task. Positive switch costs indicate longer reaction times for switch trials. RCI = response cue-interval, CSI = cue-response interval, S = short, L = long, CI = credible interval. Reprinted from Imburgio & Orr, 2021b.

As expected, a significant RT switch cost was present in all interval combination conditions; log RT during switch trials was always larger than log RT during repeat trials. As in the single-registrant paradigm, nondecision times were worse on switches than repeats only within the S/S condition. Unlike in the single-registrant paradigm, nondecision times were not better for switches than repeats in any condition, suggesting that engagement with the task cue reduced the more proactive preparation on switches than repeats seen in some single-registrant conditions. As in the single-registrant paradigm, drift rates were always better for repeat trials than switch trials.

Parameter	Direction of Effect	Interval (RCI/CSI)	*P* of Switch Effect	Sig.
Nondecision Time	Sw > Rep	S/S	100%	*
	Sw > Rep	S/L	60.87%	
	Sw > Rep	L/S	60.62%	
	Sw > Rep	L/L	87.77%	
Drift Rate	Rep > Sw	S/S	100%	*
	Rep > Sw	S/L	100%	*
	Rep > Sw	L/S	100%	*
	Rep > Sw	L/L	100%	*

Table 2.8. Switch effects on double-registrant-registrant model parameters within interval conditions. Larger drift rates and smaller nondecision times indicate better performance. Most likely direction of effect is shown. RCI = response cue-interval, CSI = cue-response interval, S = short, L = long, CI = credible interval, Sig. = significance, * = significant at 97.5% threshold. Reprinted from Imburgio & Orr, 2021b.

2.6.2. Effects of CSI Manipulation

Posterior probability distributions of RTs and model parameters across each pairwise interval comparison of interest are depicted in Figure 2.7. Statistics for relevant comparisons can be found in Table 2.7 (for RTs) and Tables 2.9 and 2.10 (for model parameters).

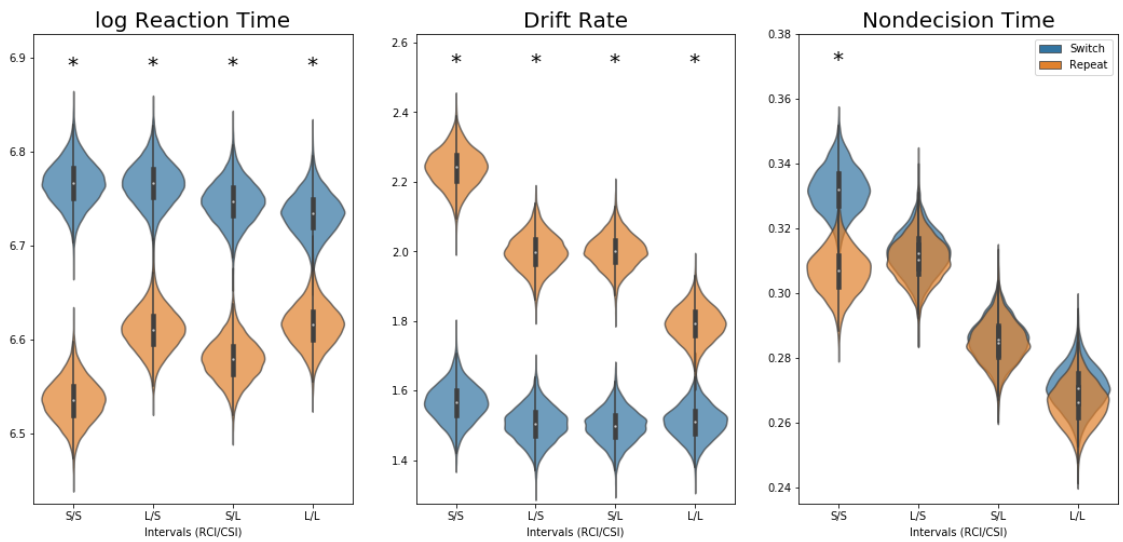

Figure 2.6. Violin plots of posterior probability distributions of double-registrant-registrant task performance and modeling parameters within each interval combination. An asterisk (*) denotes that the effect of switching was significant. RCI = response-cue interval, CSI = cue-stimulus interval. Reprinted from Imburgio & Orr, 2021b.

The comparison of intervals representing different CSIs but fixed RSIs (S/L vs. L/S) revealed no effect of CSI length on RT switch cost nor RT on switch and repeat trials individually. Similarly, CSI length did not modulate the switch effect on nondecision time. Longer CSIs yielded better nondecision times for both switch and repeat trials, indicating that longer CSIs were associated with better preparation in general. These results are in contrast with the effect of the same manipulation in the single-registrant paradigm in which CSI length did not affect preparation, indicating that engagement with the task cue does moderate the effect of cue timing on preparation. There were no effects of CSI length on any drift rate related measures.

Parameter	Trial Type	Interval Comparison (RCI/CSI)	*P* of Difference	Sig.
Nondecision Time	Switch Trials	S/L < L/S	99.75%	*
		S/L < S/S	97.47%	#
		L/L < L/S	93.36%	
	Repeat Trials	S/L < L/S	99.45%	*
		S/L < S/S	35.00%	
		L/L < L/S	97.40%	#
Drift Rate	Switch Trials	S/L > L/S	46.73%	
		S/L > S/S	20.38%	
		L/L > L/S	56.72%	
	Repeat Trials	S/L > L/S	51.23%	
		S/L < S/S	99.99%	*
		L/L < L/S	99.99%	*

Table 2.9. Comparisons of double-registrant-registrant model parameters within across interval pairs of interest. Larger drift rates and smaller nondecision times indicate better performance. RCI = response cue-interval, CSI = cue-response interval, S = short, L = long, CI = credible interval, Sig. = significance, * = significant at 97.5% threshold, # = significant at 95% threshold. Reprinted from Imburgio & Orr, 2021b.

2.6.3. Effects of RSI Manipulation, CSI Held Short

The S/L vs. S/S comparison revealed an effect of RSI length on RT switch cost such that longer RSIs reduced switch costs; however, there was no significant difference on switch and repeat trials individually.

Parameter	Direction of Switch Effect	Interval Comparison (RCI/CSI)	*P* of Difference	Sig.
Nondecision Time	Switch > Repeat	S/L < L/S	53.65%	
		S/L < S/S	100%	*
		L/L < S/L	25.99%	
Drift Rate	Repeat > Switch	S/L < L/S	41.30%	
		S/L < S/S	100%	*
		L/L < S/L	100%	*

Table 2.10. Comparisons of switch effects on model parameters across interval pairs of interest. Nondecision times are larger (worse) for switches than repeats on S/S trials, but better than repeats for other interval combinations. RCI = response cue-interval, CSI = cue-response interval, S = short, L = long, CI = credible interval, Sig. = significance, * = significant at 97.5% threshold. Reprinted from Imburgio & Orr, 2021b.

As in the single-registrant paradigm, longer RSIs resulted in a reduced effect of switching on nondecision time, indicating participants used the longer RCIs to prepare more effectively. The effect of RSI length on nondecision time for switch and repeat trials individually was not significant at the 97.5% threshold, although improvement of preparation on switch trials for longer RSIs was significant at a 95% threshold. Longer RSIs, holding CSI short, resulted in a reduction in the effect of switching on drift rate, a reduction of drift rate for repeat trials, and no effect on drift rate for switch trials; this pattern suggests that longer RSIs reduced task set inertia by harming repeat trial performance rather than facilitating switch trial performance.

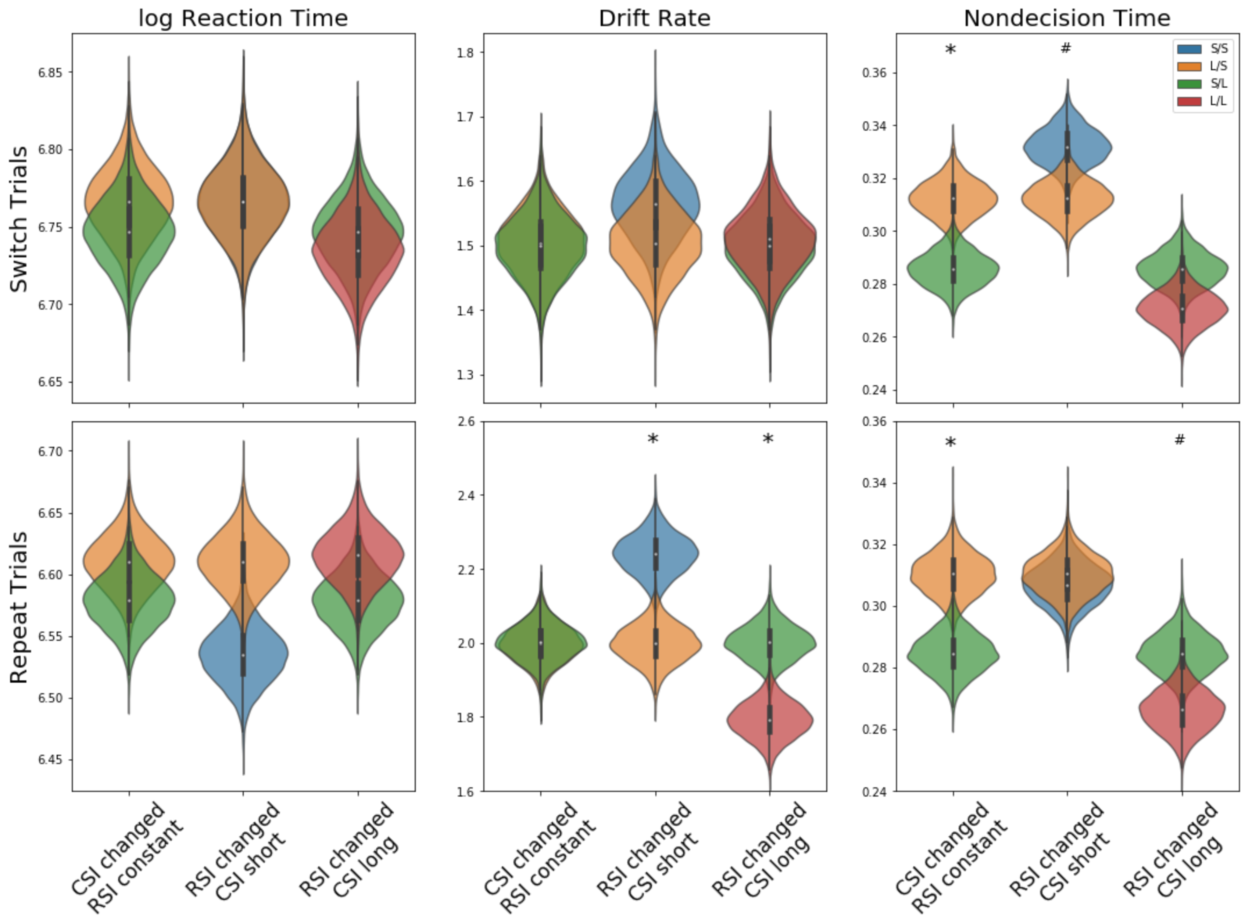

Figure 2.7. Violin plots of posterior probability distributions of double-registrant-registrant task performance and modeling parameters within switch and repeat trials across interval pairs of interest. The top row depicts switch trials, the bottom row depicts repeat trials. * = significant at 97.5% threshold, # = significant at 95% threshold. RCI = response-cue interval, CSI = cue-stimulus interval. Reprinted from Imburgio & Orr, 2021b.

2.6.4. Effects of RSI Manipulation, CSI Held Long

The L/L vs. L/S comparison revealed an effect of RSI length on RT switch cost such that longer RSIs reduced switch costs; however, there was no significant difference on switch and repeat trials individually. Here, longer RSIs did not affect nondecision time-related measures, suggesting that the longer RSIs in both conditions used for this comparison (compared to the S/S and L/S conditions) allowed for enough pre-stimulus preparation that no interval effects were visible in post-stimulus preparation (nondecision time). As in the L/S vs. S/S comparison, the L/L vs. S/L comparison revealed longer RSIs reduced the effect of switching on drift rate, reduced drift rate for repeat trials, and did not effect on drift rate for switch trials; this pattern again suggests that longer RSIs reduced task set inertia by harming repeat trial performance rather than facilitating switch trial performance, and that this effect does not depend on CSI length.

2.7. Experiment 2 (Double-registrant) Discussion

In Experiment 2, we examined the effects of switching, RSI length and CSI length on performance in a double-registrant-registrant paradigm. Broadly in line with Experiment 1 and previous work in cued task switching, drift rates were better for repeats than switches. As in Experiment 1, we found that preparation was worse for switches than for repeats only in the shortest RSI condition (S/S); in contrast to Experiment 1, however, preparation did not differ between switches and repeats in any other conditions. Together, these results suggest that participants prepare more effectively for switches than repeats in single-registrant, but not double-registrant registrant, paradigms, unless the RSI is very short.

However, in contrast to previous work in cued task switching, participants in the double-registrant registrant paradigm still did not display worse nondecision times for switches than repeats for short CSIs if the RCI was long. This might suggest that lengthening the RCI serves to reduce the effect of switch-specific preparation; in line with this, lengthening the RCI when CSI was held short reduced the effect of switching on nondecision time. However, the effect of the manipulation on switch-trial nondecision time alone was not significant at the 97.5% threshold (P = 97.47%), although the effect is in the expected direction. In any case, this interpretation is in line with conclusions regarding the role of the RSI in Experiment 1; in other words, our results suggest that in both paradigms, participants at least partially prepare for upcoming trials during the RCI, reducing the effect of switching on nondecision time.

However, while RSI manipulations did not affect drift rate in the single-registrant paradigm, the effect of switching on drift rate was consistently reduced when RSIs increased in the double-registrant registrant paradigm. This reduction in switch effects on drift rate was attributable to worse drift rates on repeat trials when RSIs were longer. This pattern is more in line with previous work in cued task switching, both with respect to the reduction in drift rate (Schmitz & Voss, 2012, 2014) and performance on repeat rather than switch trials (Grange, 2016; Grange & Cross, 2015; Horoufchin et al., 2011b, 2011a). These results suggest the effects of RSI manipulations on inertia might be more comparable to cued paradigms in double-registrant registrant voluntary paradigms than single-registrant.

Unlike in Experiment 1, changing the timing of the cue while holding RSI constant affected preparation on both switch trials and repeat trials – longer CSIs meant better preparation. This suggests that requiring participants to respond to the cue encourages participants to partially prepare after the cue, whereas cue timing did not affect performance at all when participants were not required to respond to the cue. In sum, our results suggest that both cue timing and RCI length modulate the effect of task set preparation on performance in double-registrant-registrant paradigms; however, cue timing seems to affect preparation generally while RCI length seems more related to the effect of switching on preparation.

2.8. General Discussion

The current study sought to dissociate the degree to which RSI and CSI manipulations modulate the contributions of task set preparation and task set inertia to switch costs in voluntary task switching. We examined both single- and double-registrant-registrant paradigms, hypothesizing that the engagement with the task cue required by double-registrant-registrant paradigms might change the degree to which cue timing (CSI) modulates these processes. Further, we examined the degree to which participants prepare for upcoming trials prior to cue presentation by examining the effects of RSI length on task set preparation during task performance, as well as the effects of RSI length on drift rate and task set inertia reported in previous cued task switching work.

2.8.1. Evidence for preparation prior to cue presentation

Cued task switching work has reported worse nondecision times for switches than for repeats (thought to index the contribution of preparation to switch costs) when CSIs are short, but that this difference is reduced or eliminated when CSIs are longer (Karayanidis et al., 2009; Schmitz & Voss, 2012, 2014). Here, nondecision times were only worse for switches when the RSI was short, independent of CSI length. Further, while RSI manipulations affect drift-rate related measures in cued task switching (Schmitz & Voss, 2012), they primarily affected preparation in both voluntary paradigms (both preparation on switch/repeat trials individually and the effect of switching on preparation).

This pattern is in line with previous work, which has suggested that RSI manipulations in voluntary task switching affect preparation in a manner similar to CSI manipulations in cued task switching (Yeung, 2010). In other words, because participants in voluntary paradigms can use the entire RSI to prepare for an upcoming task (rather than just the CSI in cued paradigms), manipulating the RSI necessarily affects preparation. We found this to be true whether or not participants are required to respond to the task cue itself, indicating participants use the RCI to prepare in both single- and double-registrant-registrant voluntary paradigms.

2.8.2. Evidence for proactive preparation during switch trials

In the single-registrant paradigm, nondecision times were unexpectedly better for switches than repeats (except in the S/S condition), and these effects were rather strong. This was not the case for the double-registrant-registrant version, where nondecision times across switch and repeat trials for these same conditions were virtually identical.

This suggests that, in the single-registrant version only, participants prepare more effectively during the RSI on switches than for repeats, despite the assumed necessity of loading a new task set. This is in line with neuroimaging work that suggests switches in voluntary paradigms might indicate a more proactive strategy (Orr & Banich, 2014; Orr & Weissman, 2011). Requiring participants to respond to the task cue seemed to eliminate the preparation advantage on switches, resulting in a pattern more in line with what has been reported in cued task switching (Karayanidis et al., 2009; Schmitz & Voss, 2012). However, the portion of our double-registrant-registrant participants that was excluded due to responses prior to the task choice cue should be noted here. While we chose to exclude these participants in order to ensure our analyses of CSI length were consistent within the sample, it is possible that these participants are systematically more likely to more proactively prepare on switches than repeats (resulting in a propensity for early choice responses). While this is an interesting question, we did not have the sample size to more closely examine this subgroup, or other individual differences.

In sum, our results indicate that the contribution of task set preparation to switch costs is qualitatively different in single-registrant paradigms compared to double-registrant-registrant or cued paradigms, likely due to a more proactive strategy during switch trials. The current work is not well-suited to examine whether switches are more likely to occur because of the increase in proactive preparation, or if participants actively engage in more proactive preparation because more preparation is required for switching; however, the results suggest that future work should examine this distinction further, particularly in single-registrant paradigms.

2.8.3. Response-stimulus interval effects in double-registrant paradigm mirror cued task switching

Prior work in cued task switching has reported that RSI manipulations modulate the effect of switching on drift rate, thought to index the contribution of task set inertia to switch costs (Schmitz & Voss, 2012). Here, we found no such effects of RSI length within the single-registrant paradigm (nor any effects on drift rate), suggesting that RSI manipulations primarily affect the contribution of preparation to switch costs in these paradigms.

However, we found consistent and robust effects of RSI length on drift rate in the double-registrant-registrant paradigm; longer RSIs, whether CSI was held short or long, resulted in a reduction of the effect of switching on drift rate, similar to the effects reported in cued task switching. Moreover, we found the effect was attributable to a reduction in repeat drift rate rather than a facilitation in switch drift rates. These results are in line with a number of studies that have reported the same pattern in cued task switching (Grange, 2016; Grange & Cross, 2015; Horoufchin et al., 2011b, 2011a). Notably, these studies support the idea that proactive interference during task performance originates from temporal distinctiveness between current and previous memory traces relating to task sets rather than a process of passive dissipation of task sets, and that RSI effects are additionally dependent upon similarity between current and previous RSI length.

Our results suggest that, for double-registrant-registrant paradigms only, RSI effects might be similarly attributable to temporal distinctiveness of memory traces in voluntary task switching. It is possible that the increased attention paid to the task cue in the double-registrant-registrant paradigm (due to the required response to the cue) strengthens the memory trace relating the cue to task sets; however, the current work is not well-suited to examine this. Future work might wish to explore the degree to which different choice cues and current/previous RCI length similarity moderate the effect of RSI on drift rates.

The current work, then, suggests that the effects of RSI manipulations on proactive interference in cued task switching are more comparable to RSI manipulations in double-registrant-registrant voluntary task switching than single-registrant voluntary task switching. However, RSI manipulations additionally affected preparation in both voluntary task switching paradigms.

2.8.4. Cue timing effects depend upon task design

The degree to which cue timing affected performance depended upon whether participants were required to respond to the cue to indicate their task choice. When participants were not required to respond to the cue, the timing of the cue did not affect performance in any way. However, when a task choice response was required, increasing the time between cue presentation and stimulus presentation reduced the preparation time necessary post-stimulus presentation.

Here, we suggest that the necessity of waiting for the cue to indicate task choice results in less preparation prior to the cue than in a single-registrant paradigm, although pre-cue preparation also seems to occur in both paradigms. This pattern fits with the idea that participants can technically ignore the cue entirely in purely voluntary single-registrant paradigms. In these paradigms, the cue itself is not informative beyond providing possible information about stimulus timing, which is only true for long CSI periods after the short CSI period has passed. Notably, though, the effect of cue timing in the double-registrant-registrant paradigm still does not seem to modulate the effect of preparation on switch cost; rather, longer CSIs facilitated better overall, not switch-specific, preparation.

Therefore, the current work suggests that manipulating RSI and CSI length independently within double-registrant-registrant voluntary task switching paradigms might partially dissociate the effects of switch-specific and general preparatory processes to switch costs, which prior work has suggested are separable in cued task switching (Karayanidis et al., 2011). It should be noted that an alternative interpretation of an effect on nondecision time for both switch and repeat trial types is that CSI length affects motor processes (also captured by nondecision time) in double-registrant-registrant, but not single-registrant, paradigms. Previous work has argued, and we have adopted here, the view that the contribution of motor processes to reaction times are likely consistent within a participant across conditions and thus consider nondecision time to index task preparation (Schmitz & Voss, 2012). However, given that a motor response is required immediately prior to the CSI in double-registrant-registrant paradigms, the possibility of an effect of CSI length on motor processes warrants future study, possibly including overt manipulations of motor processes.

In any case, we caution that RSI manipulations additionally affected the contributions of inertia to switch costs and preparation on switches and repeats individually; therefore, our work does not suggest that RSI manipulations only affect switch-specific preparation in double-registrant-registrant voluntary task switching.

2.8.5. Limitations and future directions

While the current study demonstrates the strength of drift diffusion modeling in quantifying preparation time during task performance, the specific timing of preparatory processes prior to stimulus presentation must be assumed based on the effects of interval manipulations on post-stimulus preparation time. Future work should examine the effects reported here using other modalities, such as EEG, to help corroborate DDM post-stimulus findings with pre-stimulus preparatory components. In particular, replicating previous findings of separable switch-specific and general processes in cued task switching (Karayanidis et al., 2011) and examining how each might relate to the effects of RSI and CSI manipulations on nondecision time in double-registrant-registrant tasks would help corroborate the explanations proposed in the current study.

Alternatively, other variants of drift diffusion models might prove useful for more directly quantifying preparation prior to stimulus presentation; for example, attractor-state-based drift diffusion models which have been employed in cued task switching quantify stability/flexibility measures prior to task performance along with a drift diffusion process during task performance (Ueltzhöffer et al., 2015). Examining the relationship between CSI, RSI, attractor states, and post-stimulus preparation might clarify relationships between pre-stimulus behavior and the effect of interval lengths on components of switch costs. Similarly, models which more directly measure timing of task choice within the RSI (rather than solely the effects of interval lengths on switch cost components) would contribute greatly to our understanding of task processing in voluntary paradigms and might help distinguish between choice strategies within and between participants.

It is important to note that the conclusions here likely only apply to purely voluntary tasks; that is, voluntary task switching paradigms that do not include intermixed cued trials. Including cued trials increases the salience of the task cue itself which likely changes the effects of RSI and CSI lengths on these processes. Future work might wish to examine these manipulations on DDM parameters and compare to the results presented here to test this idea.

2.8.6. Conclusions

The current work demonstrates the utility of drift diffusion modeling in quantifying contributions of task set preparation and task set inertia to switch costs during voluntary task switching. While we demonstrated a consistent contribution of task set inertia to switch costs, we found that task set preparation only negatively impacted switch costs when RSIs were very short. In the single-registrant voluntary paradigm, longer RCIs allowed participants to prepare more effectively on switch trials than repeat trials, supporting the idea that more proactive strategies are employed during switch trials. While RCI length in voluntary task switching modulates the contribution of task set preparation to switch costs, it additionally modulates the effect of task set inertia to switch costs in double-registrant registrant paradigms. Finally, CSI length independent of RSI length affects general preparatory processes (but not switch-specific processes) only when participants were required to respond to the task choice cue.

3. DYNAMIC COGNITIVE FLEXIBILITY: INFLUENCES OF TIME AND PERSONALITY TRAITS ON VOLUNTARY TASK SELECTION[2]

3.1. Introduction

Despite the relative popularity of research examining VTS performance (see Arrington et al., 2014 for a review; Braem, 2017b; Braun & Arrington, 2018; Fröber et al., 2019; Fröber & Dreisbach, 2017; Mittelstädt, Dignath, et al., 2018; Mittelstädt, Miller, et al., 2018), no work to date has focused on how measures of flexibility, such as switch cost and switch rate, might change throughout the course of a session. Instead, subject- or group-level averages of these measures are analyzed—the underlying assumption in these analyses is that that switch costs and switch rates either remain relatively constant throughout the task, or that any changes throughout the task are not meaningful enough to warrant examination. The current work aims to examine 1) which commonly analyzed behavioral measures change throughout performance of standard VTS paradigms, 2) to what degree these changes might inform us about cognitive processes occurring throughout task performance, and 3) to what degree these changes might inform us about individual differences in participants.

While no previous work has examined changes in performance throughout a simple VTS paradigm, there is a rich body of work documenting the existence of behavioral changes as a result of practice, boredom, fatigue, and effort avoidance in

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comparable tasks (Benoit et al., 2019; Karayanidis et al., 2003; Khan et al., 2018; Kool et al., 2010; Kool & Botvinick, 2014; Lorist et al., 2000; Nieznański et al., 2020; Otto & Daw, 2019; Plukaard et al., 2015; Rogers & Monsell, 1995). Using this work, we can draw inferences about how each process might affect common behavioral measures in VTS and create sets of predictions about the effects of each process. Below, we outline work done to examine the effects of these four factors on behavioral performance and make predictions about how each might affect voluntary task selection.

3.1.1. Changes Related to Practice

Practice effects from accumulated experience performing a task are well-documented and have been reported in a variety of paradigms (Logan, 1992) including cued task switching (Karayanidis et al., 2003; Rogers & Monsell, 1995), as have reductions in accuracy switch cost (Rogers & Monsell, 1995). While manipulations of practice effects often involve multiple sessions, it is possible that experience performing a task during a single session might yield similar reductions in overall RT, RT switch cost, and/or accuracy switch cost throughout the task. Indeed, Koch and colleagues (2018) cite evidence for a reduction of RT switch cost with only a small amount of practice. To date, no studies have examined how practice might influence switch rate; as most VTS studies instruct participants to select tasks equally often and in a random order, one might predict that switch rates will be closer to 50% with practice. However, most studies document a strong repetition bias (Arrington & Logan, 2004, 2005; Mayr & Bell, 2006) suggesting that practice effects do not significantly impact task selection.

3.1.2. Changes Related to Boredom

Second, an increase in boredom throughout the course of performing the task could affect task performance and task choice. Boredom is typically examined in vigilance tasks that require a participant to monitor for an infrequent target over long periods of time (Kurzban et al., 2013; Scerbo, 2001). However, a series of experiments on a more complex task switching paradigm examined the effects of restricting available information on subjective feelings of boredom and task switching behavior. The study concluded that the restriction of available information resulted in greater subjective feelings of boredom which were correlated with more frequent task switching (Geana et al., 2016a) — the study has since spawned decision-making models that include the effect of boredom on task choice and exploration (Geana et al., 2016b; Wolff & Martarelli, 2020). While no work to date has examined possible effects of boredom induced through simple task performance (rather than an overt manipulation) on task choice, increases in switch rates during VTS paradigms might indicate an effect of boredom consistent with previous work.

3.1.3. Changes Related to Fatigue

Third, it is possible that participants begin to experience fatigue throughout performance of the task which might affect behavioral performance. However, the majority of work examining the effects of fatigue involve manipulations or periods of time that last much longer than a standard VTS paradigm—while standard VTS paradigms generally last between 20 and 30 minutes, the length of tasks in studies of cognitive fatigue effects are often on the order of hours (Ackerman & Kanfer, 2009; Lorist et al., 2000; Plukaard et al., 2015). In studies such as these, fatigue results in general decreases in performance; in cued task-switching studies, this has been observed as reductions in overall accuracy (Benoit et al., 2019; Lorist et al., 2000) as well as increases in overall RT and increases in RT switch cost (Plukaard et al., 2015). Therefore, one might predict that these same decrements of performance over time would be present in a VTS study if significant fatigue was present towards the end of the task. Notably, these predictions are in direct contrast with predictions regarding the effects of task experience.

Furthermore, a recent study found that fatigue manipulations lasting only 5 or 10 minutes resulted in an increase in accuracy switch cost on a cued task-switching paradigm (Nieznański et al., 2020). Importantly, this change was interpreted as a compensatory mechanism engaged to combat larger performance decrements such as changes in overall RT and accuracy. The idea that such compensatory mechanisms might be invoked and obscure larger performance decrements is not new (Hockey, 2010; Robert & Hockey, 1997; Wang et al., 2016), although it has not been directly examined in VTS. However, the ability of a participant to choose tasks in a VTS paradigm allows for the reduction of switching as a possible compensatory mechanism to combat early fatigue-induced performance decrements, as repeating tasks more often would allow for better overall performance. Therefore, we hypothesized that fatigue-induced compensatory behavior might be reflected in a reduction of switch rates over time. This prediction is in direct contrast to predictions about the effects of boredom on performance.

3.1.4. Changes Related to Effort Exertion

Finally, it is possible that as participants perform the task, they exert less effort during task performance. Prior work suggests that as more effort is exerted, the subjective cost of effort exertion increases (Baumeister, 2002; Baumeister et al., 1998; Kool & Botvinick, 2014). In other words, the effort exerted to perform the task causes a reduction in the desire to exert further effort as the task goes on. In the context of VTS, the well-documented bias towards repeating tasks (Arrington & Logan, 2004, 2005; Mayr & Bell, 2006) has been interpreted as an avoidance of effort (Mittelstädt, Dignath, et al., 2018). Therefore, one might expect an increase in effort avoidance as a participant performs the task, operationalized as a reduction in switch rates. While this prediction converges with predictions regarding compensatory mechanisms resulting from fatigue, prior work has suggested that effort avoidance can be offset by the presence of monetary reward (Kool et al., 2010); therefore, the sensitivity of any possible switch rate reductions to reward manipulations might help discern between overall effort avoidance and fatigue-induced compensatory behavior.

3.1.5. Experiment Structure

The current work examined changes in performance over time in three experiments, each involving different VTS paradigms across three independently collected datasets. The first experiment involved a large sample (n = 100) and was intended to test the competing predictions one might expect of each possible cognitive process to see which might occur during a standard VTS task (the same task and sample examined in Chapter 2 Experiment 2). Improvements in RT, accuracy, RT switch cost, and accuracy switch cost would indicate significant practice effects, while decrements in these measures would indicate significant effects of fatigue. Increases in switch rate would indicate significant effects of boredom, while decreases in switch rate would indicate either compensatory behavior to combat fatigue-related decrements or a reduction in effort expenditure over time.

The second experiment involved a performance-contingent reward manipulation with varying magnitudes (Fröber et al., 2019). This experiment was intended to replicate the declines in switch rate and evidence of practice effects found in Experiment 1, as well as examine the effect of the performance-contingent reward manipulation on these effects. In particular, examining the effect of reward and motivation on switch rate reductions present in Experiment 1 was intended to rule out either fatigue-related compensatory behavior or effort avoidance as possible mechanisms underlying the reduction.

The third experiment was intended primarily to examine the effects of reward-induced motivation on the significant reduction in switch rate over time that was observed in both Experiment 1 and Experiment 2 (Braem, 2017b). Experiment 3 involved reward conditions that were originally meant to manipulate participants' average switch rates; here, the reward manipulation was used to test the effects of motivation on switch rate changes rather than overall average switch rates. Additionally, Experiment 3 included BIS/BAS scores for each participant, which allowed us to examine whether individual changes in switch rates over time could meaningfully inform individual differences in approach/avoidance behavior that prior work found to be related to sensitivity to effort exertion (Storbeck et al., 2015). Experiment 3 found additional evidence for practice effects, but no evidence for a decline in switch rates at a group level found in Experiments 1 and 2; however, individual differences in changes in switch rates over time were related to individual BIS and BAS Fun-Seeking (BAS-Fun) scores, suggesting that change in switch rate might be a valuable measure to examine even when no significant group-level change is present.

3.2. Experiment 1 Methods

3.2.1. Participants

The sample consisted of 114 undergraduate students who completed the study for course credit. Participants who switched tasks on greater than 80% of trials or less than 20% of trials were removed from analyses (*n* = 14). The dataset here is the same dataset that was analyzed in Chapter 2 Experiment 2. All study procedures were approved by the Texas A&M University Institutional Review Board.

3.2.2. Paradigm

Participants performed a modified version of a number Stroop task. Each trial was composed of a task choice phase followed by a task stimulus phase as depicted in Figure 3.1. In the task choice phase, participants were presented with a '?' in the center of the screen. The '?' indicated that participants were to choose which of two tasks to perform: a physical comparison or a numerical comparison. Participants indicated their task choice with a key press (either 'd' or 'f'), with task choice mapping counterbalanced across participants. In line with classical voluntary task switching paradigm designs (Arrington & Logan, 2004), participants were instructed to choose tasks randomly. Participants were instructed that this meant they should choose each of the two tasks about equally often throughout the experiment. Participants were also instructed that they should repeat the same task as the previous trial and choose to switch to a new task about equally often. Finally, participants were told not to use a pattern to adhere to these guidelines, but to choose randomly as though they were flipping a coin in their head to decide on each trial. There was no time limit on task choices.

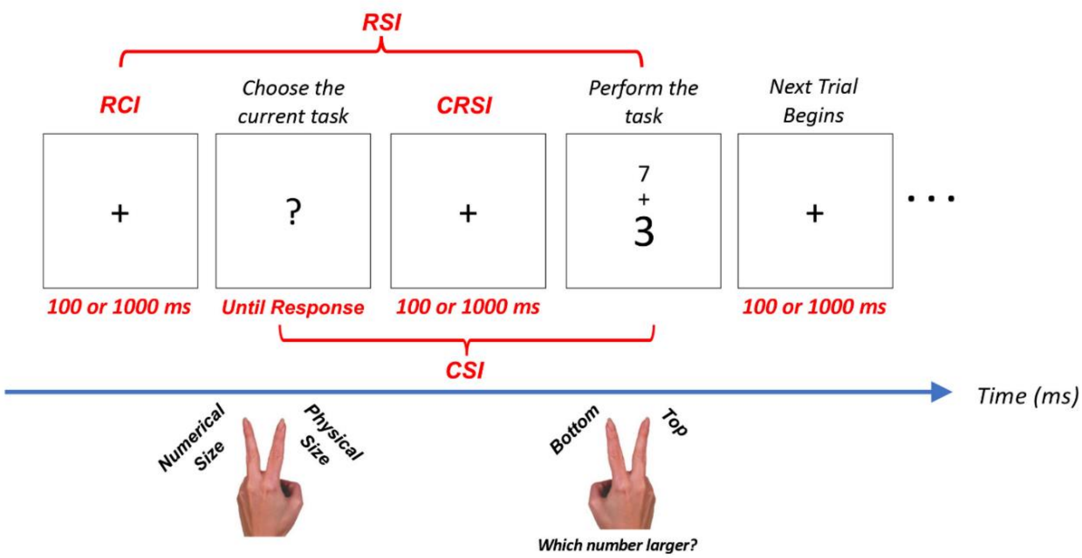

Figure 3.1. Depiction of Experiment 1 paradigm (identical to Chapter 2 Experiment 2). The choice-response-stimulus interval (CSRI) and choice reaction time compose the cue-stimulus interval (CSI). The response-cue interval (RCI) and cue-stimulus interval (CSI) compose the response-stimulus interval (RSI). Reprinted from Imburgio & Orr, 2021a.

In the task stimulus phase, participants were presented with two numbers that differed in both numerical size and physical size, one number above the fixation cross and one below the fixation cross. If participants had indicated in the choice phase that they chose to perform a numerical comparison, they were to choose the number that was numerically larger in the stimulus phase (ignoring the physical size of the numbers). If the participant had indicated in the choice phase that they chose to perform a physical comparison, they were to choose the number that was physically larger in the stimulus phase (ignoring the numerical value of the numbers). Participants indicated their response in the stimulus phase with a key press (‘j’ for the top number and ‘n’ for the bottom number).

The task response-cue interval (RCI) and task choice-stimulus interval (CSI) were either 100 and 1000ms. Each length was equally likely to occur, and the effects of these interval conditions are not analyzed here (the effects of these interval conditions in this same sample are analyzed in Chapter 2 Experiment 2). Congruent trials (numerically larger number is also physically larger) and incongruent trials were equally likely. The task consisted of 6 blocks of 65 trials each for a total of 390 trials per participant.

Prior to the full task, participants completed a practice version of the task, beginning with single task practice blocks, then a shortened version of the full task. If a participant failed to reach 60% accuracy on a given portion of practice, they were required to repeat that portion of practice until the accuracy criterion was reached. Participants were given feedback after the final practice phase that displayed their task accuracy, switch rate, and percent of trials where they chose each task. If participants switched tasks on less than 20% of trials or greater than 80% of trials, they were asked to repeat that portion of practice. Similarly, if participants chose one of the tasks more than 80% of the time, they had to repeat that portion of practice.

3.2.3. Analyses

All analyses were conducted in R version 4.0.0 (R Core Team, 2020). The first trial of each block (neither a switch trial nor a repeat trial) was removed from analyses. Trials following errors were also removed from analyses to account for post-error slowing. Trials with task RTs less than 200ms or greater than three standard deviations from the mean task RT were also removed. Normality of RT distribution was determined via visual inspection, as a Shapiro-Wilk test would be overpowered for the number of data points to detect inconsequential deviations from normality (Ghasemi & Zahediasl, 2012). Because RTs were not normally distributed, they were log transformed for analyses; the transformation yielded an adequately normal distribution.

To test whether any of the measures of interest changed over time, we utilized Bayesian multilevel regressions via the 'brms' R package (Bürkner, 2017) using trial number as an independent variable. Convergence for all models was confirmed both by visually inspecting chains and by examination of $\hat{R}$ statistics (all $\hat{R}$'s ≤ 1.01). An effect was considered significant if the coefficient's 95% credible interval (CI) did not contain zero. All coefficients are reported as standardized coefficients followed by 95% CI.

We first tested for changes in RT switch cost over time by testing an interaction between alternation and trial number on log-transformed RTs. Here, a significant interaction would indicate a change in RT switch cost over time (the difference between switch RT and repeat RT would change as a function of trial number). In this model, the subject-level main effects of alternation (repeat, switch) and trial number were also included. However, a subject-level interaction term was not included as it prevented model convergence and subject-level changes in RT switch cost were not central to the research questions in Experiment 1. Next, we tested for changes in overall RT over time using a regression model that included main effects for alternation and trial number, but not an interaction term, as group-level and subject-level IVs. Log-transformed RTs were again the DV in this model.

To examine changes in switch rate and accuracy over time, we used a logistic regression in which task choice or accuracy (switch/correct coded as 1 and repeat/incorrect coded as 0) was the DV. In models examining switch rate, trial number was a group- and subject-level IV. Here, a significant change over time in the probability of choosing to switch tasks would be indicated by a significant regression coefficient for the trial number. A positive coefficient would indicate that participants are more likely to switch tasks as the experiment progressed.

In models examining accuracy, the alternation was also included as a group- and subject-level IV. The model examining changes in accuracy switch cost included interactions between switching and trial number; a significant interaction would indicate a significant change in accuracy switch cost. To examine changes in overall accuracy, a model including no interaction term, but main effects of both switch/repeat and trial number, was also generated.

3.2.4. Experiment 1 Results

Changes in switch rate, overall RT, RT switch cost, overall accuracy, and accuracy switch cost throughout the task are depicted in Figure 3.2.

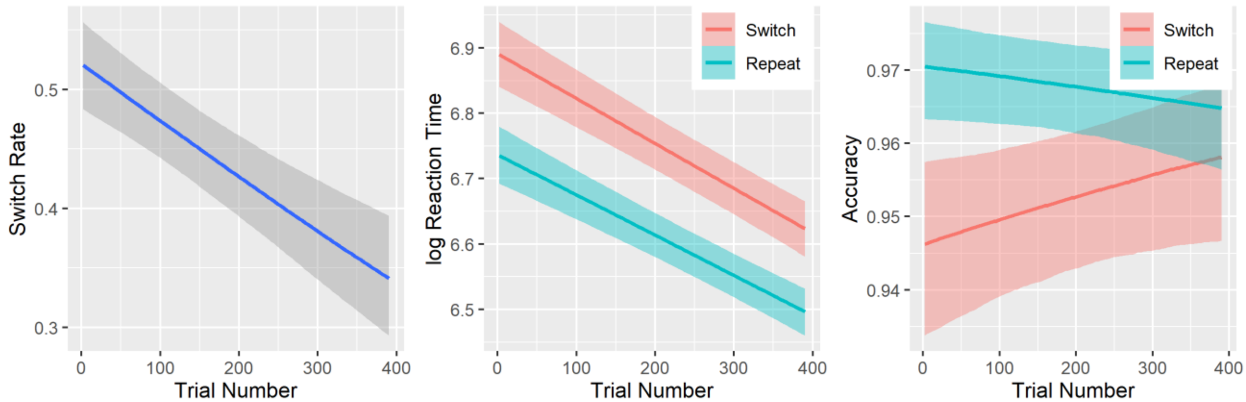

Figure 3.2. Group-level changes in switch rate (left), RT by switch condition (middle) and accuracy by switch condition (right). Main effects of trial number on switch rate and RT were significant; effect of trial number on accuracy was only significant within switch trials. Shaded areas represent 95% CI. Reprinted from Imburgio & Orr, 2021a.

The interaction between alternation and trial number did not significantly predict RT at the group level (β = -0.008 [-0.016, 0.002]), indicating there was no group-level change in RT switch cost over time. When the interaction term was removed, the main effect of switching was significant (β = 0.07 [0.06, 0.08]), indicating the expected presence of a RT switch cost. Further, the main effect of trial number was significant (β = -0.07 [-0.08, -0.06]), indicating a significant reduction in overall RT throughout task. This effect was consistent with practice effects and inconsistent with fatigue effects.

Trial number also significantly predicted task choice (β = -0.21 [-.29, -.14]). Participants were less likely to switch tasks as trial number increased, indicating an overall decline in switch rate as the task progressed. This pattern was consistent with the predictions related to effort avoidance and fatigue-related compensatory mechanisms, but inconsistent with increases in boredom.

There was a significant interaction between trial number and alternation in predicting accuracy (β = 0.13 [0.02, 0.24]). This interaction was explored by centering trial number 1.5 standard deviations above and below the mean, then comparing the effect of switching (accuracy switch cost) in each model to compare switch cost in early and late stages of the experiment. Accuracy switch cost was larger towards the beginning of the experiment (β = -0.60 [-0.82, -0.39]); towards the end of the experiment, the effect was reduced to non-significance (β = -0.21 [-0.43, 0.02]). In the model with no interaction term, the expected accuracy switch cost was present (β = -0.41 [-.57, -.26]). However, overall accuracy did not change significantly throughout the task (β = 0.02 [-.04, .08]). The overall improvements in accuracy switch cost over time were consistent with practice effects.

3.3. Experiment 1 Discussion

In Experiment 1, we identified several changes that occurred throughout performance of the task. Reductions in overall RT and accuracy switch cost were consistent with the effects of practice and inconsistent with fatigue-related performance deficits. Reductions in switch rate over time were inconsistent with increases in boredom but consistent with both reductions in effort expenditure and compensatory changes resulting from fatigue.

The reduction in overall RT, consistent with practice effects, was somewhat unsurprising—as most studies that found eventual increases in RT due to fatigue involve much longer manipulations, practice-induced improvements seemed more likely. However, the fact that RT switch cost did not improve, even though overall RT did, suggests that the practice effects seemed to work at a general level of task performance rather than at a higher level of cognitive control; in other words, participants got better at both the numerical and physical comparisons, but not necessarily better at set shifting more generally.

Given this pattern, though, the results that accuracy switch cost improved (but overall accuracy did not) was surprising. However, an examination of the effect indicated that the improvement in accuracy was qualitatively larger for switch trials than repeats (although the difference was not statistically significant). This pattern does align with the general idea of performance increases as a result of practice if accuracy was near ceiling for repeat trials—as the mean accuracy for repeats was very high (M = 95.30%), this seems like a likely explanation.

3.3.1. Experiment 1 Limitations

While the large sample in Experiment 1 was well-suited to detect changes in switch rates or switch costs over time, there was no manipulation meant to examine the mechanism underlying the change in switch rate that was detected—reductions in effort expenditure and compensatory changes to prevent fatigue-related declines are both possible.

Further, it is not possible from the results of Experiment 1 alone to rule out the influence of task-specific factors in producing the decline in switch rate rather than a more general process such as fatigue or effort avoidance that would occur in other voluntary task switching paradigms. For example, while the number Stroop has been used previously in task switching literature (Orr et al., 2012, 2019; Orr & Banich, 2014;

Petruo et al., 2019), it introduces more conflict than other task switching paradigms due to stimulus congruency effects and the use of bivalent stimuli; the resulting demands on cognitive load might affect the rate of fatigue or the rate at which effort expenditure is reduced. Therefore, generalizing the results of Experiment 1 to a different voluntary task switching paradigm which did not include these additional sources of conflict would be fruitful in helping to rule out the possibility of task-specific factors as an underlying cause of switch rate declines.

3.4. Experiment 2

In Experiment 2, we analyzed a publicly available dataset originally examined in a 2019 manuscript (Fröber et al., 2019, Experiment 1 in the original manuscript). Participants in Experiment 2 first performed a standard double-registrant voluntary task switching paradigm. However, unlike in Experiment 1, participants then performed the same task with performance-contingent rewards.

Importantly, the dataset provided an opportunity to replicate the results of Experiment 1 in a different, commonly used version of a double registrant voluntary task switching paradigm; Experiment 2 utilizes a letter-digit classification rather than a number Stroop and univalent rather than bivalent stimuli. Therefore, Experiment 2 partially served to replicate the results of Experiment 1 in a smaller sample from a separate population using a slightly altered task.

Experiment 2 also served to help rule out either effort avoidance or fatigue. Because previous work has suggested that effort avoidance can be mitigated by monetary reward (Kool & Botvinick, 2014), we hypothesized a reduction or elimination of switch rate decline would support the idea that the decline was related to effort avoidance. If the rate of decline was unaffected by reward, the decline was more likely a fatigue-induced compensatory mechanism.

3.5. Experiment 2 Methods

3.5.1. Participants

Experiment 2 consisted of 30 participants from the University of Regensburg who participated for course credit and an opportunity to win an Amazon gift card based on points earned during the ‘reward’ portion of the experiment. All steps for data preprocessing in the current analyses, as well as criteria for participant exclusion based on performance, were consistent with the original publication in which these data were reported (Fröber et al., 2019), resulting in the exclusion of two participants on the basis of excessively low voluntary switch rates. As a result, the final analyses included 28 participants.

3.5.2. Paradigm

Participants performed a double-registration voluntary task switching paradigm in which, as in Experiment 1, each trial consisted of a task choice phase followed by a task stimulus phase. However, unlike in Experiment 1, the participants chose to respond to either the size of a number (smaller or larger than 153) or whether a letter was nearer to A or nearer to Z in the alphabet.

During the task choice phase, participants were prompted to choose whether to perform the number task or the letter task. Participants indicated their response using a key press of the right hand with the mapping of key to task counterbalanced across participants. Stimuli presented on the left and right of the screen indicated which key was mapped to which task during the task choice phase. There was no time limit on task choice. As in Experiment 1, participants were instructed to respond randomly such that they chose each task about equally often and that they chose to repeat and switch tasks equally often. Participants were additionally instructed to respond quickly and accurately, again in line with the instructions in Experiment 1. During the task response phase, participants were presented either a number or a or a letter, depending on their task choice—unlike in Experiment 1, task stimuli were therefore not bivalent. Participants indicated their response to the task stimulus using a key press of the right hand using separate keys from the task choice response. There was no time limit on task stimulus responses.

Participants began the experiment with two single-task practice blocks of 16 trials followed by a voluntary choice practice block of 16 trials—these blocks are not analyzed here nor in the original publication. Following the practice blocks, the 'baseline' portion of the experiment was presented. The baseline portion consisted of 174 trials in which no reward was presented for any trials. Reaction times during the baseline portion of the experiment were used to determine subject-specific reward thresholds in the subsequent 'reward' portion of the experiment; these calculations are detailed by the authors in the original publication (Fröber et al., 2019).

The reward portion consisted of 352 trials. In the reward portion, a reward cue was presented 500ms prior to the task choice phase of each trial and remained on the screen during the task choice phase. Following correct responses, participants were informed of how many points they had earned on the current trial during a feedback phase. Following incorrect responses, participants were informed during the feedback phase that they did not earn any points. Reward cues consisted of one of four shapes and one of two line-widths. Line width of the shape indicated the magnitude of reward (low or high); the shape itself did not inform reward magnitude but was used to avoid repeats of reward cues in successive trials. Low reward and high reward trials were equally likely. Further, while low reward was only contingent upon correct responses, high reward was also contingent on individually calibrated speed of response (please refer to the original publication for details about how reaction time criteria were calculated). While the magnitude of reward and trial-level transitions between low and high reward were not of interest in the current analyses, they were the primary conditions of interest in the original analyses (Fröber et al., 2019). For the current analyses, the distinction between reward presence in the reward portion and reward absence in the baseline portion was instead the condition of interest.

3.5.3. Analyses

As noted above, data preprocessing steps for the current analyses matched the preprocessing steps described in the original publication. Two subjects were eliminated from analyses entirely on the basis of excessively low (less than 5%) switch rates during the reward phase. Trials with reaction times greater than 3 standard deviations from the mean were considered outliers and removed from analyses, as were incorrect trials, trials following errors, and the first trial of each block.

In general, analyses in Experiment 2 matched those conducted in Experiment 1 with the new inclusion of interaction terms involving the presence or lack of reward. All reported regressions are Bayesian multilevel regressions computed via the ‘brms’ R package (Bürkner, 2017). Convergence for all models was confirmed both by visually inspecting chains and by examination of $\hat{R}$ statistics (all $\hat{R}$’s ≤ 1.01). An effect was considered significant if the coefficient’s 95% credible interval (CI) did not contain zero. All coefficients are reported as standardized coefficients followed by 95% CI.

As in Experiment 1, changes in switch rates throughout the experiment were assessed using mixed Bayesian logistic regressions for which the DV was task choice (switch was coded as 1, repeat as 0); group- and subject-level IVs in this model were trial number and task phase (baseline vs. reward) as well as the interaction between task phase and trial number. The interaction in this model was intended to assess whether the presence of reward might influence changes in switch rates over time. If the interaction was not significant, we planned to remove it from the model and assess the main effects, comparing the magnitude of switch rate change in Experiment 1 to the magnitude of the same change in Experiment 2 using credible intervals of the regression coefficients. We note that while standardized coefficients are reported here, we also compared the unstandardized ‘trial number’ coefficients across Experiments, as the unstandardized coefficients represent change in a single trial for both Experiments; while we did not report unstandardized coefficients for brevity, conclusions were the same for both comparisons.

To examine changes in reaction times and RT switch cost over time, we conducted mixed Bayesian regressions in which log transformed RTs were the DV and trial number, alternation, and task phase (baseline vs. reward) were group- and subject-level IVs, along with all interaction terms between the three IVs. Following inspection of the three-way interaction in the full model to assess possible effects of reward condition on changes in RT switch cost over time, we removed the three-way interaction terms and assessed the remaining two-way interactions to test for changes in switch cost over time, reward-modulated changes in overall RT over time, and changes in overall RT switch cost. Finally, we examined a model containing only main effects to examine whether overall reductions in RT over time found in Experiment 1 were replicated in Experiment 2, controlling for effects of reward and switching on RT.

Finally, to examine accuracy-related changes, we conducted logistic regressions in which accuracy on each trial was coded as 1 (correct) or 0 (incorrect). We first examined a regression including all three IVs (alternation, trial number, and reward presence) and all possible interaction terms to test whether there were reward-modulated changes over time in accuracy switch cost. As in RT-related models, a model including all three two-way interactions was tested but no three-way interactions were then tested, followed by a model including only main effects.

3.6. Experiment 2 Results

Changes in switch rate, overall RT, RT switch cost, overall accuracy, and accuracy switch cost throughout the task are depicted in Figure 3.3. The effects of introducing reward on overall RT, overall accuracy, and switch rate are depicted in Figure 3.4.

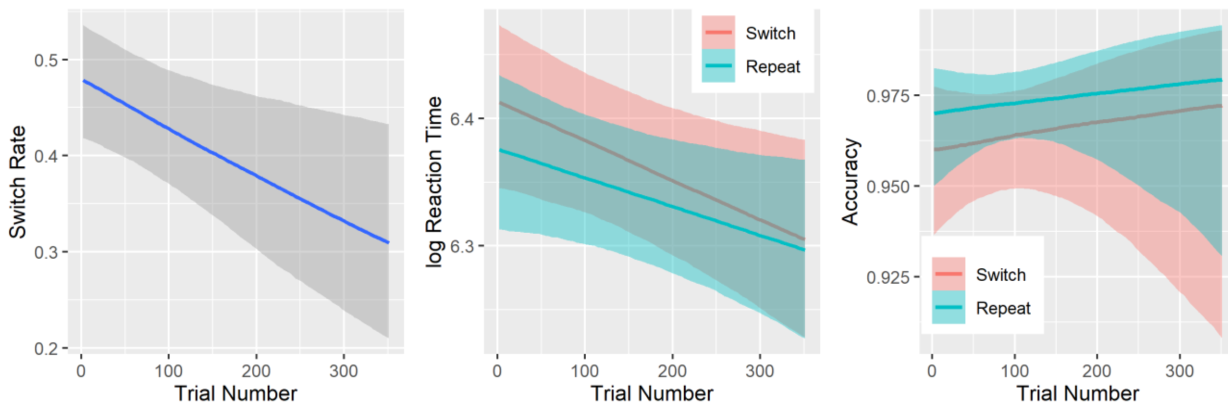

Figure 3.3. Group-level changes in switch rate (left), RT by switch condition (middle) and accuracy by switch condition (right). Main effects of trial number on switch rate and RT were significant. Shaded areas represent 95% CI. Reprinted from Imburgio & Orr, 2021a.

There was no interaction between trial number and reward presence in predicting task choice (β = -0.04 [-0.33, 0.24]), indicating that any changes in switch rates over time were not influenced by the presence of performance-contingent rewards. Because the null effect of reward on switch rate decline was crucial to ruling out effort expenditure as a mechanism of action, we conducted a follow-up test to quantify support for the null by calculating a Bayes Factor for the interaction coefficient (Lee & Wagenmakers, 2014). There was strong support for the model without the interaction term compared to the model with the interaction term (BF = 23.88), suggesting that there was indeed no effect of the reward manipulation on changes in switch rates over time.

When the interaction term was removed from the model predicting task choice, the main effect of trial number was significant; replicating the results from Experiment 1, participants chose to switch less often as the experiment progressed (β = -0.11 [-0.20,

-0.03]). There was no main effect of reward presence, indicating no effect of reward presence on overall switch rates (β = 0.36 [-0.22, 0.93]).

In the model predicting RT, the three-way interaction between trial number, alternation, and reward presence was not significant (β = 0.00 [-0.02, 0.02]). When the three-way interaction term was removed, two-way interactions between trial number and alternation (β = -0.003 [-0.008, 0.003]), trial number and reward presence (β = -0.017 [-0.001, 0.033]), and alternation and reward presence (β = -0.01 [-0.04, 0.03]) were all nonsignificant. When all interaction terms were removed, all three main effects were significant; RTs were longer for switch trials than repeat trials (β = 0.015 [0.008, 0.022]), unexpectedly slower when rewards were present than when they were not (β = 0.47 [0.39, 0.55]), and decreased throughout the experiment (β = -0.01 [-0.02, -0.005]).

The three-way interaction between trial number, alternation, and reward presence did not significantly predict accuracy (β = -0.10 [-1.07, 0.85]). Removing the three-way interaction revealed no significant two-way interactions (trial number x switch/repeat: β = 0.00 [-0.19, 0.19]; trial number x reward: β = 0.41 [-0.07, 1.00], switch/repeat x reward: β = 0.07 [-1.02, 1.03]). A model including only main effects revealed no main effect of trial number (β = 0.11 [-0.04, 0.25]) or switching (β = -0.13 [-0.30, 0.05]) on accuracy rates. However, accuracy was unexpectedly worse during the rewarded phase than the unrewarded phase (β = -1.17 [-1.91, -0.22]). Combined with the slowing of RT for the rewarded vs. the unrewarded phase, there is no support for a speed-accuracy trade-off.

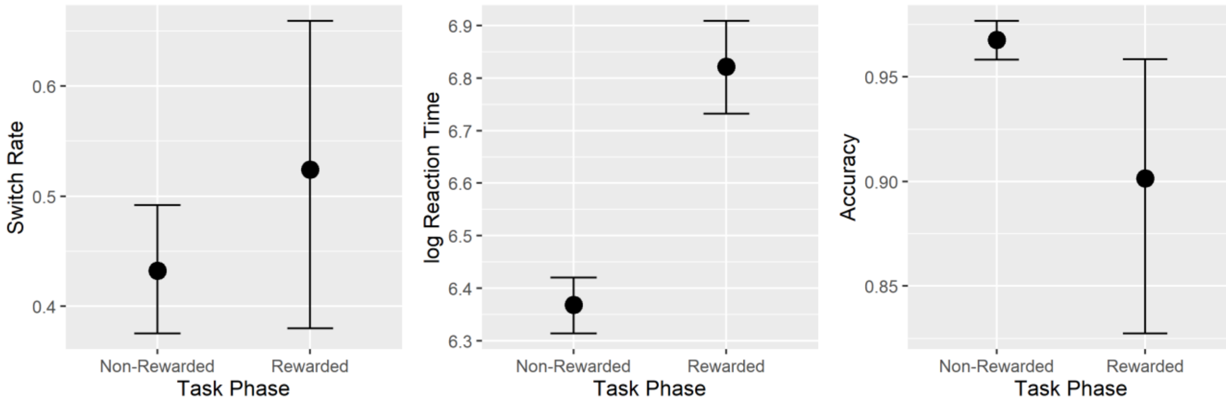

Figure 3.4. Group-level effects of reward phase on switch rate (left), RT (middle) and accuracy (right). Reaction times and accuracies were unexpectedly worse following the introduction of reward. Error bars represent 95% CI. Reprinted from Imburgio & Orr, 2021a.

3.7. Experiment 2 Discussion

As in Experiment 1, there was a significant reduction in overall RT as the task progressed, consistent with practice effects. Also consistent with Experiment 1, there was a significant decline in the rate of task switches as the experiment progressed. This decline was not affected by the introduction of a performance contingent reward, consistent with compensatory behavioral changes resulting from fatigue rather than effort avoidance. However, there were also unexpected performance decrements in overall RT and accuracy when performance-contingent reward was introduced compared to the initial non-rewarded phase of the experiment[3]; therefore, this performance decrement is also inconsistent with practice effects.

[3] Fröber & Dreisbach (2019) did not analyze data from the non-rewarded phase of the experiment as it wasn't relevant to their aims, and we note that our findings here do not contradict or invalidate the conclusions of the original manuscript.

The results of Experiment 2 indicate that declines in switch rate over time are 1) replicable, 2) detectable in a small sample (n = 28) and 3) robust across fairly different voluntary task switching paradigms. There were several notable differences between the two paradigms; most notably, Experiment 1 involved conflict-induced cognitive load due to the possibility of incongruent number Stroop stimuli and bivalent stimuli while Experiment 2 used univalent stimuli with no incongruent condition. Therefore, the presence of a switch rate decline seems robust to different variations of double-registrant voluntary task switching paradigms.

3.7.1. Experiment 2 Limitations

The fact that introducing a performance-contingent reward did not influence this decline in switch rate suggests that switch rate changes might not be due to declines in effort over time; presumably, the reward would help sustain motivation throughout the task, particularly because the rewards were linked to the possibility of winning an Amazon gift card, and such rewards have previously been found to offset effort reductions due to previous effort exerted (Kool et al., 2010). However, the introduction of reward seemed to harm, rather than facilitate, performance in terms of both overall reaction time and accuracy. It’s possible that these effects are a result of fatigue, as the rewarded phase always occurred second; therefore, the presence of reward was confounded with time spent performing the task (the authors of the original experiment did not intend to examine fatigue effects or differences across rewarded and non-rewarded conditions). However, the main effect of trial number revealed a reduction in

RT over time while controlling for rewarded vs. nonrewarded phase, which is inconsistent with fatigue.

In any case, the decrements in performance during the reward phase suggest that it is possible that the reward manipulation was not sufficient to motivate performance in participants compared to the unrewarded phase. Crucially, previous work that has found effort avoidance to be modulated by reward is generally built upon the idea that increasing the benefit of exerting effort (i.e., increasing motivation to perform well) offsets the otherwise present effort avoidance (Kool et al., 2010; Kool & Botvinick, 2014; Otto & Daw, 2019). If the monetary reward in Experiment 2 was not sufficient to motivate participants, the lack of effects on reward on switch rate decline in Experiment 2 should not be considered sufficient evidence to rule out effort avoidance as an underlying mechanism.

Another possible issue is the fact that reward in Experiment 2 was tied to performance in terms of accuracy and RT, but not to task choice. While accuracy and RT criteria for reward were calibrated to participant switch and repeat trials individually, this information was not made known to participants. Therefore, it is possible that introducing the reward might have actually encouraged repeating tasks independent of fatigue or effort avoidance; instead, participants might have been motivated to repeat more often because it is easier to respond quickly and accurately on repeat trials than switch trials.

3.8. Experiment 3

Experiment 3, which includes publicly available data originally reported by Braem (2017) aims to address these limitations. In contrast to Experiment 2, the original analysis by Braem compared rewarded and non-rewarded conditions and found expected effects of reward; therefore, it is likely that reward in Experiment 3 did sufficiently motivate participants. Further, reward in Experiment 3 was tied to task choice rather than task response, with some participants being conditioned to switch more often and some being conditioned to switch less often. The original publication reported an effect of reward condition on mean switch rates; however, if reward condition also affects *change* in switch rate over time, the change is likely not related to fatigue, but due to effort considerations. Additionally, rewarded trials in Experiment 3 were intermittent throughout the task rather than only in the second half; therefore, unlike Experiment 2, trial number and reward presence were not confounded in Experiment 3.

Further, Experiment 3 included BIS/BAS scores for each participant. This allowed for the examination of individual differences in switch rate changes in relation to approach/avoidance behavior; examining the relationship between effort avoidance and BIS/BAS scores was specifically mentioned as a suggestion for future work in the seminal 2010 manuscript on effort avoidance due to previous effort exertion by Kool and colleagues (2010). Since then, higher scores on the BIS subscale have been linked to greater aversion towards cognitive effort exertion (Storbeck et al., 2015). Therefore, if declines in switch rate are related to increased aversion to effort expenditure *due to* previous effort exertion, one might expect steeper declines in those scoring higher on the BIS subscale. Therefore, Experiment 3 examined correlations between subject-level switch rate changes and BIS/BAS subscale scores. Importantly, we also examined relationships between subject-level average switch rates and BIS/BAS scores to determine if any relationships were indeed related only to the change in switch rate rather than an overall task choice tendency.

3.9. Experiment 3 Methods

3.9.1. Participants

Experiment 3, conducted at Ghent University, consisted of 49 participants who participated for monetary compensation (10 € as well as a chance to win a 50 € gift card based on performance during 'reward' trials). As in Experiment 2, data preprocessing and exclusion criteria were identical to the original publication (in this case, preprocessed data was openly available on Open Science Framework; Braem, 2017a). Eleven participants were excluded by the authors because of excessively low voluntary switch rates. As a result, the final analyses included 38 participants. Details about sample size determination can be found in the original publication (Braem, 2017b).

3.9.2. Paradigm

Each participant performed twelve practice trials of the task followed by 4 blocks of the full task, each block consisting of 80 trials. The first half (40 trials) of each block consisted of cued choice trials, while the second half of each block consisted of voluntary choice trials.

During the cued trials, participants were first presented with a task cue phase followed by a task stimulus phase. During the task cue phase of cued trials, participants were presented with one of ten possible letters; whether the letter was a vowel/consonant indicated which of the two possible tasks they were to perform (animacy or size, with the cue-to-task mapping counterbalanced across participants). The cue remained on the screen for 1000ms. During the task stimulus phase, subjects were presented with one of 320 possible Dutch words to respond to using a key press (response-button mappings were counterbalanced across participants); the dimension of the word they were to respond to depended on which of the two tasks was indicated during the cue phase. The two possible tasks were ‘animacy’, where subjects responded to indicate whether the word described to something that was animate, or ‘size’, where subjects were to indicate whether or not the word described something that was smaller or larger than a basketball. Subjects had up to 5000ms to respond to the task stimulus. During cued trials, each task was equally probable, as were task switch and task repeat trials. Details about stimulus/cue randomization and counterbalancing, as well as more specific descriptions of task timings, can be found in the original publication (Braem, 2017b) and were not central to analyses here.

Cued trials also included reward. After a correct task response, subjects were presented with a screen that indicated they had earned either a high reward (‘+10’) or a low reward (‘+01’) for that trial. After incorrect responses, subjects presented with the Dutch word for ‘false’ (“FOUT!”) and earned no points for that trial. Subjects were told that they if they earned the most points of any participant during the cued trials, they would win the 50 € gift card.

Unbeknownst to the subjects, the probability of a low or high reward for correct trials depended upon whether the trial was a task switch or task repeat. For participants in the ‘switch reward’ condition (*n* = 19), correct responses on switch trials had an 80% chance to yield high reward and a 20% chance to yield low reward, while the probabilities were reversed on repeat trials. For participants in the ‘repeat reward’ condition (*n* = 19), there was an 80% chance of high reward (and 20% chance of low reward) on repeats and the probabilities were reversed for switch trials. Participants were told that the number of points won on each correct response was random rather than tied to switch or repeat trials.

On voluntary trials, participants were presented with a ‘#’ sign rather than a letter during the task cue portion of each trial, indicating they could respond to either the animacy or size of the word. Unlike Experiments 1 and 2, participants did not have to press a button to indicate which they had chosen. The task stimulus phase was the same on voluntary trials as it was on cued trials. Participants were instructed to choose tasks randomly using similar instructions as in Experiments 1 and 2 (each task should be chosen equally often, and they should choose to repeat and switch tasks equally often). As there was no reward on voluntary trials, they included no feedback; however, participants were told that accurate responses and an honest attempt to choose tasks randomly on voluntary trials were required for their eligibility in winning the 50€ gift card.

3.9.3. Questionnaires

All participants completed the BIS/BAS scale (Carver & White, 1994), intended to measure disposition towards rewarding and aversive stimuli. The BIS/BAS scale consists of four subscales: BIS, BAS Reward Responsiveness (BAS-Reward), BAS Fun-Seeking (BAS-Fun), and BAS Drive (BAS-Drive).

3.9.4. Analyses

Data obtained from Open Science Framework (Foster, MSLS & Deardorff, MLIS, 2017) for Experiment 3 was preprocessed and had already included participant exclusion markers, RT outlier removal, and removal of trials following errors. Therefore, exclusion criteria for the current analyses matched the preprocessing from the original publication exactly; preprocessing steps were similar to preprocessing steps from Experiments 1 and 2.

The majority of analyses in Experiment 3 mirrored those in Experiments 1 and 2. Changes in RT switch cost, accuracy switch cost, overall RT, overall accuracy, and switch rate over time were analyzed identically to previous analyses using Bayesian mixed regressions using the brms package (Bürkner, 2017) in R version 4.0.0 (R Core Team, 2020)—RTs were again log-transformed and both accuracy and switch rate were again assessed using logistic regressions. However, regressions in Experiment 3 included reward condition as an additional IV, along with interactions between reward condition and all other IVs in all other regressions. Because all participants were in only one of the two possible reward conditions, reward condition was included as only a group-level IV (and not as a subject-level IV) in all regression models. As in the previous experiments, nonsignificant interaction terms were removed from models and main effects were assessed in models that contained no interaction terms. Convergence for all models was confirmed both by visually inspecting chains and by examination of

$\hat{R}$ statistics (all $\hat{R}$'s ≤ 1.01). An effect was considered significant if the coefficient's 95% credible interval (CI) did not contain zero. All coefficients are reported as standardized coefficients followed by 95% CI.

Only voluntary trials were analyzed because our main interests were related to changes in behavior during voluntary task switching; in particular, changes in task choice/switch rate over time were the most salient finding from Experiments 1 and 2, and cued trials do not contain a task choice component. Further, the presence of reward on cued trials and lack of reward on voluntary trials would have complicated interpretations of any differences across the trial types for other DVs of interest.

Because our hypotheses related to BIS/BAS scores were motivated specifically by exploration of the mechanism underlying the decreases in switch rate found in Experiments 1 and 2, analyses involving BIS/BAS were restricted only to relationships between BIS/BAS scores and switch rates. Our primary hypothesis here was that high BIS scores—which indicate greater aversion towards negative stimuli and have been linked specifically to greater aversion towards cognitively demanding tasks (Storbeck et al., 2015)—would be related to greater declines in switch rate. To this end, we extracted subject-level trial number coefficients from the regression predicting task choice, which represent subject-level changes in switch rate (more negative coefficients meant greater decline in switch rate over time) and assessed correlations between these subject-level coefficients and subscales of the BIS/BAS.

The normality of the distributions of BIS/BAS subscale scores and subject-level coefficients was assessed using a Shapiro-Wilk test and visual inspection of quantile plots. While subject-level switch rate change coefficients were normally distributed, the distributions of BIS, BAS-Reward, and BAS-Drive scores were significantly different from normally distributed (all *p'*s ≤ .01); therefore, Spearman ranked correlations were used to assess relationships between these three subscales and the subject-level switch rate change coefficients rather than Pearson correlations that assume normality. The distribution of BAS-Fun was close to significantly different from a normal distribution ($p = .058$) and a visual inspection of the distribution indicated that it appeared bimodal, therefore, a Spearman rank-based correlation was used here as well to avoid violating the parametric assumptions of a Pearson correlation.

3.10. Experiment 3 Results

Changes in switch rate, overall RT, RT switch cost, overall accuracy, and accuracy switch cost throughout the task are depicted in Figure 5. Relationships between BIS and BAS-Fun subscales and task choice-related measures are depicted in Figure 6. There was no significant interaction between reward condition and trial number in predicting task choice ($\beta = -0.02$ [-0.18, 0.13]); Bayes factors indicated support for the model without the interaction term compared to the model with the interaction term ($BF = 5.65$). These results indicate that there was no effect of reward condition on changes in task choice over time.

When the interaction term was removed, there was a main effect of reward condition ($\beta = 0.47$ [0.12, 0.83]); replicating the original studies' findings, participants who received higher rewards on switch trials during cued trials were more likely to choose to switch tasks than participants who received higher rewards on repeat trials. In contrast to experiments 1 and 2, there was no effect of trial number on task choice (β = -0.02 [-0.10, 0.05]), indicating no significant changes in switch rate over time. Follow-up Bayesian analyses indicated support for the null; there was strong support for a model containing no group effect of trial number compared to a model with the group effect (*BF* = 8.04). Therefore, it was very likely that there was no change in switch rates over time at a group level in experiment 3.

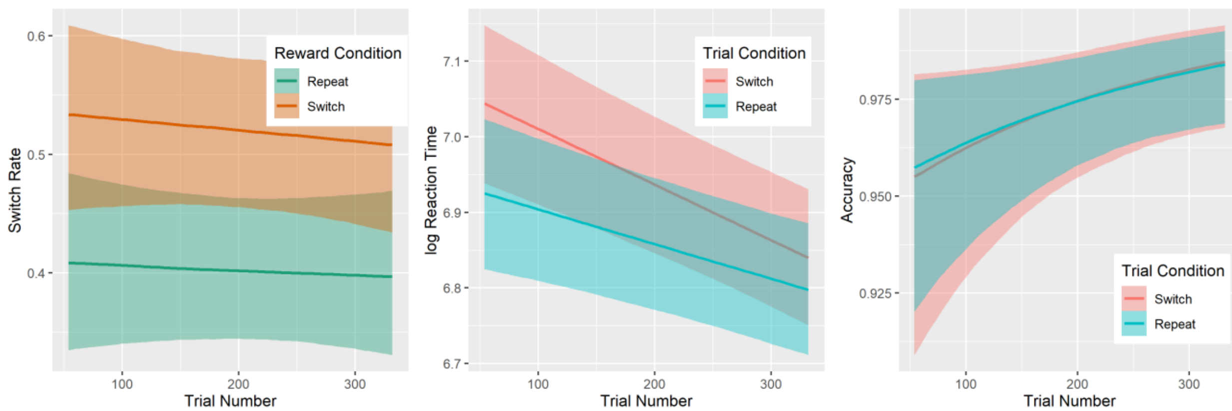

Figure 3.5. Group-level changes in switch rate by reward condition(left), RT by switch condition (middle) and accuracy by switch condition (right). Reward condition, but not trial number, significantly affected switch rate. Overall RT, RT switch cost, and overall accuracy improved over time. Shaded areas represent 95% CI. Reprinted from Imburgio & Orr, 2021a.

In predicting RT, the three-way interaction (reward condition x alternation x trial number) was not significant (β = 0.00 [-0.05, 0.05]). In a model with no three-way interaction term, the interaction between trial number and alternation was significant (β = -0.025 [-0.046, -0.004]), indicating that RT switch cost (the difference between switch RT and repeat RT) changed significantly throughout the experiment. To explore the interaction, trial number was centered at 1.5 SDs above and below its mean to quantify RT switch cost (the switch/repeat coefficient in this model) early in the experiment and later in the experiment. RT switch cost was larger earlier in the experiment ($\beta = 0.10$ [0.06, 0.14]) compared to later in the experiment ($\beta = 0.03$ [-0.01, 0.06]), consistent with practice effects. No other two-way interactions were significant (reward condition x alternation $\beta = -0.03$ [-0.08, 0.01]; reward condition x trial number $\beta = 0.01$ [-0.02, 0.04]).

In a model predicting RT with no interaction terms, there was a significant main effect of trial number ($\beta = -0.05$ [-0.06, -0.03]); in line with results from experiments 1 and 2, overall RT decreased throughout the experiment. The effect of alternation on RT was also significant ($\beta = 0.06$ [0.04, 0.09]), indicating that the expected RT switch cost was present throughout the experiment on average. There was no main effect of reward condition on RT, $\beta = 0.10$ [-0.03, 0.22].

There was no significant three-way interaction (reward condition x alternation x trial number) in the model predicting accuracy ($\beta = 0.32$ [-0.41, 1.08]).). When the three-way interaction term was removed, there were no significant two-way interactions (reward condition x alternation $\beta = 0.07$ [-0.61, 0.72]).; reward condition x trial number $\beta = -0.02$ [-0.35, 0.31]; alternation x trial number $\beta = 0.04$ [-0.36, 0.43]). When all interaction terms were removed, there was a significant effect of trial number on accuracy such that accuracy increased over time ($\beta = 0.36$ [0.19, 0.52]); the main effects of alternation ($\beta = 0.01$ [-0.35, 0.40]) and reward condition ($\beta = -0.26$ [-0.96, 0.43]) were not significant.

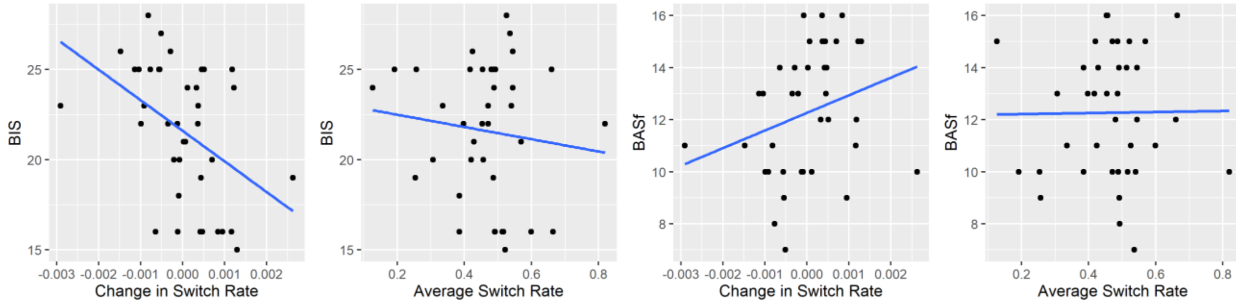

Figure 3.6. Relationships between changes in switch rates, average switch rates, and BIS/BAS-Fun scores. While trend lines shown here represent parametric linear model estimates, relationships were tested using spearman rank-correlations (which cannot be depicted) which better account for outliers, leverage points and non-normality. Hence, the trend lines shown here are purely for visualization purposes and do not represent the method by which relationships were tested. Relationships between BIS/BAS-Fun scores and changes in switch rates were significant while relationships involving average switch rates were not. Reprinted from Imburgio & Orr, 2021a.

There was a significant relationship in the predicted direction between BIS scores and subject-level changes in switch rate over time ($\rho = -.48$, $p = .002$); participants that scored higher on the BIS subscale tended to switch tasks less often as the experiment progressed. There was a significant relationship in the opposite direction between and subject-level changes in switch rate over time and BAS-Fun ($\rho = .37$, $p = .02$); subjects scoring higher on the fun-seeking subscale tended to switch tasks more often as the experiment progressed. There was no relationship between changes in switch rate and the other two subscales (BAS-Drive: $\rho = -.12$, $p = .49$; BAS-Reward: $\rho = .09$, $p = .59$). None of the subscales were significantly correlated with individual mean switch rates (all p's > .46), indicating that BIS and BAS-Fun scores were related specifically to changes in switch rates over time rather than the tendency of a participant to switch tasks on average.

3.11. Experiment 3 Discussion

Experiment 3 aimed to replicate overall patterns in Experiments 1 and 2 regarding changes in task choice, RT, and accuracy measures over time, as well as test the effect of reward manipulations related to task choice rather than task performance on changes in switch rate. Consistent with the results from Experiment 2, there was no effect of reward on changes in switch rate over time despite replicating the original authors' findings that reward condition significantly affected overall switch rates. However, unlike in Experiments 1 and 2, switch rates did not change over time at a group level in Experiment 3.

Also consistent with previous experiments, overall RT decreased over time; in line with results of Experiment 1, overall accuracy also improved throughout the task. Unique to Experiment 3 here, but consistent with previous work in cued task switching (Koch et al., 2018), RT switch cost decreased throughout the experiment. There was no effect of reward condition on any RT- or accuracy-related measures. Finally, consistent with predictions, higher BIS scores were associated with greater declines in switch rate throughout the task. Higher BAS fun-seeking scores, in contrast, predicted greater increases in switch rates throughout the task. These patterns were not present when examining subject-level switch rate averages.

3.11.1. Effects of Reward

The null effect of reward condition on changes in switch rates throughout the experiment provide further support for ruling out reduced effort exertion as a result of previous effort exertion as an underlying mechanism in the switch rate declines present in Experiments 1 and 2. However, this interpretation is complicated by the unexpected lack of overall switch rate decline present in Experiment 3. It is possible that switch rates did not decline in Experiment 3 due to differences in the task itself; for example, while Experiments 1 and 2 found changes in switch rates throughout the continuous performance of voluntary task switching, Experiment 3 involved intermittent cued blocks rather than continuous voluntary choices. Additionally, Experiment 3 included far fewer voluntary choice trials than the two previous experiments-while Experiment 1 included 390 voluntary trials and Experiment 2 included 526, only 160 of the 320 total trials in Experiment 3 were voluntary choice trials. It is possible that with more voluntary trials, a decline in switch rate would be present in a paradigm like the one used in Experiment 3.

3.11.2. Individual Differences

Although there was no group-level change in switch rate throughout Experiment 3, results indicate that individual changes in switch rates might provide additionally valuable information about individual differences in behavioral approach and avoidance tendencies. As expected, participants that scored higher on the BIS subscale of the BIS/BAS tended to switch tasks less often as the task progressed; this pattern might indicate that participants who switch less often over time might do so because they view switching as aversive, possibly due to an increased aversion to effort expenditure (Storbeck et al., 2015). Unexpectedly, subjects that scored higher on the BAS fun-seeking scale tended to switch *more* often as the task progressed; because previous work indicates that more frequent switching is indicative of boredom (Geana et al., 2016a), this relationship might suggest that individuals higher on BAS-Fun experience greater boredom throughout the task, causing more frequent exploration behavior in the form of frequent switching. However, it should be noted that the relationship between BAS-Fun and switch rate changes was not predicted and weaker (ρ = .37) than the relationship between BIS and switch rate changes (ρ = -.48); therefore, the relationship between BAS-Fun and changes in switch rate should be interpreted cautiously.

Finally, Experiment 3 provides evidence that changes in switch rates over time and overall switch rate likely measure different mechanisms. The relationships between BIS/BAS subscales were specific to switch rate changes rather than overall switch rate. Similarly, the original publications' effect of rewarding either repeats or switches more often significantly affected overall switch rate, but not changes in switch rate.

3.12. General Discussion

The current work sought to examine the degree to which common measures of interest in voluntary task switching paradigms might change throughout task performance. Previous work suggested that there were four mechanisms that might be expected to result in changes throughout task performance: practice effects causing better overall performance, fatigue effects causing worse overall performance or compensatory mechanisms to prevent performance decrements, boredom effects causing increased switching behavior, and decreased effort expenditure because of previous effort expenditure reflected in reduced switching behavior.

3.12.1. Practice Effects

The effects of practice on overall RT were consistently present; in all three experiments, overall reaction times declined significantly throughout the experiment. Decline in reaction time on its own might be indicative of reduced effort expenditure; however, overall task accuracy also increased throughout the task in Experiments 1 and 3, with no change in accuracy over time in Experiment 2. If reduced RT was a result of reduced effort rather than practice, one would expect a speed-accuracy tradeoff. Additional improvements in accuracy switch cost in Experiment 1 and RT switch cost in Experiment 3 suggest that participants do display better performance over time consistent with practice effects rather than worse performance over time consistent with fatigue.

3.12.2. Fatigue Effects

In general, there was little evidence for decrements in performance indicative of significant fatigue. The three experiments contained differing numbers of trials (ranging from 320 in Experiment 3 to 526 in Experiment 2); However, it should be noted that reward condition in Experiment 2 was confounded with time spent performing the task (the second part of the experiment was always rewarded), and there were significant reductions in accuracy and increases in RT attributed to reward condition in Experiment 2. Therefore, it’s possible that fatigue-induced decrements in performance were present in Experiment 2 (the longest of the three experiments), although interpretation of these results are complicated by the experiment’s design.

3.12.3. Changes in Switch Rates

It is notable, however, that Experiment 3 was the only of the three in which participants did not decline in switch rates. There are a few possible reasons for this, although the current work is not well situated to compare them directly. Although the overall length of the task in Experiment 3 was comparable to the task length in Experiment 1 (320 trials vs. 390 trials), only half of the trials in Experiment 3 were voluntary choice trials. It's possible that there were too few voluntary trials to detect (or elicit) a change in switch rate at the group level. However, a Bayes Factor analysis indicated strong support for the null (lack of change) rather than inconclusive evidence for the null or alternative, suggesting that the issue is not one of statistical power.

The fact that participants were simply required to make fewer choices in Experiment 3 than the other experiments might underlie the difference in strategy; previous work has found that increasing the ratio of cued to voluntary choice trials, thereby decreasing the number of task choices participants make throughout the task, results in more frequent voluntary switching (Fröber & Dreisbach, 2017). It is possible that this effect might be in part due to a reduction (or abolishment) of an otherwise present reduction in switch rates over time rather than an increase in the overall average tendency to switch tasks. The present findings that changes in switch rates over time are related to BIS and BAS-Fun scores, while mean switch rates are not, suggest that switch rate changes and average switch rate might index different cognitive processes; therefore, future investigation into whether the effect of reducing the number of voluntary trials might be better explained by modulating changes in switch rates rather than average switch rates might prove fruitful in establishing the mechanism by which reducing voluntary choices influences task choices.

In a similar vein, recent work (Dreisbach & Fröber, 2019; Foerster et al., 2020) has distinguished between manipulations that affect task choice at a local, shorter time scale (e.g. trial-level changes in reward prospect) and task choice at a global, longer timescale (e.g. context including ratio of cued to voluntary choice trials). The changes in task choice over time reported in the current work might provide another avenue by which to examine task choice at a global level (whereas previous work has generally focused only on overall average switch rates). Notably, the relationship between individual differences in task choice changes over time significantly predicted BIS and BAS-Fun scores when there was no significant change in task choice over time at a group level, suggesting that changes in task choice might be a valuable measure even for paradigms that do not elicit a group level change.

3.12.4. Limitations and Future Directions

Although the current work suggests that changes in switch rate over time might provide valuable information in future work, the cognitive mechanism underlying the change is still unclear. The reward manipulations intended to provide support for the idea that effort exertion might underly the effect in Experiments 2 and 3 failed to significantly affect the degree of change. However, because there was no group-level change in switch rate in Experiment 3, and because reward was confounded with time spent performing the task in Experiment 2, these null effects should be interpreted with caution and do not sufficiently rule out effort expenditure as a possible underlying mechanism.

The fact that BIS scores were negatively correlated with switch rate changes suggests that effort avoidance might play a role in a tendency to switch less over time, given that previous work has found a relationship between BIS scores and sensitivity to effort exertion (Storbeck et al., 2015). Further, the positive relationship between BAS-Fun and changes in switch rate might suggest that another mechanism, possibly boredom (Geana et al., 2016a), could additionally explain the effect. However, future work should seek to replicate these findings, as the relationships were examined within a sample that might be considered small for individual differences research (N = 38).

The current work compared the presence of behavioral changes across different voluntary task switching paradigms run by different labs to establish the degree to which changes might be robust across tasks. However, the relatively large differences across paradigms also makes it difficult to interpret why a specific effect might not replicate across paradigms (for example, why switch rates declined at a group level in Experiments 1 and 2 but not Experiment 3). Future work can expand on the current findings by manipulating individual aspects of a voluntary task switching paradigm to provide more insight into exactly what aspects of a task might moderate the behavioral effects presented here.

Future work using more direct manipulations of effort expenditure and fatigue might be useful to establish the degree to which each mechanism (effort avoidance due to previous expenditure vs. a compensatory strategy meant to combat fatigue) might contribute to changes in task choice over time. However, it is also possible that these two mechanisms overlap—that is, that increases in effort expenditure meant to induce effort avoidance might *necessarily* result in greater levels of fatigue resulting in a compensatory strategy—which would make devising a behavioral manipulation that affects one process and not the other very difficult. Previous work does suggest that effort avoidance is uncorrelated with the subjective feeling of fatigue (Benoit et al., 2019), though, suggesting that the two might be separable.

However, it is also possible that, in the case of VTS performance, effort avoidance is itself a compensatory strategy during the early stages of fatigue that might occur prior to subjective feelings of fatigue; if this is the case, the theoretical framework of the current study which places the two processes in theoretical opposition with each other (informed by previous work in similar paradigms) might be flawed. Future work might wish to examine the degree to which individual differences in switch rate declines in VTS paradigms might be related to individual differences in fatigue-related decrements in cued task switching paradigms, where this compensatory strategy cannot be applied, to examine whether the two mechanisms might be related.

Finally, the mechanisms proposed to underlie declines in switch rates in the current work are based in predictions related to the effects of these mechanisms in similar tasks. However, future work that establishes relationships between declines in switch rates and other measures of effort exertion and/or fatigue would be beneficial to support these ideas.

3.12.5. Conclusions

The current work examined the degree to which common measures of interest in a voluntary task switching paradigm change during performance of the task. There was consistent evidence for improvements in performance over time, indicating effects of task practice. In two of the three experiments, there was a group-level reduction in switch rates over time; while this reduction was not present in Experiment 3, analyses of individual differences in BIS/BAS scores suggest that changes in switch rates over time provide information that might prove useful for future work in cognitive flexibility examined using VTS independent of subject average switch costs. The combined results of the three experiments support the use of switch rate changes throughout task performance as a novel dependent variable of interest in future VTS use, although more work is necessary to determine which cognitive mechanisms the effect might index.

4. NEURAL CORRELATES OF CHANGES IN VOLUNTARY TASK SELECTION

4.1. Introduction

Results from Chapter 3 indicate that declines in switch rate throughout performance of a VTS paradigm might be replicable across participants and inform us about individual differences in approach/avoidance behavior. However, the cognitive mechanism underlying these changes remains unclear.

Based on previous work, I hypothesized that a reduction in switch rates over time might indicate a reduction in effort expenditure due to previous effort expenditure (Kool et al., 2010; Mittelstädt, Miller, et al., 2018) or a compensatory mechanism meant to combat decrements resulting from early fatigue (Hockey, 2010; Robert & Hockey, 1997; Wang et al., 2016). In Chapter 4, I attempted to replicate group-level reductions in switch rate using the same task as in Chapter 2 Experiment 2 and Chapter 3 Experiment 1 in a separate, smaller sample. Further, I examined the degree to which changes in switch rates might be related to several EEG correlates of fatigue and effort exertion in order to provide support for one of the proposed cognitive mechanisms.

4.1.1. Separating Effort and Fatigue with EEG Measures

Although fatigue and effort exertion have thus far been discussed as separate mechanisms, most fatigue inductions in previous EEG work involve manipulating effort exertion. Many previous studies that aim to measure either fatigue or effort exertion using EEG conflate the two processes for this reason (Balasubramanian et al., 2011; Capa et al., 2013; Lorist et al., 2000; Smit et al., 2004). However, two of the more well-established and frequently studied EEG correlates of fatigue – changes in alpha and theta power during performance (Åkerstedt & Gillberg, 1990; Balasubramanian et al., 2011; Diaz-Piedra et al., 2020; Drapeau & Carrier, 2004; Galliaud et al., 2008; Horne & Baulk, 2004; Philip & Åkerstedt, 2006; Smit et al., 2004, 2005; Trejo et al., 2005) – are potentially informative in relation to switch rate changes.

4.1.2. Frontal Alpha as a Marker of Fatigue

While many studies find changes in global alpha and parietal alpha resulting from fatigue manipulations that might equally be interpreted as effort manipulations (Balasubramanian et al., 2011; Boksem, Tops, et al., 2006; Craig et al., 2012; Trejo et al., 2005), changes in *frontal* alpha have been reported to be unrelated to cognitive effort exertion (Parvaz et al., 2012; Smit et al., 2005) but have been related to fatigue (Boksem, Meijman, et al., 2006; Craig et al., 2012; Wascher et al., 2014). Specifically, increases in frontal alpha would indicate increased fatigue, but not an increase in cognitive effort exertion.

Therefore, a relationship between changes in switch rate during VTS performance and changes in frontal alpha during VTS performance would support the idea that the behavioral change is related to fatigue rather than effort exertion. Notably, some previous work has indicated that the laterality of frontal alpha power might affect the relationship between frontal alpha and effort exertion (Parvaz et al., 2012); while the researchers suggested that the asymmetry in that particular task (cognitive reappraisal) might have been related to the verbal nature of the task, examining left and right frontal alpha separately might additionally prove fruitful here.

4.1.3. Frontal Theta as a Marker of Effort Exertion

While many studies report fatigue-induced changes in frontal theta, more recent theories regarding the role of frontal theta posit that frontal theta power indexes the need to exert cognitive control (Cavanagh & Frank, 2014). This account posits a slightly different interpretation for previous work – an increase in theta over time might indicate greater cognitive demand (effort required) due to fatigue rather than solely indexing fatigue effects; this account has since been supported by separate work examining changes in theta and alpha during task performance (Smit et al., 2005; Wascher et al., 2014). Therefore, relationships between changes in switch rates throughout VTS and changes in frontal theta throughout VTS might support effort exertion accounts rather than fatigue accounts.

Notably, though, it would also follow from this theory that a general change in theta power *would result from* the act of switching less (as less switching would require less cognitive control). Indeed, previous work in cued task switching has indicated that switching tasks results in a trial-level effect on frontal theta power following stimulus presentation (Cooper et al., 2019), as have other studies involving cognitive effort exertion outside the context of task switching (Smit et al., 2005; Wascher et al., 2014).

In other words, under this framework, the relationship between task-level changes in frontal theta and task-level changes in switch rates might be complicated by the trial-level relationship between task switching and post-stimulus frontal theta. Therefore, if switching tasks has a significant effect on theta power in the current paradigm, the effect must be controlled for when examining relationships between general changes in switch rates and general changes in theta power.

4.1.4. Beta as a Marker of Vigilance

Finally, one study examining fatigue during a driving simulation posited that, while theta and alpha power index the degree to which a person fatigues/exerts effort, beta power indexes the compensatory attempt to maintain vigilance (Craig et al., 2012). If this is the case, it is possible that changes in beta activity might differentiate between compensatory adaptations to fatigue and reductions in effort – reductions in effort would likely not be related to an index of increased vigilance, while compensatory changes meant to combat fatigue would be. Therefore, a relationship between changes in switch rates and changes in beta power throughout the task would provide evidence for the involvement of a compensatory mechanism related to fatigue in producing switch rate changes.

It should be noted that a theoretical differentiator between effort exertion and fatigue is that reductions in effort exertion can be offset by reward manipulations (Kool et al., 2010); however, one study that independently manipulated fatigue (via increased/sustained effort exertion) and reward reported effects of both manipulations on the same EEG components – while prolonged task performance over a period of two hours (the fatigue manipulation) resulted in ERN, N2, and CNV amplitude reductions, the introduction of reward resulted in modulation of these same components (Boksem, Meijman, et al., 2006). It seems unlikely that the two-hour manipulation employed in the study did not induce some level of fatigue, and the reward manipulation resulted in performance improvements indicating it sufficiently motivated participants. Therefore, ERP magnitudes (at least those relating to performance monitoring such as the ERN, N2 and CNV) seem less likely than frequency band power to help differentiate between effort exertion and fatigue.

4.1.5. Aims and Hypotheses

In sum, Chapter 4 1) aimed to replicate the group-level decline in switch rates throughout VTS performance and 2) examined whether these changes were related to changes in EEG measures to determine the mechanism underlying changes in switch rates. I anticipated that switching tasks would result in trial-level changes in theta power; therefore, I planned to examine whether the trial-level frontal theta power differed between repeat and switch trials, then control for any significant effects of switching when examining relationships between changes in frontal theta and changes in switch rates throughout the experiment.

I hypothesized that frontal theta and frontal alpha would increase throughout task performance, in line with previous work (Åkerstedt & Gillberg, 1990; Balasubramanian et al., 2011; Diaz-Piedra et al., 2020; Drapeau & Carrier, 2004; Galliaud et al., 2008; Horne & Baulk, 2004; Philip & Åkerstedt, 2006; Smit et al., 2004, 2005; Trejo et al., 2005) and indicating increases in cognitive effort required and cognitive fatigue, respectively. I also hypothesized that beta power might increase over time, representing compensatory maintenance of vigilance to combat fatigue effects.

I then hypothesized that changes in frontal alpha power (or left/right alpha power individually) or beta power might be negatively correlated with changes in switch rate, which would support the idea that fatigue contributes to switch rate declines. Further, I hypothesized that changes in frontal theta power might be negatively correlated with changes in switch rate, which would support the idea that continued effort exertion contributes to switch rate declines.

4.2. Methods

4.2.1. Participants

The sample consisted of 49 undergraduate students who completed the study for course credit. To exclude participants who did not adequately comply with instructions regarding random task choice, participants who switched tasks on greater than 80% of trials or less than 20% of trials were removed from analyses involving behavioral task performance (*n* = 7). EEG recordings for one participant were excluded from analyses involving only EEG measures due to excessive artifacts (this participant was also excluded from behavioral analyses for not meeting switch rate criteria). Final analyses involving only EEG measures involved 48 participants, while analyses involving only behavioral measures, or a combination of EEG and behavioral measures, involved 42 participants. Study procedures were determined by the Texas A&M University IRB to be exempt according to the Revised Common Rule.

4.2.2. Paradigm

Participants performed the same task switching paradigm as in Chapter 2 and Experiment 1 of Chapter 3 (see Figure 2.1). Briefly, the paradigm involved first responding to a cue on each trial to indicate which of two possible tasks to perform, followed by a response to two numbers that differed in both numerical and physical size. Participants chose to either respond indicating the number that was larger in numerical size or the number that was larger in physical size. Participants were instructed to select tasks randomly such that they switched and repeated tasks equally often and that each task was chosen equally often. Participants underwent practice blocks on which they received feedback on how well they followed the task choice instructions and task accuracy. The full task involved 6 blocks of 65 trials for a total of 390 trials.

4.2.3. EEG Recording and Processing

Continuous EEG was recorded using an ActiChamp amplifier (Brain Products GmbH, Gilching Germany) using Cz as the online reference electrode, and sixty-four ActiCap slim electrodes arranged in the 10/20 system. EEG data was digitized at a 24-bit resolution with a sampling rate of 500 Hz.

EEG data were processed offline using EEGlab toolbox version 2019.0 (Delorme & Makeig, 2004) using a standard processing pipeline involving ICA detection and removal of artifacts. Data was re-referenced to the average and band-pass filtered with a high-pass filter of 0.1 Hz. Line noise was removed using the CleanLine EEGlab plugin. Prior to ICA decomposition, the Artifact Subspace Reconstruction EEGlab plugin was used to automatically clean the data and detect bad channels for removal, after which any removed channels were interpolated. Finally, time periods before and after task performance and between task blocks were removed and data was visually inspected for large remaining artifacts prior to ICA decomposition. Next, ICA decomposition was conducted using the fastICA EEGlab algorithm, components were labelled as signal or artifact using the ICLabel plugin (Pion-Tonachini et al., 2019) to aid classification, and components were manually inspected removed if they were determined to be artifact. After data cleaning procedures, two processing pipelines were employed. The first was meant to examine the effects of switching on frontal theta power to determine whether these effects must be controlled for when examining relationships between changes in switch rates and changes in frontal theta power. The second was meant to calculate and extract changes in EEG measures throughout the task.

4.2.4. Examination of switch effects on theta power

Data were sorted into stimulus-locked switch or repeat trial epochs ranging from -300 to 1000 ms and baseline corrected using the -300 to -100 ms period, in line with previous work (Cooper et al., 2019). Data were Morlet Wave transformed and event-related spectral perturbations (ERSPs) were then calculated for correct switch trials and correct repeat trials separately, then statistically compared with ERPlab (Lopez-Calderon & Luck, 2014) at each electrode of interest for frontal theta measures (Fz, F1, F2) using FDR-corrected p-values. While clear increases in theta power post-stimulus were present as expected, the difference between switch and repeat trials was not significant (see Fig. 4.1) [4]. As such, the effects of switching on theta power were not statistically controlled for in subsequent analyses examining the relationship between switch rate changes throughout the task and frontal theta changes throughout the task.

4.2.5. Examination of changes in EEG measures throughout task

Data was baseline corrected to the subject average – this approach allowed me to test for overall changes during the entirety of task performance while still accounting for

[4] Switch vs. repeat frontal theta contrasts were also generated using Fast Fourier Transformations for the entirety of task performance in addition to the -300 to 1000 ms stimulus response period. There were no significant differences between the two conditions at any of the electrodes used to assess frontal theta.

between-subject differences in raw voltages. Traditional baseline-correction within each individual segment might obscure more general changes that the analyses was meant to extract.

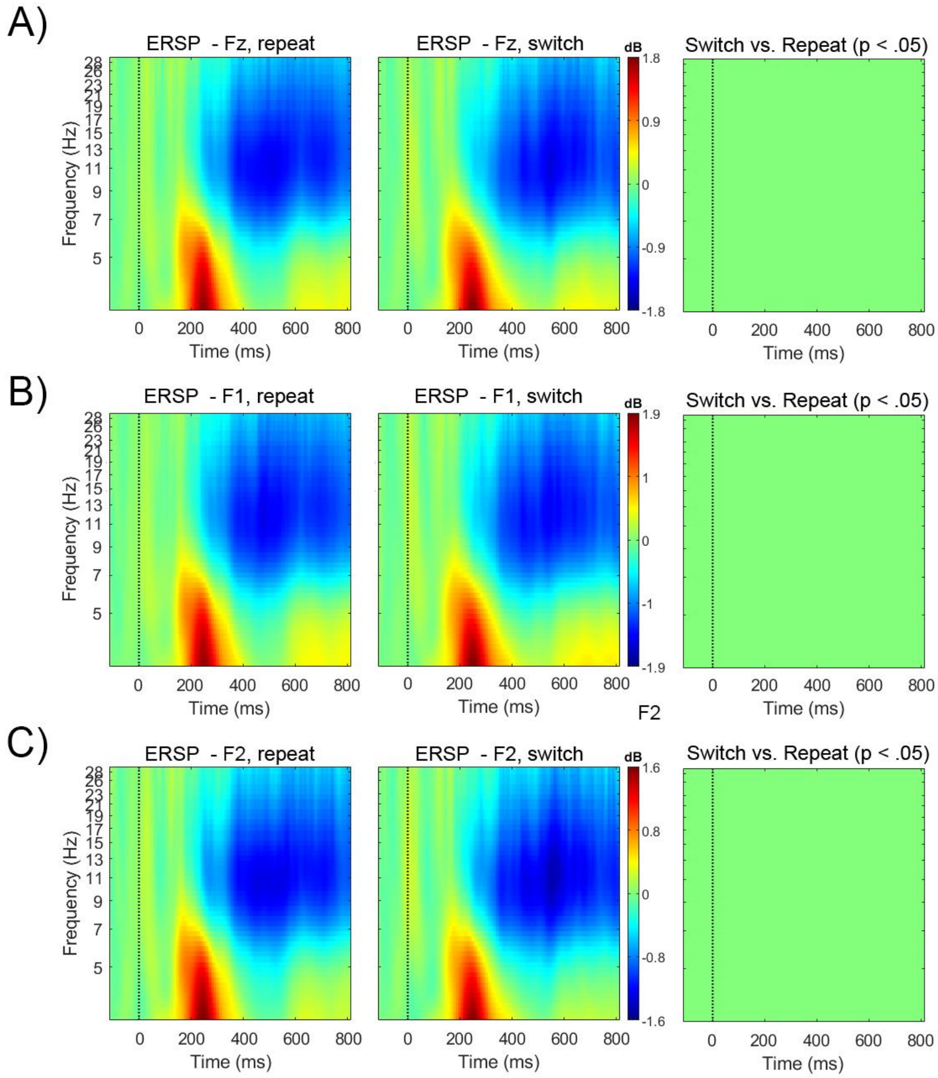

Figure 4.1. Event-related spectral perturbations (ERSPs) for repeat trials (left column), switch trials (middle column), and the comparison between trial types (right column). Empty maps in the right column indicate no significant differences at *p* < .05 using FDR-corrected p-values. Comparisons are shown for Fz (A), F1 (B), and F2 (C), the electrodes of interest for frontal theta measures.

Data was then segmented into ten-second time windows with 50% overlap; I opted to analyze time windows independent of events as I was interested in general processes throughout task performance (fatigue and effort exertion) rather than processes related to any specific part of the task; this approach is in line with previous work examining fatigue using EEG (Barwick et al., 2012; Wascher et al., 2014). Sliding windows were used over time segments with no overlap to establish a more continuous measure of change throughout the task in each measure of interest, in line with some prior work (Boksem et al., 2005; Chang et al., 2013).

Finally, data were Fast-Fourier Transformed for time-frequency analyses. Frontal theta power, frontal alpha power, frontal beta power, and global beta power were defined and calculated in line with definitions from previous work examining fatigue and effort exertion during task performance. Frontal theta was defined as activity between 4 and 7.5 Hz at Fz, F1, and F2 (Cooper et al., 2019; Craig et al., 2012), frontal alpha was defined as activity between 8 and 13 Hz at FC5, F7, F3, F5, FC6, F4, F8, and F6 (with an additional left/right subdivision of those groupings), and frontal beta was defined as activity between 14 and 30 Hz at FP1, FP2, AF3, AF4, F7, F8, F3 and F4 (Craig et al., 2012). Global beta was also calculated using all electrodes within the same frequency band as frontal beta. Power for each time window was calculated within the EEGlab toolbox and exported for analysis in R Version 4.0.0 (R Core Team, 2020).

Changes in frontal theta, frontal alpha, frontal beta, and global beta were assessed similarly to the manner in which changes in switch rate were assessed. Power measures in each spectral band (extracted from EEGlab in $\mu V^2/Hz$ units) within time window served as the DV in four separate Bayesian hierarchical regressions (one for each EEG measure), with time window entered as a group- and subject-level IV. Visual examinations of the distribution of each measure revealed that the measures were right-skewed, with some visible outliers in some time windows. In line with analysis pipelines involving behavioral data, time windows with spectral power greater than 3 standard deviations from the mean (calculated separately for each measure) were considered outliers and removed from analyses (3.33% of time windows in total were marked as outliers). Power measures were then log-transformed, which yielded adequately normal distributions[5]. Subject-level effects of time window were extracted from these regressions and used in subsequent analyses as measures of subject-level changes in each measure throughout the task. Coefficients in mixed regressions were considered significant if the 95% credible interval (95% CI) did not contain zero.

4.2.6. Analyses involving switch rates

Analyses were conducted in R Version 4.0.0 (R Core Team, 2020). For analyses involving switch rate, a preprocessing stream matching Chapters 2 and 3 was employed; Trials with reaction times greater than 3 standard deviations from the mean were considered outliers and removed from analyses, as were incorrect trials, trials following errors, and the first trial of each block (neither a switch nor a repeat).

In line with analyses in Chapter 3 and the approach taken to analyze changes in spectral power, changes in switch rates were assessed using Bayesian hierarchical

[5] Another set of analyses was conducted using power measures that were not log transformed; conclusions did not differ in any way from those presented in the current manuscript.

logistic regressions (Bürkner, 2017) where the DV was coded as 0 for repeat or 1 for switch, and cumulative trial number was entered as a group- and subject-level IV. Group-level change in switch rate over time was assessed using the results of this regression, where a coefficient was considered significant if the 95% credible interval (CI) did not contain zero. Examination of group effect in this regression was meant to confirm that overall declines in switch rate throughout the task found in Chapter 3 were replicable using the same paradigm in a different sample.

Subject-level coefficients were then extracted from this regression and used as a measure of subject-level changes in switch rates over the course of the task. Following the approach in Experiment 3 in Chapter 3, four correlations were conducted to examine relationships between changes in switch rates and changes in EEG measures; each correlation involved switch rate change as one variable and change in one of the four spectral power measures as the other variable. Shapiro-Wilk tests were then conducted to determine whether each measure was normally distributed. Shapiro-Wilk tests revealed that all measures were adequately normal (all ps > 0.43). For this reason, Pearson correlations were conducted (rather than the nonparametric spearman rank correlations in Experiment 3 of Chapter 3).

4.3. Results

Group-level changes in switch rates are displayed in Figure 4.2. Group-level changes in frontal theta power, frontal alpha power, frontal beta power, and global beta power are depicted in Figure 4.3.

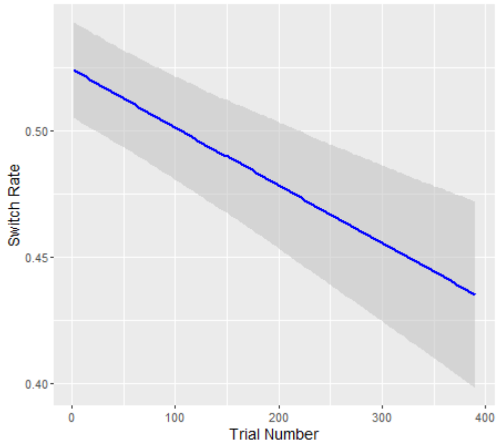

Figure 4.2. Group-level change in switch rate over time estimated using a multilevel Bayesian logistic regression. Switch rates significantly declined throughout task performance. Shaded area represents 95% CI.

There was a significant effect of cumulative trial number on the probability of switching tasks, β = -0.10 [-0.18, -0.03]. Replicating the results of Experiments 1 and 2 of Chapter 3, participants were less likely to switch on a given trial as the experiment progressed. Frontal theta power significantly increased over time throughout task performance, β = 0.03 [0.004, 0.060], possibly indicating that participants detected an increased need for effort exertion as the task progressed (Cavanagh & Frank, 2014). All three frontal alpha measures (left, right, and both), frontal beta, and global beta did not change significantly throughout task performance (frontal alpha: β = 0.01 [-0.02, 0.03]; left frontal alpha: β = -0.01 [-0.04, 0.01]; right frontal alpha: β = 0.00 [-0.03, 0.02]; frontal beta: β = 0.03 [-0.01, 0.07]; global beta: β = -0.01 [-0.04, 0.02]), indicating no significant fatigue effects nor increases in vigilance to combat fatigue as measured by EEG components.

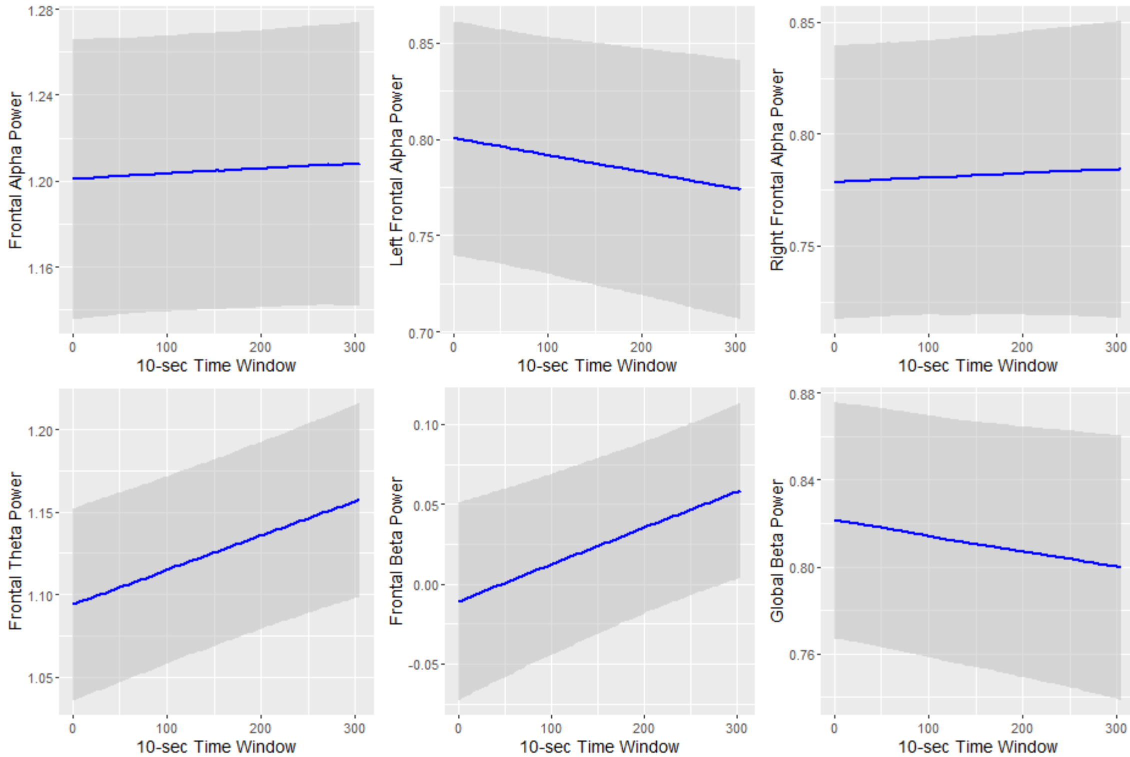

Figure 4.3. Changes in EEG measures over time. Frontal theta (bottom left) significantly increased over time. Changes in all frontal alpha measures (top row), frontal beta (bottom middle), and global beta (bottom right) were not statistically significant. All spectral power measures are in units of log(µV^2/ Hz). Shaded areas represent 95% CI.

Correlations between subject-level changes in switch rates and subject-level changes in EEG measures revealed no significant relationships between any variables of interest (frontal theta: *r*(40) = 0.07, *p* = 0.68; frontal alpha: *r*(40) = -0.21, *p* = 0.19; left frontal alpha: *r*(40) = 0.03, *p* = 0.83; right frontal alpha: *r*(40) = -0.10, *p* = 0.53; frontal beta: *r*(40) = 0.13, *p* = 0.41; frontal beta: *r*(40) = -0.04, *p* = 0.78. Contrary to hypotheses, changes in switch rates at an individual level were unrelated to changes in EEG markers of cognitive effort, fatigue, and vigilance at an individual level. Figure 4.5 depicts relationships between each subject-level change in each EEG measure and subject-level change in switch rate.

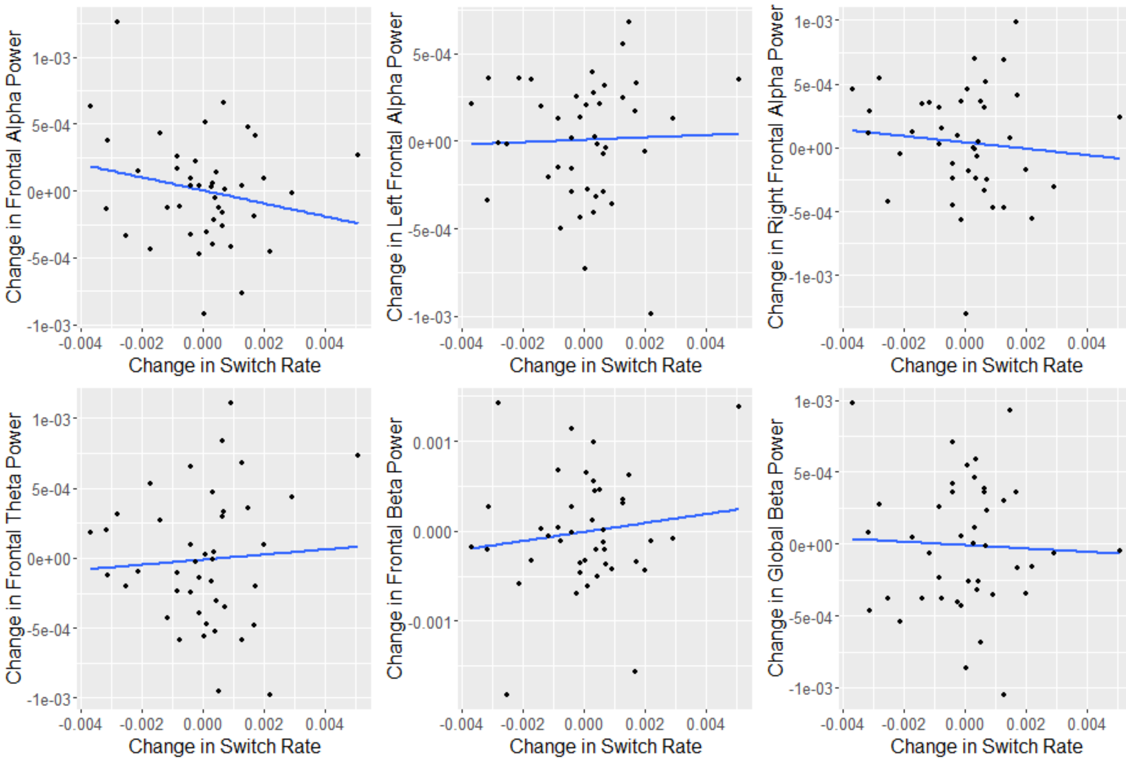

Figure 4.5. Relationships between subject-level changes in EEG measures throughout the task and subject-level changes in switch rates throughout the task. All relationships were not statistically significant.

4.4. Discussion

The experiment in Chapter 4 employed a voluntary task switching paradigm identical to the paradigm in Chapter 2 Experiment 2 and Chapter 3 Experiment 1. EEG recordings were collected throughout task performance. The experiment was intended to replicate the group-level declines in switch rate found in Chapter 3 and relate subject-level changes in switch rate to subject-level changes in spectral power to assess whether fatigue or effort avoidance might underlie switch rate changes. While I replicated the results from Chapter 3 – switch rates significantly declined throughout task performance at a group level – the degree of change in switch rate was unrelated to changes in any EEG measures of interest.

4.4.1. Lack of Support for Fatigue or Effort Avoidance Underlying Switch Rate Changes

Contrary to hypotheses, declines in switch rate were not significantly related to changes in EEG markers of cognitive effort, fatigue, or vigilance. It should be noted that the sample here (n = 42) is not particularly large for individual differences work, and so it is possible that the lack of relationships is due to a lack of statistical power. However, post-hoc Bayes Factors indicated that the null hypothesis (there is no relationship between change in a given EEG measure and switch rate decline) was more likely than the alternative, although not conclusively so. The null was more likely than the alternative for all correlations between changes EEG measures and switch rate changes, with the null being between two and three times more likely for almost every correlation; the only correlation that resulted in a BF_{01} of less than 2 was the relationship between frontal alpha (left and right combined) and switch rate changes (BF_{01} = 1.36). Therefore, it seems unlikely that, in this sample, the lack of relationships was solely due to a lack of statistical power.

It is also possible that the task was not long enough to elicit meaningful enough changes in EEG measures to detect relationships with switch rate changes. While a significant increase in frontal theta power over time (consistent with predictions) was detectable, a longer task might elicit greater changes more sensitive to subject-level relationships between behavior and EEG measures. Of the two tasks that elicited changes in switch rate in Chapter 3, the shortest was used here. There were multiple reasons for this; first, the fact that group-level declines in switch rate replicated in a smaller sample even in the shorter of the two tasks supports the robustness of the finding in general. Second, the analyses both here and in Chapter 3 are aimed primarily at understanding changes in performance during general voluntary task switching performance, not solely a lengthened version of the task, to provide maximally generalizable conclusions. Chapter 3 Experiment 2 contained more trials than Chapter 3 Experiment 1 (which Chapter 4 replicated) only because the practice portion of the experiment (not assessed in the original manuscript) in Chapter 3 Experiment 2 to assess reward effects. The original manuscript assessed 352 trials per participant (Fröber & Dreisbach, 2017), similar to the 390 trials assessed in Chapter 4 and in Chapter 3 Experiment 1. Nonetheless, it is possible that lengthening the task might elicit more substantial changes in EEG measures throughout performance which might make relationships between changes in these measures and changes in switch rate more detectable.

4.4.2. Alternative Explanations for Switch Rate Changes

It is also possible that the results of Chapter 4 (or lack thereof) indicate that declines in switch rate do not index any of the cognitive mechanisms hypothesized. These hypotheses, originally outlined in Chapter 3, arose from observations regarding general processes that occur in other paradigms. It is possible that, instead, declines in switch rate index cognitive mechanisms that are more specific to voluntary task switching paradigms.

For example, the paradigms in which declines in switch rate were detected all utilized the same task choice instructions; participants were instructed to choose tasks randomly, such that switching tasks and repeating tasks happened about equally often. These instructions are extremely common in voluntary task switching literature (Arrington & Logan, 2004; Braem, 2017b; Mittelstädt, Dignath, et al., 2018; Orr et al., 2012; Orr & Weissman, 2011), primarily serving to prevent participants from switching tasks too infrequently to assess switching effects (Arrington & Logan, 2004).

However, previous work has argued that this instruction also requires participants to maintain a long-term representation of random choice throughout task performance (Herd et al., 2014; Orr et al., 2019). Declines in switch rate, then, might index a degradation of a participant's model of random choice (as described during practice) throughout task performance. The current work is not well-suited to examine this possibility; however, future work could test this idea by examining the effect of intermittent presentation of random choice instruction throughout task performance on changes in switch rate.

4.4.3. Lack of Switch Effects on Frontal Theta at Trial Level

Unexpectedly, switch trials did not yield any significant effects on post-stimulus frontal theta compared to repeat trials. Here, it should be noted that this effect was hypothesized based on previous work in *cued* task switching (Cooper et al., 2019; López et al., 2019); work specifically examining the degree to which switching tasks affects frontal theta power in voluntary task switching is absent from the literature.

While clearly visible post-stimulus frontal theta power increases relative to a pre-stimulus baseline were present in all trials, the lack of switching effects in the current work raise questions about the degree to which switch effects on frontal theta found in previous cued task switching work might generalize to voluntary task switching. Here, the effect was examined as a precaution to determine whether it would need to be controlled for in analyses more directly related to the research questions addressed by the experiment. The lack of switch effects on frontal theta post-stimulus presentation (and throughout the experiment as a whole, see Footnote 3) served in Chapter 4 to affirm that controlling for switching effects in subsequent analyses was not necessary.

However, the results do indicate that future work examining the effects of switching on frontal theta in voluntary task switching paradigms and comparing the results to previous work in cued task switching paradigms might prove fruitful. For example, it is possible that differences in preparation timing in voluntary (compared to cued) task switching outlined in Chapter 2's drift diffusion model results might be additionally corroborated by differences in the timing of switch effects on frontal theta.

4.4.4. Limitations and Future Directions

As noted earlier, the two largest limitations of the current study were the somewhat small sample size for individual difference comparisons and the possibility that the task was too short to elicit changes in EEG measures that were strong enough to detect relationships with switch rate changes. While these experimental design choices did help demonstrate the robustness of group-level declines in switch rate detected in Chapter 3, they might have obscured the ability to draw conclusions about the cognitive mechanism(s) underlying the declines in switch rate. Future work might wish to examine these relationships using a longer version of the task, although lengthening the task might meaningfully change the degree to which effort exertion and fatigue contribute to behavioral changes.

Alternatively, direct manipulations of fatigue or effort exertion might also prove useful by providing greater variation in each over time to increase power to detect relationships between the processes and behavior. However, taking care to manipulate one process and not the other would likely prove challenging. The current work also relied solely on physiological markers of cognitive processes; future work could instead (or additionally) examine the relationships between self-report measures of fatigue or motivation and reductions in switch rate over time.

Finally, future work might test alternative explanations for declines in switch rate proposed here that are more specific to VTS paradigms than general fatigue or effort exertion. For example, intermittent task choice instructions to reinforce mental representations of random choice could be used to examine whether degradation in this representation over time might contribute to switch rate declines.

4.4.5. Conclusions

Chapter 4 once again replicated the existence of a group-level decline in switch rates during a voluntary task switching paradigm. While there was an expected increase in frontal theta power throughout task performance, changes over time in frontal theta, frontal alpha, and beta were unrelated to changes in switch rates over time. Finally, while not the focus of Chapter 4, the lack of switch effects on post-stimulus theta power indicate that future work examining the timing of switch effects on frontal theta within voluntary task switching, compared to cued task switching, might provide valuable insight into the differences between the two types of paradigms. While the results here demonstrate the robustness and replicability of switch rate reductions, the cognitive mechanism underlying the effect remains unclear.

5. CONCLUSIONS

5.1. Overview of Findings

The current work examined cognitive processes that contribute to performance on voluntary task switching paradigms. In Chapter 2, I examined the degree to which task set preparation and task set inertia contribute to switch costs, how the timing of task set preparation differs with respect to cued paradigms, and whether requiring engagement with a task choice cue moderates the timing of preparation and the degree to which it contributes to switch costs. Results indicated that in both single- and double-registrant paradigms, participants prepare for upcoming trials during the entire response-stimulus interval, that more proactive preparation occurred during switch trials, and that task choice cue timing within the response-stimulus interval only affects task set preparation when participants are required to respond to the cue.

In Chapter 3, I identified patterns of behavioral changes in three experiments that indicated performance increases consistent with practice effects. In the first two experiments, participants displayed decreases in switch rates over time. In the third experiment, which differed from the first two in a several ways, switch rates did not decrease over time at a group level, but individual changes in switch rates predicted individual differences in BIS/BAS ratings. However, the cognitive mechanism(s) underlying changes in switch rate remained unclear.

In Chapter 4, I examined whether changes in switch rates throughout task performance were related to EEG markers of cognitive effort and fatigue. I replicated the group-level decreases in switch rates found in Chapter 3, but the degree of change was not significantly related to any of the EEG measures of interest. Further, switching tasks did not affect post-stimulus frontal theta power, an effect that has been reported previously in cued task switching work (Cooper et al., 2017, 2019).

5.2. Frontal Theta as a Possible Marker for Task Set Preparation

Results from Chapter 2 indicated that, unlike in prior work examining cued task switching paradigms, post-stimulus task set preparation (operationalized using DDM parameters) was worse on switches than repeats only when the response-stimulus interval was very short. In the single-registrant paradigm, participants tended to prepare more effectively on switch trials than repeat trials, while in the double-registrant paradigm post-stimulus preparation was virtually identical across switches and repeats. Meanwhile, results from Chapter 4 indicated that post-stimulus frontal theta power was virtually identical across switches and repeats for a double-registrant paradigm.

It is possible, then, that task set preparation during task switching paradigms might be indexed by frontal theta power. While the current work has not directly tested the relationship, a combination of results here and those from previous work in task switching support the idea. Previous work in cued task switching has found that greater differences between switches and repeats in frontal theta power were associated with greater proactive control (Cooper et al., 2017) and greater switch costs (Cooper et al., 2019). The authors specifically note that this pattern indicates that frontal theta likely indexes either task set preparation or task set inertia, and that interval manipulations similar to those used in Chapter 2 might help dissociate which process frontal theta indexes.

However, the results in Chapter 2 indicate that, in a double-registrant voluntary task switching paradigm, task set preparation did not contribute to switch costs while task set inertia *did* consistently contribute to switch costs. Taken together with results from Chapter 4, that frontal theta power was unaffected by task switching in a double-registrant voluntary task switching paradigm, it seems more likely that frontal theta indexes task set preparation than task set inertia. This idea fits with theories regarding the general role of frontal theta power; if frontal theta power indexes the need to exert cognitive control (Cavanagh & Frank, 2014), the need to load a new task set should be related to increases in frontal theta power and increases in reaction time.

It should again be emphasized, though, that the relationship between frontal theta power and task set preparation was not directly tested in the current work; the effect of switching on post-stimulus frontal theta power was directly related to the hypotheses explored in Chapter 4 and thus was not examined further. However, the pattern of results in Chapters 2 and 4 indicate that future work examining the effects of interval manipulations similar to those used in Chapter 2, and the relationships between frontal theta power and drift diffusion model parameters, might be of interest in future work. In fact, one of the limitations of examining preparation in a voluntary paradigm using a drift diffusion model – that preparation prior to stimulus presentation must be inferred from preparation post-stimulus presentation – could be addressed by examining frontal theta power, as a more specific time course of switching effects on preparation might be captured using EEG measures.

5.3. Proactive Cognitive Control and Switch Rates

Results from Chapters 3 and 4 indicate that group-level declines in switch rate over time appear fairly replicable across purely voluntary (no cued trials) task switching paradigms. While I hypothesized that this pattern is likely related to a compensatory mechanism to combat early fatigue effects or a reduction in effort exertion, I was unable to find support for these ideas using EEG indices of fatigue and effort exertion. While these hypotheses arose from examining literature related to general processes that cause performance changes over time across a variety of tasks, it is also possible that processes more specific to task switching account for the behavioral pattern.

For example, results from Chapter 2 indicate that switch trials were associated with more proactive preparation; it follows, then, that reductions in the number of switch trials might be associated with reductions in proactive preparation at a trial level. If frontal theta does indeed index such preparation, one might expect that changes in the trial-level effect of switching on *pre-stimulus* frontal theta power (rather than post-stimulus or general changes in frontal theta power as examined in Chapter 4) might be associated with changes in voluntary switch rates.

However, no previous work has specifically examined changes in proactive cognitive control over time in voluntary task switching, making it is difficult to conclude that a reduction in proactive control over time is likely. Further, research in other tasks has generally found that proactive control increases over time rather than decreases (Berchicci et al., 2020; Hefer & Dreisbach, 2020). Nonetheless, it is possible that changes in proactive control over time might *partially* explain changes in switch rate; previous work has indicated that higher BAS scores are associated with greater proactive control (Boksem, Tops, et al., 2006; Jimura et al., 2010), which partially might explain the relationship between BAS-fun seeking and increases in switch rates over time found in Experiment 3 of Chapter 3.

5.4. Goal Maintenance in Voluntary Task Switching

Another mechanism specific to voluntary task switching that might account for changes in switch rates over time is the long-term maintenance of the goal to choose tasks randomly. In all tasks in the current work that elicited group-level declines in switch rates, participants are told to choose tasks randomly such that switch trials and repeat trials are chosen equally often. It has been previously argued that this (common) instruction requires participants to maintain both a short-term goal on the trial level (responding to task stimuli quickly and accurately) and a long-term goal to maintain a representation of random choice throughout the task (Herd et al., 2014; Orr et al., 2019).

Because an accurate representation of random choice (as described by task instructions) would be reflected by a 50% switch rate, and a bias towards repeating tasks is generally present in the absence of such instruction (Arrington & Logan, 2004, 2005; Mayr & Bell, 2006), the pattern present in Experiments 1 and 2 of Chapter 3 and the experiment in Chapter 4 is exactly what one might predict from a degradation of a mental model of random choice. In all cases, participants (as a group) started at about a 50% switch rate and repeated more frequently as time went on.

This explanation might also explain why the only paradigm in which a group-level switch rate decline was not present was Experiment 3 of Chapter 3; this paradigm was the only one to include intermittent cued task switching trials. It is possible that the reintroduction of voluntary trials intermittently reinforced the long-term goal of random choice (not relevant on cued trials), preventing the goal from degrading over time as it would in a paradigm without cued trials. This idea was not directly tested in the current work, but it could easily be tested in future work by simply examining the effect of presenting task choice instructions intermittently on group-level changes in switch rate.

5.5. Future Directions

The current work examines several cognitive mechanisms and behavioral patterns that occur during voluntary task switching. The results across these six experiments provide the groundwork for several concepts that future work might wish to examine.

For example, while Chapters 3 and 4 identify declines in switch rates over time, experiments and analyses focus primarily on identifying the cognitive process which the pattern might index. However, the existence of these group-level declines has broader implications for experimental design – if switch rates tend to decrease over time, task length might have an important impact on average switch rate. Future work might wish to examine when (or if) these declines tend to level off, at what point subject-level switch rate averages become internally consistent with respect to number of trials, etc.

While the results of Chapter 2 indicate that proactive cognitive control prior to stimulus presentation is greater on switch trials than repeat trials, this conclusion was drawn from modeling parameters meant to quantify preparation post-stimulus presentation. Future work should examine this idea more directly using measures and experimental designs meant to index cognitive control prior to stimulus presentation –

for example, previous work has indicated pupillometry might index proactive control (Chiew & Braver, 2014), which would also provide excellent temporal resolution to examine cognitive processes prior to stimulus presentation.

Similarly, as outlined in Section 5.2, the pattern of results in the current work indicates that frontal theta might be a plausible marker for task set preparation in voluntary task switching. Frontal theta power has previously been suggested to index proactive control in task switching (Cooper et al., 2017) and other tasks (Janowich, 2015; West et al., 2012) – combining the interval manipulations and drift diffusion model approach in Chapter 2 with an examination of frontal theta might help illuminate the relationships between proactive control, task set preparation, and task choice during voluntary task switching. Notably, the results of Chapter 2 indicate that these processes differ across voluntary and cued paradigms, so examining them specifically within voluntary paradigms is of particular interest.

Finally, as noted in Section 5.4, reductions in switch rate over time might be related to the degradation of the mental representation of random choice over time. Future work might wish to examine this possibility, possibly using intermittent instruction presentations as suggested earlier. Because examinations of switch rates generally aim to measure cognitive flexibility, not goal maintenance, understanding how both contribute to the same measure might help future studies dissociate the contributions of each.

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