Abstract

Task-switching is commonly used to investigate working memory and attentional control processes. The current study compares predictive versus non-predictive task-sequencing effects on task-switching performance. Participants completed four blocks of the Consonant-Vowel/Odd-Even (CVOE) task: Two single task pure blocks, a predictable switch block where task switching occurred every two trials, and a random switch block where switching was unpredictable. In addition to mean error rates and response latencies (RTs), we assessed sequence effects on local switch costs (i.e., switch vs. nonswitch trials) and global costs (i.e., nonswitch vs. pure trials) for both error rates and RTs along with their underlying distributions. Overall, we show that while predictive and random switching produced similar patterns for mean error rates and RTs, a dissociation occurred in RT switch costs. When switching was random, local costs were inflated. In contrast, predictive switching increased global costs. Increased local costs for random versus predictive switching reflect an increase in task-reconfiguration processes as participants struggle to reconfigure to an unpredictable task type in working memory on a subsequent trial. Separately, increased global costs for predictive switching reflect declines in task-set maintenance processes, as participants must maintain both task types in working memory while simultaneously monitoring their progress through the trial sequencing.

Word Count: 203

*Keywords:* Task-Switching; CVOE; Working Memory; Monitoring; Ex-Gaussian Distribution; Vincentile Plots

Predictive Alternating Runs and Random Task-Switching Sequences Produce Dissociative Switch Costs in the Consonant-Vowel/Odd-Even Task

The ability to attend to relevant information within one’s environment is critical for goal-directed behavior. Attention is central to this process, as it is necessary to keep internal goals active in working memory long enough to affect our actions (Norman & Shallice, 1986). Individuals who possess high attentional control capacities are more likely to ignore salient but unrelated information that would otherwise produce distractions. To investigate attentional control and working memory processes, researchers commonly use paradigms that present participants with task-related information, which is contrasted with information that is highly salient yet unrelated to current task goals (see Rogers & Monsell, 1995; De Jong, 2000, for reviews). These studies have consistently shown that when participants are required to suppress -unrelated information, both response times (RTs) and error rates increase (e.g., Jersild, 1927; Stroop, 1935). Thus, task contexts which tax working memory and attentional control produce performance declines.

Interest in the relationship between attentional control and task-performance is not new. For example, the Stroop Color Naming Task (Stroop, 1935) has received significant attention in the literature and has been described as a “gold standard” measure of attentional control (see MacLeod, 1992). This is because successful task completion requires both activation and maintenance of the task goal in working memory (e.g., naming the ink color) while simultaneously suppressing salient but task-irrelevant information (e.g., automatically reading the color name). As a result, the Stroop task is often used to investigate questions related to working memory and attentional control processes. For example, Kane and Engle (2003) showed that low working memory individuals (as determined by performance on the operation-span task) routinely committed more errors than high working memory individuals, particularly on incongruent trials in which ink colors and word names did not match. Similarly, Spieler, Balota, and Faust (1996) showed that age-related declines in working memory and attentional control impair Stroop performance. Compared to younger adults, healthy older adults showed slower RTs (but not an increase in error rates), while older adults with Alzheimer’s Disease (AD), showed large costs to both RTs and error rates, even after being age-matched to healthy older adults. Taken together, working memory is critical for keeping internal goals active, as both healthy, low-span individuals and those with working memory impairments each show greater difficulty maintaining desired task goals when suppressing information that conflicts with the current task-set.

While the Stroop task demonstrates inhibition of automatic processes such as word reading, there has been an increased focus on using task-switching paradigms to investigate questions related to attentional control and working memory (Jersild, 1927; Rogers & Monsell, 1995; see De Jong, 2000; Kiesel et al., 2010; Koch & Kiesel, 2022, for reviews). Commonly, task-switching studies have participants alternate between sets of competing tasks. Successful task completion requires activating the correct task-set in working memory while simultaneously suppressing the inactive task-set (see Koch, Poljac, Müller, & Kiesel, 2018). Because task-switching requires that participants closely monitor for upcoming task changes, the sequence in which task-switches occur likely affects performance (i.e., predictive vs. random switching; e.g., Arabaci & Parris, 2020; Minear & Shah, 2008). Thus, predictive and random switching may differentially affect working memory processes associated with task-switching performance. Below, we describe how task-switching performance can be used to assess working memory processes via the computation of local and global switch costs. We then discuss evidence suggesting that predictive and random switch sequences may differentially affect switch costs.

**Local versus Global Switch Costs**

While the direct effects of task-switching on RTs and errors can be measured by comparing trials in which individuals either repeat or switch task sets, studies often compare switch performance to a separate set of trials that only contain one task-set (i.e., *pure blocks* in which decision making uses a single rule). These pure blocks are immediately followed by *switch blocks*, which alternate between two competing task-sets (i.e., using a rule on one subset of stimuli but switching to a different rule when cued; see Wasylyshyn, Verhaeghen, & Sliwinski, 2011). To assess the impact of stressing attentional control and working memory systems, RTs and error rates are compared between pure and switch blocks. Overall, both measures increase for switch trials relative to non-switch trials, and furthermore, these costs are sensitive to breakdowns in attentional control and are often increased due to advancing age and the presence of dementia (Huff, Balota, Minear, Aschenbrenner, & Duchek, 2015) and individual differences in working memory capacity (Drahiem, Hicks, & Engle, 2010). Thus, attentional control and working memory are strongly linked to task-switching performance as maintaining multiple task-sets in working memory impairs performance.

An important advantage of pure block/switch block designs is that they allow for the computation of local and global switch costs within the same study (e.g., Huff et al. 2015; Hutchison, Balota, & Duchek, 2010; Mayr, 2001; Minear & Shah, 2008; Nashiro, Qin, O’Connell, & Basak, 2018). These costs reflect hypothesized working memory processes, and as a result, allow researchers to separately assess the effects of maintaining two task-sets in working memory on task performance (e.g., pure vs. switch blocks) and the effects of alternating task-sets within a single switch block. First, the *global switch cost* refers to the response difference between non-switch trials in the switch block and pure block trials and represents the cost of maintaining multiple task-sets in a switch block versus a single task-set within the pure block (Minear & Shah, 2008; Wylie & Allport, 2000). Global switch costs likely reflect decreased performance due to the additional burden placed on working memory from having multiple-task sets active in switch blocks versus pure blocks in which only one task-set is used (Kiesel et al., 2010; Logan, 2007). Separately, the *local switch cost* refers to the difference between switch and non-switch trials presented within the switch block. Local costs represent task-set reconfiguration processes, which are thought to reflect retrieval of the correct task set from memory (Monsell, Yeung, & Azuma, 2000). Task-set reconfiguration processes are inherent to switch, but not non-switch blocks, as they are driven by participants being forced to change task-sets within the same block (Rogers & Monsell, 1995; see Huff et al., 2015).

Several factors have been shown to influence the magnitude of switch costs. For example, exaggerated switch costs have been found for *bivalent stimuli* which contain features relevant to two task sets (e.g., Luwel, Schillemans, Ongehan, & Vershaffel, 2009). Unlike *univalent* stimuli, bivalent stimuli activate both task-sets used in a switch task (e.g., presenting participants with letter-number pairs and having them switch between classifying the letter or the number) and as a result, responses to bivalent stimuli are often slowed (e.g., bivalency cost; Meier & Rey-Mermet, 2012; Woodward, Meier, Tipper, & Graf; 2003). While several bivalent switch tasks have been developed (e.g., Stroop task-switching: Spieler et al., 1996; alphabet-arithmetic task: Koch, Prinz, & Allport, 2005), in the current study, we utilize the Consonant-Vowel/Odd-Even task (CVOE; Minear & Shah, 2008; Huff et al., 2015; Rogers & Monsell, 1995), which involves the classification of letter-number pairs (e.g., A 15). Depending on the cued task-set, participants are instructed to either classify the letter in the pair as a consonant/vowel or the number as odd/even. An advantage of the CVOE task is that it assesses task-switching using tasks that are relatively equivalent in terms of difficulty (see Rogers & Monsell, 1995). Furthermore, because this task can be easily configured with both pure and switch blocks, local and global switch costs can each be computed. Thus, the CVOE task can be used to investigate hypothesized working memory processes in addition to factors affecting trial-level performance.

Bivalent stimuli are often more challenging, as the additional difficulty imposed by the stimuli cueing multiple task-sets is particularly taxing for attentional control and working memory systems. As a result, these stimuli are often used to investigate situations in which working memory and attentional control systems are impaired, such as normative and atypical age-related changes (e.g., Huff et al., 2015; Tse, Balota, Yap, Duchek, and McCabe; 2010). For example, Huff et al. (2015) compared CVOE task-switching between young adults, healthy older adults, and older adults with very mild AD. Overall, very mild AD older adults committed more errors and had slower RTs versus young adults and healthy older adults. Importantly, global switch costs for errors and RTs increased as functions of age and AD status, suggesting that the requirement to keep two task-sets active placed additional burdens on working memory. Finally, local cost RTs decreased for AD individuals, suggesting that they were not as well tuned to the task-set versus younger adults and healthy older adults. These findings strongly suggest that working memory is critical for task-switching performance, as individuals with impaired working memory systems consistently show decreased task-switching performance versus individuals with intact working memory systems.

**Predictive vs. Random Task Switching**

While previous studies have investigated the link between working memory and task-switching by comparing switch costs between younger and older adults, manipulations which tax working memory systems would be expected to similarly affect switch costs. One factor which has been previously explored is the sequence in which task switches occur. First, switches can occur via a predictable pattern, such as an alternating-runs sequence (Rogers & Monsell, 1995; Huff et al., 2015). In this sequence, task changes occur as a function of run length (*r*), with switches occurring in *r* trial intervals (e.g., AABBAABB for *r* = 2). Because of the predictive nature of this sequence, participants likely become aware of when task-switches will occur. Alternatively, switches may occur randomly, such that the instructions for the upcoming trial are unknown until participants receive a cue. Random task switching can be further divided based on when participants receive change cues. In task-cueing paradigms, participants receive cues at each trial, while intermittent-instruction paradigms randomly interrupt task sequences with instructions to change (Gopher, Armony, & Greenshpan, 2000; Meiran, 1996; see Monsell, Sumner, & Waters, 2003, for a review of task-switch sequencing). Unlike predictive switching in which task changes occur following a set interval, random-switch sequences more closely approximate the types of unpredictable task changes that individuals encounter in their daily lives. Thus, compared to a predictive sequence, the use of random switching likely affords greater external validity.

Previous research has investigated the effects of random switching on switch costs, RTs, and error rates. For example, Monsell et al. (2003) compared performance on a four-run alternating switch task to a random task-cueing switch paradigm. Overall, random switching was more difficult than predictive switching as participants in the random group took more trials to recover from a switch compared to when switching was predictive. However, direct comparisons of local and global switch costs between random and predictive switching were not included as the authors were primarily interested in the effects of response-stimulus interval and run length on the local switch cost (rather than a direct comparison of presentation pattern), and they did not include a pure block comparison, making global switch cost calculations unavailable.

Separately, Minear and Shah (2008) had participants complete both predictive and random switch sequences in the CVOE task. Using a pre/post design, participants first completed the full CVOE task set (pure and switch blocks with predictive and random sequencing) which was followed by a battery of transfer tasks and a second full CVOE task set 24-48 hours following the initial CVOE task. While the authors focus was on pre/post transfer effects, they reported slower RTs and higher error rates on the CVOE task when switching was random versus predictive. Comparisons between local and global switch costs as function of presentation sequence were again not reported, however, a visual inspection of their pre-test CVOE data suggests that global costs increased when switching was random while local costs may have been greater when switching was predictive. Unfortunately, the lack of statistical comparisons make it difficult to ascertain whether these patterns were reliable, and if so, to estimate the effect sizes of different sequencing types.

**Distributional Analyses of RTs**

Task-switching paradigms commonly use RTs as indicators of task performance, which are generally analyzed in terms of mean or median scores. However, because RT distributions are almost always positively skewed (i.e., most RTs generally occurring at the faster end of the distribution), performing an analysis of only mean RTs may overlook data that are psychologically informative regarding cognitive processes (Balota & Yap, 2011; De Jong, 2000). To evaluate skewness, researchers have increasingly moved away from standard measures of central tendency and instead towards analyses of RT distributions. The characteristics of these distributions can successfully capture important aspects of human cognition, including word recognition (e.g., Andrews & Heathcote, 2001; Balota & Spieler, 1999), semantic priming (e.g., Balota, Yap, Cortese, & Watson, 2008), selective attention (Lamers, Roelofs, & Rabeling-Keus, 2010; Spieler, Balota, & Faust, 2000), and, importantly, attention and working memory processes assessed via task-switching (Huff et al., 2015; Tse et al., 2010).

Given the increased focus on RT distributions, we report two types of distributional analyses: Vincentile plots and ex-Gaussian analyses. First, the Vincentile plots order all RTs for each response from the fastest to the slowest responses for each trial at the participant level and then bin the ordered data into groups of equal size. For example, a Vincentile plot using four bins would first rank the RTs from each participant from fastest to slowest. Next, for each participant, the fastest 25% of the RTs would be binned and averaged, followed by the second fastest 25%, the third fastest 25% of RTs, and then the final 25% of RTs. These four bins (termed Vincentiles) are then averaged across participants and plotted, which provides information regarding the shape of the RT distribution as a function of trial-ordered bin. Separately, for the ex-Gaussian analysis, participants’ raw RTs are fit to a theoretical exponential-Gaussian distribution, which provides a close approximation of the empirical RT distribution (Ratcliff, 1979). Three parameters define this distribution: Mu and sigma parameters represent the mean and standard deviation, respectively, and tau represents the tail of the distribution which includes the slowest responses. Changes in mu reflect a shift in the overall RT distribution while changes in tau represent changes to the tail which are more likely to be the more difficult trials. Regarding task performance, breakdowns in attentional control abilities may produce decrements in task-goal maintenance and inhibition processes, leading to slower RTs than individuals with more intact attentional control abilities. This would result in RT distributions with greater skew in the tail of the distribution and the tau parameter. Furthermore, when task-switching, tau would be expected to increase whenever switching provokes additional strain on attentional control systems. Thus, tau would be expected to show an increase for random rather than predictive switching.

Finally, as noted by Tse et al. (2010), distributional analyses provide a more fine-grained approach relative to relying solely upon means, as conditions that produce similar mean RTs could produce different underlying distributions (see Balota et al., 2008). Given the benefits of using these analyses when investigating attentional control processes, we included these distributional analyses to complement traditional mean analyses.

**The Present Study**

Given the relationship between working memory processes and task-switching, the present study investigated how different switch sequences affect task-switching performance and, specifically, the effects of these patterns on local and global task-switching costs. In doing so, we first compared error rates and RTs between predictive trial sequencing presented via alternating runs (e.g., CV-CV-OE-OE-CV-CV) and a non-predictive, random task-switch sequence (e.g., CV-OE-OE-OE-CV-OE). We then assessed task-sequence effects on switch costs. Overall, we expected that mean error rates and RTs would be higher on switch trials (regardless of presentation sequence) relative to pure trials, given that pure blocks only require participants to complete a single task-set. Within switch blocks, we expected that participants would be particularly impacted whenever switching occurred randomly, as the lack of a discernable pattern would prevent expectancies of upcoming trials. As a result, we anticipated that participants would produce greater error rates and have slower RTs when switching was random versus predictive. We additionally anticipated that RT differences would be reflected in the distributional analyses, with random switching producing exaggerated responses in the slowest bins in the Vincentile plots and tau in the ex-Gaussian analysis.

Regarding switch costs, we anticipated that because local switch costs reflect task-set reconfiguration processes, random switching may increase local switch costs, as the unpredictable nature of random sequencing should be particularly taxing on these processes relative to predictive switching. While this prediction contrasts with findings reported by Minear and Shah (2008), we based our prediction on previous research suggesting that RTs decrease across successive repetitions of the same task-set (Milán, Sanabria, Tornay, & González, 2005; Monsell et al., 2003). Unlike predictive switching, where task changes reliably occur every two trials, the random switch sequence often presents participants with several consecutive trials of the same task-set prior to a switch, leading to greater task-set inertia relative to the predictive sequence. Furthermore, it is likely that the inactive task-set becomes progressively inhibited as participants advance through a run, making switching particularly taxing following a longer sequence of consecutive trial types (e.g., Allport, Styles, & Hsieh, 1994). As such, we anticipated that random switching would inflate local switch costs by both decreasing RTs on consecutive non-switch trials and increasing RTs via greater task-set inertia when a switch is encountered.

Separately, we expected that predictive switching would inflate global costs. This is because, in addition to maintaining multiple task-sets in working memory, the predictive sequence allows participants to attend to the position of each trial within the sequence while simultaneously monitoring their progress through each two-trial run. When a switch is encountered, participants must disengage from the current task set while re-activating the appropriate task-set in working memory. As a result, attention and working memory processes are more likely to be taxed versus pure block trials due to continuous updating as the trial sequence progresses. For random switching, however, the lack of a consistent task sequencing makes it impossible for participants to monitor their progress. Thus, we anticipated a dissociation between local and global switch costs between trial sequences.

**Method**

**Participants**

One hundred University of Southern Mississippi undergraduates participated in exchange for partial course credit. Data from 9 participants were removed due to excessive error rates in either the pure or switch blocks (i.e., mean error rates within a block that were greater than 3 standard deviations above the mean), which suggested that participants did not correctly follow task instructions. Additionally, data for two participants were removed due to an experimenter programming error. A sensitivity analysis conducted with *G\*Power* (Faul, Erdfelder, Lang, & Buchner, 2007) suggested that our final sample of 89 participants had adequate power (.80) to detect small-or-larger main effects (Cohen’s *d* ≥ 0.20; *α* = .05). All participants were native English speakers who reported normal or corrected-to-normal vision.

**Materials**

To create the stimuli, we generated a series of letter-number pairs (e.g., A 15) using a procedure modeled after Huff et al. (2015) and Minear and Shah (2008). First, an equal number of consonants and vowels were randomly generated, with the constraint that the letters were always selected from A, D, E, H, I, J, O, P, S, or U. A series of numbers was then randomly generated between 1 and 99, with the constraint that half of the numbers selected were even. To create the letter-number pairs, the list of randomly generated consonants was split in half, with half paired with odd numbers and the remaining half paired with even numbers. This process was then repeated for vowels. This resulted in an equal number of each of the four possible stimulus pair types (Consonant-Odd, Consonant-Even, Vowel-Odd, Vowel-Even) within each block. Letters and numbers repeated within blocks, however, pairs were arranged within each block such that letters and/or numbers did not repeat on consecutive trials.

**Procedure**

The CVOE task presented participants with two sets of instructions, which either differed between blocks (pure blocks) or varied between trials (switch blocks). For each trial, a letter-number pair was presented in the center of the computer screen, with the letter always appearing on the left-side of the pair and the number always appearing on the right (e.g., A 15). Participants were tasked with either classifying whether the letter was a consonant/vowel (CV trials) or whether the number was odd/even (OE trials). Specifically, participants were instructed to press the *q* key for consonants/odd numbers or the *p* key for vowels/even numbers, which were selected given they are on opposites sides of a standard QWERTY keyboard. Depending on a trial’s task-set, the words consonant or vowel and odd or even were presented at the top of the screen in the left and right corners, respectively. This served as a reminder to participants of the key mappings for the response types and were provided for all trials, regardless of block type. Individual trials were self-paced, and participants were instructed to respond as quickly as possible while maintaining accuracy. Stimuli were presented in 30-point Courier New font, and trials were presented with a 500 ms intertrial delay.

Trials were arranged into four blocks, with each block containing an equal distribution of *q* and *p* responses. Following the design of Huff et al. (2015), participants first completed two pure blocks (CV and OE) before completing two switch blocks (predictive and random sequencing). Prior to the start of the first pure block, participants were informed of which task-set to use when completing each trial (CV or OE). Participants then completed 10 practice trials corresponding to the block’s task and received verbal feedback on their performance. Following completion of the practice phase, participants immediately began the first pure block. Pure blocks each contained 96 trials and focused exclusively on one of the two tasks, with one block containing the CV task and the other the OE task. Following completion of the first pure block, participants completed the second pure block, which utilized the remaining task-set. This block again began with a set of 10 practice trials (corresponding to the given task-set), and participants again received verbal feedback before completing the second pure block.

Immediately after completing the two pure blocks, participants began the two switch blocks. In the switch blocks, task changes occurred at the trial level rather than the block level. Participants were instructed that the switch blocks would utilize the task-sets from the preceding pure blocks, however, they were informed that the task-set would sometimes change. Participants were additionally instructed that task changes would be cued by the word “letter” or “number”, which corresponded to the CV or OE task, respectively. This task-cue was located directly above the stimulus pair and was displayed concurrently with the stimulus for the duration of each trial. Participants were informed that the task-cue could potentially change following each key press, however, they received no prior instructions regarding the specific sequence in which task-switches would occur. To practice the switching task and become familiar with the prompts, participants first completed a set of ten practice switch trials. Following this practice session, participants immediately began the first switch block. Trials within switch blocks were arranged such that they were presented either with a predictive alternating-runs pattern (e.g., CV, CV, OE, OE, CV, CV, etc.; see Huff et al., 2015) or presented using a random sequence (e.g., CV, OE, OE, OE, CV, OE, etc.). Each switch block contained 120 trials, which consisted of 59 switch trials (i.e., a CV trial followed by an OE trial) and 61 nonswitch trials (i.e., two consecutive OE trials). Like pure blocks, each switch block corresponded to one of these two presentation modes (predictive or random). Thus, participants completed one pure CV block, one pure OE block, one predictive switch block, and one random presentation switch block. Block presentation was randomized across participants; however, following the design of previous research (e.g., Huff et al., 2015; Minear & Shah, 2008), blocks were always ordered such that participants completed the two pure blocks before completing the two switch blocks. This ensured that baseline performance on pure blocks was not influenced by previous exposure to task-switching instructions.[[1]](#footnote-1)

Across blocks, participants were instructed to respond to each trial as quickly as possible without compromising accuracy (Figure 1 illustrates sequence of each trial). To ensure accurate response latencies, participants were further instructed to place their index fingers on the two keys throughout the duration of the trials. Participants completed the study on a laptop running E-Prime 3.0 software (Psychology Software Tools, 2016), and all participants were tested individually in a laboratory setting with an experimenter present. The total experiment took approximately 20 minutes to complete.

**Results**

For all analyses, significance was set at the *p* < .05 level. Partial-eta squared (*ηp*2) and Cohen’s *d* effect size estimates were computed for all significant analyses of variance (ANOVAs) and *t*-tests, respectively. We report traditional *p*-values for all non-significant comparisons, which are further supplemented with a Bayesian estimation of the strength of evidence in favor of the null hypothesis, which compares a model that assumes a significant effect to one that assumes a null effect (Masson, 2011; Wagenmakers, 2007). This analysis returns a probability estimate termed *p*BIC (Bayesian Information Criterion) which represents a probability estimate that the null hypothesis is retained. Unlike other commonly used estimates (e.g., Bayes factors; Kass & Rafferty, 1995), *p*bic does not make use of arbitrary cut off scores to determine magnitude or strength of evidence for/against the null and instead, simply provides a probability estimate regarding the reliability reported null effects. Therefore, all null effects found using standard null-hypothesis significance testing are accompanied by a *p*BIC estimate.

In the following analyses, we first examine mean error rates across trial types (pure, predictive switch, predictive nonswitch, random switch, and random nonswitch) and switch costs (local vs. global). We then assess changes in mean RTs across trial types and switch costs. Following the design of Huff et al. (2015), RT analyses only included correct trials. Additionally, we employed a pre-analysis trimming procedure to reduce the likelihood of RT analyses being disproportionately influenced by extreme scores, which likely reflect a lack of task engagement. RT outliers were computed at the participant level and were defined as any responses occurring three standard deviations above or below each participant’s respective mean. Across participants and block types, this process removed fewer than 2% of all total trials.

Finally, we report a set of distributional analyses modeled after Tse et al. (2010) and Huff et al. (2015). These analyses first compare mean Vincentiles for each trial type and switch cost type before fitting each measure to an ex-gaussian distribution to assess tau parameter changes as a function of trial type.

**Mean Error Rates**

Mean error rates as a function of trial type are reported in Table 1. Overall, participants committed the most errors on predictive switch trials (6.12%), followed by random switch trials (5.17%), predictive non-switch trials (3.49%), pure trials (3.25%), and random non-switch trials (3.01%). A one-way repeated measures ANOVA confirmed that error rates differed as a function of trial type, *F*(4, 352) = 20.29, *MSE* = 8.16, *ηp*2 = .19. Post-hoc *t*-tests revealed that this effect was driven by increased errors for switch trials relative to nonswitch and pure trials, *t*s ≥ 3.63, *d*s ≥ 0.43. For switch trials, mean error rates were marginally greater when trials were presented using predictive than random sequencing, *t*(88) = 1.92, *SEM* = 0.50, *p* = .06, *d* = 0.21, *p*BIC = .60. However, no differences were detected between pure and nonswitch trials, regardless of switch trial sequencing, *t*s < 1, *p*s ≥ .48, *p*BICs ≥ .88.

Next, we compared differences in switch costs for percentage of errors as a function of presentation and cost type (Table 2). A 2 (Cost Type: Local vs. Global) × 2 (Presentation: Predictive vs. Random) repeated measures ANOVA yielded a significant main effect of Cost Type, *F*(1, 88) = 26.83, *MSE* = 19.03, *ηp*2 = .23, such that collapsed across presentation modes, local switch costs exceeded global costs (2.39% vs. 0.00%). Additionally, this analysis revealed a marginal effect of Presentation, *F*(1, 88) = 3.68, *MSE* = 5.43, *p* = .06, *p*BIC = .60, *ηp*2 = .04. Collapsed across cost types, switch costs were greater for predictive (1.43%) than random switching (0.96%). The interaction between Cost Type and Presentation, however, was not reliable, *F*(1, 88) < 1, *MSE* = 17.35, *p*BIC = .90.

**Mean RTs**

Next, we assessed changes in mean RTs across trial types. As reported in Table 1, mean RTs were fastest when participants responded to pure block trials (677 ms) followed by random non-switch trials (1260 ms), predictive non-switch trials (1328 ms), predictive switch trials (1414 ms), and random switch trials (1451 ms). A one-way repeated measures ANOVA confirmed the presence of trial type differences, *F*(4, 352) = 357.72, *MSE* = 19.03, *ηp*2 = .80. Post-hoc testing, however, indicated that for switch trials, RTs did not differ between predictive and random switching, *t*(88) = 1.69, *SEM* = 21.58, *p* = .09, *p*bic = .69. All other comparisons were significant, *t*s ≥ 3.56, *d*s ≥ 0.20.

Regarding RT switch costs, a 2 (Cost Type: Local vs. Global) × 2 (Presentation: Predictive vs. Random) repeated measures ANOVA yielded a significant effect of Cost Type, such that global costs (617 ms) were greater than local costs (138 ms), *F*(1, 88) = 271.36, *MSE* = 75069.95, *ηp*2 = .76. The main effect of Presentation was not reliable, *F*(1, 88) = 2.87, *MSE* = 10075.84, *p* = .09, *p*bic = .69, but a significant interaction was detected, *F*(1, 88) = 26.87, *MSE* = 24744.18, *ηp*2 = .23. For local costs, the switch costs were greater when switching was random versus predictive (191 ms vs. 86 ms, respectively; *t*(88) = 5.14, *SEM* = 19.50, *d* = 0.27). However, this pattern reversed for global costs, in which switch costs were greater when switching was predictive versus random (651 vs. 583; *t*(88) = 3.56, *SEM* = 20.60, *d* = 0.64).

**Vincentile Plots**

Figure 2 depicts Vincentile plots as a function of trial type. The RTs used to construct these plots are the same as those used in the mean RT analyses above. As illustrated in Figure 2, RTs increased across bins, regardless of trial type. Additionally, RTs were lowest for pure trials, followed by random non-switch trials, predictive non-switch trials, predictive switch trials, and random switch trials. These patterns were confirmed by significant effects of Bin, *F*(5, 440) = 370.58, *MSE* = 279313.51, *ηp*2 = .81, and Trial Type, *F*(4, 352) = 357.65, *MSE* = 154415.08, *ηp*2 = .80. Additionally, a significant interaction was detected, *F*(20, 1760) = 102.60, *MSE* = 14800.05, *ηp*2 = .54, such that increases in RTs across the distribution were steeper for switch and non-switch trials relative to pure trials.

Local and global switch costs for each Vincentile bin are displayed in Figure 3. Consistent with previous findings (e.g., Huff et al., 2015), global costs exceeded local costs, *F*(1, 88) = 271.77, *MSE* = 471176.79, *ηp*2 = .76, and costs changed as a function of bin position, *F*(5, 440) = 233.80, *MSE* = 31851.37, *ηp*2= .72. A significant Cost Type × Bin interaction confirmed the presence of a dissociation between switch costs, such that collapsed across presentation sequence, local costs decreased across bins while global costs increased, *F*(5, 440) = 133.06, *MSE* = 64826.43, *ηp*2 = .60, indicating that cost differences were greatest in the slowest trials. Additionally, a Bin × Presentation × Cost Type three-way interaction was also found, *F*(5, 440) = 2.97, *MSE* = 29296.63, *ηp*2 = .03. This interaction indicated that although local costs were lower for predictive than random sequencing and global costs were lower for random than predictive sequencing, the relative differences between sequence types were greater for local costs than global costs, particularly in middle bins. In other words, local costs were more sensitive towards sequencing differences than global costs, but this pattern was not found in the fastest or slowest bins.

**Ex-Gaussian Distribution of RTs**

Finally, we assessed changes in tau as functions of trial type (Table 3) and local and global switch costs (Table 4). Overall, tau significantly differed between trial types, *F*(4, 352) = 102.23, *MSE* = 15317.13, *ηp*2 = .54. Post-hoc testing indicated that for switch trials, no differences in tau occurred as a function of presentation sequence, *t* < 1, *p* = .87, *p*bic = .90. However, for non-switch trials, Tau was greater when switching was predictive versus random, *t*(88) = 2.17, *SEM* = 18.07, *p* = .03, *d* = 0.14. Regarding switch costs, tau was greater for global costs versus local costs, *F*(1, 88) = 252.88, *MSE* = 28881.22, *ηp*2 = .74, consistent with the Vincentile plots. Additionally, tau was greater for when switching was predictive versus random, *F*(1, 88) = 4.37, *MSE* = 33003.65, *ηp*2 = .05. However, the Cost Type × Presentation Sequence interaction was non-significant, *F*(1, 88) < 1, *MSE* = 6506.01, *p* = .87, *p*BIC = .90.

**General Discussion**

Our primary goal was to assess the effects of predictive and random presentation sequences on task-switching performance. In doing so, we investigated sequence effects on local and global switch costs, as previous studies investigating random switching have omitted this comparison (e.g., Altmann, 2007; Minear & Shah, 2008; Monsell et al., 2003). We utilized the CVOE switch task, as it allowed for easy computation of each cost type while using a bivalent response stimulus. Participants first completed two pure blocks before completing two switch blocks, which corresponded to the predictive and random switch sequences. Thus, pure blocks were compared to switch blocks when task switching utilized a perceivable pattern and when switching occurred with no apparent pattern. Analyses of trial types allowed us to directly assess changes in task performance as functions of block type and switch sequence, and additionally, allowed us to compute local and global switch costs, which provide insights regarding hypothesized working memory and attentional processes underlying task-switching performance. Specifically, we computed local switch costs as the difference between switch and non-switch trials occurring within the same block, which assessed changes in performance due to task-reconfiguration processes. Thus, local switch costs assessed changes in task performance due to retrieving the correct task-set. Separately, global switch costs were derived by comparing performance on single task trials within pure blocks to non-switch trials within switch blocks. Global switch costs, therefore, evaluated any performance changes due to maintaining multiple task-sets in working memory while completing the switch-task.

Consistent with our predictions, participants produced fewer errors on pure trials than switch trials, a pattern consistent with previous CVOE studies (e.g., Huff et al., 2015; Tse et al., 2010). However, for switch trials, no differences in error rates were detected as a function of presentation sequence. These patterns similarly extended to RTs, such that participants were faster at responding to pure trials relative to switch and non-switch trials. However, as with accuracy, RTs on switch trials did not differ between the predictive and random switch sequences. Thus, compared to predictive switching, random switching did not reduce participant accuracy or response latencies at the individual trial level. While this finding contradicts our prediction that the greater difficulty of the random switch block would reduce performance relative to predictive switching, we note that the degree of difficulty between the two switch patterns may not have differed sufficiently, leading to similar levels of performance observed at the trial-level. Given that the present study did not directly assess participants’ perceptions of task difficulty, future research may wish to explore this notion.

We then computed local and global switch costs for error rates and RTs. Overall, error rate switch costs were only marginally greater when switching was predictive versus random. However, for RTs, an interesting pattern emerged: Random switching produced greater local switch costs, while predictive switching led to greater global switch costs. This pattern for RTs was similarly observed using Vincentile plots. The finding that local costs were greater in random sequencing suggests that unpredictable switch trials are especially taxing when participants must reconfigure task-sets. Additionally, the finding that the predictive sequence increased global costs suggests that on non-switch trials, working memory is not only impacted by maintaining two task-sets, but also requires participants to monitor their progress across trials to anticipate whether the upcoming trial will switch or remain the same. However, as noted by an anonymous reviewer, the longer RTs for predictive non-switch trials similarly produced lower local costs for predictive switching. Thus, switch trials would similarly be expected to differ between switch sequences. However, given that no significant RT differences were detected between switch trials, caution may be needed when interpreting these patterns.

Overall, our finding that random switching increased local costs is consistent with our predictions regarding sequence effects as well as the broader task switching literature. For example, using a predictive presentation sequence, Huff et al. (2015) showed that individuals with relatively intact attentional control systems (e.g., healthy younger and middle-aged adults) generally produced large local switch costs versus individuals with impaired attentional control systems (e.g., older adults and very mild AD individuals). They reasoned that individuals with high integrity working memory and attentional control systems were more likely to become well-tuned to a given task-set versus impaired individuals. Thus, when participants encounter a task-set in a predictive switch block, inertia from the previous task-set slows the processes necessary to respond to this change, leading to inflated local costs (i.e., carry-over effects). These effects are likely exaggerated when switching is random, given the additional burdens random switching places on attentional control and working memory systems. Furthermore, because RTs generally decrease as a function of run length (i.e., the number of consecutive trials using the same task-set; e.g., Milán et al., 2005; Monsell et al., 2003), increased local costs for random switching may also reflect the random switch block having more consecutive task repetitions in which participants may naturally become faster over these repetitions while also inhibiting the non-active task-set, making it more difficult to reconfigure to the alternate task-set when a switch is encountered (Allport et al., 1994).

We suggest that inflated local costs for random switching may reflect contributions from two complementary processes: Impaired performance due to the inherent difficulty of unpredictable switching taxing task-set reconfiguration processes and task-set inertia from prolonged exposure to repeated trial types versus predictive switching. First, predictability would be expected to benefit performance on switch trials, as if participants can successfully predict upcoming task changes, they can more easily begin the task-set reconfiguration processes required to activate the dormant task-set. Findings from the present study are consistent with this notion, as RTs for predictive switch trials were numerically lower than random switch trials. Second, inflated local costs for random switching likely also reflect greater task-set inertia when switching is random, given that the random switch block is more likely to contain longer runs of the same task-set. Because the random switch sequence is likely to contain several consecutive non-switch trials, task-set inertia effects are more likely to occur with this switch pattern relative to the two-run predictive sequence. Consistent with this account, participants’ RTs were faster for non-switch trials when switching was random versus predictive and, critically, RTs were also slower for switch versus non-switch trials within random switch blocks. Taken together, inflated local RT costs for random switching appear to be strongly linked to task-set inertia effects, though more research will be needed to fully explore this notion (e.g., direct comparisons of run-lengths, etc.).

While our findings for local switch costs are consistent with our initial predictions, we note an important distinction between how local and global switch costs are calculated which potentially limits the interpretation of local cost differences observed between random and predictive switching. Unlike global switch costs in which all differences between random and predictive switching are computed relative to pure block performance, local switch costs reflect the difference between switch and non-switch trials occurring within the same block. As a result, baseline performance (i.e., non-switch trials) is impacted by differences in switch sequence. This is evident in the present study, as differences in local costs between presentation sequences were primarily driven by changes in non-switch trials. Thus, although our computation of local switch costs was consistent with how previous task-switching studies have computed this cost-type (e.g., Huff et al., 2015; Minear & Shaw, 2008, Monsell et al., 2000), caution is needed when comparing local switch costs between presentation sequences. As such, future studies may wish to account for this by computing additional switch costs using a separate presentation sequence which would be less likely to tax working memory systems (e.g. A-B-A-B).

Regarding global switch costs, our finding that predictive switching increased this cost type was similarly in-line with our predictions. Because global switch costs reflect the additional demands of maintaining two task-sets in working memory versus completing a single task, it is unsurprising this cost was elevated when switching was predictive, as in addition to keeping two task-sets active in working memory, participants also had to monitor their position within each run sequence. This extra monitoring placed an additional cost to participants’ working memory and attentional control systems, slowing performance on non-switch trials relative to pure trials. Future research may wish to further explore this notion by increasing run difficulty, such as having participants complete longer run sequences (e.g., 4-4), varying run lengths in predictable patterns (e.g., 2-3-2-3; 3-2-3-2, etc.), or by including additional task-sets, rather than limiting switch sequences to two tasks as is commonly reported in the literature (e.g., A-A-B-B-C-C).

Additionally, we note that our findings for global cost increases are consistent with previous research showing that breakdowns in attentional control systems similarly inflate these costs. Indeed, compared to healthy younger adults, both older adults and AD individuals have been shown to produce higher global costs relative to young adults who have more robust working memory systems (e.g., Belleville, Bherer, Lepage, Chertkow, & Gauthier, 2008; Huff et al., 2015; Kray, Li, & Lindenberger, 2002, etc.). Furthermore, while the present study only included younger adults, we note that previous research suggests that younger adults perform similarly to healthy older adults on several memory tasks when placed under conditions of divided attention (e.g., Castel & Craik, 2003; Craik, 1982; etc.). Thus, while the mechanisms underlying deficits in attentional control systems may differ, it is evident that as working memory systems become increasingly taxed, maintaining multiple task-sets becomes increasingly difficult, as evidenced by decreased task performance.

Finally, in addition to traditional mean analyses, we followed the designs of Huff et al. (2015) and De Jong (2000) and similarly assessed changes in switch costs using Vincentile analyses. Overall, local costs demonstrated a decrease across bins, particularly when switching was predictive, as indicated by quicker RTs in later bins. This finding, however, contrasts with Huff et al., 2015, who showed that local switch costs for younger adults increased across bins. This discrepancy, however, may have resulted from methodological differences between the two studies. First, Huff et al.’s switch block contained half as many total trials (60 trials) as we included in our switch blocks (120 trials each). Our inclusion of more trials within switch blocks may have changed the shape of bin patterns due to the additional number of trials per bin. Furthermore, the additional trials along with our inclusion of a second switch block may have led to potential fatigue effects. However, findings from De Jong (2000) suggest that although block length can influence switch-task performance, longer blocks should produce higher RTs and switch costs relative to short blocks. Instead, this discrepancy may have resulted from learning effects, as our inclusion of both additional trials within each block and an additional switch block may have caused participants to become more attuned to each task-set relative to the shorter blocks used by Huff et al. Second, we note that the sample used in the present study (89 participants) was considerably larger than the sample reported by Huff et al. (30 participants). As a result, our sample may have provided a more accurate representation of mean RTs across trial types as well as their associated switch costs.

Similarly, methodological differences may explain the discrepancy between our findings for predictive versus random switch costs and those reported by Minear and Shah (2008). For example, Minear and Shah were primarily interested in assessing transfer effects on learning rather than providing a direct comparison of predictive and random switching on task-performance on switch-costs. Further, like Huff et al. (2015), Minear and Shah employed a smaller sample (*n* = 31 for all groups vs. *n* = 89 in the present study). Thus, our sample may have provided a more reliable representation of mean RTs across trial types as well as their associated switch costs. However, given the discrepancies noted above, more research is needed to fully understand the effects of switch-sequencing on local and global switch costs and the underlying working memory processes they reflect. Separately, we note that while the present study used analyses of local and global switch-costs to assess changes in working memory processes between switch sequences, we did not include direct measures of working memory performance. As such, future work exploring the role of working memory processes within the context of task-switching may wish to provide more direct assessments of these processes and assess their relationships with task-switching behavior, including working memory span measures (e.g., OSPAN; Turner & Engle, 1989; see Conway et al., 2005) and neurological measures (see Chai, Abd Hamid, & Abdullah, 2018).

Finally, to supplement the Vincentile analyses, we also included an ex-Gaussian analysis of global and local switch costs. Analysis of the tau parameter, however, failed to produce the interactive pattern observed in the previous RT cost analyses. Instead, an increase to both cost types was observed for predictive versus random switching. Thus, while the present study largely suggests that predictive and random switching differentially affect each switch cost type, this pattern may be limited to less difficult trial types rather than those falling within the tail of the ex-Gaussian distribution. Thus, future research on task-switching effects should continue to make use of these distributional analyses when analyzing response latencies.

**Summary and Conclusion**

The present study investigated the effects of predictive and random switch sequences on attentional control and working memory processes assessed via task-switching performance. Using the CVOE switch task, we show that although mean error rates and RTs do not differ based on switch presentation sequence, differences emerge for RT switch costs. First, task-set reconfiguration processes associated with local switch costs become exaggerated when switching is unpredictable (vs. predictable) and participants are unable to prepare for an upcoming change in tasks. Separately, task-set maintenance processes associated with global switch costs become exaggerated when switching is predictable (vs. unpredictable) as participants must maintain two task-sets while simultaneously monitoring their progression across the sequence. Finally, distributional analyses provide additional insight into these patterns. Taken together, our findings provide a greater understanding of how predictive and non-predictive task-switching sequences affect reconfiguration and maintenance processes in younger adults.

**Open Practices Statement**

Subject-level data files and *R* code for all analyses have been made available at <https://osf.io/hzwc4/>. The experiment reported was not pre-registered.

**Declaration of Interest**

The authors report no conflicts of interest.

**Ethical Compliance Statement**

All materials and procedures reported in this study were approved by the University of Southern Mississippi Institutional Review Board (protocol #IRB-21-393) and found to be in accordance with the 1964 Helsinki Declaration ethical principles. Informed consent was obtained from all individuals who participated in this study.

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Table 1

*Mean Errors and RTs as a Function of Trial Type.*

|  |  |  |  |
| --- | --- | --- | --- |
| Measure | Trial Type | *M* | ± 95% *CI* |
| Error Rates | Pure | 3.25 | 0.59 |
|  | Predictive Non-Switch | 3.49 | 0.83 |
|  | Random Non-Switch | 3.01 | 0.67 |
|  | Predictive Switch | 6.12 | 1.11 |
|  | Random Switch | 5.17 | 0.76 |
| RTs | Pure | 677 | 33 |
|  | Predictive Non-Switch | 1328 | 74 |
|  | Random Non-Switch | 1260 | 68 |
|  | Predictive Switch | 1414 | 70 |
|  | Random Switch | 1451 | 83 |

*Note:* Error rates are reported as a percentage. RTs are reported in ms.

Table 2

*Mean Local and Global Switch Costs for Errors and RTs as a Function of Presentation Sequence.*

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Measure | Presentation | Cost Type | *M* | ± 95% *CI* |
| Error Rates | Predictive | Local | 2.63 | 0.88 |
|  |  | Global | 0.24 | 0.76 |
|  | Random | Local | 2.13 | 0.69 |
|  |  | Global | -0.24 | 0.68 |
| RTs | Predictive | Local | 86 | 36 |
|  |  | Global | 651 | 55 |
|  | Random | Local | 191 | 31 |
|  |  | Global | 583 | 48 |

*Note:* Error rates are reported as a percentage. RTs are reported in ms.

Table 3

*Ex-Gaussian Tau Parameter as a Function of Trial Type.*

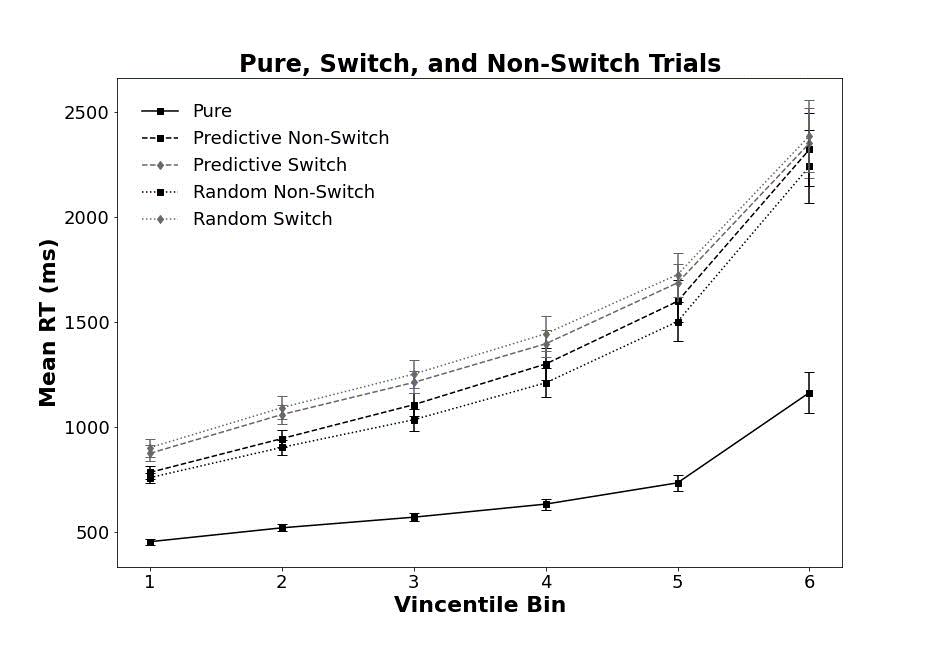
|  |  |  |
| --- | --- | --- |
| Trial Type | *M* | *± 95% CI* |
| Pure | 224.24 | 28.29 |
| Predictive Switch | 509.30 | 53.67 |
| Random Switch | 512.10 | 53.02 |
| Predictive Non-Switch | 546.11 | 60.76 |
| Random Non-Switch | 507.27 | 51.12 |

Table 4

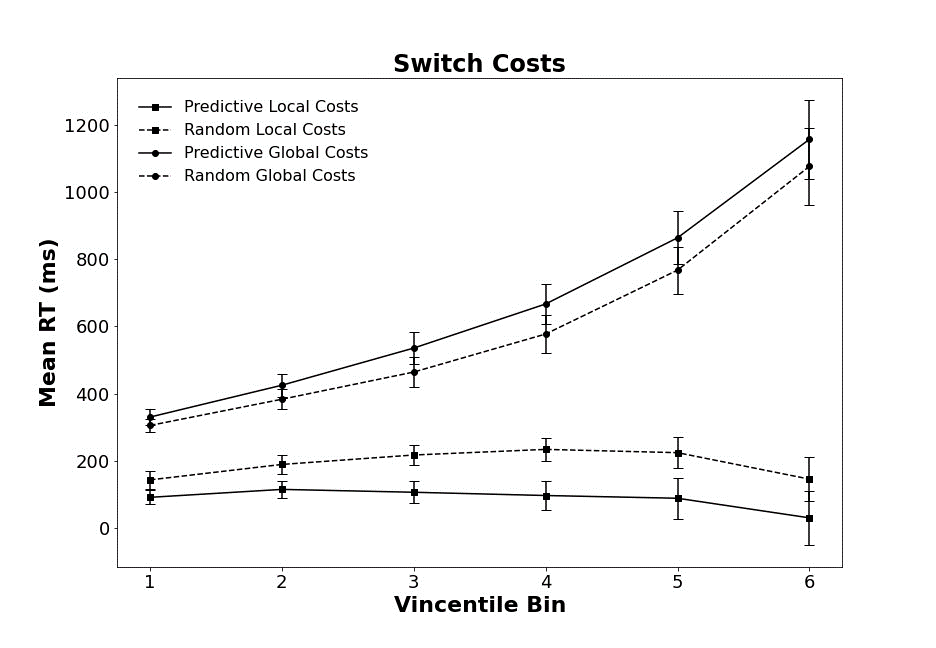
*Ex-Gaussian Tau parameter as Functions of Switch Cost Type and Presentation Sequence.*

|  |  |  |  |
| --- | --- | --- | --- |
| Presentation | Cost Type | *M* | *± 95% CI* |
| Predictive | Local | 36.81 | 37.36 |
|  | Global | 321.87 | 44.35 |
| Random | Local | -4.83 | 28.42 |
|  | Global | 283.04 | 36.00 |

*Figure 1*. Time course for pure block trials (left) and switch block trials (right). Each trial was separated by a 500 ms intertrial delay in which participants viewed a blank screen (middle panels).



*Figure 2*. Mean RT Vincentile bin data points for pure, non-switch, and switch trials. Switch and non-switch trials are split by predictive and random presentation sequences. Bars denote 95% *CI*.



*Figure 3*. Local and global Vincentile switch costs for predictive and random switching. Bars denote 95% *CI*.

1. As noted by an anonymous reviewer, a potential concern of this counterbalance design is that participants who complete the predictive switch block prior to the random switch block may show biased performance on random switching, as they may search for a non-existent pattern. To test this possibility, we compared the effects of block order on error rates, RTs, and switch costs. No main effects or interactions of block order were detected (*p*s ≥ .20), indicating that completing the predictive switch block prior to the random switch block did not influence task-switching. [↑](#footnote-ref-1)