Investigating Predictive vs. Random Task-Switching Using the CVOE Task

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Abstract

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Selectively attending to relevant information within one’s environment is a key for successfully staying on task when engaging in goal-directed behavior. Attentional systems play a critical role in this process, as individuals with strong attentional are more likely to ignore highly salient but unrelated environmental cues that would otherwise produce distractions. Traditionally, researchers have investigated attentional control using by presenting participants with situations in which task-related information (i.e., congruent trials) is contrasted with information that is task-unrelated (i.e., incongruent trials). These studies consistently show that when participants are presented with incongruent trials, both response times (RTs) and error rates are increased relative to congruent trials. Thus, participants are slower to respond and are less accurate in their responses whenever they must suppress task irrelevant information to successfully complete a task.

One of the most well-known examples of this effect was originally reported in Stroop’s (1935) seminal study investigating color naming. Stroop had participants read lists of color words, which had been printed in an ink that was either congruent with the word (i.e., the word “Blue” printed in blue ink) or incongruent (e.g., “Blue” printed in green ink). Participants were instructed to name the color ink in which the word had been printed, rather than reading the word. Overall, both RTs and error rates were increased for color words presented in an incongruent ink (e.g., “Blue” presented in green ink) relative to when a congruent ink was used (e.g., “Blue” presented in blue ink). Often, these decreases in performance observed for incongruent trials are further exaggerated whenever the incongruent trials immediately follow congruent trials (i.e., congruency sequence effect, CSE; Aschenbrenner & Balota, 2018, Egner, 2007).

The Stroop color naming task has received significant attention in the literature. Commonly, researchers have employed this task to as a measure of attentional control, either individually [CITE] or as a subset of attentional control batteries [CITES]. For example, researchers interested in the effects of both healthy and unhealthy aging on attentional control processes have employed variations of the Stroop task to assess declines in attentional process that occur a function of aging [CITES]. For example, Spieler, Balota, & Faust (1996) showed that performance on the Stroop task decreased as a function of both healthy aging and Alzheimer’s Disease (AD) diagnosis. Specifically, compared to younger adults, healthy older adults showed increased RTs (but not error rates). For AD individuals, however, large costs to both RTs and error rates were observed, even when matched to healthy individuals of the same age. More recently, Hutchison, Balota, & Ducheck (2010) showed the Stroop Color Naming task could be used to discriminate healthy aging from AD, suggesting that this task is sensitive to declines in attentional control inherent to AD. It is evident, therefore, that attentional control is critical for keeping internal goals active, as participants with impaired attentional control systems experience greater difficulty staying on task.

While the Stroop color naming task has been commonly used to investigate attentional control processes [CITES], researchers have increasingly used task-switching paradigms as a method of investigating questions surrounding attentional control process. In a standard task-switching paradigm, participants alternate between completing a set of contrasting tasks (Jersild, 1927; CITE, see XXX). Often, participants are presented with at least types of experimental conditions. First, participants complete *pure blocks* which focus exclusively on one task (i.e., participants only complete addition problems). Participants then complete *switch blocks* in which they must quickly alternate between two contrasting tasks (i.e., addition on trial one but subtraction on trial two). Response times (RTs) and error rates are then compared between the two blocks. Overall, studies investigating task-switching have repeatedly shown that participants commit more errors and have slower RTs for switch trials compared to non-switch trials (i.e., switch costs; [CITE]), and, like the Stroop task, declines in attentional control can exaggerate these costs [CITE].

Although a variety of paradigms have been used to investigate task-switching effects, the present study focuses specifically on task-switching paradigms in which a comparison can be made between local and global switch costs (e.g., Huff, Balota, Minear, Aschenbreener, & Ducheck, 2015; Mayr, 2001; Minear & Shah, 2008; etc.). These paradigms initially present participants with a set of pure blocks (one corresponding to each task-set) which are subsequently followed by a switch block in which switch and non-switch trials are interleaved (e.g., switch, non-switch, switch, non-switch, etc.). First, the *global switch cost* refers to the difference between switch trials and pure block trials and represents the cost of maintaining multiple task configurations in a switch block compared to a single task configuration within the pure block (Minear & Shah, 2008; Wylie & Allport, 2000). Alternatively, the *local switch cost* is found by computing the difference between switch and non-switch trials presented within the same switch block. Local costs represent task-set reconfiguration processes that occur due to participants changing tasks-sets within the same block of trials (Rogers & Monsell, 1995; see Huff, et al., 2015, for a review).

While participant characteristics such as aging have been shown to influence task-switching performance (e.g., Huff et al., 2015; [CITE], etc.), the stimuli used can also have an effect. For example, previous research has shown that switch costs are particularly magnified whenever the stimuli do not clearly signal to participants which of the two tasks is to be performed (Luwel, Schillemans, Ongehan, & Vershaffel; 2009). Termed *bivalent* stimuli, these items activate both task-sets used in a switch task (i.e., presenting participants with letter-number pairs and having them switch between classifying the letter or the number). Compared to *univalent* stimuli which only correspond to one task-set (i.e., presenting participants with only letters or numbers), responses are often slowed, as participants must consider both task sets (e.g., bivalency cost; Woodward; Meier, Tipper, & Graf; 2003). Because bivalent stimuli are more challenging for participants, researchers have often commonly incorporated them when developing task switching paradigms (e.g., XXX, CITE; XXX, CITE]). One example is the Consonant-Vowel Odd-Even task (CVOE; Minear & Shah, 2008), which presents participants with letter-number pairs (e.g., A 15). Depending on the cued-task set, participants are instructed to classify the letter in the pair as being a consonant/vowel or the number as odd/even. Because this task presents participants with a set of pure blocks before the switch block, the CVOE task allows for the measurement of both local and global switch costs.

Within the past decade, researchers have made extensive use of the CVOE task to investigate questions related to cognition. Often, these studies have focused on assessing differences in task-switching performance between younger and older adults. For example, Tse, Balota, Yap, Duchek, & McCabe (2011) compared performance between young, healthy older adults, and older adults with mild cognitive impairments on three attentional control measures including the CVOE task. Overall, [SOMETHING ABOUT COSTS] their findings suggested that the CVOE task could effectively be used to differentiate between healthy aging and MCI. [BALOTA AND HUTCHISON, 2011?]

More recently, Huff et al. (2015) compared CVOE task-switching between young adults, healthy middle aged and older adults, and MCI older adults. Overall, MCI older adults committed more errors and had slower RTs relative to both young adults and non-impaired older adults, with task performance particularly affected for switch trials compared non-switch trials in which the task-set does not change (Huff et al., 2015). [TRANSITION] global switch costs (switch trials compared to pure trials) increased as a function of both age and MCI status, suggesting that…[EXPAND]. For local costs [Summary] Thus, [TRANSITION/CONCLUSION STATEMENT]

Although researchers have used CVOE task-switching to investigate a variety of questions related to attentional control, much of this work has been conducted using switch blocks in which switches occur in a predictive pattern. Commonly, these studies have organized trials within switch blocks using an *alternating runs* sequence, such that participants always complete the same type of trial twice before being switched to the second task (e.g., CV-CV-OE-OE, etc.; see Rogers & Monsell, 1995). As a result of this presentation sequence, every other trial is a switch trial, with one non-switch trial interleaved between each switch trial. While this pattern [UPSIDE TO IT], [POTENTIAL PROBLEMS WITH THIS – PREDICTABILITY!] [INTRODUCE RANDOM SWITCHING HERE]

While studies employing the CVOE have commonly used the alternating runs sequence, we note that Minear and Shah (2008) included a random switching comparison group in addition to the traditional alternating runs switch group. [WHAT DID THEY FIND? WERE THEY DOING SOMETHING DIFFERENT THAN US?] [OTHER STUDIES THAT HAVE DONE RANDOM SWITCHING?] Thus, the present study [WHY ARE WE DOING RANDOM?]

**Distributional Analyses of RTs**

Across task-switching studies, [EXPAND – SOMETHING ABOUT RTS BEING FUNDAMENTAL] Commonly, researchers have commonly relied upon analysis of mean or median RTs as a method to gain insight into attentional processes. However, because RT distributions are almost always positively skewed (i.e., most RTs generally occurring at the faster end of the scale), performing an analysis of only mean RTs may produce results that are misleading (see Balota & Yap, 2011 for a review). To account for this, researchers have increasingly moved away from using traditional measures of central tendency when assessing RTs, and instead, have elected to focus on RT distributions. [TRANSITION] For example, Hultsch, McDonald, & Dixon (2002) showed that RT variability was more effective at discriminating between healthy and MCI older adults relative to mean RT performance.

Previous research has shown that RT distributions can accurately capture several aspects of human cognition, including semantic priming (Balota, Yap, Cortese, & Watson, 2008) and word recognition [CITE]. Importantly, RT distributions have also been shown to accurately capture attentional control within the context of task-switching. For example, Tse et al. (2011) [SUMMARY] More recently, [HUFF ET AL HERE] [CONCLUSION STATEMENT HERE]

[BREAKDOWN THE ATTENTION STUDY FINDINGS HERE]

Given the benefits of using RT distributions to investigate cognitive processes, the present study incorporates these distributional analyses in addition to traditional analyses of means. Specifically, we investigate RT distribution via two types of analyses: 1) Averaging RTs across participants and binning them via a Vincentile analysis and 2) fitting individual RTs to an ex-Gaussian distribution. First, the Vincentile analysis rank orders all RTs for each trial type at the participant level and then bins the ordered data into groups of equal size. For example, a Vincentile analyses using four bins would first each participant’s RTs from fastest to slowest. Next, for each participant, RTs within the first 25% of the data would be averaged, followed by the second 25%, third the 25%, and the final 25%. This process is then repeated for each participant, and Vincentiles are computed by taking the average of each bin across participants. [TALK ABOUT THE SHAPE OF THE DISTRIBUTION?] [NEED TO EXPAND SOMEHOW]

The ex-Gaussian analysis [EX-GAUSS HERE]

**The Present Study**

The goal of the present study was to expand upon previous research investigating CVOE task-switching by comparing error rates and RTs between participants who complete predictable alternating runs switch blocks (e.g., CV-CV-OE-OE-CV-CV) and those who receive switch blocks in which switching occurs at random (e.g., CV-OE-OE-OE-CV-OE). Overall, we expected that mean error rates and RTs would be higher on switch blocks (regardless of presentation sequence) relative to pure blocks, given that pure blocks only require participants to engage in a single task-set. Within switch blocks, we expected that participants would particularly struggle whenever switching occurred at non-predictive intervals due to the lack of a discernable pattern. We therefore anticipated that the random switch block would produce more errors and higher RTs relative to the alternating runs switch block, and further, that these difficulties would produce greater local costs compared to the alternating runs switching, as [WHY?] Finally, regarding global costs [GLOBAL COSTS PREDICTION]

**Method**

**Participants**

A total of 100 undergraduate students were recruited from the University of Southern Mississippi’s undergraduate research pool and completed the study 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 > 3 standard deviations above the mean), which indicated that participants did not correctly follow task instructions. Additionally, data for two participants were removed due to a coding error. A sensitivity analysis conducted with *G\*Power* [CITE] indicated that our final sample of 89 participants was sufficient to detect XX effects [STATS]. All participants were native English speakers who reported normal or corrected to normal vision. Participant demographics are reported in Table X.

**Materials**

To create the stimuli, we generated a series of letter-number stimulus pairs (e.g., A 15) using the following process. First, an even number of consonants and vowels were created. These letters were always selected from A, D, E, H, I, J, O, P, S, or U. Next, a series of numbers were randomly selected between 1 and 99, with the constraint that half of the numbers selected were always even. To create the pairs, half of the consonants were paired with an odd number, while the remaining half were 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 repeats did not occur on consecutive trials.

**Procedure**

The CVOE task presented participants with two sets of instructions, which either differed between blocks (pure blocks) or as a function of trial (switch blocks). For each trial, a letter-number pair was presented in the center of the computer screen, and participants were tasked with classifying whether the letter was a consonant/vowel (CV trials) or an odd/even number (OE trials). Depending on the type of trial, the words consonant/vowel or odd/even were presented at the top of the screen in the left and right corners to serve as a reminder. Participants were instructed to press the *q* key for consonants/odd numbers or the *p* key for vowels/even numbers. These keys were selected given that they are on opposites sides of a standard QWERTY keyboard. 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 (alternating runs and random presentation). Participants initially completed a set of 10 practice trials which corresponded to the first pure block’s task (CV or OE) 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 a second set of practice trials (corresponding to the task in the second pure block) before completing the second pure block.

Immediately following completion of the two pure blocks, participants began the two switch blocks. In the switch blocks, the task change occurred at the trial level rather than the block level. For each trial, participants were prompted with the word “letter” or “number”, which corresponded to the CV or OE task, respectively. This prompt was located above the stimulus pair, and participants were informed that the prompt could potentially change following each key press. 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 the switch blocks were arranged such that they were presented either with an alternating runs pattern (e.g., CV, CV, OE, OE, CV, CV, etc.; see Huff et al., 2015) or presented using a random presentation sequence (e.g., CV, OE, OE, OE, CV, OE, etc.). Each switch block consisted of 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 the pure blocks, each switch block corresponded to one of these two presentation modes (alternating runs or random). Thus, participants completed one pure CV block, one pure OE block, one alternating run switch block, and one random presentation switch block. Block presentation was randomized across participants; however, blocks were always ordered such that participants completed the two pure blocks before completing the two switch blocks (Huff et al., 2015; Minear & Shah, 2008).

Across blocks, participants were instructed to respond to each trial as quickly as possible without compromising accuracy. The task was presented to participants on a laptop running E-Prime 3.0 software [CITE], and all participants were tested individually in a laboratory setting. The total experiment lasted approximately 20 minutes.

**Results**

For all analyses, significance was set at the *p* < .05 level. Generalized-eta squared (*η*2G) and Cohen’s *d* effect size estimates were computed for all significant analyses of variance (ANOVAs) and *t*-tests, respectively. In addition to reporting effect size indices, we supplemented all standard null-hypothesis testing 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 the likelihood that the null hypothesis is retained. Therefore, all null effects include a *p*BIC estimate.

In the following analyses, we first examine mean error rates across trial types (pure, alternating switch, alternating nonswitch, random switch, and random nonswitch) and switch cost (local vs global). We then assess changes in mean RTs across trial types and switch costs. For completeness, error rates and RT comparisons are reported in the Appendix (Tables AX and AX, respectively).

Following the design of Huff et al. (2015), RT analyses only utilized correct trials. Additionally, we employed a trimming procedure to reduce the likelihood of RT analyses being disproportionately influenced by extreme scores. RT outliers were defined as any responses three standard deviations above or below of each participant’s respective mean. Overall, this trimming procedure eliminated xx% of pure block trials, xx% of nonswitch trials, and xx% of switch trials. Finally, [DISTRIBUTIONAL STUFF HERE]

**Mean Error Rates**

Mean error rates as a function of trial type are displayed in Figure 1 (top panel). Overall, participants committed the most errors on alternating runs switch trials (6.12%), followed by random switch trials (5.17%), alternating runs nonswitch trials (3.49%), pure trials (3.25%), and random nonswitch 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, *η*2G = .09. Post-hoc *t*-tests revealed that this effect was driven primarily 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 alternating runs compared to random presentation, *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 block presentation, *t*s < 1, *p*s ≥ .48, *p*BICs ≥ .88.

Next, we compared differences in switch costs for errors as a function of presentation and cost type (Figure 1, bottom panel). A 2 (Switch Cost: Local vs Global) × 2 (Presentation: Alternating Runs vs Random) yielded a significant main effect of Switch Cost, *F*(1, 88) = 26.83, *MSE* = 19.03, *η*2G = .10, such that collapsed across presentation modes, local switch costs exceeded global costs (2.39 vs. -0.01). Additionally, this analyses revealed a marginal effect Presentation, *F*(1, 88) = 3.68, *MSE* = 5.43, *p* = .06, *p*BIC = .60, *η*2G = .01. The interaction between Switch Cost and Presentation, however, was not significant, *F*(1, 88) < 1, *MSE* = 17.35, *p* = .99, *p*BIC = .90.

**Mean RTs**

As displayed in Figure 2 (top panel), participants were quickest when responding to trials presented in pure blocks compared to switch and non-switch trials. A one-way repeated measures ANOVA confirmed the presence of trial type differences, *F*(4, 352) = 357.72, *MSE* = 19.03, *η*2G = .10. Post-hoc testing indicated that this effect was largely driven by differences in RTs between trials presented in the pure and switch blocks

**Vincentile Plots**

[VINCENTILES] [WILL NEED TO RUN ANOVAS]

**Ex-Gaussian Distribution of RTs**

[EX-GAUSS]

**General Discussion**

The goal of the present study was to [SUMMARY PARAGRAPH – MAIN ANALYSES] Overall… [EXPAND]

[SUMMARY PARAGRAPH – DISTRIBUTIONAL ANALYSES]

[SOMETHING HERE – I’LL FIGURE IT OUT LATER]

[AGING IMPLICATIONS]

[FUTURE DIRECTIONS]

**Summary and Conclusion**

[WORDS HERE]

**References**

[TABLE 1]