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

Nicholas P. Maxwell1, Jacob Namias1, & Mark J. Huﬀ1

* The University of Southern Mississippi

Author Note

Correspondence concerning this article should be addressed to Mark J. Huff, 118 College Dr, Hattiesburg, MS, 39406. E-mail: [mark.huff@usm.edu](mailto:nicholas.maxwell@usm.edu). [OSF NOTE HERE]

Abstract

Abstract will go here. . .

*Keywords:* Keyword1; Keyword2; Keyword3; Keyword4

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

The ability to successfully switch between differing tasks is an important component of daily life, as it allows individuals to respond appropriately to complex situations and environmental changes. Take, for example, a student completing an online homework assignment. While completing the assignment, the student may repeatedly switch between using the web browser on their computer and checking their class notes. However, the same environmental variables can invoke the use of multiple task sets, with the task set selected dependent on the desired outcome. For instance, in the example above, although the student is currently using the computer to complete a homework assignment, at any time, they could potentially switch to using their email client, social media, or a myriad of other potential programs that are simultaneously available. Thus, attentional control is an important component of task-switching, as it allows the activation of the required task set while suppressing the others [CITE].

Empirically, researchers have investigated the effects of switching on task performance through the use of various *task switching* paradigm. In a standard task switching study, participants are presented with a pair of simple yet contrasting tasks (i.e., participants complete an addition task on trial one but a subtraction task on trial two). Commonly, participants are instructed to quickly alternate between completing the tasks, with reaction times (RTs) and error rates the primary dependent variables of interest. These studies generally include at least two conditions: A *switch* condition in which participants alternate between the two contrasting tasks and a *pure* condition in which only one task is completed. Performance is then compared between the two conditions. Overall, previous research has consistently shown that when individuals are forced to alternate between tasks, reaction times and error rates are increased, and participants typically commit more errors relative to when tasks are completed separately (see xxx for a review). Thus, individuals appear to have more difficulty shifting between mental tasks compared to repeating the same task.

[STROOP]

[PARAGRAPH HERE ON VARIOUS TASK SWITCHING PARADIGMS?] [TRANSITION]

Previous research has consistently shown that switching is more effortful for participants whenever the task involves *bivalent* stimuli (i.e., stimuli with two response meanings) when compared to *univalent* stimuli, which only contain a single response meaning [Merian, 2000; Monsell, 2003; see XXX for a review]. [EXPAND]

**Measuring Switch Costs**

Although several task-switching paradigms have been popularized in the literature (see XXXX for a review), for the present study, we chose to explicitly focus on paradigms that allow for a direct comparison of local and global switch costs [CITE HERE]. These tasks present participants with blocks containing switch and non-switch trials interspersed within the same block (referred to as switch blocks) and pure blocks in which participants complete all trials using only one set of task instructions [CITE]. [EXPAND] The *global switch cost* refers to…[LOCAL SWITCH COSTS]

[EXPLAINATIONS OF SWITCH COSTS]

[SEWIT AND OTHERS?]

The Consonant-Vowel Odd-Even task (CVOE; Minear & Shah, 2008) is a simple task-switching paradigm that allows the measurement of both local and global task switching costs. [OVERVIEW OF THE CVOE/HOW DOES IT COMPARE TO OTHER SWITCH TASKS?]

[TRANSITION TO GET US TO AGING] Regarding switch tasks such as the CVOE, older adults with mild cognitive impairments (MCI) like as Alzheimer’s Disease often commit more errors and have slower RTs relative to younger adults and non-impaired older adults. Additionally, task performance for MCI older adults is particularly affected for switch trials compared to trials in which the task set does not change. Work by Huff et al. (2015) has additionally shown that global switch costs (switch trials compared to pure trials) increase as a function of age and MCI status, suggesting that…[EXPAND]. [ADD A SENTENCE OR TWO HERE ON WHY THE CVOE SPECIFICALLY IS USEFUL]

Previous work on task switching using the CVOE paradigm has traditionally presented trials using an *alternating runs* pattern. In this presentation sequence, subjects complete the same type of trial twice before the instructions switch participants to the second task (i.e., the pattern of trials would be CV, CV, OE, OE, CV, CV). The result of this pattern is that every other trial (following the initial trial) is a switch trial, as it occurs following a change in the task set. [POTENTIAL PROBLEMS WITH THIS – PREDICTABILITY!]

**Distributional Analyses of RTs**

Researchers studying attentional systems commonly rely upon mean response scores (i.e., error rates and RTs) as a method to gain insight into these processes. However, because distributions of RTs are almost always positively skewed, with the majority of RTs generally occurring at the faster end of the scale, an analysis of only means may not provide results that are misleading (see Balota & Yap, 2011, for a review). To account for this, researchers have increasing moved away from the use of traditional measures of central tendency when assessing RTs, instead focusing on the RT distribution [SEE XXX FOR A REVIEW]. RT distributions have been shown to capture aspects of human cognition, including semantic priming (Balota, Yap, Cortese, & Watson, 2008), word recognition [CITE], and, importantly, attentional control within the context of task switching [CITE HUFF PAPER AND TRY TO FIND ONE MORE].

In the present study, we further analyze RTs using two types of distributional 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**

[TRANSITION – SET UP HYPOTHESES SEGUE INTO METHODS] The present study expands on previous CVOE task switching studies (e.g., [XXX AND XXX]) by incorporating both an alternating runs switch task and a randomized switch task (i.e., CV, OE, OE, OE, CV, OE) in which no discernable pattern of task switching can be detected.

**Alternating Runs vs. Random Switching**

[WORDS HERE] Overall, we expected that mean error rates and RTs would be higher on Switch Blocks relative to Pure Blocks. Furthermore, we expected that participants would particularly struggle with the switch task when switching occurred at non-predictive intervals due to the lack of pattern. We anticipated that these difficulties would result in higher error rates and greater RTs for random switch trials relative to alternating runs switch trials.

Regarding switch costs, we expected that local costs would be higher on the random switch task relative to the alternating runs. [WHY?] 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.

**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 an xx 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 rate 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**

[SUMMARY PARAGRAPH – MAIN ANALYSES]

[SUMMARY PARAGRAPH – DISTRIBUTIONAL ANALYSES]

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

[AGING IMPLICATIONS]

[FUTURE DIRECTIONS]

**Summary and Conclusion**

[WORDS HERE]

References