TITRATING COGNITIVE CONTROL: TRIAL-LEVEL DYNAMIC USE OF PROACTIVE AND REACTIVE COGNITIVE CONTROL

by

Elizabeth A. Wiemers

A Dissertation

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Doctor of Philosophy

Department of Psychological Sciences

West Lafayette, Indiana

August 2020

THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Thomas S. Redick, Chair
Department of Psychological Sciences

Dr. Robert W. Proctor
Department of Psychological Sciences

Dr. Gregory S. Francis
Department of Psychological Sciences

Dr. Darryl W. Schneider
Department of Psychological Sciences

Approved by:
Dr. Margo J. Monteith

ACKNOWLEDGMENTS

I would like to thank my research advisors, Sara Finley and Katherine Moore, who helped me build a firm foundation in research, and my graduate advisor, Tom Redick, who has been the mentor that I aspire to be. I would also like to thank my dissertation committee who have given generously of their time and provided invaluable feedback and advice. The support and guidance of all of these individuals have immeasurably impacted my growth as a researcher and scholar. Further, I would like to thank Ashlyn Hines-Lanham and Melissa Malter for their assistance with data collection during Experiment 1, and Julie Smith for her help with formatting this document.

The support that made pursuing this dream possible began long ago. I must also thank my family, especially my parents, Nancy and Wes, for always supporting my curiosity with encouragement, science kits, and so much more. I would also like to thank my husband, Daniel, whose unwavering optimism, encouragement, and love have been an invaluable constant in my life these last few years. The support and encouragement of these, and many more, has kept me grounded and able to focus on my goals.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Cognitive control is accomplished by a set of higher-order cognitive processes that are recruited to aid in the completion of various tasks. A popular proposed mechanism is the Dual Mechanisms of Control (Braver, Gray, & Burgess, 2007), proposing proactive and reactive mechanisms. While neuroscience studies provide evidence that these are two distinct processes, it remains unclear whether the processes are competing, or whether they can be used together. That is, are the two processes able to both be enacted to some degree? Further, whether these mechanisms can be titrated to produce a gradient-like use of control on a trial-level basis is unknown. These are the two primary pursuits of this dissertation. Experiment 1 shows the titrated pattern of control use, indicating (a) sensitivity to task demands, and (b) dynamic use of proactive and reactive control at the trial level, in a new task. Further, a novel contribution is the observation of ability to titrate the use of control. Additional experiments relate performance on this task to working memory (Experiment 2), replicate the findings in an online format (Experiment 3), and differentiate performance from distance effects commonly seen in relative judgment tasks (Experiment 4). This work has implications for the understanding of how cognitive control functions and how dynamically the use of these mechanisms can be adjusted.

INTRODUCTION

Individuals have some ability to direct goal-relevant cognitive processes. Throughout the history of psychological research, these control functions have been given a number of names and hypothesized mechanisms. Attention control, executive control, and cognitive control are frequently interchangeably used to describe such processes (for a recent review, see Gratton, Cooper, Fabiani, Carter, & Karayanidis, 2017). As Gratton and colleagues describe, these terms are used with slightly different implications, at least some of the time. They describe these distinctions as largely implying the timescale at which relevant mechanisms are being evaluated, with the broadest executive function describing long-term goal maintenance, cognitive control describing task-level adjustments, and attention control describing adjustments at the trial level. However, opinions on this distinction vary.

Various mechanisms for these control processes have been proposed, and further theories for when and why these processes are recruited have been explored. Some have posited that these processes can be explicitly controlled, changing with strategy instructions (Braver, Paxton, Locke, & Barch, 2009). Others have questioned whether these processes can be influenced by automatic processes (Verbruggen & Logan, 2009) or whether the processes are volitional at all, going so far as to consider cognitive control a self-regulating byproduct of associative learning (Abrahamse, Braem, Notebaert, & Verguts, 2016). While this topic has been studied for much of the history of psychology, many questions remain.

The theories for what cognitive control entails have varied over the years. Early on, Kahneman (1970) described attention control as a mechanism to resist distraction, focusing primarily of allocation or orienting of the control mechanism. Posner and Petersen (1990) built on this orienting theory with the introduction of an alerting mechanism to describe a broader executive control process. Miyake et al. (2000) replaced orienting with shifting attention and proposed that orienting, updating, and inhibition encompass the diverse aspects of a unified cognitive control system. Curtis and D’Esposito (2003) more broadly suggested control was maintenance of the information in working memory over sustained periods of time. As Gratton et al. (2017) point out, these researchers were also evaluating cognitive control along different timescales, leading to some of the variations in processes and naming schemes. However, all of these researchers are describing the direction of attention in the face of or expectation of interference.

There is some additional discussion regarding which processes, such as conflict monitoring, may be part of cognitive control, rather than interacting with it. Kerns et al. (2004) consider conflict monitoring to be a process by which the need for cognitive control is signaled in the anterior cingulate cortex, somewhat less directly part of the cognitive control mechanism. Botvinick, Braver, Barch, Carter, & Cohen (2001) considered monitoring for conflict and then making appropriate adjustments to be a primary function of cognitive control. Aron (2011) described proactive control as a mechanism by which subjects respond to conflict by preparing to stop, slowing just enough after conflict to make a decision about the next stimulus before responding. This is considered to be different from reactive control where the stopping mechanism is much more heavily relied on. Somewhat similarly, Brown (2013) proposed that the conflict monitoring activity observed in the anterior cingulate cortex was not simply monitoring, but proactively evaluating possible responses and directly supports cognitive control.

Germane to the current work, another theory combined aspects of some of these earlier theories and modeled a proposed system of two types of cognitive control – *proactive*, addressing expectation, and *reactive*, addressing presence of interference and conflict separately (Braver, Gray, & Burgess, 2007; De Pisapia & Braver, 2006). This theory was named the Dual Mechanisms of Control framework. Like Kahneman, Braver et al. were interested in the allocation of control, investigating a timescale for when control would be enacted. According to Braver et al, proactive control is a top-down process that involves maintaining goal-relevant information in anticipation of use in upcoming situations that may involve interference. In the context of a task, this may involve cognitive and motor preparation in anticipation of a target given a particular cue (e.g., task-switching, prospective memory, continuous performance tests). Reactive control, conversely, is a bottom-up process involving waiting for interference to occur before thinking back to goal-relevant information to inform necessary responding. In a task context, this would present as waiting for the target before thinking back to the cue to determine the necessary response. In an update regarding this framework, Braver (2012) stated that it might be possible to use some combination of these processes simultaneously as they may be separate processes, with neural correlates in different brain regions.

Neurophysiological Correlates of Control

The dual mechanisms of control framework has support from the neuroscience literature. While cognitive control generally has been hypothesized to be supported by an entire network of neural components (see Cole & Schneider, 2007), the dual mechanisms of control framework makes very specific predictions about where and when proactive and reactive control should be evident in the brain. Different regions of the brain are more active during proactive control use than during reactive control use. During proactive control use, functional Magnetic Resonance Imaging (fMRI) shows longer activation in anterior lateral prefrontal regions above baseline (De Pisapia & Braver, 2006), and event related potential (ERP) data shows medial frontal negativity (West & Bailey, 2012). Conversely, with reactive control use, transient activation in the anterior cingulate cortex and lateral prefrontal cortex are implicated by fMRI (De Pisapia & Braver, 2006), and medial posterior negativity emerges in ERP (West & Bailey, 2012), overlapping with processes involved in dealing with conflict adaptation and interference. Lesion studies have also supported the involvement of these brain regions. For example, anterior cingulate cortex damage has been found to cause a variety of symptoms that indicate cognitive control deficits (Bush, Luu, & Posner, 2000). However, Fellows and Farah (2005) proposed that the anterior cingulate cortex might not be necessary for cognitive control as they found performance remained intact for patients with damage in that area.

Critical for the functionality of the dual mechanisms of control framework, temporal dissociations have also been found such that proactive control is associated with activity in the prefrontal cortex in the time between the cue and target, whereas reactive control is associated with prefrontal cortex activation after target onset (Braver, Paxton, Locke, & Barch, 2009). Braver and colleagues even showed shifts in these regions toward proactive and toward reactive control activation patterns with strategy instructions and rewards or penalties. Together with the physiological dissociations, these findings support the dual mechanisms of control framework in that there does seem to be separation neurologically and temporally in relation to behavioral outcomes that have been proposed to reflect proactive and reactive control.

Further, there is neural evidence for the flexible use of proactive and reactive control. Braver et al. (2009) showed shifts in neural signatures in both younger (to reactive) and older adults (to proactive) from the beginning of the task to the end of the task with reward and penalty manipulations. Supporting the argument that this network is flexible, a monitor has been proposed to direct the use of these mechanisms. After reinforcement learning the anterior insula and inferior frontal gyri have shown elevated activity posited to retain the control demands of the task and send signals to the anterior cingulate cortex and dorsolateral prefrontal cortex where control is taking place (Jiang, Beck, Heller, & Egner, 2015). As the various theories of cognitive control differ on timescale, it is important to evaluate the flexibility of cognitive control over the course of different time scales, particularly at the trial level.

Previous Tasks

Many tasks have been used to investigate cognitive control broadly, such as go/no-go, stop-signal, flanker, and Stroop tasks. The go/no-go and stop-signal tasks are typically considered sustained attention or inhibition tasks, depending on trial type frequencies. Control is seen in these tasks in that preparation is key to fast responding on most trials, and inhibition is key to withholding a response to infrequent no-go or stop-signal trials as a reaction to a designated stimulus or signal. Preparation is a key component of several of the cognitive control accounts (Braver, 2012; Posner & Peterson, 1990), as is inhibition (Miyake et al., 2000). The flanker task is a selective attention task where subjects must respond to the qualities of the central stimulus only in the presence of flanking congruent or incongruent distractors. These distractors, when incongruent, give information that would indicate the opposite response to the correct response, a conflict. Therefore, cognitive control is used to direct or orient attention to only the task-relevant stimulus and inhibit the irrelevant and conflicting information (Verbruggen, Notebaert, Liefooghe, & Vandierendonk, 2006). Similarly, the Stroop task is thought to elicit cognitive control due to the incongruent/conflict trials, particularly in versions where the incongruent trials occur less often than the congruent trials (Appelbaum, Boehler, Davis, Won, & Woldorff, 2014).

Within the dual mechanisms of control framework, the go/no-go and stop-signal tasks would indicate proactive control with fast responding that is very accurate in the go and regular trials but very inaccurate in the no-go and stop-signal trials. In contrast, reactive control would be indicated by slow but accurate performance across trial types. Therefore, global speed/accuracy tradeoffs would be conflated with changes in proactive and reactive control use (Fellows & Farah, 2005). In the flanker task, reactive control is used when incongruent trials follow congruent trials, and proactive control is elicited when an incongruent trial follows another incongruent trial because the preparation will begin after the first incongruent trial in expectation of incongruency in subsequent trials (Suzuki & Shinoda, 2015). The Stroop task is similar in that reactive control is considered sufficient for congruent trials, but proactive control is beneficial for incongruent trials, particularly when they are infrequent (Appelbaum et al., 2014).

The aforementioned tasks have been widely studied in broader cognitive control theories, but the dual mechanisms of control framework is perhaps more easily studied when the task is structured in a way that performance benefits from each proactive and reactive control in separate trial types. Accordingly, studies investigating the dual mechanisms of control framework have largely used the ‘AX’ version of a ‘continuous performance task’ (AX-CPT). A bit of a misnomer, the task is not truly continuous, as cue-probe pairs are demarcated with an inter-stimulus interval (ISI) between the trials. The distinction between proactive and reactive control plays out reasonably well in the AX-CPT because specific responses can be prepared based on the cue information. This type of preparation is not possible, at least to the same degree, in the other cognitive control tasks like Stroop, flanker, and go/no-go.

The AX-CPT is derived from other continuous performance tasks. This task requires subjects to respond to all stimuli with a given keypress unless that stimulus is an X that followed an A cue, in which case an alternate response is made (Figure 1). Typically, the A-X pairing appears on 70% of trials, encouraging subjects to use the A cue to prepare the A-X response, as only 10% of trials (A-Y trials) violate this pattern. In preparing for and expecting, the X that follows the A most of the time, subjects are using proactive control. This preparation is beneficial for performance the majority of the time a subject sees an A, but can be costly on the few trials where that expectation is violated. In these instances of violated expectation (A-Y trials), reactive control is the more beneficial strategy, as a Y-probe never indicates a target response should be made.

The other 20% of trials, B-Y and B-X trials, have a non-A cue, indicating that no matter what follows, a non-A-X keypress is required, also allowing for preparation. Proactive control is beneficial in such a case, because the expectations are predictive 100% of the time following a B-cue, allowing fast and accurate responding. For the B-Y trials, reactive control may be somewhat slower but should be equally reliable as again the Y-probe never requires a target response. However, reactive control may be less efficient on B-X trials, as an X-probe usually elicits a target response and accuracy would depend on memory to recall whether the cue was an A or a B, which may or may not lead to more errors, but certainly costs more time.

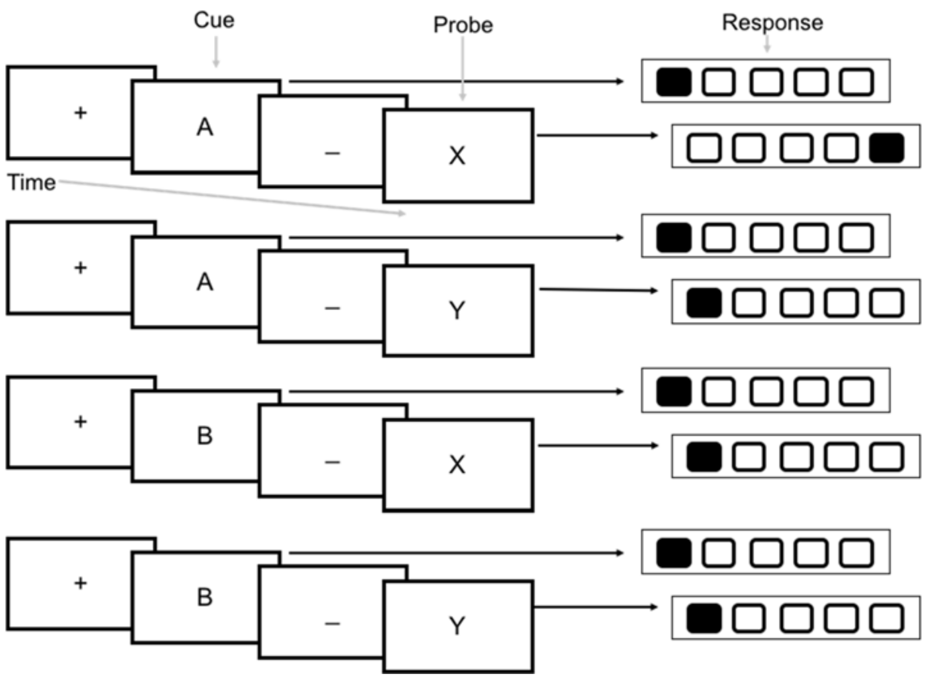


Figure 1. Depiction of AX-CPT trial types and example corresponding response box keypresses.

Findings From the AX-CPT Literature

The AX-CPT has been a useful tool in evaluating cognitive control, particularly within the dual mechanisms of control framework. Proactive and reactive control use has been shown to vary between individuals on several dimensions. For example, older age (Paxton, Barch, Storandt, & Braver, 2006), patient status such as having schizophrenia (Edwards, Barch, & Braver, 2010), and lower working memory (Redick, 2014) are all associated with more reactive and less proactive control use. Use of proactive and reactive control has also been shown to vary with training (Braver, Paxton, Locke, & Barch, 2009) and practice (Paxton, et al., 2006).

Cognitive control use can also vary within an individual. Munakata, Snyder, and Chatham (2012) found that as children grow, they begin to respond to external pressures to enact reactive control, and then shift to proactive control. Further, they found there was a later shift from relying on external cues to developing internal cues for control use. In healthy young adults, proactive control has been shown to increase and reactive control to decrease, with time on the task even in the absence of instructional cues to focus on proactive control, with trial type frequencies that encourage proactive control use (Wiemers & Redick, 2018). Analogous shifts are seen for older adults, who are also initially inclined to use reactive control more often, when given extended practice with or without directed strategy training (Paxton et al., 2006).

Braver (2012) posits that cognitive control developed partly to manage and prepare for instances of interference or conflict. For instance, when A-X happens the majority of the time, seeing a Y after an A (an A-Y trial) produces conflict because it is contrary to the expectation. Accordingly, conflict monitoring has been evaluated in the AX-CPT, similarly to the way it has been evaluated in other tasks that have incongruent trials. Conflict adaptation has been found in the AX-CPT such that A-X trials that follow conflict (A-Y) trials are slower than no-conflict (B-Y) trials (Wiemers & Redick, 2018). This finding is in line with post-conflict and post-error adjustments seen in other cognitive control tasks such as flanker and Stroop (Clayson & Larson, 2011; Unsworth, Redick, Spillers, & Brewer, 2012).

Just as the presence of conflict can alter behavior, trial type frequencies play a large role in performance. The proportions of congruent and incongruent trials in tasks like flanker and Stroop were already discussed as eliciting different amount of proactive and reactive control (Appelbaum et al., 2014). Similarly, in the AX-CPT, trial-type frequencies alter the amounts of proactive and reactive control needed. Redick (2014) found that large proportions of A-X or the otherwise typically conflicting A-Y trials elicited more overall proactive control use. In an A-X-majority task, this results in fast and accurate responding to A-X trials and lower accuracy on A-Y trials. In the A-Y-majority task, the expectation is reversed such that the non-target response is expected and prepared for, resulting in fast and accurate A-Y responses, and lower accuracy on the infrequent A-X trials. However, a version with equal proportions of A-X and A-Y trials made reactive control the optimal performance choice for A-cue trials. A further investigation by Richmond, Redick, and Braver (2015) equated the frequency of the A-X and B-Y trials. This method equated the proportions of A- and B-cues and the X- and Y-probes, to further investigate the use of proactive and reactive control, and resulted in some individuals maintaining proactive control use, resulting in fast and accurate A-X responses and slower and less accurate A-Y responses, in this additional version while others did not. Namely, those higher in working memory capacity, an individual differences measure related to variety of higher order cognitive processes, were much more likely to use proactive control than their lower working memory peers.

Shortcomings of the AX-CPT

The AX-CPT is sufficient for showing global differences in cognitive control, and to some degree dynamic changes in cognitive control use, such as a shift toward proactive control on a task in which proactive control is beneficial the majority of the time (Wiemers & Redick, 2018). However, due to the nature of the task in the standard version, there are very few of the B-X and A-Y trials, which are most useful for looking at proactive and reactive control. These trials occur only 10% of the time each. With these proportions, it can become cumbersome to collect sufficient data to evaluate the infrequent B-X and A-Y trials. Further, this task is limited in that cognitive control is evaluated as a dichotomous process as only trial types that investigate these two possibilities are available. That is, the process is talked about as being proactive or reactive, with no possibility for 'somewhat proactive' or 'more reactive', for example. If the process is not dichotomous, or if there are two processes but they can work simultaneously and are not mutually exclusive, as has been suggested by some (e.g., Braver, 2012; Mäki-Marttunen, Hagen, & Espeseth, 2019), then the AX-CPT would not capture that.

A more sensitive measure would be necessary to answer such questions. In an effort to mitigate these problems, I propose a new task that has similar structure, but moves through trials more quickly because each stimulus is the cue for the next stimulus, in contrast to the explicit cue-probe trial structure of the AX-CPT. This design cuts down the presentation time of a given trial by essentially overlapping them. Critically, the task design creates a range of predictability based on the 'cue', and cognitive control may vary as a function of the stimulus's predictive validity. This would provide an opportunity to measure the extent of subjects' dynamic control.

Analytically, the AX-CPT is limited, too. Signal detection indices (bias and sensitivity), indicating overall preference for making a target response, have been used to index control (Cohen, Barch, Carter, Servan-Schreiber, 1999; Gonthier, Macnamara. Chow, Conway, & Braver, 2016; Redick & Engle, 2011, Wiemers & Redick, 2018). However, measures like *d'* (sensitivity) and *C* (bias), can be difficult to interpret in tasks where trial type frequencies are so imbalanced (Thomson, Besner, & Smilek, 2016). Instead, evaluating the levels of proactive and reactive control often rely solely on accuracy and response time (RT) patterns. For example, fast and accurate responding to frequent target trials (A-X) or non-target conflict (B-X) trials indicates proactive control, whereas slow but accurate responding to infrequent A-Y trials indicates more reactive control.

Other indices of control have also been used in the AX-CPT. For example, a ratio can be calculated with the formula [(AY-BX)/(AY+BX)] to measure control because proactive control use would result in poor A-Y performance and better B-X performance (Edwards, Barch, & Braver, 2010; Paxton et al., 2006). However, this calculation is based on the lowest frequency trials, and small changes in accuracy can affect this calculation dramatically. Further, this calculation has no way of comparing proactive and reactive control use. Increased reactive control use would result in better A-Y performance, but B-X performance would rely on an additional memory component.

More sensitive analyses would be helpful to determine how proactive and reactive processes function. That is, to be able to answer my primary question about the use of both proactive and reactive control together to some degree, a new task is needed that has trial types that do not have optimal strategies that are primarily proactive or primarily reactive, but some middle level where more dynamic use would be most beneficial for performance.

The New Task

This new task involves presenting Arabic numerals 1 through 9. The participant's task is to press one button if the current number is larger than the previous and a different button if the current number is smaller than the previous (Figure 2). These instructions have the benefit of being much more intuitive than the arbitrary letter pairings of the AX-CPT. This paradigm also allows all stimuli to be both the probes and the cues, doubling the number of trials presented in a given length of time. This also increases the number of trials that are indicative of each type of control.

An ideal subject would be sensitive to the probabilities of particular responses in this task and use proactive control to the extent it is beneficial for task performance. For example, proactive control would be most beneficial for trials where there is a 1 followed by another number (1-N) or a 9 followed by another number (9-N), as the current stimulus would always be more than 1 and less than 9, respectively. However, 2-1 and 8-9 trials would be similar to A-Y trials, where there is an expectation of an X following an A, in that a subject is expecting a number larger than 2 and smaller than 8, respectively. A 1 following a 2 (or a 9 following an 8) violates this expectation of a larger (or smaller) number, similar to a Y violating the expectation of an X following an A.

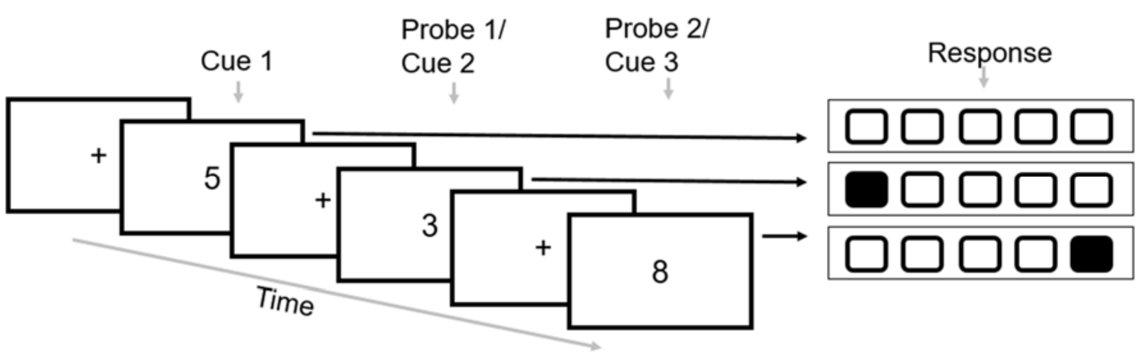


Figure 2. Depiction of new task and example response box keypresses.

Conversely, where no trials cue the use of reactive control in the standard AX-CPT, a 5 in the new task should elicit reactive control as the optimal response strategy, because it does not allow for accurate preparation of a specific response; the following number is equally likely to be larger (6 to 9) or smaller (1 to 4). Further, trials with 3-N, 4-N, 6-N, and 7-N are intermediates, not analogous to any AX-CPT trials. These new types of trials could be particularly informative as to the intricacy of dynamic control. Subjects may adjust the strength of proactive control, manifesting as a smooth gradient of RTs with the fastest at the poles (1 and 9) and slowing closer to 5. Alternatively, it could be that proactive and reactive control are two separate processes that cannot overlap. This would lead to abrupt groupings with distinctly different outcomes. Such a pattern would be indicated by the data from 1-N, 2-N, 8-N, and 9-N trials being very similar – fast and consistent RTs and high accuracy. A separate grouping of data from 4-N, 5-N, 6-N trials would exhibit less accurate responses and slower and more variable RTs. It is uncertain what would happen with 3-N and 7-N trials in such a situation. Trials with 3- and 7-cues would likely cluster with either the trials where the predictive validity is high or where it is equivocal. Because 3-N and 7-N performance may vary for different individuals, there could be large between-subject variability in both accuracy and RTs.

These various trials are critical to the goal of evaluating a dynamic use of cognitive control. With this task providing a stairstep of benefit from proactive to reactive back to proactive as stimulus identity increases (from 1 to 5 to 9), it is possible that I could capture dynamic use of proactive and reactive control. This rapid collection of trial responses allows for more trials in the same amount of time the AX-CPT takes to complete. Especially when considering that the trials could be collapsed symmetrically about 5, the current task increases the number of trials available for evaluating reactive control.

One major concern with the new task is the sensitivity to differentiate between the proposed titration hypothesis, where use of proactive control increases as cues move away from 5, and a numerical distance account, where time to respond depends on how close to the reference point (cue) the number is. Distance effects have been studied extensively since Moyer and Landauer (1967) reported them in an initial study examining how relative size judgements were made. The main finding is that relative size decisions are faster and more accurate the further apart the numbers are. For example, the decision "smaller or larger than 5" is easier to make for 9 than for 6. Many of the studies since these initial findings have held the reference point constant, evaluating the conditions in which distance effects are elevated or dampened. However, distance effects are particularly of concern in the present task because the reference point changes on each trial complicating the comparison of one trial type to another, which is critical for the cognitive control predictions.

Some of the predictions of the titration model rely on the use of the cue to prepare for a response, which suggests the responding should be influenced significantly by the cue, or reference point for the judgement. Holyoak (1978) describes similar findings due to reference point judgments and magnitudes. Holyoak found that increased distance from the reference point was usually related to extended response times. Further, pairs of the same distance were found to be judged slower and less accurately the larger they were. For example, the pair 8-9 was judged slower than the pair 1-2, even though both pairs are different by 1. The relative difference is smaller for 8 and 9 making them ‘seem’ closer.

From the task-switching literature, similar relative numerical judgement tasks with changing reference points have been used to investigate distance effects in relation to switch costs. Schneider and Logan (2007) used two reference points, 2 and 7, so that some digits (those outside of 2-7) would be consistently mapped to a response while others (those between 2 and 7) would vary depending on the reference point. They found that distance effects, slower RTs for closer targets, were present for each reference point. Additionally, responses were slower to varied targets regardless of reference point, and distance effects were still seen within these varied targets, as well. One implication for the current task is that N-1 and N-9 trials are consistently mapped, where N-2 through N-8 trials are variably mapped, which according to Schneider and Logan could lead to different effects between these trial types. Specifically, the N-1 and N-9 trials could be particularly fast because of their consistent mapping.

The key concern is whether the pattern attributed to the proactive and reactive control differences is sufficiently explained by the distance effects. The cognitive control account and distance effect account give subtle but important differences in the model and these models can therefore be compared to evaluate the relative fit. If the data are fit better by the distance effect model, there would be doubt cast on the control account being necessary to explain behavior in this task. However, if the titrated control model fits the data better, it would suggest that the distance model is not sufficient, and the control account better describes the behavior. There is no question as to whether distance effects will be present, but rather whether they are sufficient.

The titration hypothesis makes several specific predictions that would not result from a distance effect alone. The trials that should look most like the distance effect are the 5-N trials, where no predictive value comes from the cue and the cue-target pair must be fully considered together, as in a typical relative number judgement task. Conversely, on 1-N and 9-N trials, the predictive validity from the cue is 100%, so fast and accurate responses should occur to the target regardless of the target identity or distance from the cue. 2-N and 8-N trials are not 100% predictive but are highly predictive, with 87.5% of targets being larger or smaller respectively. Consequently, subjects would prepare to make the majority response and be relatively fast and accurate when a majority-response target appears. Critically, for a 2-1 trial or an 8-9 trial, that expectation is violated, so despite being only 1 digit from the reference point, responses would be particularly slow to these targets.

Further predictions of the titration hypothesis include the symmetry of trials based on predictiveness of the cue. The magnitude effects noted by Holyoak (1978) imply that rather than being symmetrical about 5, the cues larger than 5 in the digit task may result in slower responding to targets than those smaller than 5, particularly for targets that are also larger than 5. Conversely, cue-target pairs that are both below 5 may be particularly fast. The titration hypothesis would predict fairly symmetrical response times about 5 because they would be based on the predictive validity of the cue, rather than the identity of the cue. For example, 2-N trials would roughly mirror 8-N trials such that 2-3 and 8-7 would be equivalent and 2-6 and 8-4 would be equivalent. While these differences sometimes work against one another, generally the distance effect is expected to be present. However, it is not expected to be sufficient to describe the data, particularly in these key areas where the predictions diverge.

EXPERIMENT 1

There were two major aims for Experiment 1. The first goal was to demonstrate that this task is a sensitive measure with which to investigate cognitive control mechanisms. Comparisons to the AX-CPT literature are made to show the similar performance based on proactive and reactive control. Additionally, the new intermediate trial types allow for a more nuanced evaluation of this question than the AX-CPT.

The second goal was to address the question of whether the titrated or grouped pattern emerges, indicating how dynamically these control processes can be used and possibly whether they can interact. As discussed, proactive and reactive control are often considered separate processes, with distinct neural signatures physiologically and temporally. In contrast, some work has shown simultaneous use and improvement in both, indicating that these separate processes can be enacted at the same time (e.g., Cinullera, Fuentemilla, Brignani, Cucrell, & Miniussi, 2014; Mäki-Marttunen, et al., 2019). However, these studies have not shown titrated use at the trial level, but rather trial-to-trial or block-to-block dynamic use.

The hypothesis is that a titrated pattern will emerge indicating that both processes can be enacted simultaneously, and that they can modulate each other proportionally to task demands. The alternative, dichotomous, pattern would indicate that these processes cannot be enacted simultaneously, or they are simultaneous but competitive in nature.

Method

Experiment 1 was preregistered at osf.io/h6x3y. I adhered to the preregistration, except for the additional exploratory analyses for the proactive index. The idea for this index was developed after data collection but before analyses. Additionally, a hybrid model and a distance model were added after preregistration to further evaluate the titration hypothesis.

Participants

A total of 103 young adults completed the study for either partial course credit toward their introductory psychology course or for $10 USD. Two subjects did not complete the session due to crashing the program by hitting the Windows key, and a third subject chose to leave early.

Therefore, there are complete data for $N = 100$ subjects. However, 5 subjects had low responding or low accuracy (less than 50% accuracy on 3 or more blocks) that was substantial enough to warrant exclusion because there would be too few trials for analyses of correct RTs. This occurred for a few reasons: not understanding the response deadline component until several blocks into the task, lack of effort including texting during the blocks, or falling asleep. Ultimately, the data analyzed are from the remaining $N = 95$ subjects. As my preregistered goal of $N = 100$ accounted for potential exclusion of subjects, $N = 95$ is sufficient for my purposes. All subjects who completed the study were between the ages of 18-30 years old and reported normal or corrected-to-normal vision and fluency in English.

Task

The task was created for this project using E-Prime 2.0. Subjects saw digits 1-9 appear one at a time in the center of the screen and were asked to make a 'z' key response with their left index finger if the current number was smaller than the previous number and a '?/' key response with their right index finger if the current number was larger than the previous number. Before completing the task, there was a 10-trial practice section, for which feedback was given after each stimulus. For each of ten blocks, there was a starting number for reference to which no response was made, and then 80 additional numbers to which a response was made. A number appeared for 500 ms before a fixation cross took its place and remained onscreen for 2000 ms. Responses were recorded up to 1000 ms from the onset of the number. After each block, a break screen appeared giving the subjects feedback on their accuracy and how many responses were too slow (see Figure 3). Responses that were too slow were counted as inaccurate.

Procedure

Groups of 1 to 11 subjects completed the session together in a shared lab space with cubicles for each individual. After consenting and completing a brief demographic questionnaire, subjects completed the task. The session took about 45 minutes to complete. Whenever each individual finished, they were given a debriefing form and allowed to quietly exit.

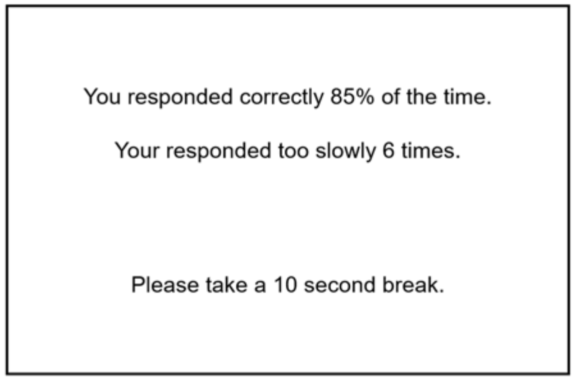
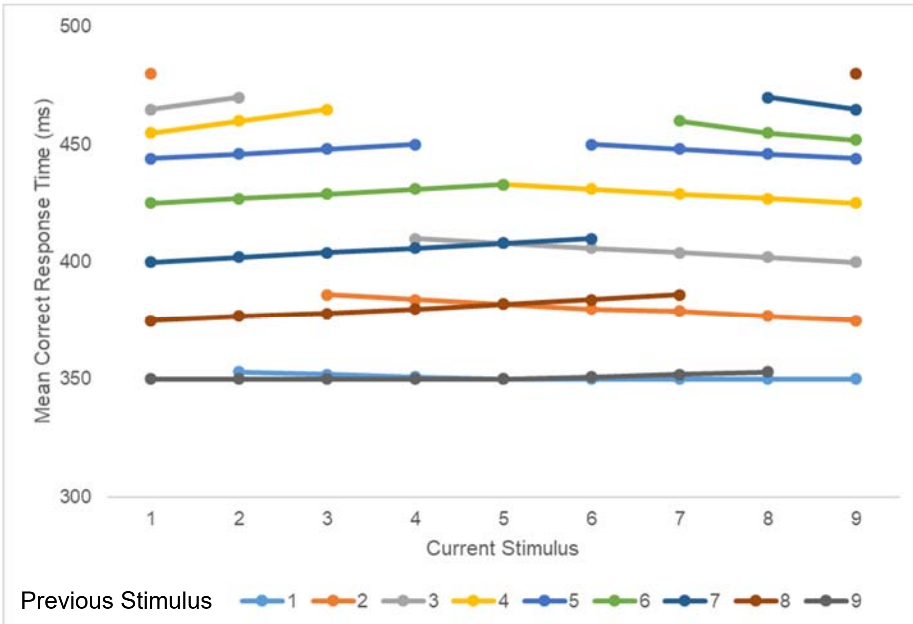


Figure 3. Depiction of example feedback screen subjects saw during each break.

Analyses

The first question this study was intended to answer was how sensitive individuals were to trial-level differences in the need for proactive control. As an initial look at the sensitivity to task demands, the data were visualized by plotting the grand mean RT for correct responses separated by current and previous stimulus. If cognitive control is more of a titrated ability, the data would look more like the hypothetical data in Figure 4A. The 2-N trials, which elicit right responses 87.5% of the time, would look not quite like either the 1-N trials, which elicit right responses 100% of the time of 5-N trials, which correspond to right responses 50% of the time, but would fall somewhere in between. Similarly, the trials with incrementally lower probabilities of 'larger' responses (2-N > 3-N > 4-N) would look incrementally more similar to the 50% trials. However, if cognitive control was dichotomous and competitive, the pattern of data would look like the hypothetical data in Figure 4B. On trials where there is an 87.5% chance of a larger number, either proactive control would win and be enacted to prepare for a 'larger' response or reactive control would win and be enacted based on the target that appears. If proactive control won, the trial would look exactly like a trial where the previous number was a 1 and all following stimuli would be larger. If reactive control won, the trial with 87.5% 'larger' responses would look more like the trials with equal prediction (5-N).

A



B

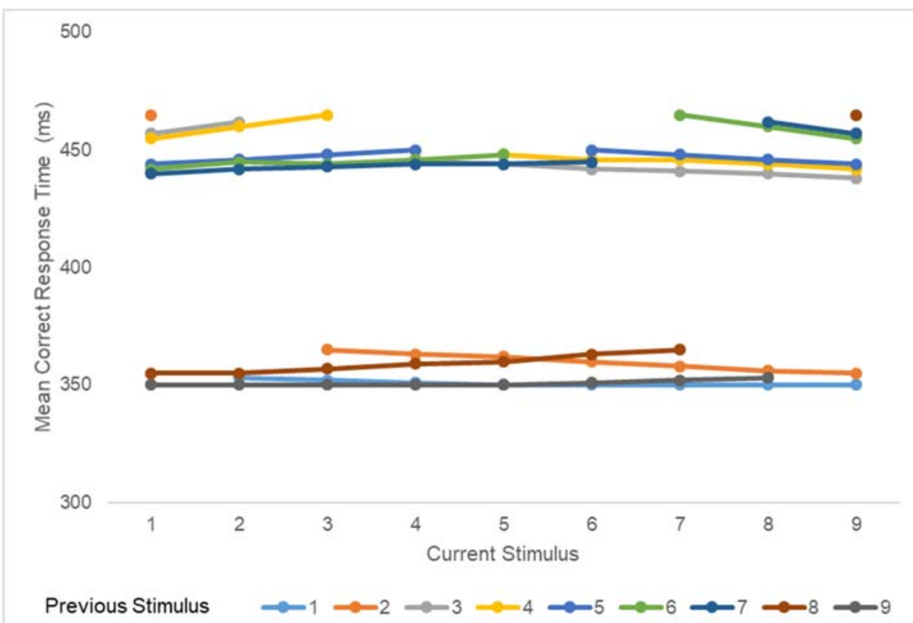


Figure 4. Hypothetical results for Titrated (A) and Dichotomous (B) processes.

In addition to this visualization, the models were compared for the two hypothesized patterns to determine which pattern fit the data better when considering trial-level data. One model was constructed to predict RTs based on the previous trial stimulus. That is, the distance of the previous trial stimulus from 5 was the sole predictor of performance. This model looks at the strength of the cue alone but does not account for the full pattern of interest. Accordingly, corresponding models with target effects and cue-target interactions were evaluated for each theory. This model allows for the gradient pattern expected, considering each level of proactive control benefit as a separate predictor and the cue-target interaction which is critical for examining both proactive and reactive control use. The alternate model groups previous stimuli by whether proactive or reactive would be most likely if they were more dichotomous. Here, 1-N, 2-N, 8-N, and 9-N were grouped as more proactive, and 3-N through 7-N as more reactive. It was unclear, *a priori,* what performance on 3-N and 7-N might look like, but as there is more uncertainty in these trials, I anticipated they might be grouped with the more reactive trials. As there is a very low probability of the 2-1 and 8-9 trials, I anticipated 2-N and 8-N might show performance similar to the 1-N and 9-N trials.

To compare to previous work with the AX-CPT task, some simpler questions were investigated through more traditional analyses. Accuracy and RT means and variabilities were evaluated. The trials most analogous to "AY" conflict trials in the AX-CPT were reviewed in the new task. These are the trials where there was a 1 following a 2 or a 9 following an 8. In the standard AX-CPT, 'Y' only follows 'A' on 12.5% of the trials where an 'A' cue has occurred; in the current task, 1 only follows 2 on 12.5% of the trials where a 2 has occurred. These are both situations where expectation is violated and reactive control actually benefits the participant, by being able to choose the correct response despite the lower probability that such response would be needed. Subjects who are enacting proactive control on these types of trials will prepare the incorrect response, leading to either quick false responses or slower correct responses due to the need to disengage the incorrect, but more probable, response. If a subject were being completely reactive across trial types, no difference in speed or accuracy would be found on these trials versus any others.

Finally, in an effort to quantify the overall gradient pattern for use in individual differences research, I created a proactive index. Because the 5-N trials (trials where 5 is the digit that precedes the current stimulus) indicate an equal likelihood of the two response options, these trials can be considered a reactive control baseline. The degree to which a subject is inclined to enact proactive control then can be measured by comparing this reactive baseline to the 1-N and 9-N trials, where proactive control leads to fast and accurate responses 100% of the time. If a subject is never engaging proactive control, these trials will look very similar to the 5-N trials, whereas proactive control use would lead to a larger difference. First, I averaged the 1-N and 9-N trials together, and then subtracted that average from the 5-N trials. For correct RTs, reactive control leads to slower responding, so a larger positive number in this index suggests more proactive control use. This index is for RTs, rather than the accuracy or the *d'* sensitivity measure used with the AX-CPT. This is because the comparison here is quite different. The *d'* measure taking into account hit rates (A-X target responses) and false alarms (B-X incorrect target responses) in the AX-CPT is focused on the target X, where in this control index, the cue is the key determinant of performance due to the level of proactive control that it may elicit.

Results

Descriptive Statistics

Correct RT means are summarized in Table 1, and correct RT individual standard deviations are summarized in Table 2. Responses were particularly fast when the previous stimulus was 1 (1-N) or 9 (9-N), which follows from a proactive control account such that ability to prepare should be beneficial on these trials. This finding is also in line with previous findings regarding mapping consistency. Though the mapping for the specific targets is not consistent, the mapping is consistent for any target following a 1 or a 9. The presence of this strong mapping effect further supports the presence of proactive, rather than reactive control for these trials. Responses were progressively slower approaching previous stimulus 5 (5-N). That is, responses to 2-N trials were generally faster than responses to 3-N trials and so on. This pattern suggests that subjects were sensitive to the varying benefit of using proactive control in the task, and the lack of benefit of proactive control use for 5-N trials.

Variability in RTs, as measured by individual standard deviations, were similar across trial types. However, responses tended to increase in variability toward the diagonal in the table. That is, responses were more variable when the current stimulus was close in numerosity to the previous stimulus. Overall, individual standard deviations (ISDs) were larger moving away from 5-N trials.

Proactive control is not useful in the 5-N trials, so most participants should be treating those trials similarly – waiting until the digit appears, and then choosing the appropriate response. In contrast, individuals may be more or less likely to use proactive control than other subjects even when it is most useful, leading to higher variability in these trials.

The average error rate across trial types was 11%. Errors for individual trial type combinations are listed in Table 3. This error rate encompasses both incorrect responses and non-responses or past-deadline responses. Non-responses occurred in approximately 2.7% of total trials in the final sample. The majority of any one subject's non-responses came from the same block and usually their first block.

Pattern

The hypothesized pattern for a titrated relationship between proactive and reactive control was somewhat supported. While there is a jump from 1-N/9-N to the other trial types, the overall observed pattern (Figure 5A) does show this incremental pattern of the titration hypothesis (Figure 4A).

While the pattern does not perfectly match the hypothesized pattern, it is clear that there is some level of sensitivity to the task demands. There is a clear separation of the 1-N and 9-N trials from the rest. However, the remaining trials do not group tightly together as they would in the dichotomous model. Rather, there are clear separations in the predicted titrated pattern within these trial types. With the exception of the added benefit afforded to 1-N and 9-N trials, this pattern fits well visually with the titrated model.

Not wanting to rely on visual patterns, mathematical models were developed to compare these two hypotheses, titrated versus dichotomous. To prepare for this, the following data transformations occurred: 1. Data were collapsed such that Previous Trial folded symmetrically at five (e.g., 7's were recoded as 3's and 6's recoded as 4's). 2. The new folded variable was subtracted from 5 so that 5 was a meaningful zero intercept, and the effect of the distance from 5 could be more easily interpreted. 3. Dummy variables were created to group trials in "Proactive" and "Reactive" for Model 2.

Table 1. Response Time Means and Standard Deviations for Previous Stimulus and Current Stimulus for Experiment 1

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean*	*SD*
1		373	360	370	357	356	358	363	356	362	7
		(89)	(76)	(88)	(71)	(76)	(71)	(74)	(68)		
2	472		463	436	427	430	434	434	424	440	18
	(60)		(73)	(77)	(66)	(75)	(69)	(68)	(55)		
3	479	478		450	447	449	445	445	434	453	16
	(62)	(66)		(69)	(78)	(71)	(69)	(64)	(59)		
4	474	469	475		459	460	457	446	453	462	10
	(72)	(71)	(67)		(69)	(64)	(61)	(59)	(54)		
5	465	462	464	475		459	460	445	434	464	6
	(62)	(71)	(74)	(68)		(68)	(66)	(67)	(55)		
6	452	453	456	473	491		479	470	466	467	14
	(58)	(71)	(67)	(74)	(79)		(66)	67)	(58)		
7	440	437	452	473	473	494		477	476	465	20
	(59)	(65)	(68)	(78)	(75)	(78)		(61)	(61)		
8	431	429	442	449	466	473	457		466	452	17
	(60)	(70)	(70)	(74)	(80)	(71)	(84)		(53)		
9	360	358	356	367	375	368	363	379		366	8
	(66)	(72)	(73)	(69)	(86)	(77)	(85)	(99)			
Mean	446	432	434	437	437	436	433	434	442	437	5
SD	39	44	48	44	48	50	47	42	39	42	

Table 2. Response Time Individual Standard Deviation Mean for Previous Stimulus and Current Stimulus for Experiment 1

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean ISD*	*SD*
1		133	128	121	113	117	111	119	104	118	9
		(60)	(62)	(56)	(49)	(47)	(51)	(54)	(40)		
2	84		126	109	101	105	106	102	90	103	13
	(42)		(55)	(46)	(47)	(51)	(52)	(46)	(43)		
3	86	92		110	107	99	95	95	87	96	9
	(47)	(45)		(46)	(44)	(49)	(49)	(41)	(43)		
4	87	92	103		113	105	98	88	92	97	9
	(42)	(45)	(46)		(50)	(47)	(46)	(46)	(42)		
5	86	96	99	98		101	101	93	85	95	6
	(40)	(45)	(53)	(44)		(44)	(47)	(45)	(39)		
6	88	100	100	110	115		104	94	82	99	11
	(45)	(48)	(50)	(51)	(49)		(43)	(50)	(39)		
7	78	95	98	110	112	116		101	87	100	13
	(35)	(44)	(46)	(50)	(50)	(54)		(46)	(45)		
8	79	101	105	102	119	113	116		83	102	14
	(32)	(49)	(43)	(47)	(51)	(46)	(46)		(43)		
9	110	114	113	124	138	126	127	136		123	10
	(50)	(46)	(53)	(52)	(62)	(53)	(53)	(62)			
Mean	87	103	109	111	115	110	107	104	89	104	10
SD	10	14	12	9	11	9	10	16	7	10	

Table 3, Mean Percent Error and Standard Deviations for Previous Stimulus and Current Stimulus for Experiment 1

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean*	*SD*
1		12	13	8	6	6	5	4	4	7	4
		(13)	(14)	(12)	(10)	(9)	(9)	(9)	(8)		
2	17		20	13	8	7	7	5	5	10	6
	(15)		(17)	(12)	(11)	(10)	(9)	(7)	(7)		
3	14	17		18	11	9	8	5	6	11	5
	(14)	(17)		(15)	(11)	(14)	(11)	(9)	(8)		
4	11	17	18		15	15	10	10	7	12	3
	(13)	(13)	(16)		(14)	(12)	(12)	(11)	(8)		
5	10	9	13	16		16	17	10	9	13	3
	(11)	(12)	(13)	(15)		(15)	(15)	(12)	(10)		
6	8	10	12	15	24		18	12	14	14	5
	(12)	(12)	(14)	(15)	(17)		(16)	(12)	(13)		
7	6	9	9	12	19	24		15	14	13	6
	(10)	(11)	(11)	(13)	(14)	(18)		(13)	(14)		
8	4	7	7	10	15	17	22		16	12	6
	(8)	(10)	(11)	(12)	(16)	(17)	(16)		(16)		
9	4	4	6	8	7	9	12	15		8	4
	(8)	(8)	(9)	(11)	(10)	(10)	(13)	(17)			
Mean	9	10	12	12	13	13	12	9	9	11	2
SD	5	4	5	4	6	6	6	4	5	2	

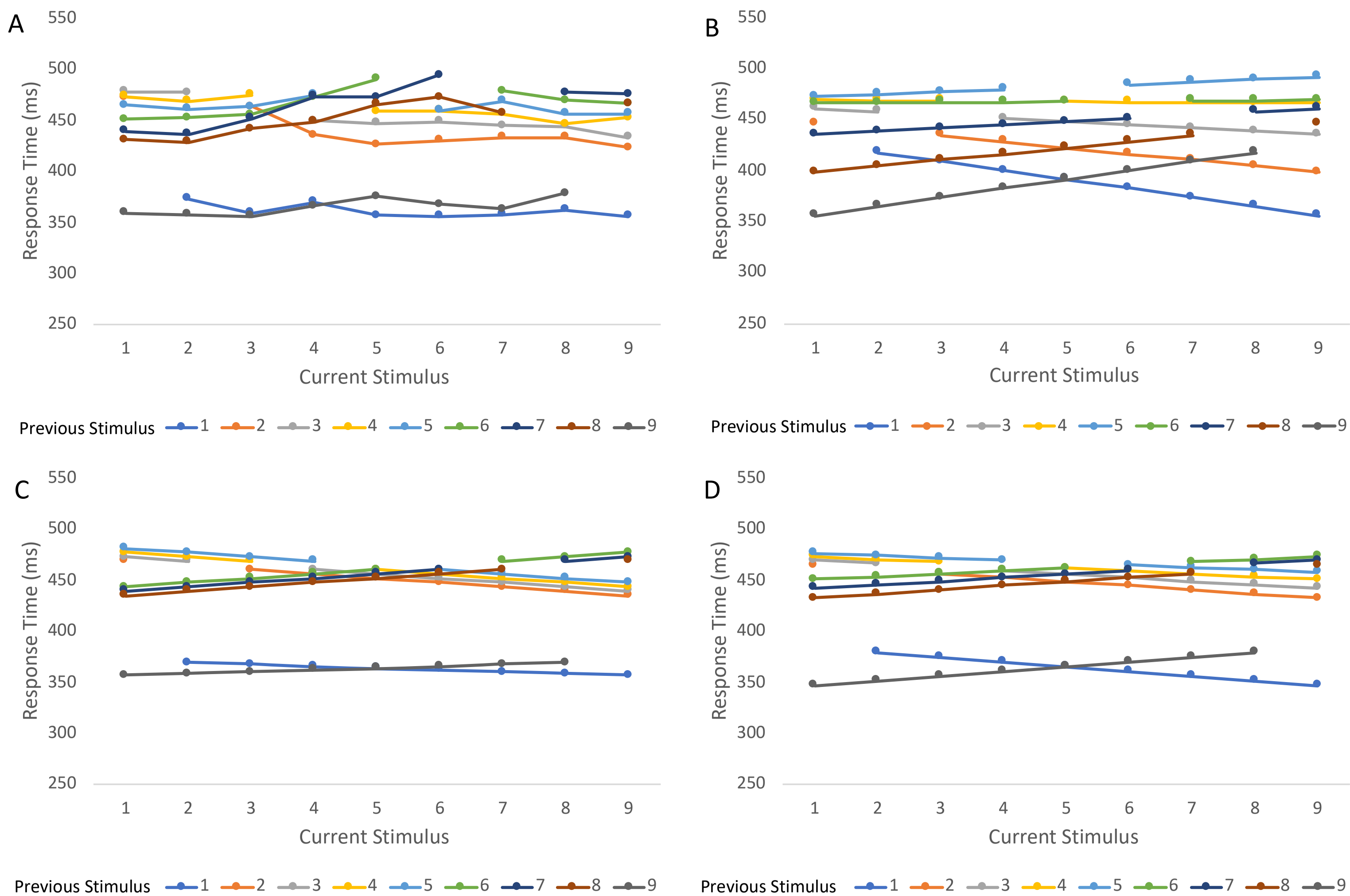


Figure 5. Observed (A) and Modeled Titration (B), Dichotomous (C), and Hybrid (D) patterns for Experiment 1 correct response times.

The titrated model (Model 1) allows the previous stimulus to load separately but ordered, accounting for proactive and reactive control in a titrated pattern. Of note, PreviousStimulus is a coded variable such that the cue stimuli are collapsed about 5 then given a number for their distance from 5. This allows the model to use 5 as a reference point and distance from 5 as progressively more influential, as the titrated model would predict. All models include a random intercept for Subject, accounting for individual differences in overall speed of responding.

For Model 2, first, trials 1-N, 2-N, 8-N, and 9-N were grouped as 'proactive' according to the initial alternative hypothesis (Model 2a). However, upon viewing the data pattern, it was clear that this would inhibit the model from fitting well, and a second grouping of 1-N and 9-N versus the rest (Model 2b) was made to adjust the alternate model to something that more closely approximated the observed data. Therefore, the following three models were compared:

(1) Titrated model: $ResponseTime_i = (b_0 + b_{0i}) + (b_1)PreviousStimulus + r_i$

(2a) Dichotomous model: $ResponseTime_i = (b_0 + b_{0i}) + (b_1)Grouping1289 + r_i$

(2b) Dichotomous model: $ResponseTime_i = (b_0 + b_{0i}) + (b_1)Grouping19 + r_i$

These models were run using the lme4 package in R. As they are not nested models, the comparison is not a hypothesis test, but rather comparing AIC and BIC values. Table 4 presents these values. Lower values suggest better model fit. The model grouping 1-N and 9-N by themselves (Model 2b) fit much better than the model grouping 2-N and 8-N with 1-N and 9-N (Model 2a), suggesting the post-hoc adjustment was appropriate. However, Model 2b also fit better than the titrated model (Model 1).

Table 4. Model Comparison for Experiment 1

	Cue		Cue-Target	
Model	AIC	BIC	AIC	BIC
Titrated model (1, 3)	836097	836134	835193	835248
Dichotomous model (2a, 4a)	837273	837310	836400	836455
Dichotomous model (2b, 4b)	833878	833915	833296	833351
Hybrid model (H1, H2)	833679	833724	833275	833339

Note. Smaller numbers indicate better model fit, but the units of these measures themselves are meaningless.

Models 1 and 2 only consider the effect of the cue, but the target also plays a role, especially when reactive control is enacted. Target is coded as the distance from the cue, retaining a positive or negative sign to indicate the direction from the cue as these are expected to be different in the titrated model. For example, a 2-1 trial is very different than a 2-3 trial in the titrated model, and this coding scheme accounts for that. Model 3 adds a main effect of target as well as a cue-target interaction term to the titrated model, and Model 4a and Model 4b do the same for the dichotomous models:

(3) Titrated model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{PreviousStimulus} + (b_2)\text{Target} + (b_3)\text{PreviousStimulus*Target} + r_i$

(4a) Dichotomous model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{Grouping1289} + (b_2)\text{Target} + (b_3)\text{ Grouping1289*Target} + r_i$

(4b) Dichotomous model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{Grouping19} + (b_2)\text{Target} + (b_3)\text{ Grouping19*Target} + r_i$

As with the simpler models, AIC and BIC were compared to evaluate which model better fits the data. These values are again reported in Table 4. The dichotomous model is preferred, with the lowest AIC and BIC of the three models. Further, Model 4b is preferred to Model 2b, which shows that the addition of target information helps the model. Figure 5 shows the averaged estimates for the titrated interaction model (Figure 5B) and the dichotomous interaction model (Figure 5C).

Bayesian model comparisons were also used to evaluate the models. These were also run in R, using the generalTestBF function. The models were otherwise identical to the frequentist models. However, as the post-hoc adjustment to the dichotomous model was well established, only the Grouping19 versions were used. Table 5 shows the Bayes Factors for both the Cue and Cue-Target interaction models. They have been named with 'B' then the name of the corresponding frequentist model. So, Model B1 is the cue-only model for the titrated hypothesis, Model B2 is the cue-only dichotomous model, Model B3 is the titrated interaction model and Model B4 is the dichotomous interaction model. Larger Bayes Factors indicate stronger evidence for a given model against a null, intercept-only model. The relative Bayes Factor of one model over the other shows the strength of evidence for the numerator model if greater than 1 and evidence for the denominator model if between 0 and 1. Models are specified as follows:

(B1) Bayes Titrated model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{PreviousStimulus} + r_i$

(B2) Bayes Dichotomous model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{Grouping19} + r_i$

(B3) Bayes Titrated model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{PreviousStimulus} + (b_2)\text{Target} + (b_3)\text{PreviousStimulus*Target} + r_i$

(B4) Bayes Dichotomous model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{Grouping19} + (b_2)\text{Target} + (b_3)\text{PreviousStimulus*Target} + r_i$

Table 5. Bayesian Model Comparisons for Experiment 1

Model	Cue	Cue-Target
Titrated model (B1, B3)	$1.92e^{922}$	$6.19e^{1080}$
Dichotomous model (B2, B4)	$4.70e^{1328}$	$1.28e^{1438}$
Hybrid model (BH1, BH2)	$1.99e^{1363}$	$1.12e^{1436}$
Comparison		
Titrated/Dichotomous	$4.08e^{-407}$	$4.82e^{-358}$
Hybrid/Dichotomous	$4.25e^{34}$	0.01

Note. Large and small values have been reported in scientific notation. For the comparisons, values above one favor the numerator model and values between zero and 1 favor the denominator model.

Both the Cue and Cue-Target model comparisons show decisive evidence in favor of the dichotomous model versus the titrated model, indicating that the dichotomous hypothesis more accurately reflects the behavior observed. Figure 5 shows the observed averaged data for each cue and target pairing (Figure 5A). It also shows averaged estimates for the titrated model (Figure 5B) and the dichotomous model (Figure 5C). It is clear from these projections that neither model is capturing the whole pattern, as the titrated model is clearly incapable of producing the gap between 1-N and 9-N trials and the remaining trials and the dichotomous model is not fully capturing the separation occurring in the 2-N through 8-N grouping.

Hybrid Model

The titration process, however, could still be occurring, and therefore be an important component for accurately modeling the behavior. It is possible that the titration component is necessary to describe behavior in the 2-N through 8-N trials, but the grouping factor from the dichotomous model is necessary to capture some additional phenomenon that may be occurring. To investigate this possibility, an additional model was estimated. This model is a post hoc adjustment to the titration model and should be considered exploratory. It was not included in the preregistration and was specified after seeing the results from the models that had been preregistered. The idea for this model is that the titration hypothesis may describe the majority of the pattern, but the 1-N and 9-N trials have something additional going on that requires a grouping factor to accommodate this gap. That is, both the titration factor and the grouping factor are needed to accurately reflect the behavior. So, the grouping factor "Group19" from the dichotomous models was added on to the titration models as a main effect only. This factor simply allows the model to boost the 1-N and 9-N trials closer to the observed performance level without affecting the other trial types. Both cue-only and cue-target interaction models were estimated as both frequentist and Bayesian models. Other than the addition of the Group19 main effect, they are the same as the titration models described previously. Frequentist hybrid models have been numbered with an H and Bayesian hybrid models have been numbered with BH. Models are specified as follows:

(H1) Hybrid model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{PreviousStimulus} + (b_2)\text{Group19} + r_i$

(H2) Hybrid model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{PreviousStimulus} + (b_2)\text{Target} + (b_3)\text{PreviousStimulus*Target} + (b_4)\text{Group19} + r_i$

(BH1) Hybrid model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{PreviousStimulus} + (b_2)\text{Group19} + r_i$

(BH2) Hybrid model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{PreviousStimulus} + (b_2)\text{Target} + (b_3)\text{PreviousStimulus*Target} + (b_4)\text{Group19} + r_i$

The AIC and BIC for models H1 and H2 are presented in Table 4. They produce the lowest AIC and BIC of the four models. This is in line with the visual discrepancy in Figure 5, that neither the titration nor the dichotomous models capture the pattern fully. This suggests that the information in the titration model is preferred when the addition of a grouping factor allows 1-N and 9-N trials to deviate from the group. The modeled data are presented in Figure 5D, which illustrates the additional information allows the model to be visually much more similar to the observed data.

The Bayesian model comparisons are presented in Table 5. The results are in line with the frequentist models in that the hybrid model is preferred above the dichotomous model for the cue-only model. Again, this supports the idea that the titration hypothesis is supported if 1-N and 9-N trials are allowed to deviate. However, the cue-target model disagrees with the frequentist models and the cue-only model and instead favors the dichotomous model. A *BF* = 0.01 favors the comparison model (in this case the dichotomous model) to the degree of a *BF* = 100. While this seems like a very weak number compared to the others in the analyses, which have been orders of magnitude larger, a 100 is generally considered very convincing.

Distance Effect

Bayesian models were employed for this analysis. This comparison was not preregistered, but it is critical to the understanding of feasibility of a titration hypothesis. For the Directional model, the Target is classified with the plus or minus indicating the direction from the cue, in addition to the numerical distance (e.g., 2-3 = 1, 2-1 = -1) from the cue, as it was for the titrated models. This is renamed TargetDirectionalDistance for this comparison for clarity. For the Distance only model, the Target is classified by the absolute value of the distance (e.g., 2-3 = 1, 2-1 = 1) from the cue, taking into account the distance but not direction from the cue. This is named TargetAbsoluteDistance for this comparison, for clarity. Table 6 lists Bayes Factors for Directional (Model B5) and Distance only (Model B6) for a Target-only model and Directional (Model B3) and Distance only (Model B7) for a Cue-Target interaction model. The Directional Cue-Target model is identical to the titration Cue-Target model (Model B3), so it has not been renamed.

(B5) Bayes Directional model: $\text{ResponseTime}_i = (b_0 + b_{0i}) +$

$(b_1)\text{TargetDirectionalDistance} + r_i$

(B6) Bayes Distance Only Model: $\text{ResponseTime}_i = (b_0 + b_{0i}) +$

$(b_1)\text{TargetAbsoluteDistance} + r_i$

(B7) Bayes Distance Model: $ResponseTime_i = (b_0 + b_{0i}) + (b_1)PreviousStimulus + (b_2)TargetAbsoluteDistance + (b_3)PreviousStimulus*TargetAbsoluteDistance + r_i$

There is a strong preference for the directional model for the Target-only model (Model 5) and the Cue-Target interaction model (B3). This indicates that distance alone is not sufficient to describe the pattern of data and that the directional information is important, as predicted with the titration hypothesis.

Table 6. Bayesian Model Comparison of Directional Versus Distance Effect for Experiment 1

Models Experiment 1	Target	Cue-Target
Directional model (B5, B3)	$1.51e^{494}$	$1.29e^{1080}$
Distance Only model (B6, B7)	$5.14e^{410}$	$1.82e^{1033}$
Relative BF	$2.95e^{83}$	$3.40e^{45}$

Proactive Index

Reactive control should lead to optimal performance, as fast and accurate as possible, for the trials where the previous trial was a 5, as the 5 provides no predictive information. Preparation of a response, which is often a result of using proactive control, would be detrimental in that the prepared response would be accurate only 50% of the time, and inhibiting an initial response in favor of a corrected response would be more costly to performance. Therefore, with the expectation that proactive control produces faster responding, more proactive subjects should have a larger difference from the reactive baseline performance on 5-N trials than less proactive individuals. Subjects were generally more proactive on the 1-N and 9-N trials (1- or 9-N M = 364 ms, SD = 65 ms) than the 5-N trials (5-N M = 464 ms, SD = 55 ms), with an average difference index of 100 ms (*SD* = 48 ms). However, they were quite variable from one another, with scores ranging from 1 ms to 223 ms. The distribution of this index is shown in Figure 6.

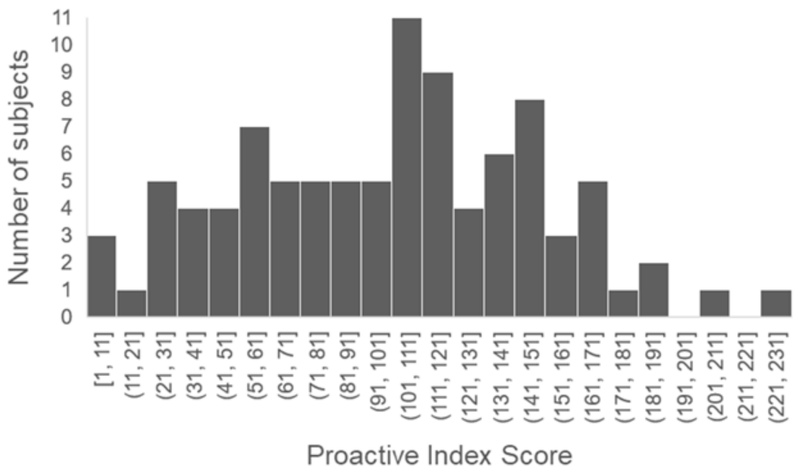


Figure 6. Distribution of proactive index scores for Experiment 1.

Comparison to AX-CPT

To compare to the previous literature, the trials most similar to critical trials in the AX-CPT were analyzed. Analogous to B-X trials are those where proactive control leads to highly accurate quick responding, because a B-cue never indicates a target press for the subsequent letter. However, reactive control leads to lower accuracy and possibly slower responses, as the subject must think back from the X to determine whether the cue was A (meaning the X is a target) or a B (meaning the X is not a target). Trials analogous to B-X trials are the trials where the current stimulus would typically require a particular response but requires the opposite response due to the cue: 1-2, 1-3, 2-3, 8-7, 9-7, and 9-8. Conversely, proactive control leads to poorer performance on A-Y trials, where the expectation of an X has been induced by the cue A, but the Y then violates that expectation and a non-target response is required. Analogous to this trial type are those trials where the cue strongly predicts a particular response, but the other response is required: 2-1, 3-2, 3-1, 8-9, 7-8, and 7-9.

To compare the effects of these trials, the 6 mentioned trial type combinations were collapsed. Paired samples *t*-tests were employed to determine if there were differences in these two groups of trials. For the error rates, (‘B-X’ *M* = 16%, *SD* = 10%; ‘A-Y’ *M* = 17%, *SD* = 10%), there was no difference between the 'B-X' grouping and the 'A-Y' grouping, $t(94) = 0.03$, $p = .861$. However, the mean RTs were different between the two trial type groups, $t(94) = 18.28$, $p < .001$, with the 'B-X' trials being faster (M = 397 ms, SD = 65 ms) than the 'A-Y' trials (M = 473 ms, SD = 50 ms). This provides some evidence for proactive control use, as faster B-X trials would follow from preparing a non-target response in the AX-CPT. Similarly, fast and accurate responding to the less-frequent response in the Digit Decision task also indicates use of the cue to prepare the appropriate response. The error rates have large variabilities, which may indicate that on an individual level some individuals would have higher 'B-X' or higher 'A-Y' errors, but there is large person-to-person variability in the sample.

Discussion

The pattern of mean RTs suggests that both proactive and reactive mechanisms are being used on appropriate trials, at least the majority of the time. As these trials are intermixed, either both mechanisms are enacted together, or subjects are able to rapidly switch between them. The gradient or titrated pattern suggests that both may be active at the same time to varying degrees. I opt for this explanation over a continuum explanation due to work by Braver that suggests neurophysiological evidence for separate mechanisms, rather than a single mechanism that is more or less proactive at a given time. These two mechanisms then would both be active, but the proactive mechanism may have priority. However, to catch conflict trials, such as a 1 following a 2, when the expectation is that 87.5% of numbers following a 2 will be larger, would require that there be an inhibitory mechanism at the ready for such occasions. Is this the reactive mechanism?

The overall pattern was not fit particularly well by either the original titration model or the dichotomous model. Of the two hypothesized models, the dichotomous model was preferred, likely because the residuals resulting from the missing separation in the 2-N through 8-N trials were much smaller than the large residuals that would remain from the 1-N and 9-N trials not being allowed to deviate in the initial titration model. Unsatisfied with either model, a new model was evaluated post hoc. This new model added the grouping component to the titration model and was then preferred to either model for both the cue-only and cue-target interaction models for the frequentist models, and the cue-only model for the Bayesian models. However, it was not preferred to the dichotomous model for the Bayesian analysis. So, the hybrid model is generally, but not unanimously, favored.

Despite being called the 'hybrid' model due to the way it is specified, it is unclear what the grouping mechanism would necessarily be estimating. It seems unlikely that there would be two sets of mechanisms for control, one of which is dichotomous and the other titrated. Rather, it seems more likely that something like the mapping effect would be causing the special status of the 1-N and 9-N trials moving away from the otherwise titrated pattern of behavior. This mapping effect is seen consistently throughout relative number judgement tasks. However, it would generally be expected to influence targets (e.g., N-1 and N-9 trials, which are consistently mapped) rather than the cue, which itself is consistently mapped but is not necessarily followed by consistently mapped stimuli.

This seems to be a special case of the mapping effect where proactive control is used to impose a mapping effect onto otherwise variably mapped stimuli. That is, after a 1-cue, a 2-target may appear. A 2 usually elicits a "smaller" judgment, but requires a "larger" judgement in this case. It is variably mapped, and further is mapped mostly to the opposite of the necessary response in this instance. However, due to the proactive control afforded by the 1-cue, that participant can ignore the target identity, which would have variable mapping, and prepare to make a specific and correct response. This consistent mapping only occurs for the 1-N and 9-N trials, and is therefore a likely candidate for the mechanism behind their special status. The Group19 main effect would sufficiently account for this component.

Another concern regarding the feasibility of the titration hypothesis was the distance effect. Differences in RTs occur for number comparison judgements due to numerical distance effects. For example, it is easier to pick the larger of 4 and 9 than it is to pick the larger of 4 and 5. As numbers get closer, RTs slow. This effect was anticipated in this task. However, the degree to which it can explain the full behavior pattern was the key concern. If the distance effect was sufficient to cause the behavior, there would be no need to discuss the effect of cognitive control on the data. However, the titration models were preferred to the distance effect models, indicating that the distance effects present were not sufficient to describe the pattern and that the titration model added important information such that it was better able to fit the observed data.

The proactive index is of particular interest. The amount of variability in this index is promising for use as a measure of individual differences. Some subjects clearly are not showing a difference at all between 5-N and 1- and 9-N trial RTs, where others are showing very large differences. This indicates that some individuals may not use proactive control even when it is beneficial, resorting to reactive control for all trials, indiscriminately (Figure 7A), or in the grouped pattern (Figure 7B). However, others, who are showing large differences, may be more inclined to use more proactive control when it is useful, and perhaps more dynamic shifting between proactive and reactive (Figure 7C).

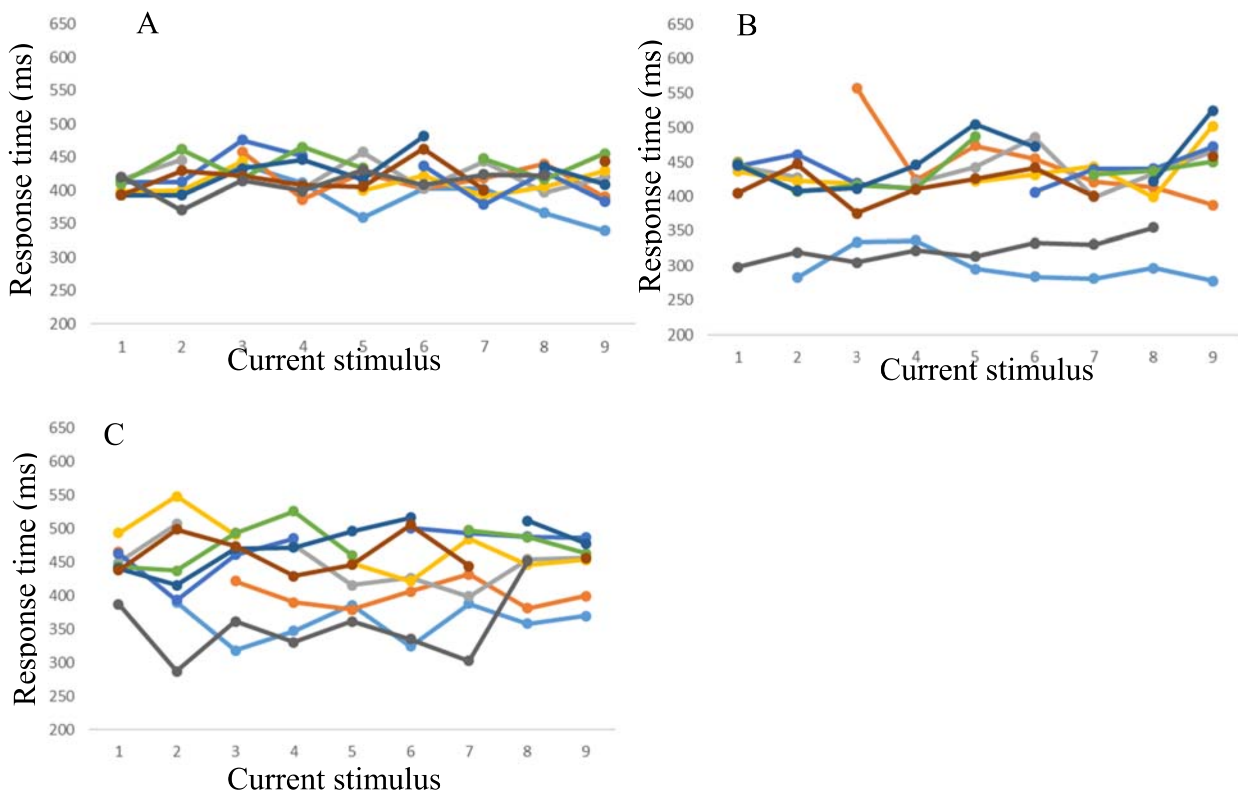


Figure 7. Exemplar subject data for subjects more inclined toward overall reactive control (A), reactive control except on 1-N and 9-N, and more proactive or more dynamic control (C).

EXPERIMENT 2

As the pattern has been established to show subjects are capable of sensitivity to the differences in benefit of using proactive versus reactive control at the trial level, one question that follows is how individuals vary in this sensitivity. Experiment 1 showed substantial variability in the proactive index measure, and these differences are confirmed by looking at example individuals with varying patterns (Figure 7). These individual differences make sense in the context of the vast literature on working memory relationships with cognitive control ability.

Working memory has been proposed to relate to many higher-order cognitive constructs. Working memory was at one time thought to be interchangeable with short-term memory until modeling methods provided evidence for their distinctiveness (Engle, Tuholski, Laughlin, & Conway, 1999). Working memory has also been proposed to be interchangeable with intelligence or *g*, but similarly is not quite the same despite high correlation (Ackerman, Beier, & Boyle, 2005). Individual variability in working memory capacity has even been proposed to be due to cognitive control variation, although evidence from visual search and task-set switching tasks do not often support this close relationship (Kane, Conway, Hambrick, & Engle, 2007). More recently, working memory has been thought to reflect maintenance of task-relevant information compared to intelligence reflecting disengagement when information becomes irrelevant, with both relying on cognitive control (Shipstead, Harrison, & Engle, 2016; Engle, 2018).

Though working memory and cognitive control are not entirely the same, they are highly related in many situations. Across cognitive control tasks, higher working memory has been associated with greater proactive control use and low working memory has been associated with greater reactive control use. This is evident in the Stroop task where only high working memory individuals showed maintained use of proactive control across many trials to anticipate conflict from incongruent stimuli (Hutchison, 2011; Kane & Engle, 2003). Working memory is also consistently related to performance on the go/no-go task where cognitive control is necessary for fast and accurate responding to frequent go trials and crucially to manage infrequent no-go trials (Redick, Calvo, Gay, & Engle, 2011; Wiemers & Redick, 2019).

In the AX-CPT, working memory is also consistently related to performance. Higher working memory individuals tend to use more proactive control, resulting in faster and more accurate responding the majority of the time, particularly on A-X and B-X trials (Ball & Brewer, 2018; Redick, 2014; Redick & Engle, 2011; Richmond, Redick, & Braver, 2015; Stawarczyk, Majerus, Catale, & D'Argembeau, 2014; Wiemers & Redick, 2018). However, individuals with low working memory are just as capable of using proactive control, evidenced by equally fast and accurate performance in the fastest quantile of RTs on A-X trials (Wiemers & Redick, 2018). They seem to use it less consistently, as evidenced by a much slower slowest quantile of RTs compared to higher working memory individuals.

Beyond the overall performance boost with which higher working memory is typically associated, several additional findings have occurred. Individuals with low working memory have difficulty maintaining the cue information across predictive proportions. Redick (2014) manipulated the frequencies of A-cue trials to try to determine the source of the deficit for low working memory individuals. A standard AX-CPT-70 was used where 70% of the trials are A-X trials. Then, proportions of A-X (now 10%) and A-Y (now 70%) were flipped resulting in the AX-CPT-10. In the AX-CPT-10, 90% of trials had a non-target response, but A-cues were equally predictive of a specific response. Additionally, an AX-CPT-40 with 40% A-X trials and 40% A-Y trials, was created, making the A-cue not predictive and erasing the benefit of using proactive control on A-cue trials. The results showed lower working memory individuals had higher error rates on A-X trials no matter what the proportions of trials were, and had higher B-X errors on the AX-CPT-70 and AX-CPT-40, where A cued X the majority of the time or equally as often as it cued Y. These results lead to the conclusion the low working memory individuals are not as likely as high working memory individuals to engage in proactive control use.

Richmond, Redick, and Braver (2015) followed up on low working memory individuals' AX-CPT behavior by investigating whether a new "C-X" trial type, requiring a third response, would alter their performance. They found that this additional response shows low working memory individuals are using reactive control, rather than using the response frequencies to make a decision about the correct response. Together, these findings show a clear picture that higher working memory individuals are more likely to maintain cue information and enact proactive control. Additionally, while lower working memory individuals can use proactive control, they are more likely to rely on reactive control use the majority of the time.

Working memory was not accounted for in the model in Experiment 1 in the current research, which may account for some difficulty modeling the data. A random intercept for subject accounted for individual differences, but it does not have the ordered nature of the working memory variable. Experiment 2 remedies that issue by including working memory measures to capture this individual differences component. This addition also allows more connections to be drawn to previous work involving the AX-CPT task. Further, this additional information advances the understanding of lower working memory behavior concerning proactive and reactive control use. While the AX-CPT studies have revealed a lower propensity for proactive control use, that is not the only possibility.

With the understanding that proactive and reactive control can work together in this titrated manner, two possibilities emerge. Lower working memory individuals could be using proactive control less often or they could be using less proactive control overall. The additional trial types in the new digit decision task will allow this distinction to be made. Less frequent proactive control use would result in RTs being just as fast and accurate as their higher working memory peers some of the time, but less frequently resulting in slower and less accurate responding that is more variable at the aggregate level. However, consistent but quantitatively less proactive control use would result in less variable performance but still not as fast and accurate as their higher working memory peers overall who would be consistently using more proactive control.

Present Study

The goal for Experiment 2 is to determine the relationship between working memory and cognitive control as measured within the new digit decision task I created and tested in Experiment 1. As higher working memory has generally been associated with more proactive control use, and low working memory has been associated with more reactive control use, several specific predictions follow. Low working memory individuals will be less sensitive to the benefits of using proactive control in certain trial types more than others, leading to less variability across trial types (similar to Figure 7A). Without as much proactive control use, in either frequency or quantity, low working memory individuals will be less accurate overall and more variable in RTs within trial types as they use control mechanisms less consistently. High working memory individuals should use more proactive control overall, resulting in faster and more accurate overall performance. High working memory individuals are also more likely to be sensitive to the predictive validity of the various digits and would be more likely to show the titrating pattern (similar to Figure 7C). It is perhaps the middle working memory individuals who would show enough proactive control use to have fast and accurate 1-N and 9-N trials, but with more reactive control performance on the rest, resulting in a pattern more similar to Figure 7B.

Method

Methods for Experiment 2 were preregistered at osf.io/s5uhz, and have been followed closely. As noted, the hybrid model and distance model were not preregistered.

Participants

To investigate the working memory and cognitive control relationship in the new task, a new group of 143 subjects were asked to complete two complex span working memory tasks in addition to the control task. This allowed for replication of Experiment 1 and extension to investigate working memory differences in this task. These subjects were from the same subject pool as Experiments 1, receiving partial course credit for participating, but had not participated in Experiment 1. Of the 143 subjects who participated, 2 did not finish the session, and 5 additional subjects had poor accuracy and were removed from the data set. As in Experiment 1, this cut was made for subjects whose accuracy was below chance, 50%, on 3 or more blocks. As a result, 136 subjects remained in the final sample and are included in the following analyses.

Tasks

Operation span (Redick et al., 2012; Unsworth, Heitz, Schrock, & Engle, 2005). This complex span task asks subjects to recall a series of letters in order. Interleaved between the presentation of each letter, shown individually onscreen, is a math problem and a proposed solution that subjects are asked to verify as a true or a false solution. There are 3 each of set sizes 3 to 7 accumulating in a total possible score of 75. Subjects are asked to maintain a math problem accuracy of 80%. The length of time the math problems are presented is calculated based on the average time that subject took to answer math problems in a section of practice with only math problems (no letters to remember) before the start of the task. This timing discourages strategy use of withholding response on the math problems to allow for verbal repetition of the to-be-remembered items. This task is depicted in Figure 8.

Symmetry span (Redick et al., 2012; Unsworth, Redick, Heitz, Broadway, & Engle, 2009). This task is a spatial version of the operation span task in which subjects are asked to recall a series of red square locations in a grid that were presented interleaved with black and white grid images for which subjects were asked to verify whether the black and white image was symmetrical. There are 3 each of set sizes 2, 3, 4, and 5 resulting in a total possible score of 42. The presentation times are calculated in the same way as in the operation span task, and subjects are told not to use physical representations such as touching the screen or desk to mark locations with their fingers. This task is depicted in Figure 9.

Digit task. This task was largely the same as the one used in Experiment 1. However, to minimize the loss of observations and subjects due to slow responding, the fixation cross turned red when the subject had failed to respond in time. In Experiment 1, an average of 2.7% of trials were lost due to slow responding in the final sample, with the largest losses occurring in block 1. Rather than feedback only at the breaks regarding how many trials were too slow, this gives subjects immediate feedback and encourages faster correction of this error. Generally, subjects did not have this issue after the first block or so, after the first feedback screen in which too-slow responses started to occur more frequently. So, more immediate feedback might minimize this issue. Additionally, the practice was adjusted to repeat if accuracy is less than 80%, to further mitigate this concern.

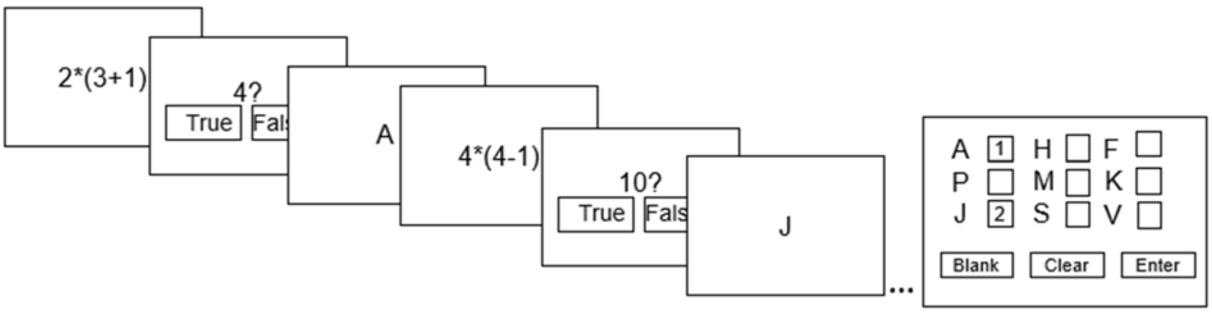


Figure 8. Illustration of the Operation Span Task.

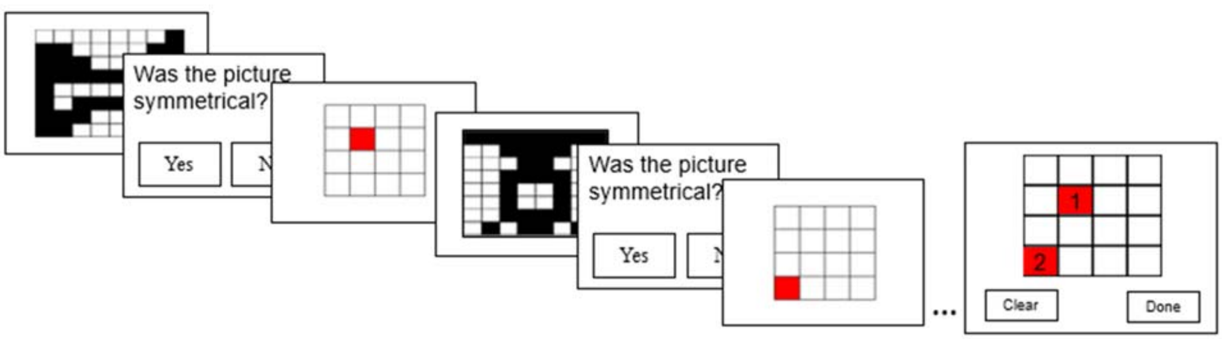


Figure 9. Illustration of the Symmetry Span Task.

Procedure

As in Experiment 1, groups of 1 to 11 subjects completed the session together in a shared lab space with cubicles for each individual. After consenting and completing a brief demographic questionnaire, subjects completed the operation span task, symmetry span task, and digit task. The session took about 60 to 75 minutes to complete. When each individual finished, they were given a debriefing form and allowed to quietly exit.

Analyses

Analyses were essentially the same as in Experiment 1, except where working memory was added. Analyses of accuracy, RT means and individual standard deviations, and proactive index were evaluated with the covariate working memory. Variables were also correlated with working memory. Models were also similar to Experiment 1, with the exception of the addition of working memory. Working memory was added to the models to evaluate the impact of individual differences.

Results

Descriptive Statistics

The overall pattern of correct RTs closely replicated the pattern from Experiment 1. However, there was a shift such that RTs in Experiment 2 were about 20 ms on average slower than in Experiment 1. Correct RTs for Experiment 2 are summarized in Table 7. RT ISDs are summarized in Table 8. The accuracy by trial type interaction replicates in pattern but is shifted to slightly higher accuracy in Experiment 2 from Experiment 1. Error rates for Experiment 2 are summarized in Table 9.

Table 7. Response Time Means and Standard Deviations for Previous Stimulus and Current Stimulus for Experiment 2

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean*	*SD*
1		390	397	391	389	392	391	387	382	390	4
		(105)	(103)	(109)	(98)	(98)	(103)	(97)	(90)		
2	489		493	475	459	464	457	452	444	467	18
	(76)		(94)	(90)	(77)	(82)	(77)	(79)	(71)		
3	494	497		496	476	482	483	465	469	483	12
	(76)	(82)		(86)	(82)	(86)	(81)	(77)	(76)		
4	489	494	496		493	486	491	485	479	480	6
	(75)	(78)	(80)		(84)	(83)	(82)	(77)	(73)		
5	476	487	491	505		495	495	488	490	491	8
	(76)	(79)	(80)	(84)		(77)	(71)	(74)	(76)		
6	478	475	481	490	518		511	505	497	494	16
	(79)	(83)	(80)	(79)	(86)		(75)	(76)	(74)		
7	472	468	485	492	511	522		508	500	495	19
	(73)	(74)	(86)	(79)	(86)	(79)		(75)	(73)		
8	454	456	458	470	486	506	498		499	478	21
	(74)	(79)	(81)	(77)	(83)	(82)	(89)		(71)		
9	377	377	389	388	394	402	404	413		393	13
	(92)	(101)	(94)	(103)	(103)	(108)	(114)	(121)			
Mean	466	456	461	463	466	469	466	463	470	464	4
SD	38	46	44	47	50	48	45	44	40	42	

Table 8. Response Time Individual Standard Deviation Mean for Previous Stimulus and Current Stimulus for Experiment 2

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean ISD*	*SD*
1		136	137	137	125	126	124	126	111	128	9
		(60)	(57)	(62)	(58)	(52)	(48)	(52)	(43)		
2	89		126	117	109	108	100	93	87	104	14
	(44)		(57)	(48)	(52)	(48)	(49)	(44)	(37)		
3	85	98		118	112	111	101	95	92	101	11
	(41)	(39)		(46)	(51)	(50)	(46)	(43)	(41)		
4	86	103	102		111	106	103	102	88	100	9
	(40)	(53)	(48)		(46)	(45)	(51)	(44)	(40)		
5	82	97	103	104		108	102	100	88	98	9
	(44)	(47)	(46)	(48)		(47)	(45)	(44)	(41)		
6	83	94	104	103	110		111	96	88	99	10
	(44)	(46)	(48)	(50)	(48)		(51)	(45)	(42)		
7	91	91	106	105	112	117		100	84	101	11
	(43)	(42)	(49)	(49)	(48)	(51)		(42)	(37)		
8	90	104	99	104	110	118	121		86	104	12
	(44)	(45)	(44)	(50)	(49)	(46)	(47)		(41)		
9	112	125	131	124	137	139	145	153		133	13
	(42)	(48)	(50)	(47)	(50)	(57)	(60)	(64)			
Mean	90	106	113	114	116	117	114	108	91	108	10
SD	9	16	15	12	10	11	16	21	8	13	

Table 9. Mean Percent Error and Standard Deviations for Previous Stimulus and Current Stimulus for Experiment 2

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean*	*SD*
1		15	10	9	5	4	5	3	3	7	4
		(16)	(12)	(13)	(9)	(7)	(8)	(6)	(6)		
2	13		18	11	7	6	7	4	3	9	5
	(14)		(16)	(14)	(10)	(9)	(11)	(7)	(7)		
3	11	14		17	10	10	8	6	4	10	4
	(12)	(14)		(14)	(13)	(11)	(9)	(8)	(8)		
4	9	10	15		12	11	11	9	6	10	2
	(13)	(12)	(14)		(12)	(12)	(11)	(10)	(9)		
5	8	8	9	15		14	14	10	8	11	3
	(11)	(11)	(11)	(15)		(13)	(13)	(12)	(11		
6	6	7	9	13	20		18	12	9	12	5
	(8)	(11)	(12)	(13)	(16)		(15)	(14)	(10)		
7	6	6	7	9	13	18		14	10	11	4
	(8)	(10)	(10)	(12)	(12)	(15)		(15)	(11)		
8	3	4	6	6	9	14	16		12	9	5
	(7)	(8)	(9)	(10)	(12)	(14)	(14)		(12)		
9	3	4	4	5	7	6	10	13		6	3
	(7)	(8)	(8)	(9)	(9)	(9)	(15)	(15			
Mean	7	9	10	11	11	10	11	9	7	9	2
SD	3	4	5	4	5	5	5	4	3	2	

Pattern

The pattern in the RTs closely resembles that of Experiment 1. Again, this pattern, seen in Figure 10, does not perfectly resemble either of the proposed patterns, but has a titrated pattern for 2N through 8N with a gap between all of those and 1-N and 9-N, which are together at a shorter RT. The observed RTs are depicted in Figure 10A.

The titrated and dichotomous models specified in Experiment 1 were fit to the Experiment 2 data to again investigate this pattern. The modeled data are presented in Figure 10 for both the titrated (B) and dichotomous (C) models. Similar to Experiment 1, the lowest AIC and BIC in this comparison is Model 2b, the dichotomous model with 1-N and 9-N grouped together and the remaining trial types grouped together. The interaction models were also compared. Similar to the simple models and Experiment 1 models, the dichotomous model is preferred. Table 10 shows the AIC and BIC for both the cue-only and the interaction models.

The Bayesian models specified in Experiment 1 were also used to compare the hypothesis models' fit for Experiment 2. The Bayes Factors for these models are reported in Table 11. For the relative Bayes Factor, numbers greater than 1 show evidence for the titrated model. The Bayesian models show preference for the dichotomous model for both the Cue (Model B2) and Cue-Target (Model B4) models. These results suggest the dichotomous pattern does a better job of describing the observed data than the titrated pattern.

Table 10. Model Comparison of Cue Models for Experiment 2

	Cue		Cue-Target	
Model	AIC	BIC	AIC	BIC
Titrated model (1, 3)	1228490	1228528	1226899	1226956
Dichotomous model (2a, 4a)	1229915	1229953	1228569	1228626
Dichotomous model (2b, 4b)	1225427	1225465	1224696	1224753
Hybrid model (H1, H2)	1225144	1225192	1224521	1224587

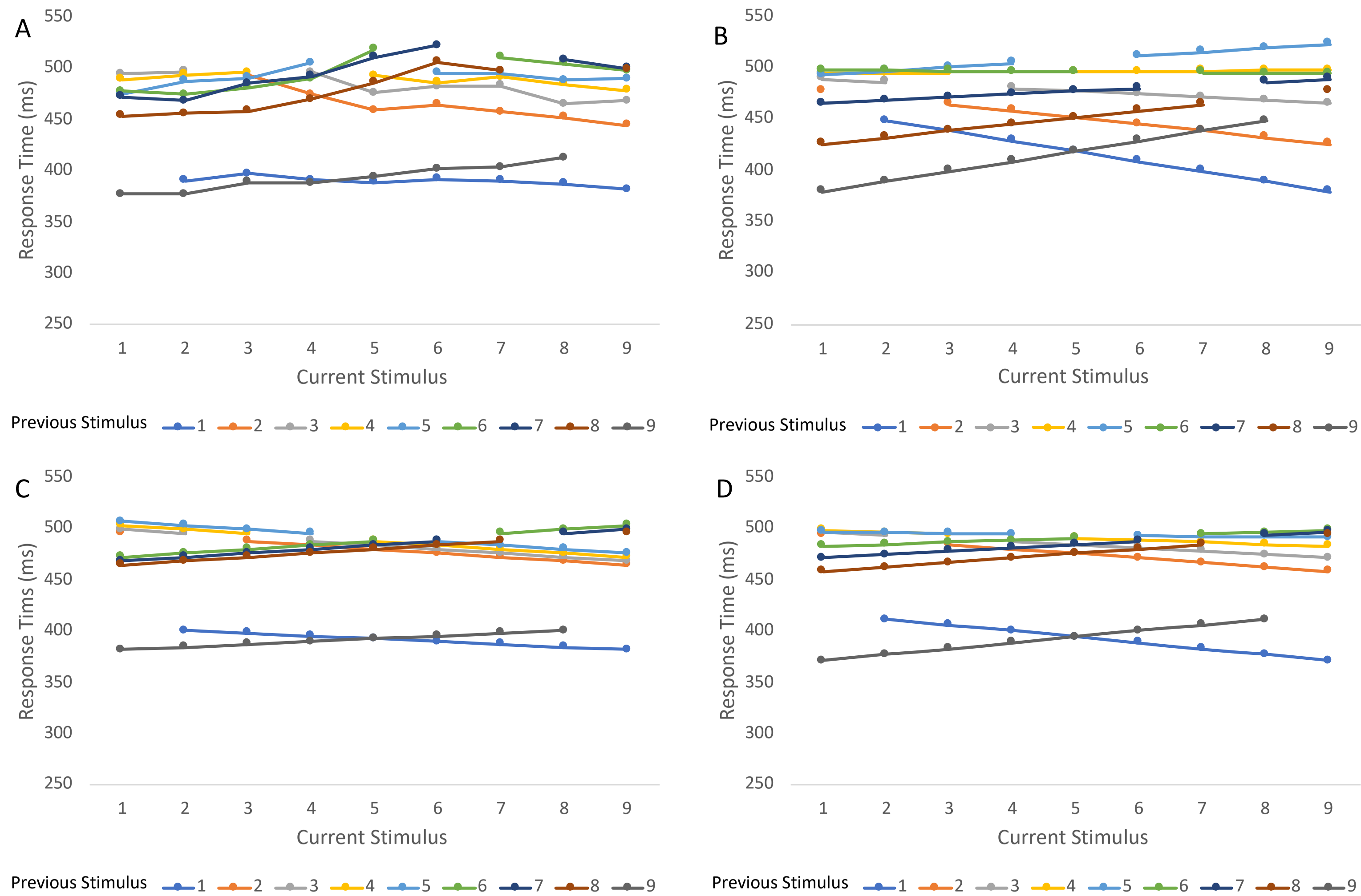


Figure 10. Observed (A) and Modeled Titration (B), Dichotomous (C), and Hybrid (D) patterns for Experiment 2 correct response times.

Table 11. Bayesian Model Comparison of Cue and Cue-Target Models for Experiment 2

Model	Cue	Cue-Target
Titrated model (B1, B3)	$6.73e^{1125}$	$1.05e^{1375}$
Dichotomous model (B2, B4)	$3.07e^{1634}$	$7.41e^{1747}$
Hybrid model (H1, H3)	$5.87e^{1674}$	$8.87e^{1768}$
Comparison		
Titrated/Dichotomous	$2.19e^{-509}$	$1.41e^{-373}$
Hybrid/Dichotomous	$1.91e^{40}$	$1.27e^{21}$

Hybrid Model

As with Experiment 1, this model is a post-hoc model that was not preregistered. The models are identical to those specified in Experiment 1. The pattern of RTs projected by this model is shown in Figure 10D. As with Experiment 1, the hybrid model more closely approximates the observed data. Model H1, the hybrid cue-only model, was compared to Model 2b, the preferred dichotomous model. The AIC and BIC are reported in Table 10 and show that the hybrid model is again preferred over the dichotomous and titrated models. The cue-target models (H2 and 4b) were also compared, and again the hybrid model has the lowest AIC and BIC.

Bayesian models were also run for the hybrid model and are reported in Table 11. Decisive evidence is found in favor of the hybrid models over the dichotomous models for both the cue-only model (H1) and the cue-target model (H3). Again, these results suggest that while the dichotomous model fit better than the original titrated model, a titrated model is preferred when the 1-N and 9-N trials are allowed to deviate from the rest.

Distance Effect

Bayesian models from Experiment 1 were again employed for this analysis. Table 12 lists Bayes Factors for Directional (Model B5) and Distance only (Model B6) for a Target model and Directional (Model B3) and Distance-only (Model B7) for a Cue-Target interaction model. In Experiment 2, the preference for the directional model is again clear. There is decisive evidence in favor of the directional model (Models B5, B7) for the Target-only model and for the Cue-Target interaction model.

Table 12. Bayesian Models for Experiment 2 Comparing Directional and Distance Only

Model	Target	Cue-Target
Directional model (B5, B3)	$2.01e^{587}$	$2.32e^{2414}$
Distance Only model (B6, B7)	$1.30e^{562}$	$4.08e^{1299}$
Relative BF	$1.55e^{25}$	$2.57e^{75}$

Proactive Index

Proactive index scores are shown in Figure 11. As in Experiment 1, the distribution is fairly normal and there is a range of scores. Subjects were generally more proactive on the 1-N and 9-N trials (1- or 9-N M = 391 ms, SD = 91 ms) than the 5-N trials (5-N M = 490 ms, SD = 67 ms), with an average proactive index score of 99 ms (SD = 46 ms). However, they were quite variable from one another ranging from the smallest change at -55 ms to the largest change at 241 ms.

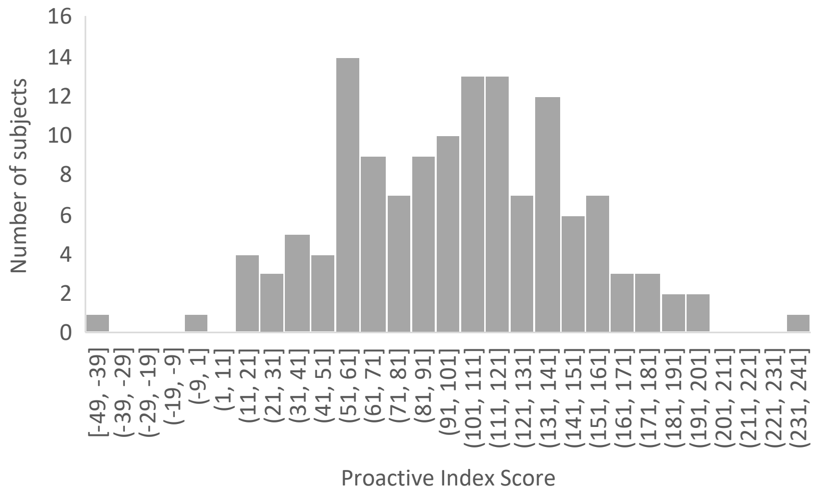


Figure 11. Distribution of proactive index scores for Experiment 2.

Working Memory

Working memory was correlated with the variables to assess relationships with overall performance. Working memory was calculated by taking the average of the two *z*-scores from the operation span task and symmetry span task for each individual. These scores were correlated at $r = .45$, $t(134) = 5.81$, $p < .001$, $BF = 359990$. This aggregate score was then used for all correlations. Correlations were evaluated using correlationBF in R. As expected, working memory was negatively correlated with errors, $r = -.27$, $t(134) = -3.24$, $p = .002$, $BF = 24.87$. Working memory was not correlated with grand mean RTs, $r = .06$, $t(134) = 0.66$, $p = .51$, $BF = 0.244$, or RT ISDs, $r = -.16$, $t(134) = -1.86$, $p = .066$, $BF = 1.01$. Critically for the current project, working memory was not related to the proactive index measure, $r = -.12$, $t(134) = -1.43$, $p = .156$, $BF = 0.52$.

The lack of performance differences as a function of working memory can be seen in the overall pattern. Three possible patterns were proposed, which can be visualized by averaging the RTs by trial type for the top, middle, and lower third of working memory. Figure 12 shows these averaged RTs by working memory level, and shows that the patterns are very consistent across working memory.

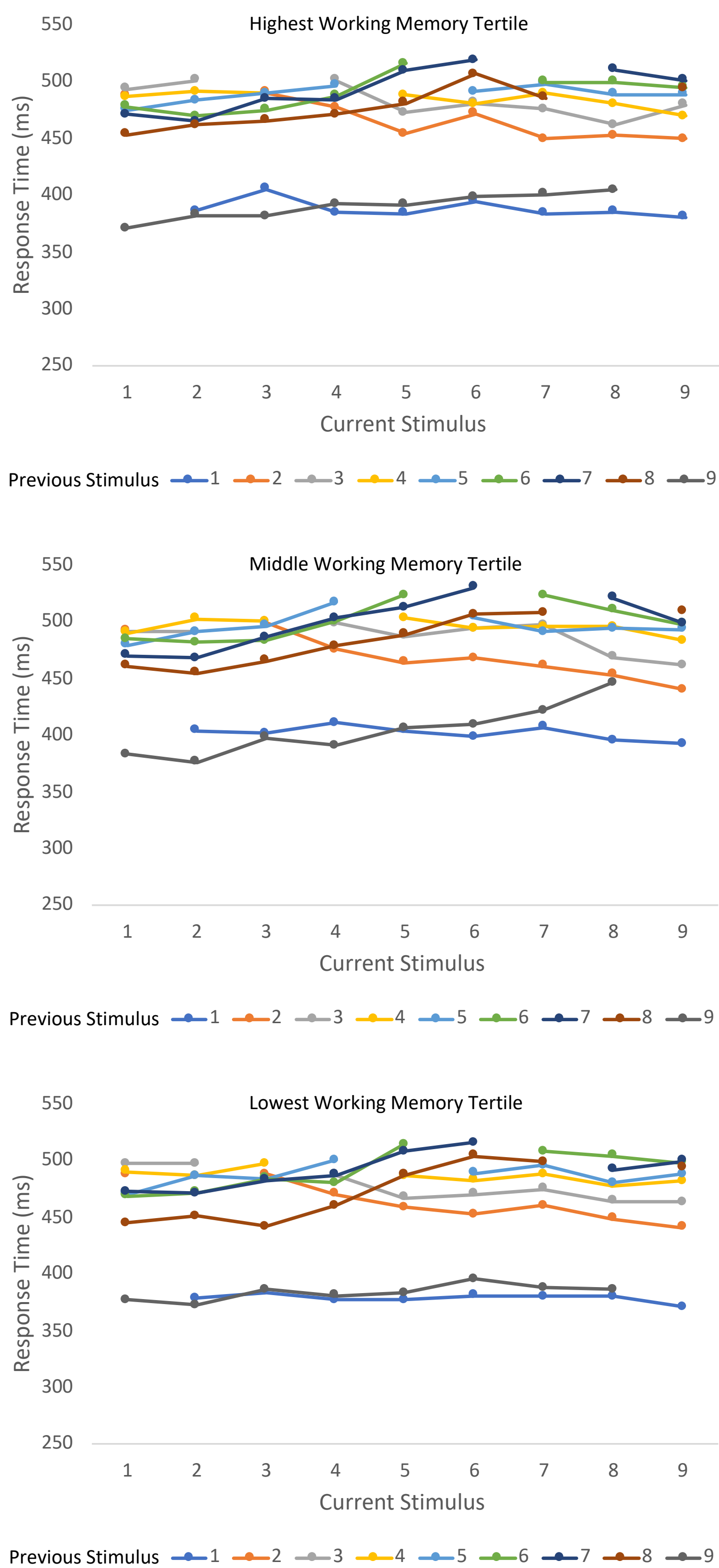


Figure 12. Correct response time patterns averaged by tertile of working memory.

To quantify these observations, models with and without working memory are compared to evaluate the impact of working memory on the model performance. Models are the same as the titration cue-target interaction models described previously except that working memory has been added as a main effect and interaction term. Models were specified as follows:

(5) Titrated Working Memory Model: $\text{ResponseTime}_i = (b_1)\text{PreviousStimulus} + (b_2)\text{Target} + (b_3)\text{WorkingMemory} + (b_4)\text{PreviousStimulus*Target} + (b_5)\text{PreviousStimulus*WorkingMemory} + (b_6)\text{WorkingMemory*Target} + (b_7)\text{WorkingMemory*PreviousStimulus*Target} + r_i$

(B8) Titrated Working Memory Model: $\text{ResponseTime}_i = (b_0 + b_{0i}) + (b_1)\text{PreviousStimulus} + (b_2)\text{Target} + (b_3)\text{WorkingMemory} + (b_4)\text{PreviousStimulus*Target} + (b_5)\text{PreviousStimulus*WorkingMemory} + (b_6)\text{WorkingMemory*Target} + (b_7)\text{WorkingMemory*PreviousStimulus*Target} + r_i$

These comparisons are listed in Table 13. Model 5 is the same as Model 3, reported earlier, except that working memory has been added as a main effect and interaction term. The AIC was lower for Model 5 (AIC = 1226870) versus Model 3 (AIC = 1226899) indicating that the addition of working memory improves the model. Interestingly, the BIC is lower for Model 3 (BIC = 1226956) versus Model 5 (BIC = 1226965). Looking at Model 5, the main effect of working memory was not significant, $t(137.76) = 0.45$, $p = 0.96$. The three-way interaction and the interaction with target were also not significant, $t(98565) = 1.11$, $p = 0.27$ and $t(98565) = 1.00$, $p = 0.32$, respectively. However, the interaction between working memory and cue was significant, $t(98565) = 3.43$, $p < 0.001$. These results taken together show that working memory may be influential, but not likely to the degree it was expected.

Table 13. Model Comparison With and Without
Working Memory

Model	Cue-Target	
	AIC	BIC
Titrated (3)	1226899	1226956
Titrated*WM (5)	1226870	1256965

Bayesian versions of these models were also compared, as shown in Table 14. Model B8 is the same as the earlier reported Model B3 except that the main effect and interactions with working memory were added. Model B8 is decisively preferred to Model B3, indicating that working memory greatly improves the model. However, when using generalTestBF, all model possibilities are generated, and the best fitting model of those generated was not the full model. Somewhat in line with the frequentist model, the best model had the three main effects, the two-way interaction between cue and target and the two-way interaction between cue and working memory (*BF* = $5.44e^{1392}$). This was not the hypothesized model and accordingly will not be interpreted further.

Table 14. Bayesian Model Comparison
With and Without Working Memory

Model	Cue-Target
Titrated*WM (B8)	$1.07e^{1390}$
Titrated (B3)	$1.05e^{1375}$
Relative BF	$1.02e^{15}$

Discussion

In replicating Experiment 1, this study further provides evidence that this task is sensitive to changes in cognitive control at the trial level. Further, the dichotomous model was again preferred to the titrated model, but the hybrid model provided the best fit. This also replicates Experiment 1 findings and shows that the titration hypothesis holds with the exception of the 1-N and 9-N separation. Again, it is not yet clear what that mechanism is, as it also did not appear to be affected by working memory in any way, with all three working memory tertiles showing very similar patterns overall. The distance effects were again present but not sufficient to explain the behavior observed without cognitive control. That is, the titration model was again preferred to the distance-only model.

A typical relationship between working memory and overall task accuracy was found such that higher working memory corresponded with higher accuracy. However, RTs and variability, the control-related performance measures, were largely not influenced by working memory. In earlier AX-CPT work, I showed that lower working memory subjects were equally capable of using proactive control to produce fast and accurate responses, they were just much less likely to do so (Wiemers & Redick, 2018).

Accordingly, it was somewhat surprising not to see similar relationships to working memory in Experiment 2. The models suggested that working memory was important for the models generally, but the relationship was inconsistent at best, with the BIC showing preference for the non-working memory model and there being no main effect of working memory. However, the AIC and Bayesian comparisons showed preference for the working memory model. Further, the correlation expected with the critical proactive index measure was not found. If working memory is important for these relationships, then the proactive index is not the way to discover it.

While working memory may not be the critical individual difference factor for these investigations, a deeper look at the interplay of proactive and reactive control is still a reasonable next step. As working memory was not related in the expected ways, the further investigations move away from that line of questioning and focus back in on the digit task and what can be discovered about control based on Digit Task performance. Particularly, what adjustments to the task might lead to predictable changes in the use of proactive and reactive control? Critically, can these changes further rule out alternate explanations such as the distance effect explanation?

EXPERIMENT 3

Before further investigation could be done, a global pandemic led to restrictions on in-person data collection. Accordingly, the follow-up experiment to Experiments 1 and 2 needed to be moved online. This change posed several difficulties, as this task had not been used outside of the lab before. Experiment 3 attempts to replicate Experiment 1 in the remote online format. Online data collection is quickly becoming a critical tool for researchers, as in-lab data collection becomes increasingly challenging or undesirable due to restrictions on access to populations needed for individual differences research.

However, online data collection inevitably requires relinquishing the careful control of the cognitive psychology laboratory setting. Necka, Cacioppo, Norman, and Cacioppo (2016) surveyed what may be considered problematic behaviors in research and found that online participants were more likely to multitask and take breaks to go do something else before coming back to the task later. These types of behaviors are problematic because they inherently mean that the task is not completed in the same conditions as other subjects who solely focus on the task for the duration asked of them. These differences could lead to variation other than that of primary interest to the researchers.

Taking research out of the lab also often involves technologies that are potentially less sensitive when recording behavioral measures such as response times. However, recent studies have found that home-based studies replicate lab-based findings very closely including for measures that require high precision such as response time (Miller, Schmidt, Kirschbaum, & Enge, 2018). Miller et al. tested three RT-based attention tasks within-subjects both in the lab and at home and found that performance was consistently highly correlated. So, while challenging, it is feasible to successfully collect attention-based research data online. Experiment 3 addresses whether the challenges associated with online data collection lead to changes in proactive and reactive control.

Method

The methods for Experiment 3 are very similar to Experiment 1, with the major exception of being transferred to an online format, built in Psycopy and run via the Pavlovia.com and gitlab.com online platform. Experiments 3 and 4 were run concurrently due to time constraints, but the interpretation of Experiment 4 depends on Experiment 3, so Experiment 3 is discussed first.

Experiment 3 was not formally preregistered, but was intended to be a replication of Experiments 1 and 2 and accordingly closely follows methods from the previous experiments. Slight adjustments to the task are described below, but analyses are the same as Experiment 1.

Participants

Participants were students receiving partial course credit for participation from the same pool as Experiments 1 and 2 but having not participated in either, and paid participants recruited via twitter, reddit (r/Purdue), and university message boards. These recruitment strategies were intended to largely appeal to the same university students and community members that may have participated in a traditional lab version of this study. While 100 individuals were sought, many challenges arose from online data collection leading to a lower useable sample than would otherwise occur at that participation level. Data collection was stopped instead when the time available for the project had run out.

All participants were required to be between the ages of 18 and 30 years old, have normal or corrected-to-normal vision, and be fluent in English. Of the 113 participants for whom data files were generated, 2 chose to exit early after doing several task blocks, 2 chose to leave after initiating a session but before beginning the task, 1 was removed for initially reporting they fit the age requirement but later stating they were actually 45, 10 had poor accuracy according to the same rule used previously (some of which were close to zero percent after pressing buttons for only a few trials then letting the task run on without ever responding again), 1 additional had low accuracy due to pressing only one key for three entire blocks after pressing no buttons for one block, and 5 took an extremely long time during breaks that were requested to be kept to 10 seconds, extending the session past a reasonable point. The reasonable timepoint rule was intended to remove those who took such a long break that it essentially could have been considered two sessions, so those with 40 minutes or more for their longest break time were removed. These criteria resulted in a final sample of 92 individuals for the analyses.

Task

The digit task was as close as possible to the Eprime task described in Experiment 2. Working from the Eprime task, the task was recreated in Psycopy, a free download platform for experiment building, which uses primarily Python and Javascript, with additional drag and drop functions. Once programmed, it was uploaded to gitlab where it can interface with Pavlovia, an experiment hosting site.

The task was essentially the same as Experiment 2 for the subjects participating for credit. However, a slight change was made as participation shifted to paid subject recruitment due to the number of individuals who simply opened the task and let it run to completion without ever pressing a button. To avoid this temptation, a response was required on each trial, though recorded differently than an on-time response. This change ensures that participants do the task asked of them, but that it can also be scored the same as it was previously. Additionally, due to programming constraints, the practice section of the task was made a standard 20 trials, instead of repeating the initial 10 trials only if poor accuracy occurred.

Procedure

Via email, before signing up, participants were asked to use a browser other than Firefox due to a compatibility issue identified early in the data collection. They were also asked to keep the built-in breaks to their intended length of just a few seconds. Instructions included finding a quiet space and avoiding cell phone use during the task. In this email, participants were also given a link to Sona, a website that manages participant signups. From Sona, participants were directed to the experiment site, which opened as a full screen browser window on their computer. Participants were then asked to fill in basic demographic information, were presented with the consent information, and then began the task.

At the end of the task, participants were presented debriefing information onscreen. Then, they were redirected back to the sign-up page where participation was recorded. Participants were aware that to opt out, they could press the escape (ESC) key at any time, where they would be redirected back to the sign-up page to record participation. Participants receiving credit were automatically granted credit. Participants receiving payment were emailed an Amazon gift credit at a rate of $10 USD per hour.

Analyses

Analyses were identical to Experiment 1.

Results

Descriptive Statistics

Experiment 3 seems to fit right between Experiments 1 and 2 in terms of grand mean RT of 458 ms (versus 437 ms in Experiment 1 and 464 ms in Experiment 2). Grand mean error rates are close with 9% in Experiments 2 and 3 and 11% in Experiment 1. Interestingly, Experiment 3 has the lowest grand mean ISD RT at 95 ms (versus 104 ms in Experiment 1 and 108 ms in Experiment 2). While Experiment 3 showed generally similar RTs to Experiment 2, the critical A-Y analogous trials, 2-1, 3-2, 3-1, and 8-9, 7-9, and 7-8, were all particularly fast compared to Experiment 2, more similar to the overall faster Experiment 1 RTs. Correct mean RTs are summarized in Table 15, RT ISDs in Table 16, and error rates in Table 17.

Pattern

The pattern of average correct RTs looks similar to the patterns found in Experiments 1 and 2 (Figure 13A). However, it seems possibly less distributed in the 2N-8N grouping, which would suggest less of the titrated pattern. This would follow from having an overall smaller ISD RT in Experiment 3.

Again, the models used in Experiments 1 and 2 were used to evaluate the pattern according to the alternative hypotheses. Because the Grouping 19 dichotomous model has consistently outperformed the Grouping 1289 model in Experiments 1 and 2, only the Grouping19 dichotomous model is compared moving forward. First, the titration (1 and 3) and dichotomous (2 and 4) models were compared for both cue-only and cue-target interaction models. As reported in Table 18, the dichotomous model is favored, having lower AIC and BIC, for both the cue only and cue-target interaction models. This is in line with the previous two experiments.

Table 15. Response Time Means and Standard Deviations for Previous Stimulus and Current Stimulus for Experiment 3

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean*	*SD*
1		395	398	397	383	389	385	383	379	389	7
		(110)	(108)	(95)	(96)	(88)	(90)	(84)	(82)		
2	460		491	481	458	466	467	457	442	465	14
	(65)		(85)	(104)	(84)	(92)	(85)	(80)	(72)		
3	479	478		493	469	474	464	426	456	472	11
	(65)	(75)		(87)	(72)	(76)	(77)	(67)	(65)		
4	480	480	494		476	482	490	477	466	481	8
	(71)	(74)	(75)		(73)	(86)	(74)	(69)	(65)		
5	474	475	480	491		484	494	480	476	482	7
	(62)	(62)	(69)	(72)		(77)	(72)	(72)	(65)		
6	465	464	482	487	509		492	492	478	484	14
	(66)	(67)	(70)	(78)	(81)		(70)	(80)	(63)		
7	463	458	474	486	501	506		487	480	482	16
	(67)	(74)	(68)	(70)	(82)	(78)		(76)	(68)		
8	454	453	460	480	482	496	512		464	475	20
	(67)	(73)	(83)	(89)	(85)	(93)	(98)		(64)		
9	384	381	387	389	398	402	402	410		394	10
	(84)	(88)	(93)	(93)	(102)	(105)	(108)	(125)			
Mean	457	448	458	463	460	462	463	456	455	458	4
SD	31	38	42	43	46	43	46	39	33	38	

Table 16. Response Time Individual Standard Deviation Mean for Previous Stimulus and Current Stimulus for Experiment 3

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean ISD*	*SD*
1		141	129	126	121	116	119	118	104	122	10
		(64)	(50)	(49)	(47)	(42)	(50)	(52)	(44)		
2	126		85	105	103	101	93	82	83	97	14
	(34)		(30)	(71)	(68)	(62)	(62)	(49)	(54)		
3	67	96		79	89	105	99	92	88	89	11
	(42)	(30)		(41)	(42)	(48)	(44)	(44)	(49)		
4	87	79	97		74	92	97	104	95	91	9
	(42)	(40)	(29)		(40)	(53)	(41)	(47)	(42)		
5	98	95	79	99		85	93	94	100	93	7
	(51)	(49)	(40)	(29)		(45)	(43)	(41)	(49)		
6	90	94	89	83	98		.71	.83	.98	88	9
	(38)	(46)	(44)	(41)	(27)		(37)	(39)	(53)		
7	98	103	100	91	79	98		72	83	91	11
	(44)	(47)	(46)	(40)	(47)	(28)		(39)	(42)		
8	83	95	101	103	90	84	98		64	90	12
	(42)	(49)	(53)	(43)	(42)	(42)	(29)		(39)		
9	81	79	89	94	106	106	86	96		92	10
	(53)	(45)	(64)	(63)	(61)	(56)	(28)	(27)			
Mean	91	98	96	98	93	98	94	93	90	95	3
SD	17	19	15	15	15	11	14	14	13	10	

Table 17. Mean Percent Error and Standard Deviations for Previous Stimulus and Current Stimulus for Experiment 3

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean*	*SD*
1		19	12	9	6	4	5	3	4	8	5
		(16)	(12)	(11)	(8)	(7)	(8)	(6)	(8)		
2	9		23	17	7	5	6	5	4	10	6
	(9)		(20)	(21)	(13)	(11)	(13)	(10)	(10)		
3	10	10		20	11	7	7	5	6	9	4
	(14)	(12)		(18)	(12)	(10)	(10)	(10)	(9)		
4	7	9	13		12	9	10	7	6	9	2
	(11)	(12)	(14)		(14)	(12)	(13)	(11)	(11)		
5	7	6	10	13		13	13	8	7	10	3
	(10)	(8)	(12)	(14)		(14)	(14)	(10)	(10)		
6	6	5	7	10	17		13	8	8	9	4
	(11)	(9)	(10)	(11)	(15)		(12)	(11)	(10)		
7	6	6	8	9	14	20		9	7	10	4
	(10)	(12)	(11)	(10)	(13)	(16)		(10)	(11)		
8	5	4	6	8	13	12	20		9	10	5
	(11)	(9)	(12)	(14)	(20)	(15)	(21)		(7)		
9	3	3	4	5	8	8	11	17		8	5
	(6)	(7)	(7)	(8)	(10)	(11)	(13)	(16)			
Mean	7	8	10	11	11	10	11	8	6	9	2
SD	2	5	6	5	4	5	5	4	2	1	

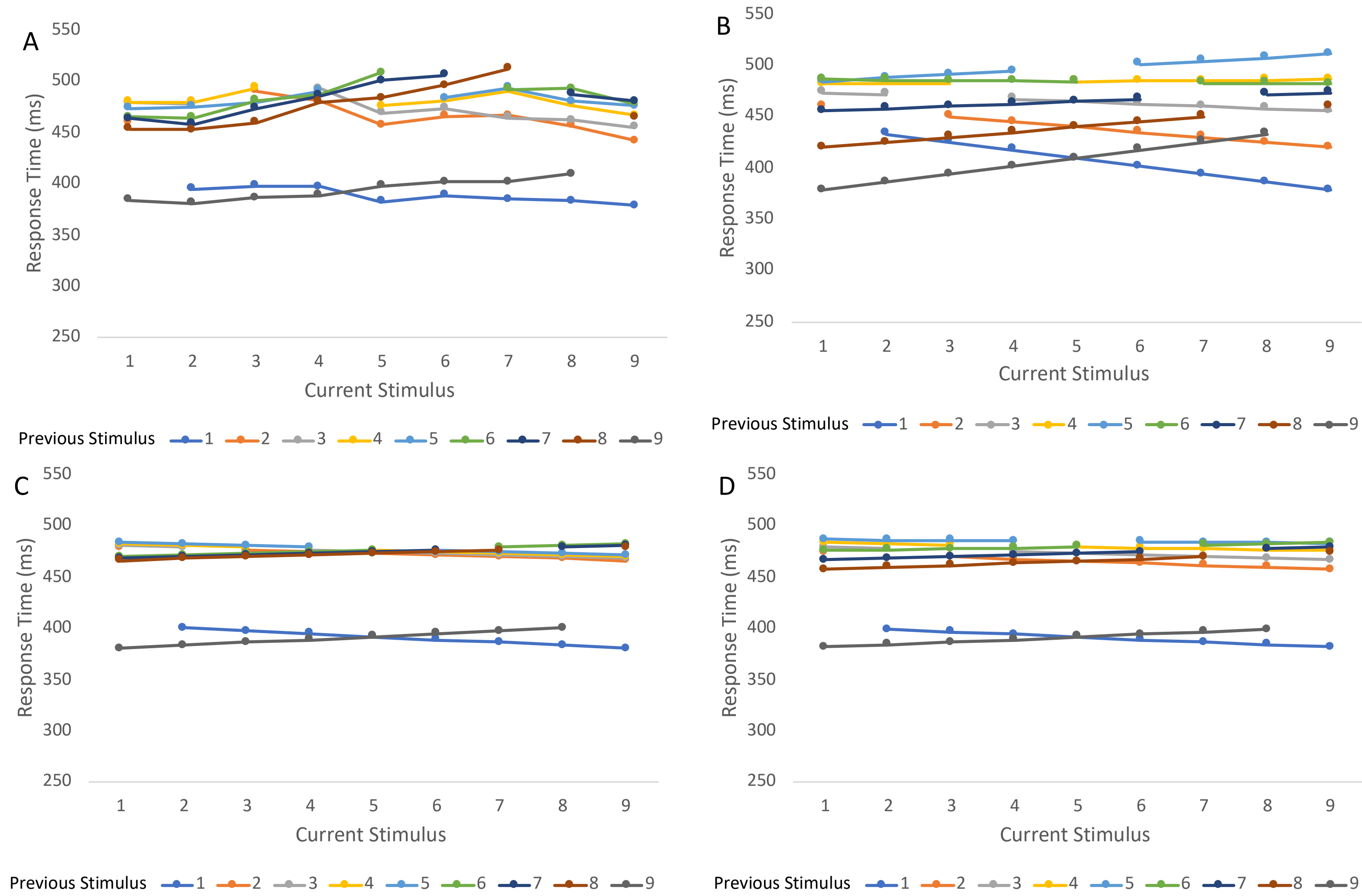


Figure 13. Observed (A) and Modeled Titration (B), Dichotomous (C), and Hybrid (D) patterns for Experiment 3 correct response times.

Table 18. Model Comparison for Experiment 3 Models

	Cue		Cue-Target	
Model	AIC	BIC	AIC	BIC
Titrated model (1, 3)	825952	825988	824907	824962
Dichotomous model (2, 4)	823742	823779	823607	823662
Hybrid model (H1, H2)	823612	823658	823505	823569

Note. Smaller numbers indicate better model fit, but the units of these measures themselves are meaningless.

Bayesian models previously specified in Experiment 1 were also used to evaluate this comparison. These results are reported in Table 19. For both cue-only and cue-target interaction models, there is a strong preference for the dichotomous model. Again, this replicates the previous experiments.

Table 19. Bayesian Model Comparison for Experiment 3

Model	Cue	Cue-Target
Titrated model (B1, B3)	$1.23e^{839}$	$3.38e^{1012}$
Dichotomous model (B2, B4)	$3.09e^{1208}$	$2.13e^{1226}$
Hybrid model (H1, H3)	$1.05e^{1226}$	$2.29e^{1241}$
Comparison		
Titrated/Dichotomous	$4.98e^{-370}$	$1.59e^{-214}$
Hybrid/Dichotomous	$4.23e^{17}$	$1.07e^{15}$

Note. Large values have been reported in scientific notation.

Hybrid Model

Once again, the observed data (Figure 13A) is not closely matched by the projected data of either of the proposed models. The titration model projection (Figure 13B) does not capture the separation of 1-N and 9-N trials from the rest, and the dichotomous model projection (Figure 13C) does not capture the separation among the 2-N through 8-N trials. The same hybrid models previously specified for Experiment 1 were used. The AIC and BIC for model H1 and H3 are reported in Table 18 with the comparable frequentist models. The hybrid model shows the lowest AIC and BIC again for both the cue-only and the cue-target models suggesting that it more closely describes the observed data than either the dichotomous or titrated models.

Comparable Bayesian models (BH1 and BH2), previously specified in Experiment 1, were again used to compare to the Bayesian dichotomous hypothesis models. These relative Bayes Factors are presented in Table 19. As in Experiments 1 and 2, the hybrid model is strongly preferred to the dichotomous model.

Distance Effect

The same Bayesian models were used as in Experiments 1 and 2 to evaluate whether the distance effect was sufficient to explain the pattern of behavior or whether the addition of directional information, as predicted to be important in the titration model, would be beneficial for model fit. Target (B5 and B6) and Cue-Target interaction (B3 and B7) models were compared and are reported in Table 20. Both comparisons show strong evidence for the directional model over the distance model. This suggests the titration model is providing additional information above and beyond the distance effect that is important for fitting the model.

Table 20. Bayesian Model Comparison of Directional Versus Distance Effect for Experiment 3

Models Experiment 3	Target	Cue-Target
Directional model (B5, B3)	$8.09e^{395}$	$3.38e^{1012}$
Distance Only model (B6, B7)	$1.67e^{382}$	$1.53e^{972}$
Relative BF	$4.83e^{13}$	$2.21e^{40}$

Proactive Index

The proactive index was also replicated nicely in Experiment 3. The distribution had a range of scores again and looked somewhat normal, though the distribution is shifted slightly to the left compared to the previous experiments (Figure 14). Subjects were generally more proactive on the 1-N and 9-N trials (1- or 9-N *M* = 335 ms, *SD* = 88 ms) than the 5-N trials (5-N *M* = 481 ms, *SD* = 59 ms), with an average proactive index score of 90 ms (*SD* = 54 ms). However, they were quite variable from one another, the smallest change being -27 ms and the largest change being 305 ms.

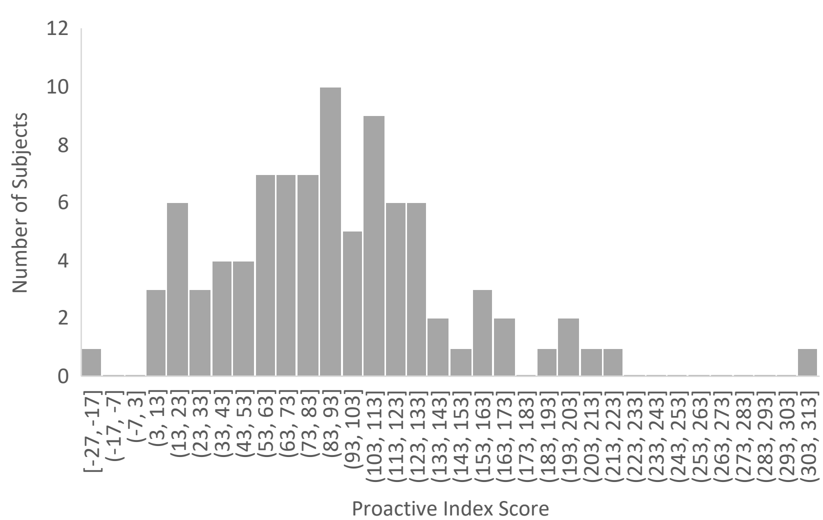


Figure 14. Distribution of proactive index scores for Experiment 3.

Discussion

Experiment 3 closely replicates Experiments 1 and 2, making the critical leap from the highly-controlled lab space to less-controlled online data collection environments, despite data collection challenges and concerns about lack of control over the sessions. RTs and error rates were generally similar to the previous experiments. Particularly, the mean RTs and error rates are close to those found in Experiment 2, which were shifted slightly slower and more accurate compared to Experiment 1. Mean RTs were faster for the critical 2-1 and 8-9 trials in Experiment 3 than Experiment 2, though they were similar to Experiment 1. These critical trials also had somewhat lower error rates than Experiment 1, though these are more in line with Experiment 2. RT ISDs, however, are somewhat smaller in Experiment 3 than Experiments 1 and 2. Of note, the closer procedures are in Experiments 1 and 3, as participants in Experiment 2 were given the complex span tasks prior to beginning the digit task. Model comparisons were all in agreement with the previous 2 experiments.

Overall, this suggests that the transition from the lab to online did not dramatically alter performance. The one concern is the number of subjects that were dropped (21 of 113) versus the previous experiments (Experiment 1: 8 of 103; Experiment 2: 7 of 143). However, this certainly seems to be a general concern of online data collection rather than a difference in task performance. Those who were not meeting accuracy requirements were generally not responding at all or pressing a single key for entire blocks.

This performance would not occur in the lab because a gentle reminder that a button press is necessary on each trial would be given if someone were to stop responding or a reminder to use both hands (and subsequently both keys) would be given if one were idly pressing the same key and doing something else with their then free hand. In the lab, participants can be asked to leave for blatantly disregarding instructions, or they can ask questions if there is a lack of understanding. Neither are easily implemented in online data collection, though email was closely monitored to trouble-shoot any technical difficulties that occurred during the sessions whenever possible. Online data collection can only be controlled to a much lesser degree than the lab space. However, efforts were made to structure the task, including adding the required response, in such a way that would mitigate these concerns whenever possible without affecting the integrity of the task or session. In summary, Experiment 3 closely replicates the previous lab experiments despite the somewhat challenging circumstances surrounding online data collection.

EXPERIMENT 4

There was strong evidence for the hybrid model across Experiments 1, 2, and 3. The hybrid model adds a grouping component to the titration model, with the resulting model consistently outperforming the other models. However, there remained the possibility that the observed pattern could also be largely explained by distance effects. This was tested previously by model comparison, which resulted in consistently favoring the titration model over the distance effect only model. However, it had not yet been investigated through a task manipulation. Experiment 4, accordingly, involves manipulating the task such that proactive control is no longer a beneficial strategy for key trial types, specifically 2-N and 8-N. The distribution of smaller and larger targets on these trials was changed from 12.5% / 87.5% to 50% / 50%.

If proactive control is playing a key role in behavior, as proposed in the titration hypothesis, and subjects use less proactive control in this modified task, the behavior will look quite different in Experiment 4 from those before it. Specifically, the 2-N and 8-N trials would look much more similar to the 5-N trials, as the cues are now equally uninformative. If proactive control were maintained in this task, the expectation would be that 2-1 and 8-9 trials, in relation to other 2-N and 8-N trials, would show elevated error rates due to the preparation of the opposite response and slow RTs due to needing to inhibit the prepared response and switch to the correct response.

If the distance effect is sufficient to explain the pattern of data, and proactive control is successfully diminished in this task, the performance on either side of the reference point would be more symmetrical. Further, trials would have similar distance effects to those seen in 5-N trials. For example, a 2-4 trial should look more similar to a 5-7 trial. However, these may still be scaled slightly to the reference point as magnitude effects are also common in this type of task. Model results would then favor the distance effect model over the titration hypothesis model.

Method

Participants

Participants were again both students participating for credit recruited through their course and students and community members for $10/hour recruited through online advertisements and emails. Again, none of the participants in Experiment 4 had participated in Experiments 1, 2, or 3. The same rules from Experiment 3 were used for inclusion. Of 105 generated files, these criteria resulted in the removal of 5 participants who chose to exit the session early, 5 who stopped or never started pressing any buttons during the task, and 7 who did not meet the accuracy requirement. These criteria resulted in a final sample of 88 participants for the analyses.

Task

The task was the same as Experiment 3 except that the selection weight for stimuli was manipulated on certain trials, instead of being equal probability. Specifically, after a 2 or an 8 there was a 50% chance that the next number would be smaller or larger. With 800 trials, there are about 89 trials per cue. With a 12.5% chance of a 1 following a 2 in the original task, this leads to about 11 instances of smaller versus 78 instances of larger numbers following the 2. With a 50% chance, there are then about 44 instances of each smaller and larger numbers following a 2. This increase in the number of instances was intended to impact the amount of proactive control enacted on these trials. The proportions of selections of other trials were not affected. However, there were inherently more 1N and 9N trials because of the increased probability of a 1 occurring after a 2 and a 9 occurring after an 8. Additionally, an instruction was added during the instructions screens to indicate that this expectation that holds for other cues would be intentionally violated for these two trial types.

Procedure

Procedures were identical to Experiment 3, as the recruitment happened concurrently, and the same task site and program selected the experiment (3 or 4) randomly for each subject. The task session was identical to Experiment 3 and took about 45 minutes to complete.

Analyses

Analyses were identical to Experiments 1 and 3.

Results

Descriptive Statistics

Experiment 4 correct mean RTs were fairly similar to Experiments 2 and 3. Mean error rates, however, were slightly higher, more similar to Experiment 1. RT ISD was similar to Experiments 1 and 2. Correct mean RTs are summarized in Table 21, RT ISDs in Table 22, and error rates in Table 23.

Pattern

The general pattern of correct mean RTs is fairly similar to those observed previously. However, the 1-N and 9-N trials are slightly shifted slower than in the previous experiments. Regardless, there is still a clear pattern of titration in the 2-N through 8-N group and a gap separating them from the 1-N and 9-N trials (Figure 15A).

Again, the same models were used to evaluate this pattern. First, to compare the titrated and dichotomous alternative hypotheses, both cue-only and cue-target interaction models were compared. Table 24 reports the AIC and BIC values for these models. In both the cue-only and the cue-target models, the dichotomous model is favored, having a lower AIC and BIC.

Equivalent Bayesian models were again evaluated and are reported in Table 25. As has been the case previously, the Bayesian models for cue-only and cue-target interaction both favor the dichotomous model over the initial titration model. This suggests that despite the slightly slower 1-N and 9-N trials in the current experiment, the gap between them and the remaining trials is still more influential to the model fit than the separation among the 2-N through 8-N trials that is missing in the dichotomous model. Again, it is clear from Figure 15 that the titrated (B) and dichotomous (C) model projections both have not particularly closely reflected the observed data (A).

Table 21. Response Time Means and Standard Deviations for Previous Stimulus and Current Stimulus for Experiment 4

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean*	*SD*
1		404	413	414	402	400	408	394	396	404	7
		(134)	(122)	(125)	(119)	(106)	(101)	(100)	(95)		
2	492		483	478	460	458	467	457	446	468	15
	(76)		(103)	(85)	(82)	(85)	(78)	(88)	(80)		
3	488	498		502	471	474	476	472	467	481	13
	(69)	(87)		(89)	(81)	(82)	(80)	(76)	(74)		
4	483	483	500		493	486	483	483	468	485	9
	(64)	(75)	(80)		(90)	(82)	(80)	(79)	(72)		
5	481	480	489	500		498	499	484	485	489	8
	(65)	(79)	(73)	(85)		(90)	(83)	(72)	(76)		
6	473	472	487	493	522		505	493	487	492	15
	(65)	(74)	(81)	(89)	(87)		(76)	(76)	(66)		
7	474	466	477	491	512	520		499	491	49f1	17
	(75)	(81)	(82)	(86)	(99)	(94)		(71)	(68)		
8	457	452	460	474	495	508	498		487	479	20
	(70)	(81)	(76)	(86)	(89)	(95)	(101)		(74)		
9	384	387	391	404	407	399	409	414		399	10
	(92)	(99)	(106)	(109)	(114)	(124)	(126)	(132)			
Mean	466	455	463	470	470	468	468	462	466	465	4
SD	35	40	39	39	45	46	39	38	32	37	

Table 22. Response Time Individual Standard Deviation Mean for Previous Stimulus and Current Stimulus for Experiment 4

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean ISD*	*SD*
1		135	131	130	122	122	123	118	116	125	6
		(65)	(58)	(57)	(51)	(54)	(58)	(59)	(54)		
2	90		119	113	101	95	103	91	89	100	10
	(44)		(49)	(51)	(47)	(47)	(43)	(43)	(40)		
3	82	97		119	106	105	95	96	87	98	11
	(43)	(43)		(46)	(53)	(44)	(45)	(45)	(42)		
4	83	88	99		102	102	89	97	81	93	8
	(42)	(44)	(41)		(45)	(45)	(40)	(44)	(42)		
5	88	91	96	98		102	105	100	87	96	6
	(41)	(43)	(40)	(41)		(51)	(54)	(53)	(44)		
6	80	91	94	100	105		100	92	81	93	8
	(45)	(45)	(41)	(45)	(50)		(42)	(44)	(41)		
7	82	91	98	103	105	112		94	82	96	10
	(40)	(42)	(46)	(50)	(51)	(43)		(40)	(37)		
8	92	87	95	101	110	117	115		86	100	11
	(46)	(43)	(44)	(45)	(49)	(53)	(52)		(46)		
9	105	110	120	125	130	129	136	145		125	12
	(53)	(48)	(52)	(63)	(56)	(55)	(58)	(65)			
Mean	88	99	106	111	110	110	108	104	88	103	9
SD	8	17	15	12	10	11	16	19	11	13	

Table 23. Mean Percent Error and Standard Deviations for Previous Stimulus and Current Stimulus for Experiment 4

Previous	Current Stimulus									Overall	
Stimulus	1	2	3	4	5	6	7	8	9	*Mean*	*SD*
1		22	17	14	8	5	6	5	4	10	6
		(22)	(19)	(16)	(11)	(9)	(9)	(9)	(7)		
2	15		23	17	10	7	6	6	5	11	6
	(14)		(18)	(17)	(9)	(11)	(8)	(10)	(9)		
3	9	14		22	12	9	10	8	7	11	5
	(12)	(14)		(17)	(13)	(12)	(12)	(11)	(10)		
4	10	11	16		14	10	11	7	7	11	3
	(11)	(13)	(14)		(15)	(11)	(12)	(10)	(9)		
5	8	10	12	16		15	15	11	9	12	3
	(10)	(9)	(12)	(13)		(14)	(16)	(13)	(12)		
6	7	7	10	14	23		15	12	9	12	5
	(9)	(11)	(130	(14)	(19)		(14)	(13)	(12)		
7	4	7	8	11	20	25		12	10	12	6
	(8)	(11)	(11)	(15)	(18)	(20)		(14)	(13)		
8	5	6	7	9	14	19	25		14	12	6
	(11)	(12)	(12)	(12)	(16)	(19)	(19)		(13)		
9	3	6	6	7	10	11	14	20		10	5
	(7)	(9)	(11)	(11)	(17)	(15)	(17)	(20)			
Mean	8	10	12	14	14	13	13	10	8	11	2
SD	4	5	6	5	5	6	6	5	3	1	

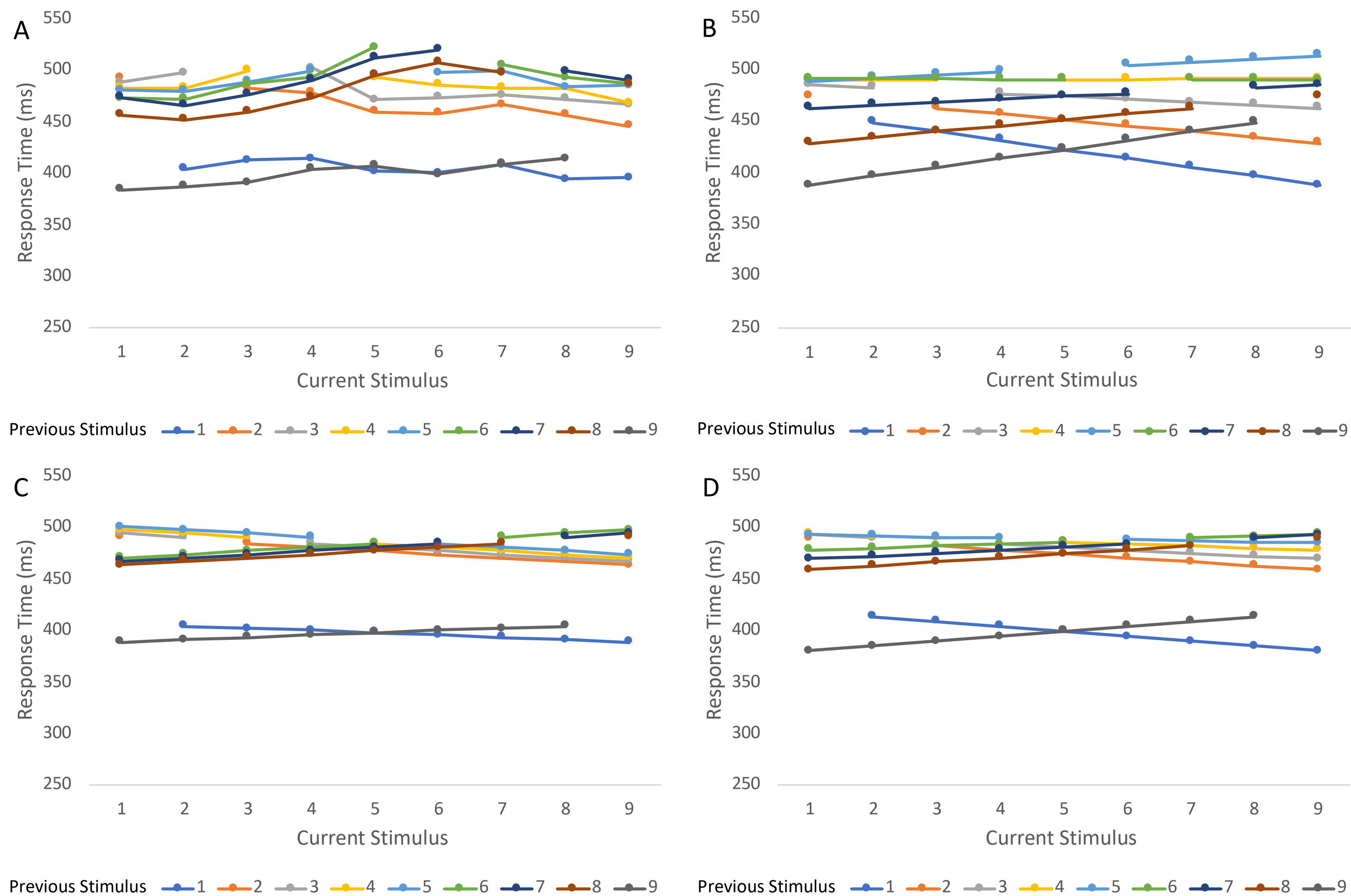


Figure 15. Observed (A) and Modeled Titration (B), Dichotomous (C), and Hybrid (D) patterns for Experiment 4 correct response times.

Table 24. Model Comparison for Experiment 4

Model	Cue		Cue-Target	
	AIC	BIC	AIC	BIC
Titrated model (1, 3)	774092	774128	773288	773342
Dichotomous model (2, 4)	772344	772380	771974	772028
Hybrid model (H1, H2)	772214	772260	771911	771974

Note. Smaller numbers indicate better model fit, but the units of these measures themselves are meaningless.

Table 25. Bayesian Model Comparison for Experiment 4

Model	Cue	Cue-Target
Titrated model (B1, B3)	$2.45e^{604}$	$1.20e^{711}$
Dichotomous model (B2, B4)	$3.09e^{882}$	$1.55e^{932}$
Hybrid model (BH1, BH2)	$3.81e^{903}$	$4.51e^{937}$
Comparison		
Titrated/Dichotomous	$7.90e^{-279}$	$7.76e^{-222}$
Hybrid/Dichotomous	$1.23e^{21}$	291928

Note. Large values have been reported in scientific notation.

Hybrid Model

The hybrid model was again evaluated to investigate whether the titration pattern is better if the 1-N and 9-N trials are allowed to deviate from the rest. Both frequentist (Models H1 and H2) and Bayesian models (Models BH1 and BH2) were evaluated. The AIC and BIC values are reported in Table 24 and show that for both the cue-only and the cue-target interaction models, the hybrid model is preferred to the dichotomous model. The equivalent Bayesian models are compared in Table 25. Again, for both the cue-only and cue-target models, the hybrid model is strongly preferred to the dichotomous model.

Distance Effect

The distance effect was also evaluated by comparing models, described in Experiment 1. The Bayes factors for these models are reported in Table 26. For both the target-only model and the cue-target interaction model, the directional model was again strongly favored. Where this result was expected in Experiments 1 through 3, it was somewhat surprising here given the manipulation of 2-N and 8-N trials to rely less on proactive control.

Table 26. Bayesian Model Comparison of Directional Versus Distance Effect for Experiment 4

Models	Target	Cue-Target
Directional model (B5, B3)	$1.14e^{294}$	$1.20e^{711}$
Distance Only model (B6, B7)	$1.48e^{283}$	$1.56e^{680}$
Relative BF	$7.70e^{10}$	$7.70e^{30}$

Proactive Index

While the proactive index scores are generally similar to the previous experiments, with a broad and fairly normal distribution, Experiment 4 produced the most negative and near-zero proactive index scores, possibly indicating a shift toward less-proactive performance in this task versus in the previous experiments (Figure 16). Despite this shift, subjects were generally more proactive on the 1-N and 9-N trials (1- or 9-N M = 398 ms, SD = 100 ms) than the 5-N trials (5-N M = 488 ms, SD = 67 ms), with an average difference index of 89 ms (SD = 61 ms). However, they were quite variable from one another ranging from -31 ms to 252 ms.

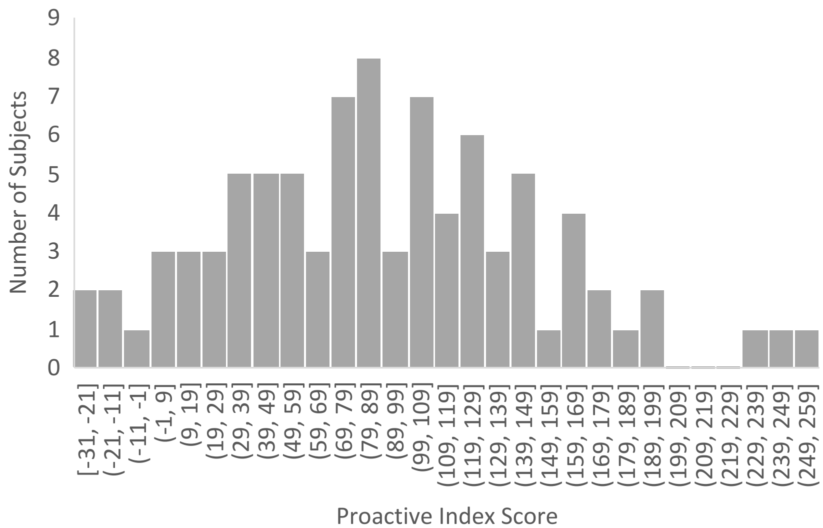


Figure 16. Distribution of proactive index scores for Experiment 4.

Manipulation

The key difference in Experiment 4 from the others is that 2-N and 8-N trials had a 50% chance of N being a smaller or larger number. In Experiments 1 through 3, a 1 only followed a 2 12.5% of the time, and the same for 9 following 8. The remaining 87.5% of the time, N was larger than 2, or smaller than 8, respectively. The expectation was that subjects would use less proactive control on these trials, making them more similar to 5-N trials. Being more reactive should result in slower but accurate responding. Certainly, the 2-N and 8-N trials in this experiment are somewhat slower than in Experiments 1 and 2. They are very close with the 2-N and 8-N trials for

Experiment 3, with the exception of the 2-1 and 8-9 trials. These critical 2-1 and 8-9 trials are slower in Experiment 4, which could be indicative of more reactive control.

Though accuracy should be high for reactive control use, it is not necessarily more or less so than proactive overall. Accordingly, the slightly higher overall error rates for Experiment 4 do not necessarily speak to control use. Error rates would be expected to be lower specifically on the 2-1 and 8-9 trials, which when approached with proactive control may result in higher errors. That is, reactive control, which would be more beneficial with the trial proportions in Experiment 4, could result in fewer errors given that expectations are not present to inflict incorrect anticipatory responses. However, reactive control also relies more on memory due to thinking back to the cue rather than preparing the response when the cue has been presented. The mean error rate for 2-1 trials in 15% (*SD* = 14%) and for 8-9 is 14% (*SD* = 13%), which is actually higher than the most comparable study, Experiment 3 (2-1 *M* = 9%, *SD* = 9%; 8-9 *M* = 9%, *SD* = 7%). This would not be expected unless memory errors were playing an unusually strong role.

Discussion

Experiment 4 provided an opportunity to further investigate the possibility of the distance effect explaining a large portion of the behavior seen in the digit task. The distance effect was a prominent concern for interpreting the results because it is a well-established effect seen in relative number judgment tasks similar to the digit task used in this project. While it was expected, then, that the distance effect would occur, it was a concern whether this effect would be sufficient to describe behavior without needing to incorporate control. The previous 3 experiments showed preference for the titrated model above the distance-only model. In Experiment 4, the task was manipulated to further explore this possibility. Specifically, the 2-N and 8-N trials were altered to remove predictive value by setting the probability of the target response being smaller or larger to 50%.

Experiment 4 seems to agree with the previous experiments, perhaps more than might be expected given the manipulation. It is of course entirely possible that participants either did not read the instruction that specified that proactive control would not be beneficial for 2-N and 8-N trials, forgot about it, or thought it was a trick and prepared in a proactive manner, regardless. However, given the overall pattern of modeling results in Experiment 4, it seems more likely that the effect of the manipulation was just too small. Experiment 4 certainly shows notable differences from the previous three experiments, including being overall slower and less accurate than the most comparable, Experiment 3. However, these differences were not large enough or in the specific places needed to affect the model comparison outcomes. Perhaps this makes sense, given only 2 of the 9 cues were manipulated. Slower and less accurate overall responding may indicate slightly less proactive control overall, but not a complete lack of it. It would still be beneficial on several trial types, so it is likely that at least some of the subjects are still using proactive control on some or even most of the task.

One potential concern with Experiment 4 is that it may not have been a strong enough manipulation, or it was too nuanced and therefore taxing for participants to keep track of the extra information. This may have led to a lack of change in performance for some or all subjects. That is, subjects may have ignored or been unable to maintain this altered expectation and assumed the typical expectancy anyway due to the structure of the majority of the task. Further, because 2-1 trials made up half of the 2-N trials, participants saw fewer of each of the remaining 2-N targets than they normally would. It is possible that instead of registering the distribution as half smaller and half larger, the participants could have been maintaining the probability as mostly 2-1, and only a few of anything else following 2. While the responses are distributed evenly, the visual stimuli are not and could bias participants toward expecting 1 after a 2, instead of removing the expectation.

Accordingly, it is possible that participants even took a strategy that was more proactive than expected in response to the increase in 2-1 and 8-9 trials. They may have prepared for a 2-1 or an 8-9 as those were then individually most frequent despite only happening 50% of the time. This would be similar to preparing for the full set of smaller digits after a 5, but is a much smaller task set (1 versus 4) to watch for. Despite being *more* similar to the 5-N trials than they were previously, the 2-N and 8-N trials were not entirely analogous due to this affordance of strategy use. While this would reflect a different type of proactive strategy than was previously afforded by the 2-N and 8-N trials, it is still proactive in a way.

To target this distance effect comparison, a future study may need to implement a stronger manipulation that takes away all expectancy and therefore any benefit of using proactive control. This could then be compared to the present studies to evaluate how much of the pattern may be due to the distance effects rather than cognitive control. However, it is clear from this study that cognitive control is used in this task and is beneficial to the models above a distance effect alone.

GENERAL DISCUSSION

The primary goals of this project were to expand the understanding of the dynamic use of cognitive control and to establish this digit task as a new and nuanced method for doing so. The hypotheses were rooted in the Dual Mechanisms of Control framework of Braver et al. (2007), but have implications for the broader field studying cognitive control. Further, relationships with working memory were evaluated.

Experiment 1 provided an initial investigation into the feasibility of using this 'greater or less than' digit task to study cognitive control. The results indicate that the participants were sensitive to the task demands. However, while the dichotomous model was supported over the initial titration model, neither hypothesized pattern was particularly satisfying in regard to the observed data. The hybrid model was developed post-hoc to account for the possibility that the titration model may still best describe the behavior for the 2-N through 8-N trials, needing an additional component to allow for the 1-N and 9-N trials then to deviate from the remaining group. This model was preferred over both hypothesized models. A distance effect model was also explored in an effort to determine whether the distance effect would be sufficient to describe the behavior observed, without consideration of cognitive control. It was not, as the titration model was highly preferred to the distance model. The proactive index was calculated to investigate the extent of individual difference in the task, which showed a range of scores that looked promising for future comparison to individual differences measures such as working memory.

Experiment 2 measured working memory in addition to digit task performance to evaluate the relationships between working memory and cognitive control. While these relationships have been found in prior studies using other tasks, the relationships were somewhat mixed with the digit task. Working memory is often related to both speed and accuracy but was only related to accuracy in the current study. It was especially surprising, given previous work with the AX-CPT, that working memory was not related significantly to the proactive index measure. Experiment 2 otherwise closely replicated Experiment 1, finding again that the dichotomous model was preferred to the titration model, but the hybrid model was favored over both. Additionally, the distance effect was evaluated again and was again not preferred over the titration model.

Experiment 3 was a necessary replication of Experiment 1 due to a shift in data collection from the lab space to online data collection. The transition initially held some challenges, such as participants leaving the task running without ever pressing a button. However, simple adjustments, like requiring a response to move on, helped mitigate these data collection issues. Despite the drastic differences in level of control between the lab and presumably quite variable home environments in which these studies took place, Experiment 3 again nicely replicated Experiment 1, and the non-working memory parts of Experiment 2. This outcome provides the assurance that, while not ideal, online data collection for cognitive control studies is a feasible option that will likely yield interpretable results.

In Experiment 4, the task was manipulated to further explore the possibility of a distance effect explaining a large part of the pattern of behavior. Specifically, the 2-N and 8-N trials were manipulated to remove the expectation of a larger or smaller response, respectively. Rather than occurring the majority of the time, the larger and smaller responses were made equally probable on these trials, equal to 5-N trials. While the actual predictive value was removed, the expectation of particular individuals cannot be guaranteed. Therefore, the similarity in behavior between Experiment 4 and the previous three experiments could be due to a lack of fidelity to the instructions. It is not clear whether the few performance differences in this task were substantial enough to suggest the manipulation had the intended effect. The pattern is overall quite similar to the previous experiments and the models still agree that the titration hypothesis model is preferred to the distance effect-only model. Accordingly, further research may be needed before fully ruling out the distance effect as an explanation for the pattern of behavior seen in these experiments.

Together these experiments provide some initial insight into an alternative to the dichotomous view of the dual mechanisms of control. The preference for the hybrid model across all four experiments is ultimately a preference for a titrated control pattern. An additional component, separating the 1-N and 9-N trials from the remaining trials is needed. However, the remaining components of the model are the titration model components. So, ultimately this project shows strong evidence that cognitive control can be used more dynamically than has been generally proposed in the DMC framework. The DMC framework has largely been evaluated in the AX-CPT task that only affords talk of proactive control in some instances and reactive control in others. The task created and tested in the current project allows for additional possibilities that reveal this titration pattern. These results expand on the idea of proactive and reactive control mechanisms by showing that these mechanisms can be dynamically implemented to degrees appropriate for a nuanced task. This project also has implications for broader understanding control mechanisms.

Similar ideas to proactive and reactive control are found across many literatures. Prospective memory, for example, is often broken down into ‘monitoring’ accounts and ‘spontaneous retrieval’ accounts. Monitoring involves maintaining preparation of the intended action or maintaining a search for the cue that requires that action, similar to proactive control. Spontaneous retrieval is less well-understood, but Bugg, McDaniel, and Einstein (2013) propose that it likely involves reactive control in that control would suddenly be required to facilitate the task switch from the ongoing task to the prospective memory task, at least. Reactive control could also be seen to be a response to the conflicting task goals that are induced by this key stimulus, even if monitoring/proactive control was in use to detect this stimulus. This idea would be in conflict with a strict dual mechanisms interpretation where the control mode must ‘switch’, but could be accommodated by the titration hypothesis where there is the possibility that levels of control within each proactive and reactive control could be independently increased.

The present studies’ results also have interesting implications for the number judgement literature, highly relevant due to the nature of the digit task used in the present experiments, in that they seem to go against some very common findings. For example, Holyoak (1978) discusses magnitude effects, where RTs are slower for deciding between two relatively larger numbers versus two relatively smaller numbers. This requires the use of magnitude ratios, rather than distance to account for the differing RTs between otherwise equidistant pairs. In the present work, a magnitude effect pattern is not found. Trials with 9 as the cue are faster than 8-N trials, which are faster than 7-N trials. The opposite would be true in the presence of magnitude effects.

Dehaene (1989) proposes that moving or imbalanced reference points eliminate magnitude effects because the judgments are made relative to an internal reference point at either end of the full range. Dehaene found that when a reference point was closer to one end, the judgments for numbers between the reference point and the end were faster than those beyond the reference point in relation to the closer end. For example, a reference point of 35 in a range of 20-99 would have a faster comparison to 20 than to 50. Schneider and Logan (2007) found the same pattern in a task more somewhat more similar to the present work using 0-9, and changing the reference point between 2 and 7. In their task, 2-1 was faster than 2-3. However, in the current project, 2-1 is slower than 2-3. The typical symbolic distance effect and magnitude effect patterns are not found. This only makes sense if the subjects in the current project were aware of the trial type probabilities and preparing for them by implementing some level of proactive control. Together with the modeling results, this lends further argument against a distance effect account and in favor of the titration account of the pattern of RTs in the present studies.

Many potential follow-ups could further specify, explore, and test the mechanisms needed for this proposed dynamic control system. If proactive and reactive control processes were mutually exclusive and competing, or perhaps opposite ends of the same process, they would be inversely related. That is, increased proactive control use would lead to decreased reactive control use. However, if they are truly separate, independent, processes that can be flexibly used simultaneously, it should be possible for use of each to increase without cost to the other process.

Other mechanisms for increasing proactive or reactive control have been investigated. For example, Janowich and Cavanagh (2018) found via meta-analysis that designs with varied ISIs lead to more reactive control overall than studies that used consistent (predictable) ISIs. However, comparing the results from AX-CPT-70 from Redick (2014), with a predictable 4500 ms ISI, to the variable ISI (5000 and 1000 mixed) of Redick and Engle (2011) which were otherwise similar tasks and procedures, the meta-analysis is not painting a full picture. For low working memory subjects in Redick and Engle (2011), the variable ISI resulted in longer RTs (indicative of reactive control) for both short and long ISI trials within the mixed blocks when compared to the low working memory subjects from Redick (2014). However, high working memory subjects showed faster RTs (indicative of proactive control) on B-Y and B-X trials on the long ISI trials in the mixed blocks.

As mentioned, I showed in an earlier study that in the AX-CPT-70, a task where proactive control was beneficial for overall performance, time on a task lead to increased overall proactive control use for low working memory subjects (Wiemers & Redick, 2018). In addition to time on task, explicit instructions and strategy training or practice can increase proactive control use (Braver, Paxton, Locke, & Barch, 2009; Paxton et al., 2006). These types of improvements follow from an initial relationship such that low working memory individuals use proactive control less often than high working memory individuals. However, in Experiment 2 of the current project, the working memory relationships were less clear. Working memory was related to overall error rates and improved the models, but was not related to RTs or the proactive index, critical to determining levels of control use.

It is possible that proactive control use in this more dynamic task has levels that are more readily available for lower working memory individuals in a way that is not afforded by the AX-CPT. The performance on 1-N and 9-N trials being so starkly different from 2-N and 8-N trials could reflect strongly different levels of proactive control as is suggested by the titration account, or it could be reflecting a different type of proactive control use. Anecdotally, in the AX-CPT participants are asked to keep their fingers on the buttons at all times but sometimes can be seen lifting the finger that corresponds to a future incorrect response to physically prepare to make only the correct response, with no risk of forgetting and making the incorrect response. This type of physical preparation is afforded in the 'B-X' and 'B-Y' trials with 100% accuracy, similar to the 1-N and 9-N trials in the current task. This physical preparation could be less dramatic, with a slight pressure on the anticipated response key mentally and physically marking the future correct response without technically 'breaking the rules', too. In either case, this is likely a very different preparation than the more mentally taxing preparation involved in being 'mostly' prepared to hit the 'larger' key for a 2-N trial. For example, on a 2-N trial, one might be preparing for the 'larger' response, but they could also be preparing to inhibit this response for the infrequent 2-1 trials. The mental preparation could be analogous to the dialogue, "2 means probably larger, prepare to press right" or "Is it a 1 or not? Yes = left, No = right".

The mental preparation is present in both cases, but physical preparation may only be present in the first instance. These are both forms of proactive control, which would lead to the lack of correlation between control use and working memory as measured by RTs because low working memory individuals could be using as much or almost as much proactive control, just of a different type. Future studies would be needed to explore this possibility.

However, less physical preparation would likely result in slower RTs that would not show this nicely graded pattern. Though, if the mental preparation on 2-N trials is to compare to 1, then on 3-N trials the mental preparation could be "Is it a 1 or 2?", which would take a little longer, and so on. In that framing, this pattern of RTs could also be thought of as reflecting increasing task sets. However, this thinking is still preparatory in nature and would fall under the realm of proactive control.

While the idea of the current project was to delve into the nuances of control use, the separability of proactive and reactive control was not addressed. Other factors not considered in the present work have been shown to influence control use and have been used to try to disentangle these two processes. Rewards (manipulating motivation) and task-informative cues have been shown to increase proactive control use (e.g., Boehler, Schevernels, Hopf, Stoppel, & Krebs, 2014; Chiew & Braver, 2016). Strategy training has also been used to influence proactive and reactive control use (e.g., Gonthier, Macnamara, Chow, Conway, & Braver, 2016). Motivation, cues, and strategy training were all used to investigate whether shifts in proactive and reactive control could be induced. These studies resulted in an understanding that control was a flexible mechanism that could be shifted from one to another dynamically.

However, these efforts do not speak to whether these processes could be manipulated separately. While the current project aims to further the understanding of how dynamically control can be implanted, it also does not ultimately determine whether both can simultaneously be dynamically used. In fact, to date, very few studies have attempted to manipulate proactive and reactive control either together or without detriment to the other process (reactive or proactive control). One such attempt by Mäki-Marttunen, et al. (2019) found some evidence of proactive control increase via reward with lower A-Y accuracy, but not corresponding higher B-X accuracy. Standard and high-load versions of the AX-CPT were used, and point rewards were offered. Participants were asked to try to get as many points as possible, and their score would be given to them at the end. RTs were faster in the reward condition, which also points to proactive control use. They also used load conditions to induce reactive control, with higher cognitive load intended to induce more reactive control, though it is unclear why this would be the case. Proactive control would be more beneficial in a high-cue-load paradigm due to the memory component of reactive control. B-X errors increased under high load regardless of reward, which could simply be due to a memory constraint, rather than reactive control use. Further, the study has a hallmark problem of the AX-CPT-70 in that only 15 trials are being evaluated for each of the critical trial types (A-Y and B-X each at 10% of 150 trials).

The present work focused on whether proactive control could be used in a more nuanced way, with an assumption that reactive control would be similarly used to balance performance. That is, on the middle-predictive trials like 3-N and 4-N, some proactive and some reactive control would both be employed to result in a sort of somewhat proactive/somewhat reactive middle ground appropriate to the level of uncertainty. In the present project however, this is mostly framed in levels of proactive control, avoiding this two-sided framing, as it is more difficult to determine how to look at both at once in the current task structure.

Some evidence from the current project does suggest this may be the case, however. Certain “B-X” analogous trials, such as 2-1 or 8-9 trials, sometimes showed performance indicative of reactive control (i.e., fewer errors and faster RTs) compared to trials where the more frequent response was correct (“A-X” analogous trials such as 2-3 or 8-7). While the relative speed on these 2-N and 8-N trials would suggest overall proactive control use, the relatively strong performance on the 2-1 and 8-9 trials would normally be interpreted as indicating reactive control performance. So, one possible interpretation is that both are being employed to a high degree on these trials. However, it is also possible that this performance pattern is reflecting a different type of proactive control that involves preparing for these ‘B-X’ analogous trials instead of being surprised by them. More work would need to be done to investigate these alternative possibilities and disentangle these control mechanisms in this situation before claiming that both proactive and reactive are represented strongly in these trials.

As such, it remains a question for future studies, whether proactive and reactive control can be truly separated behaviorally, consistent with their suggested neurophysiological separation, and whether they can be flexibly employed simultaneously. Future experiments with versions of this new digit task will need to show whether both proactive and reactive control can be improved simultaneously, without detriment to the other mechanism. These are questions that could be explored using this new digit task in a very nuanced way not afforded by other tasks such as the AX-CPT. Remaining questions also include whether the hybrid model is accounting for a mapping effect or a different additional necessary factor, whether the distance effect alone would show a similar pattern if proactive control could be removed entirely, and whether proactive and reactive control can be manipulated independently. The development of this task lays a foundation on which these questions can be studied.

In conclusion, the goal for this project was to show four things. 1. I developed a new task that is more sensitive to the nuances of cognitive control mechanisms, specifically when investigating within the dual mechanisms of control framework. 2. I advanced the knowledge regarding how differences in working memory affect the use of cognitive control. 3. I determined that online data collection is feasible despite the challenges of studying cognitive control in low-control settings. 4. I ensured that the titration pattern could not be reduced to a misreading of numerical distance effects. These contributions to the field have implications for the understanding of the dual mechanisms of control framework and more generally the understanding of cognitive control mechanisms, positing that these mechanisms may be more flexible than previously thought, and introduce a task that allows for further exploration of this theory.

LIST OF REFERENCES

Ackerman, P. L., Beier, M. E., & Boyle, M. O. (2005). Working memory and intelligence: The same or different constructs? *Psychological Bulletin, 131*(1), 30-60. doi:10.1037/0033-2909.131.1.30

Abrahamse, E., Braem, S., Notebaert, W., & Verguts, T. (2016). Grounding cognitive control in associative learning. *Psychological Bulletin, 142*(7), 693-728. doi:10.1037/bul0000047

Appelbaum, L. G., Boehler, C. N., Davis, L. A., Won, R. J., & Woldorff, M. G. (2014). The dynamics of proactive and reactive cognitive control processes in the human brain. *Journal of Cognitive Neuroscience, 26*(5), 1021-1038. doi:10.1162/jocn_a_00542

Aron, A. R. (2011). From reactive to proactive and selective control: Developing a richer model for stopping inappropriate responses. *Biological Psychiatry, 69,* e55-e68. doi:10.1016/j.biopsych.2010.07.024

Ball, B. H., & Brewer, G. A. (2018). Proactive control processes in event-based prospective memory: Evidence from intraindividual variability and ex-gaussian analyses. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 44*(5), 793-811. doi:10.1037/xlm0000489

Boehler, C. N., Schevernels, H., Hopf, J.-M., Stoppel, C. M., & Krebs, R. M. (2014). Reward prospect rapidly speeds up response inhibition vie reactive control. *Cognitive, Affective, & Behavioral Neuroscience, 14,* 593-609. doi:10.3758/s13415-014-0251-5

Botvinick, M. M., Braver, T. S., Barch, D. M., Carter, C. S., & Cohen, J. D. (2001). Conflict monitoring and cognitive control. *Psychological Review, 108*(3), 624-652. doi:10.1037//0033-295X.108.3.624

Boudewyn, M. A., Long, D. L., Traxler, M. J., Lesh, T. A., Dave, S., Mangun, G. R., Carter, C. S., & Swaab, T. Y. (2015). Sensitivity to referential ambiguity in discourse: The role of attention, working memory, and verbal ability. *Journal of Cognitive Neuroscience*, 27(12), 1–15. doi:10.1162/jocn_a_00837

Braver, T. S. (2012). The variable nature of cognitive control: A dual mechanisms framework. *Trends in Cognitive Sciences, 16*(2), 106-113. doi:10.1016/j.tics.2011.12.010

Braver, T. S., Gray, J. R., & Burgess, G. C. (2007). Explaining the many varieties of working memory variation: Dual mechanisms of cognitive control. In A. R. A. Conway, C. Jarrold, M. J. Kane, A. Miyake, & J. Towse (Eds.), *Variation in working memory* (pp. 76-106). New York, NY: Oxford University Press.

Braver, T. S., Paxton, J. L., Locke, H. S., & Barch, D. M. (2009). Flexible neural mechanisms of cognitive control within human prefrontal cortex. *Proceedings of the National Academy of Sciences, 106*(18), 7351-7356. doi:10.1073/pnas.0808187106

Brown, J. W. (2013). Beyond conflict monitoring: Cognitive control and the neural basis of thinking before you act. *Current Directions in Psychological Science, 22*(3), 179-185. doi:10.1177/0963721412470685

Bugg, J. M., McDaniel, M. A., & Einstein, G. O. (2013). Event-based prospective remembering: An integration of prospective memory and cognitive control theories. In D. Reisberg (Ed.), *The Oxford handbook of cognitive psychology* (pp. 267-282). Oxford, England: Oxford University Press.

Bush, G., Luu, P., & Posner, M. I. (2000). Cognitive and emotional influences in anterior cingulate cortex. *Trends in Cognitive Sciences, 4*(6), 215-222. doi:10.1016/S1364-6613(00)01483-2

Chiew, K. S., & Braver, T. S. (2016). Reward favors the prepared: Incentive and task-informative cues interact to enhance attentional control. *Journal of Experimental Psychology: Human Perception and Performance, 42*(1), 52-66. doi:10.1037/xhp0000129

Clayson, P. E., & Larson, M. J. (2011). Conflict adaptation and sequential trial effects: Support for the conflict monitoring theory. *Neuropsychologia, 49*(7), 1953-1961. doi:10.1016/j.neuropsychologia.2011.03.023

Cohen, J. D., Barch, D. M., Carter, C., & Servan-Schreiber, D. (1999). Context-processing deficits in schizophrenia: Converging evidence from three theoretically motivated cognitive tasks. *Journal of Abnormal Psychology, 108*(1), 120-133. doi:10.1037/0021-843X.108.1.120

Cole, M. W., & Schneider, W. (2007). The cognitive control network: Integrated cortical regions with dissociable functions. *NeuroImage, 37,* 343-360. doi:10.1016/j.neuroimage.2007.03.071

Cunillera, T., Fuentemilla, L., Brignani, D., Cucurell, D., & Miniussi, C. (2014). A simultaneous modulation of reactive and proactive inhibition processes by anodal tDCS on the right inferior frontal cortex. *PLoS ONE, 9*(11), e113537. doi:10.1371/journal.pone.0113537

Curtis, C. E., & D'Esposito, M. (2003). Persistent activity in the prefrontal cortex during working memory. *Trends in Cognitive Sciences, 7*(9), 415-423. doi:10.1016/S1364-6613(03)00197-9

De Pisapia, N., & Braver, T. S. (2006). A model of dual control mechanisms through anterior cingulate and prefrontal cortex interactions. *Neurocomputing, 69,* 1322-1326. doi:10.1016/j.neucom.2005.12.100

Dehaene, S. (1989). The psychophysics of numerical comparison: A reexamination of apparently incompatible data. *Perception & Psychophysics, 45*(6), 557-566. doi:10.3758/BF03208063

Edwards, B. G., Barch, D. M., & Braver, T. S. (2010). Improving prefrontal cortex function in schizophrenia through focused training of cognitive control. *Frontiers in Human Neuroscience, 4*(32). doi:10.3389/fnh.2010.00032

Engle, R. W. (2018). Working memory and executive attention: A revisit. *Perspectives on Psychological Science, 13*(2), 190-193. doi:10.1177/1745691617720478

Engle, R. W., Tuholski, S. W., Laughlin, J. E., & Conway, A. R. A. (1999). Working memory, short-term memory and general fluid intelligence: A latent variable approach. *Journal of Experimental Psychology: General, 128,* 309-331. doi:10.1037/0096-3445.128.3.309

Fellows, L. K., & Farah, M. J. (2005). Is anterior cingulate cortex necessary for cognitive control? *Brain, 128,* 788-796. doi:10.1093/brain/awh405

Gratton, G., Cooper, P., Fabiani, M., Carter, C. S., & Karayanidis, F. (2018). Dynamics of cognitive control: Theoretical bases, paradigms, and a view for the future. *Psychophysiology, 55*(3), 1-29. doi:10.1111/psyp.13016

Heitz, R. P., & Engle, R. W. (2007). Focusing the spotlight: Individual differences in visual attention control. *Journal of Experimental Psychology: General, 136*(2), 217-240. doi:10.1037/0096-3445.136.2.217

Holyoak, K. J. (1978). Comparative judgments with numerical reference points. *Cognitive Psychology, 10*, 203-243. doi:10.1016/0010-0285(78)90014-2

Hutchison, K. A. (2011). The interactive effects of listwise control, item-based control, and working memory capacity on Stroop performance. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 37*(4), 851-860

Janowich, J. R., & Cavanagh, J. F. (2018). Delay knowledge and trial set count modulate use of proactive versus reactive control: A meta-analytic review. *Psychonomic Bulletin & Review, 25,* 1249-1268. doi:10.3758/s13423-018-1502-1

Jiang, J., Beck, J., Heller, K., & Egner, T. (2015). An insula-frontostriatal network mediates flexible cognitive control by adaptively predicting changing control demands. *Nature Communications, 6*(8165), 1-11. doi:10.1038/ncomms9165Kahneman, D. (1970). Remarks on attention control. *Acta Psychologica, 33*, 118-131. doi:10.1016/0001-6918(70)90127-7

Kane, M. J., Conway, A. R. A., Hambrick, D. Z., & Engle, R. W. (2007). Variation in working-memory capacity as variation in executive attention and control. In A. R. A. Conway, C. Jarrold, M. J. Kane, A. Miyake, & J. N. Towse (Eds.), *Variation in working memory* (pp. 21-48). New York, NY: Oxford University Press.

Kane, M. J., & Engle, R. W. (2003). Working-memory capacity and the control of attention: The contributions of goal neglect, response competition, and task set to Stroop interference. *Journal of Experimental Psychology: General, 132*(1), 47-70. doi:10.1037/0096-3445.132.1.47

Kerns, J. G., Cohen, J. D., MacDonald, III, A. W., Cho, R. Y., Stenger, A., & Carter, C. S. (2004). Anterior cingulate conflict monitoring and adjustments in control. *Science, 303*, 1023-1026. doi:10.1126/science.1089910

Mäki-Marttunen, V., Hagen, T., & Espeseth, T. (2019). Proactive and reactive modes of cognitive control can operate independently and simultaneously. *Acta Psychologica, 199*, advanced online publication. doi:10.1016/j.actpsy.2019.102891

Miller, R., Schmidt, K., Kirschbaum, C., & Enge, S. (2018). Comparability, stability, and reliability of internet-based mental chronometry in domestic and laboratory settings. *Behavior Research Methods, 50,* 1245-1358. doi:10.3758/s13428-018-1036-5

Miyake, A., Friedman, N. P., Emerson, M. J., Witzki, A. H., Howerter, A., & Wager, T. D. (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. *Cognitive Psychology, 41,* 49-100. doi:10.1006/cogp.1999.0734

Munakata, Y., Snyder, H. R., & Chatham, C. H. (2012). Developing cognitive control: Three key transitions. *Current Directions in Psychological Science, 21*(2), 71-77. doi:10.1177/0963721412436807

Necka, E., Cacioppo, S., Norman, G. J., & Cacioppo, J. T. (2016). Measuring the prevalence of problematic respondent behaviors among MTurk, campus, and community participants. *PLoS ONE.* doi:10.137/journal.pone.0157732

Paxton, J. L., Barch, D. M., Storandt, M. & Braver, T. S. (2006). Effects of environmental support and strategy training on older adults' use of context. *Psychology and Aging, 21*(3), 499-509. doi:10.1037/0882-7975.21.3.499

Posner, M. I., & Petersen, S. E. (1990). The attention system of the human brain. *Annual Review of Neuroscience, 13,* 25-42. doi:10.1146/annurev.ne.13.030190.000325

Redick, T. S. (2014). Cognitive control in context: Working memory capacity and proactive control. *Acta Psychologica, 145,* 1-9. doi:10.1016/j.actpsy.2013.10.010

Redick, T. S., Broadway, J. M., Meier, M. E., Kuriakose, P. S., Unsworth, N., Kane, M. J., & Engle, R. W. (2012). Measuring working memory capacity with automated complex span tasks. *European Journal of Psychological Assessment, 28*(3), 164-171. https://doi.org/10.1027/1015-5759/a000123

Redick, T. S., Calvo, A., Gay, C. E., & Engle, R. W. (2011). Working memory capacity and go/no-go performance: Selective effects of updating, maintenance, and inhibition. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 37*(2), 308-324. doi:10.1037/a0022216

Richmond, L. L., Redick, T. S., & Braver, T. S. (2015). Remembering to prepare: The benefits (and costs) of high working memory capacity. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 41*(6), 1764-1777. doi:10.1037/xlm0000122

Schneider, D. W., & Logan, G. D. (2007). Defining task-set reconfiguration: The case of reference point switching. *Psychonomic Bulletin & Review, 14*(1), 118-125. doi:10.3758/BF03194038

Shipstead, Z., Harrison, T. L., & Engle, R. W. (2016). Working memory capacity and fluid intelligence: Maintenance and disengagement. *Perspectives on Psychological Science, 11*(6), 771-799. doi:10.1177/1745691616650647

Stawarczyk, D., Majerus, S., Catale, C., & D'Argembeau, A. (2014). Relationships between mind-wandering and attentional control abilities in young adults and adolescents. *Acta Psychologica*, 148, 25-36. doi:10.1016/j.actpsy.2014.01.007.

Suzuki, K., & Shinoda, H. (2015). Transition from reactive control to proactive control across conflict adaptation: An sLORETA study. *Brain and Cognition*, *100,* 7-14. doi:10.1016/j.bandc.2015.09.001

Thomson, D. R., Besner, D., & Smilek, D. (2016). A critical examination of the evidence for sensitivity loss in modern vigilance tasks. *Psychological Review, 123*(1), 70-83. doi:10.1037/rev0000021

Unsworth, N., Heitz, R. P., Schrock, J. C., & Engle, R. W. (2005). An automated version of the operation span task. *Behavior Research Methods, Instruments, & Computers, 37*(3), 498-505. doi:10.3758/BF03192720

Unsworth, N., Redick, T. S., Heitz, R. P., Broadway, J. M., & Engle, R. W. (2009). Complex working memory span tasks and higher-order cognition: A latent-variable analysis of the relationship between processing and storage. *Memory, 17*(6), 635-654. doi:10.1080/09658210902998047

Unsworth, N., Redick, T. S., Spillers, G. J., & Brewer, G. A. (2012). Variation in working memory capacity and cognitive control: Goal maintenance and microadjustments of control. *The Quarterly Journal of Experimental Psychology, 65*(2), 326-355. doi:10.1080/17470218.2011.597865

Unsworth, N., & Spillers, G. J. (2010). Working memory capacity: Attention control, secondary memory, or both? A direct test of the dual-component model. *Journal of Memory and Language, 62*, 392-406. doi:10.1016/j.jml.2010.02.001

Verbruggen, F., & Logan, G. D. (2009). Automaticity of cognitive control: Goal priming in response-inhibition paradigms. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 35*(5), 1381-1388. doi:10.1037/a0016645

Verbruggen, F., Notebaert, W., Liefooghe, B., & Vandierendonk, A. (2006). Stimulus- and response-conflict-induced cognitive control in the flanker task. *Psychonomic Bulletin & Review, 13*(2), 328-333. doi:10.3758/BF03193852

West, R., & Bailey, K. (2012). ERP correlates of dual mechanisms of control in the counting Stroop task. *Psychophysiology, 49,* 1309-1318. doi:10.1111/j.1469-8986.2012.01464.x

Wiemers, E. A., & Redick, T. S. (2018). Working memory capacity and intra-individual variability of proactive control. *Acta Psychologica, 182,* 21-31. doi:10.1016/j.actpsy.2017.11.002

Wiemers, E. A., & Redick, T.S. (2019). Task manipulation effects on the relationship between working memory and go/no-go task performance. *Consciousness and Cognition, 71,* 39-58. doi:10.1016/j.concog.2019.03.006