IS EVERYTHING UNDER CONTROL? A REEXAMINATION OF INDIVIDUAL VARIATIONS IN COGNITIVE CONTROL

by

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A dissertation submitted to the faculty of
The University of Utah
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

Department of Psychology

The University of Utah

December 2014

The University of Utah Graduate School

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ABSTRACT

To investigate controlled processes, cognitive psychologists often rely on oppositional logic, pitting automatic and controlled processes against one another, measuring speed and accuracy of responding to incongruent stimuli (e.g., *RED* printed in green ink). These investigations have been critical to understanding cognitive control, but present a limited and mostly pejorative view of automatic processes. Through the studies in this dissertation, we explored a larger and more beneficial role for automatic processes. In the two preliminary experiments, we administered a high-congruency Simon task, with either a warning to encourage control or no warning where automatic and controlled processing were emphasized equally. The results suggested that high spans can exert or withhold control to a greater degree than low spans, based on simple changes to task instructions. The dissertation experiments replicated and extended these findings. The first two experiments were a speed-blocked variation of the Simon task, again with warning or no warning instructions as the only difference between experiments. Next, to see if these Simon task findings generalized, we administered the stop-signal paradigm as a multitasking extension of oppositional logic tasks and again found evidence of those higher in cognitive control having greater flexibility between automatic and controlled aspects of the task. Combined, the experiments suggest those with high levels of control are more flexible in their allocation of cognitive control and automaticity than low spans who rigidly apply both types of processing. High spans' flexibility is discussed as greater tolerance of automatic processing brought about by stronger inhibitory control.

To Kennedy, that she may know the only limits are those we create in our mind. Dream big, work hard, and never stop playing

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ACKNOWLEDGMENTS

To my advisor Jason Watson for his tireless support and optimism in my ability to succeed. Through his efforts I was able to improve my ability to think, write, create, and analyze. He taught me that our greatest scientific tool is the critical examination of the thoughts in our head. Through this I learned that the unexamined idea is like Socrates' unexamined life; it is not worth having.

To my first academic advisor, David Strayer, who saw my potential years before I ever did. Without him I would have never had the confidence to pursue the dream of becoming a doctor. He was my first guide and he continues to be one of my biggest cheerleaders.

To my husband, Justin, who told me I was meant to be more than just a mother at the age of 23. He forced me to return to school and pursue this dream. He has been an unwavering source of support, love, and guidance. This dissertation is possible because I could stand on the firm foundation of support he gave me.

CHAPTER 1

INTRODUCTION

It is commonly believed that human cognition consists of both controlled and automatic processes. Controlled processes, often referred to as cognitive control, are the mechanisms whereby people consciously direct behavior in a goal-directed and flexible manner based on explicit knowledge and expectations (McBride, Boy, Husain, & Sumner, 2012; Schneider & Shiffrin, 1977). In contrast, automatic processes have traditionally been considered unconscious, fast, and inflexible in their execution (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977). Cognitive psychologists have been primarily interested in understanding controlled processes. With this focus, we have learned much about the development, neurobiology, and psychology associated with the controlled aspects of our cognitive experience, but as a consequence of this focus on controlled processing, much of what we know about automatic processing's role in higher order cognition is tied to the dichotomous ways in which we study these processes.

A majority of what we know about the nature of controlled processing has come from oppositional task paradigms that place controlled processing in direct conflict with automatic processing for successful task completion. A common example of this approach is response inhibition or "conflict" tasks such the Eriksen flanker task (see Eriksen & Eriksen, 1974), the Stroop color-naming task (e.g., Stroop, 1935) and the

Simon task (for a review see Lu and Proctor, 1995). When a stimulus is presented in a response inhibition task, two responses are activated. According to the Activation-Suppression model (e.g., Ridderinkof, 2002; see Figure 1), one activated response is the“direct route,” which is based on the prepotent or automatic features in the stimulus. The second response activated by a stimulus is the “indirect” or novel aspects of the stimulus. This portion of the stimulus is generally less prepotent compared to the automatic feature and is therefore chosen by researchers via task instructions as the portion of the stimulus to be acted upon. Returning to the arrow-variant of the Simon task, the spatial location is the more prepotent aspect of the stimulus, whereas the arrow direction is the more novel, task appropriate, controlled portion. When the spatial location and arrow direction are congruent, it is simple to respond to the direct route, and one can actually respond correctly by relying on the direct route, indirect route, or both. However, when the arrow direction and spatial location are incongruent, controlled processing has to be exerted in order to override the direct route/automatic tendencies. The Activation-Suppression model suggests “selective suppression” of the direct route allows one to make the appropriate response selection relying on the indirect route to execute it (e.g., Ridderinkof, 2002; see Figure 1).

The way we deal with conflict that arises from incongruent trials has been key to understanding how controlled processing overrides our automatic tendencies. The horse-race model proposed by Logan and Cowan (1984) is often used to explain how this process occurs. According to the model, when an incongruent stimulus is presented, the automatic and controlled portions of the stimulus race to beat the other in an attempt to be the selected response. If the automatic tendencies win, a participant responds in error. If

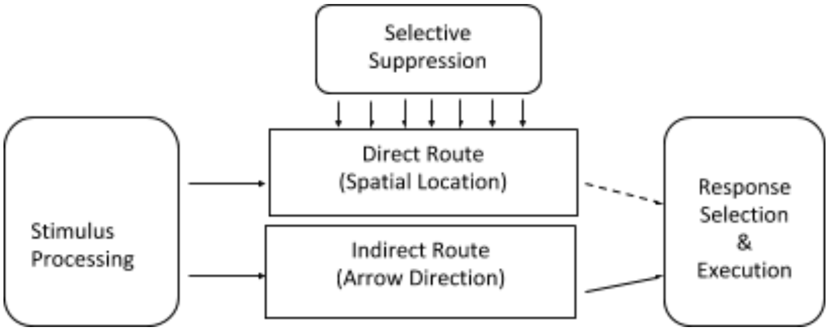

Figure 1. The Activation-Suppression Model (Adapted from Ridderinkof, 2002). When a stimulus is being processed, two selection routes (direct and indirect) are activated. On congruent trials where the two routes can simultaneously be activated, quick response section and execution is made. On incongruent trials, the indirect route is properly selected and executed only through selective suppression of the direct route through controlled processing.

the controlled processes win, a participant correctly responds. Critical support for the horse-race model comes from research using the stop-signal paradigm (Bissett & Logan, 2011). In this task, the majority of trials are *go* trials that require only a simple discrimination between two objects with a left or right button response (e.g., if a square appears, press the left button; if a circle appears, press the right button). However, 25% of the trials are *stop signal* trials where an auditory stop signal cue is presented after the stimulus, indicating participants should withhold their response on that trial. Performance on the stop-signal paradigm is dependent on the relative finishing times of the more automatic go trial processes, and the controlled stop signal trial processes (i.e., the horse-race; Logan & Cowan, 1984). If the stop signal process finishes before the go, then a participant will successfully inhibit his or her response. If the go process finishes before the stop signal process, then a participant will fail to inhibit his or her response. When a participant successfully inhibits a response, the program increases the response threshold, creating a longer latency between the stimulus and the potential stop signal cue. As participants perform the task, an algorithm calculates their *point of no return,* which is the latency at which they can no longer withhold a response, when a stop signal is given (Osman, Kornblum, & Meyer, 1986). Success on the stop-signal paradigm therefore requires balancing both the automatic and controlled portions of the task so that one can respond quickly on the go trials while also being able to accurately inhibit a response given the stop signal. The ability to do so requires flexibly adapting control to the stimulus condition. In addition, control is also critical as the time between stimulus presentation and stop signal increases due to a greater demand on control processing to inhibit an increasingly activated go response.

Evidence of this claim comes from group-level variation in the point of no return for people with compromised inhibitory control. For example, several studies have demonstrated that the point of no return is decreased in younger children (Williams, Ponesse, Schachar, Logan, & Tannock, 1999), older adults (Kramer, Humphrey, Larish, Logan, & Strayer, 1994), impulsive people (Logan, Schachar, & Tannock, 1997), and children with attention-deficit/hyperactivity disorder (ADHD; e.g., Senderecka, Grabowska, Szewczyk, Gerc, & Chmylak, 2012) in comparison with appropriate control groups where attention is not compromised. Due to inhibitory deficits suffered by most of these groups, it has often been concluded that the difference between special populations and controls is a greater ability on behalf of the controls to flexibly regulate automatic processes, thereby producing an elongated point of no return.

Similarities between the horse race model and the Activation-Suppression model highlight the importance of inhibiting automaticity for the sake of control (Botvinick et al., 2001). In the Activation Suppression Model, inhibition occurs when the automatic or direct route is suppressed, allowing the indirect route to properly respond. In the horse race model, inhibition is required as a way to balance the demands of the go and stop signal trials within this paradigm. In this way, automaticity and control are separable processes that seem to work in opposition to one another for the sake of their distinct goals.

Alternative accounts of automatic and controlled processing suggest controlled cognition is not in a horse race with automaticity; rather controlled cognition is the executive whose role it is to determine the situations where automatic processing should be inhibited. Kahneman’s (2011; see also Kahneman and Tversky, 1973) classic work on this matter recognized two systems synonymous with automatic (system 1) and controlled (system 2) processing that have distinct roles in human information processing. Similar to the Activation-Suppression model, he suggests controlled processes are primarily in charge of determining how automatic processes will be implemented. Additionally, he suggests intelligence is a key determinant of how efficient the control system is at regulating automatic processes. This suggestion is in keeping with a large body of research on individual differences in controlled processing that uses working memory capacity, which is related to measures of fluid intelligence, to examine how control is implemented.

Working memory capacity refers to a specific theoretical perspective on shor*t*-term memory where information is actively processed and manipulated (i.e., storage under conditions of concurrent cognitive load, as opposed to more traditional shor*t*-term memory measures of storage alone). Individuals vary in the amount of information they can process at one time, as well as their ability to selectively maintain the most important information (as opposed to distracting information that is not task relevant). To measure individual variations in working memory capacity, researchers have commonly used one of several complex span tasks. On their surface, a complex span task looks similar to a simple span task where people are instructed to memorize a set of letters, numbers, or words. However, complex span tasks differ from simple span tasks because they are a dual task that require people to memorize some list (i.e., words, letters, numbers) while also interleaving a second task that requires basic processing (e.g., reading sentences or solving simple math problems) that is unrelated to the memory task. Performance on complex span tasks is often sorted into quartiles with the highest (high spans) and lowest (low spans) quartiles of participants used as “extreme” comparison groups. Individual differences researchers who take a finer grained level of analysis to examine the nature of automatic and controlled processing commonly use extreme group analyses of this ilk.

The additional processing required in complex span tasks involves a higher order cognitive ability because performance on a complex span task reliably predicts performance on a wide variety of real-world and laboratory cognitive tasks. For example, performance in reading comprehension (MacDonald, Just, & Carpenter, 1992), complex learning (Kyllonen & Stephens, 1990; Shute, 1991), reasoning (Kyllonen & Christal, 1990), driving (Strayer, Cooper, & Medeiros-Ward, 2010; Watson et al., 2013), Stroop (Kane & Engle, 2003), inattentional blindness (Seegmiller, Watson, & Strayer, 2011) antisaccade (Unsworth, Shrock, & Engle, 2004), and Simon tasks (Miller, Watson, & Strayer, 2012) have all been predicted by performance on a complex span task.

Based on the assumptions of the Activation-Suppression model, better performance on complex span tasks is due to a greater ability to suppress prepotent/direct route information for task-relevant/indirect route information. High spans appear more capable of flexibly adapting to the stimulus and exerting control when necessary. Strong evidence of these differences comes from response inhibition tasks, which are a common way to explore how individual variations in inhibitory control are associated with performance on complex span tasks. Various manipulations to response-inhibition tasks have been informative in understanding parameters in which high and low spans do and do not differ. For example, a powerful task manipulation is to vary the ratio of incongruent and congruent trials. In a five experiment study, Kane and Engle (2003) found in conditions with more incongruent trials (i.e., 100% or 80% differences between high and low spans were only modestly different in the response latency, with high spans showing a trend towards being faster to respond. However, under high congruency conditions, (i.e., 20% or 25% on incongruent trials), accuracy differences between high and low span participants emerged, with high spans being significantly more accurate than low spans. The authors suggest the marked difference in performance is primarily due to goal maintenance. Specifically, in the low congruency task, the large proportion of incongruent trials serves as an external reminder to maintain the task goal, but in the high congruency condition, the external reminders of the goal are rare, requiring participants to maintain access to the goal for successful task completion. Based on Kane and Engle's (2003) interpretation of the data, high spans are better at maintaining access to the goal information during high congruency tasks, which leads to greater accuracy, particularly on incongruent trials where goal maintenance was most critical.

Another interesting aspect of Kane and Engle's (2003) data was the reaction time (RT) differences between high and low spans on congruent and error trials. Most notably in the high congruency condition, low spans had shorter RTs on congruent trials as well as on error trials (which were almost exclusively incongruent trials). Taken together, these shorter RTs may indicate that low spans switched into an automatic response pattern that served them well on most trials (i.e., shorter RTs on congruent trials) but cost them on incongruent trials, as evidenced by the significantly higher error rates. This classic speed/accuracy trade-off provides evidence that low spans were responding in an automatic way that heightened speeded performance over controlled accuracy. However, it is not clear from this data if low spans *chose* the automatic strategy or if a systematic failure to implement timely control increased their error rates on incongruent trials.

Related research would suggest that it was likely not a strategic choice that led to low spans' dominantly automatic response pattern. For example, McNamara and Scott (2001) found high spans are more likely to use a strategy to improve working memory performance than low spans. Further evidence comes from a study by Linderholm, Cong, and Qin (2008) examining individual differences in perceived (versus actual) reading comprehension. In two conditions high and low spans either received strategy instructions or did not. The authors observed that high spans were far more likely to use the strategic instructions to improve performance than the low spans. These specific task instructions are similar to intriguing work exploring how warning instructions affect false memory formation for high and low spans. In a study by Watson et al. (2005), high and low span participants were given a list of associated words (e.g., *bed, rest, wake, awake*) designed to activate related words that are highly associated but not presented (e.g., *sleep*). After seeing the list of words, participants wrote down all the presented words they could remember, which could include false memories of the highly associated but not presented "trick words." Watson and colleagues' critical manipulation was explicit instructions warning some groups about the tendency to create false memories of words associated but not presented. Across two studies Watson et al. found that high spans used the warning to reduce the frequency of false recall, but low spans did not. These studies suggest that high spans are more likely to use strategy information, either given as general instructions or presented as a warning, to improve their performance. Notably, low spans' performance is statistically the same across conditions. However, it is also important to note that Engle et al. (Conway et al., 1999; Heitz & Engle, 2007; Kane & Engle, 2000) have suggested it may not be a strategy, per se, that drives the observed differences in between high and low spans. It may instead be that when high spans look strategic in their task performance, it is because they are quicker and/or more likely to engage in controlled processing than low spans.

Research exploring potential latency differences in the implementation of controlled processing was conducted by Heitz and Engle (2007) using trial-blocks of speed deadlines to constrain response time. Neurophysiological research exploring the use of speed deadlines has found that at the shortest speed deadlines (e.g., 200 and 300 ms), there is no evidence of stimulus processing; therefore, responding is at or below chance (Gratton et al., 1988). As the deadlines increase, greater stimulus processing occurs, which allows controlled processes to activate, if necessary, based on the response required (Gratton et al., 1988). Heitz and Engle were interested in ascertaining if span differences could predict the rate at which controlled processes were implemented. By giving participants deadlines, researchers are able to achieve a distribution of RTs that can then be plotted with accuracy to visualize the rate of accuracy improvement (i.e., conditional accuracy functions; see Heitz & Engle, 2007). These researchers found that high spans did have a more rapid increase in accuracy performance on the incongruent trials of a response-inhibition task (see Figure 2), implying they are quicker to activate and implement control (though it is noteworthy that lows spans ultimately reached the same asymptote, only more slowly).

The findings from Heitz and Engle (2007) have similarities to the horse race model account of latency differences for controlled and automatic processing, based on baseline inhibitory control. Previously cited data indicated that patient populations with inhibitory deficits had shorter points of no return due to a more sluggish controlled

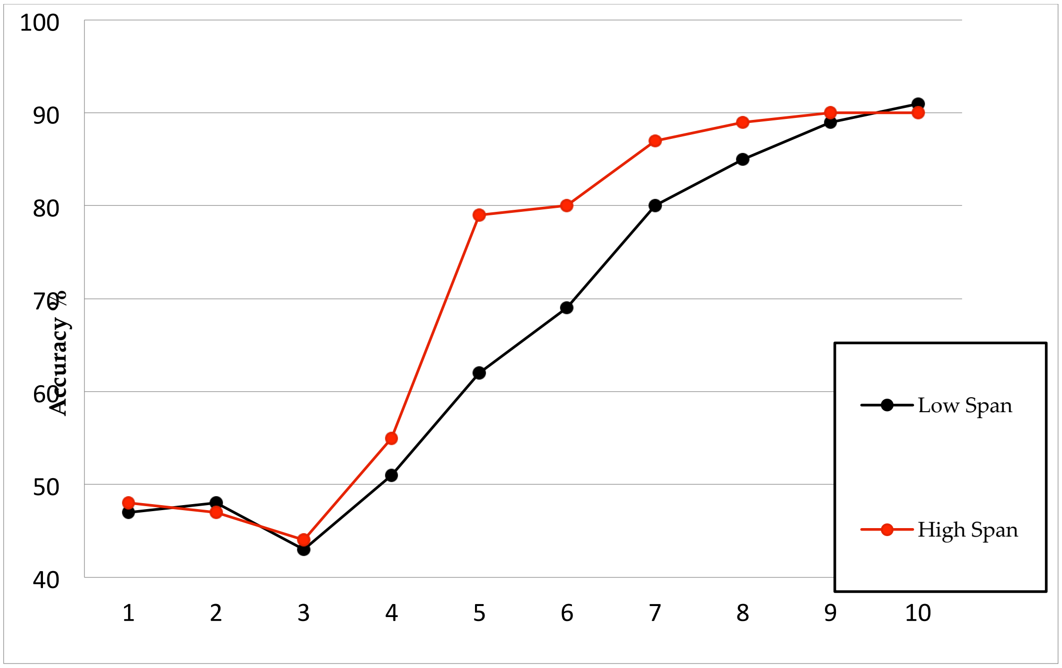

Figure 2. Eriksen Flanker: Incongruent Trials, Conditional Accuracy Functions of Incongruent Trials (adapted from Heitz & Engle, 2007; Experiment 1). High span accuracy begins marginally less significant than low spans but rapidly improves across the 10 RT deciles. By the longest latencies, high and low spans are performing at similar asymptotic levels.

processing and faster automatic processing. In Heitz and Engle's study, low spans (who are believed to have compromised inhibitory control compared to high spans) were similarly more sluggish in implementing control on incongruent trials. However, on congruent trials, where automaticity is key, there were no span differences.

However, due to the way these tasks and models are designed we may be missing other important aspects of the full range of cognitive processing. For example, in Logan's horse race model, automatic and controlled processes are implied to be inherently adversarial opponents. If we are to always consider automatic processing as dichotomously opposed to controlled processing then, just like the two horses, there needs to be one winner. Under this oppositional logic, we should want controlled processing to "win." In fact, response inhibition tasks imply controlled processing are *supposed* to win. If automatic processing wins, it is a cognitive failure and counted as an error when data are analyzed (particularly on incongruent trials). It is only when automatic processing, as in the case of congruent trials, is serving controlled processing that it is seen as an asset to our cognitive goals of successful task completion.

The question can be raised of how we justify this oppositional logic in a real-world context? While there are certainly times when control needs to be exerted in order to successfully complete a task or execute a behavior, these situations are a small fraction of our total cognitive experience. In a typical day many of us will complete most tasks automatically, with little thought to what we are doing (Bargh, 1997). Far from being a negative aspect of our cognition, we need automatic processing to dominate our cognitive experiences because the resources available for controlled cognition are finite (Wickens, 1991). Daniel Kahneman (2011) refers to controlled processing as the "lazy controller."

He says that “In the economy of action, effort is a cost, and the acquisition of skill is driven by the balance between benefits and costs. Laziness is built deep into our nature.” (p. 226) Further, according to the principle of least effort, given multiple options that achieve the same goal, over time people will naturally move to the option that requires the least amount of effort (Zipf, 1949). Goschke (2005) suggests that the act of seeking out a path of least effort is driven by a “control dilemma,” which is the tension between the need to exert control in opposition to our cognitive system’s drive to automate.

If it is the case that our cognitive system seeks to automate to the greatest degree appropriate, the way we approach questions of cognitive processing should be based more on the role of automaticity in our behaviors. For example, research concerning individual differences in cognitive control might gain critical insights about variations in automatic behaviors. Are those with greater control less capable of “turning off” or down regulating the level of control in order to automate when necessary? If this is the case, then those with greater control might be better at one aspect of processing, as elucidated via studies relying on opponent process logic, but lack in another perhaps more important aspect. Alternatively, and perhaps more likely, those with a greater ability to control processing may also be better at automating when the task demands require little control. In the latter alternative, this would make for the ideal processing system—one that is efficient in its implementing and relinquishing of control. However, to achieve such efficiency, this system would need to be flexible, allowing for automatic and controlled processing to fluidly adapt to the task demands. Put differently, having great strength in controlled cognition means very little if you are rigid in implementing it when engaged, for example, in tasks that would benefit from automatic processing.

CHAPTER 2

PRELIMINARY EXPERIMENTS

Preliminary studies from our lab examined individual differences in automatic and controlled behaviors using a high-congruency response-inhibition task (i.e., the Simon task). In the first task, participants were given a warning about the rare incongruent trials that encouraged them to maintain the task instructions. Based on research noted earlier, we believed this would encourage high, but not low, spans to exert greater control on incongruent trials as evidenced by lower error rates. The second task had the same experimental protocol as the first, except participants were given no warning instructions. Without a warning we were able to examine how high and low span participants resolve incongruent trials in the absence of explicit instructions. Based on existing research, we created dueling *exertion* and *withdrawal* hypotheses for the no warning experiment. The exertion hypothesis suggests high spans would have higher accuracy on incongruent trials compared to low spans due to their greater ability to exert controlled processing. In contrast, our withdrawal hypothesis suggests that due to the high congruency conditions, high spans would withdraw control and rely more heavily on the automatic features of the task to aid in response selection. The withdrawal of control would lead high spans to have lower accuracy on incongruent trials, making their performance similar to low spans. The results presented below provide evidence that high spans have a greater ability to flexibly adapt the relative contribution of automatic and controlled processes based on task demands.

Preliminary Experiment 1

In the first experiment, we were interested in how high and low spans would differ on a high congruency Simon task across three sessions of trials. We believed the additional sessions might reveal a differential ability to maintain control over long durations where strategies might emerge in response to congruency proportions and further dissociate performance between high and low spans. Our task instructions were modeled after Kane and Engle's (2003) Stroop study, reported earlier, wherein participants are cautioned about the prepotent, but task irrelevant, portions of congruent trials. With this warning, we believed high spans would have greater accuracy than low spans on the incongruent trials while completing the trials at a similar pace (i.e., a similar pattern of data as Kane and Engle, 2003).

Method

Participants

University of Utah undergraduates (*N* = 103; 53 high span, 50 low span) were given research participation credit for their time in this study.

Procedure

Participants first completed the OSPAN task (see *Tasks*) then, after a 5-minute break, completed three sessions of a high-congruency Simon task with the following warning instructions read to the participants at the beginning of every session:

> In this experiment you will be presented with an arrow pointing to either the left or right on the computer screen. The arrow could appear on the left half or right half or center of the screen. Please ignore the location of the arrow and simply respond based on the direction of the arrow by pressing a key on either the left or

> right side of the keyboard corresponding to the direction of the arrow. If the direction of the arrow is left, press the "q" key. If the direction of the arrow is right, press the "p" key.
>
> You may find on many of the trials the arrow direction and the arrow location are the same, making it easy to respond to the spatial location of the arrow. But these are distracter trials that make you reliant on the spatial location.
>
> Remember this is not the task instruction and may cause you to perform poorly on the trials we are most interested in where the spatial location and arrow direction differ. For that reason, it is extremely important that you ALWAYS ignore the spatial location of the arrow and focus instead on the direction the arrow is pointing.
>
> Please respond as quickly and accurately as possible.

A 5-minute break was given between each session.

Tasks

OSPAN. During the OSPAN (cf., Unsworth et al., 2005), participants verified if a math problem (e.g., (8/4) + 3 = 4) was completed correctly, by pressing either true or false on the computer screen. As they completed each math problem, they saw a letter they were supposed to memorize for later recall. After varying numbers of these equation-letter pairs, participants were prompted to recall all of the letters from each set in the order they were presented. Trials were randomized such that participants could not predict the set size of upcoming equation-word pairs (where set sizes might range from 3 to 7 equation-word pairs). Participants were given points equal to the set size when all of the words in that set were recalled correctly in serial order (i.e., an absolute span score). This score could range from 0–75. Math accuracy was also tracked to ensure that a given participant's math accuracy was at or above 85% and to encourage compliance with the dual-task math/memory instructions. Those scoring below 80% math accuracy were removed from subsequent analyses.

Simon task. In our variation of the Simon task (cf., Castel, Balota, Hutchison, Logan, & Yap, 2007; Simon, 1969), participants were instructed to push one button with their left hand when they saw a left facing arrow (e.g.,←) and to push a different button with their right hand for a right facing arrow (e.g.,→). Arrows were presented for an orientation judgment in one of three different conditions: neutral, congruent, or incongruent.[1] In the neutral condition, arrows were presented centrally (see Figure 3a). In the congruent condition, arrows were presented on the same side of visual space as they were facing (e.g., a righ*t*-facing arrow was presented in the right side of space, a few degrees from a central fixation area; see Figure 3b). In the incongruent condition, arrows were presented on the opposite side of visual space as they were facing (e.g., a righ*t*-facing arrow was presented in the left side of space, again a few degrees from a central fixation area; see Figure 3c).

Because the arrow direction and spatial location were the same, congruent trials can be completed with little difficulty. In contrast, on incongruent trials where the spatial location and the arrow direction were in conflict, one must overcome the prepotent tendency to respond to the spatial location in order to respond to the task-relevant arrow direction. To further magnify the spatial conflict, we presented participants with a high congruency version of the Simon task, where 75% of the trials were congruent, 12.5% were incongruent, and 12.5% were neutral (see Footnote 1). Previous research, using the Stroop task, has shown that high congruency proportions encourage participants to respond on the basis of the most salient aspect of the stimulus, which increases the

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[1] Data from the neutral condition were omitted from the analyses presented in Preliminary Experiment 1 and 2. The current study is seeking to understand the transitions between automatic and controlled processing that are best exemplified in the congruent and incongruent trial types.

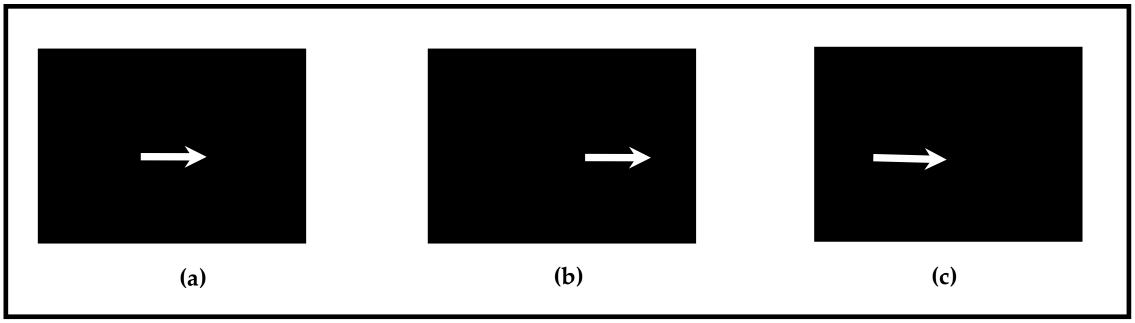

Figure 3. Representation of the Three Simon Task Conditions: (a) Neutral, (b) Congruent, and (c) Incongruent (Castel et al., 2007).

conflict when rare incongruent trials are presented (Kane & Engle, 2003).

Results

RT and accuracy data were analyzed using a 2 (span group; high v. low) X 2 (congruency; congruent v. incongruent) X 3 (session) repeated-measures ANOVA. Data were corrected using Greenhouse-Geisser. Because the correction did not change the significance of uncorrected analyses, we present uncorrected degrees of freedom, for ease of reading for all Simon task results. Trials with RTs <50 ms or >1500 ms were excluded from all analyses reported below (removing <1% of data).

There were two significant main effects from the RT data (see Figure 4). First, the analysis on correct trials of the RT data indicated a main effect of congruency (*F*[1, 101] = 679.23, *p* <.001) where congruent trials were faster (*M* = 382.59) than incongruent trials (*M* = 467.93). There was also a main effect of session (*F*[2, 202] = 112.61, *p* <.001) with trials getting progressively faster from session one (*M* = 456.54) to session two (*M* = 416.24) to session three (*M* = 403.01). There was not a significant interaction between congruency and session (*F*[2, 202] = 6.12, *p* = .09) as RTs in both congruent (409.07, 374.63, 364.07) and incongruent (504.02, 457.84, 441.95) trials decreased at a similar rate across the three sessions.

As we predicted, there was no main effect of span (*F*[1, 101] = .86, *p* = .86) between low (*M* = 426.00) and high spans (*M* = 424.52) in their RT performance. Nor were any interactions with span significant. Specifically, the interaction between span and congruency (*F*[1, 101] = 2.84, *p* = .10) was not significant, with low and high spans performing similarly on congruent (*M* = 380.57[low] vs. 384.61 [high]) and incongruent [*M* = 471.43 [low] vs. 464. 43 [high]) trials. Nor was the span by session interaction

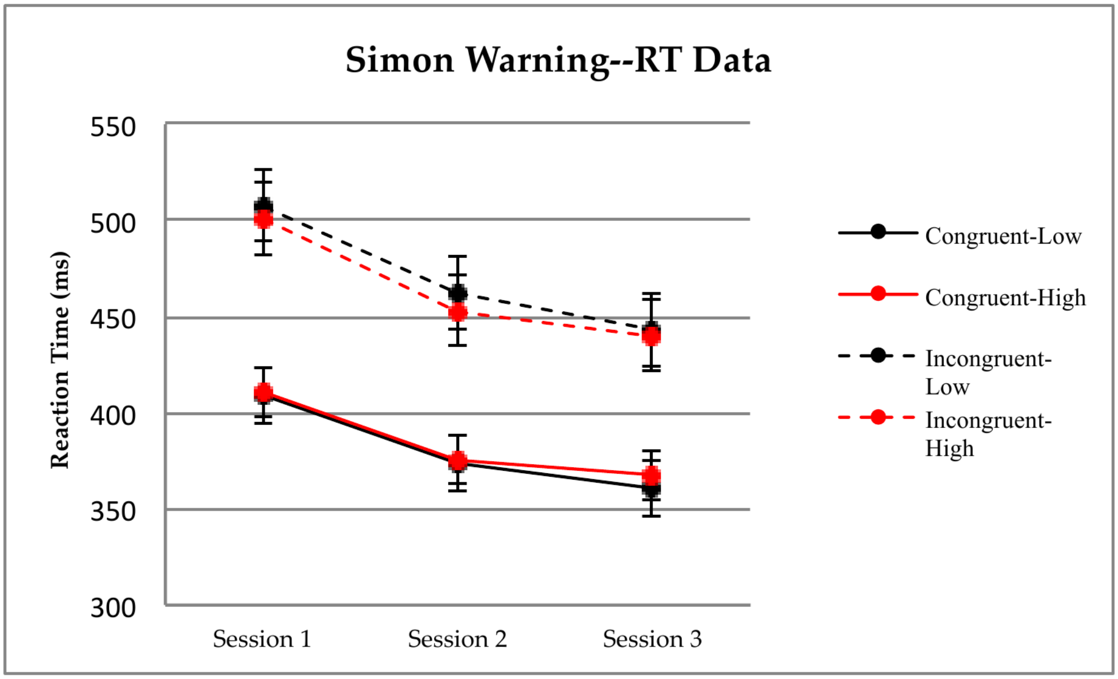

Figure 4. Simon Warning: RT Data. RT means for high and low spans, plotted as a function of session for congruent and incongruent trials. Error bars represent the standard error of the mean (SEM).

significant (*F*[2, 202] = .28, *p* = .75), with similar performance across the three sessions for low (457.62, 418.17, and 402.21) and high spans (455.46, 414.30, and 403.80). Finally, the three-way interaction among span, congruency, and session was not significant (*F*[2, 202] = .12, *p* = .89).

Accuracy in the warning experiment produced the same two main effects as the RT data, as well as the interaction between congruency and session that was not significant in RT (see Figure 5). Specifically, we found a significant main effect of congruency (*F*[1, 101] = 290.16, *p* < .001), where performance on congruent trials was significantly more accurate (99.25%) than incongruent trials (76.3%). There was also a main effect of session (*F*[2, 202] = 42.13, *p* < .001) with all participants decreasing in accuracy from session one (90.8%) to session two (87.1%) to session three (85.3%). An interaction between congruency and session was also significant (*F*[2, 202] = 49.92, *p* < .001) where congruent trials showed no change across the three sessions (99.3%, 99.2%, 99.2%, respectively) while the incongruent conditions showed an overall decline across the three sessions (82.2%, 75.1%, and 71.5%, respectively).

As predicted, span differences were found in accuracy that were not significant in the RT data. First, there was a main effect of span (*F*[1, 101] = 4.33, *p* = .04) where high spans (89.3%) were more accurate overall than low spans (86.2%). In addition, as seen in Figure 5, most importantly, there was a significant congruency by span interaction (*F*[1, 101] = 5.13, *p* = .03) where high spans (99.2%) and low spans (99.2%) performed. equivalently on congruent trials. In contrast, they had differential performance on incongruent trials with high spans (79.3%) outperforming low spans (73.2%). However, the session by span interaction was not significant (*F*[2, 202] = .85, *p* < .43), nor was the

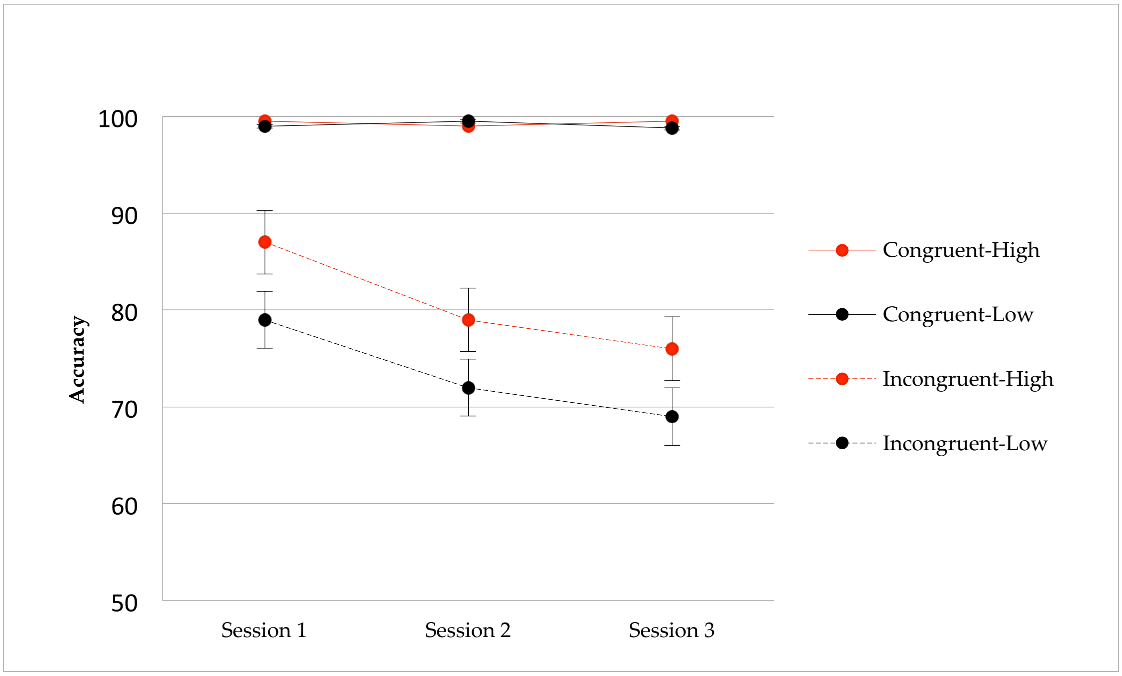

Figure 5. Simon Warning: Accuracy Data. Accuracy means for high and low spans, plotted as a function of session for congruent and incongruent trials. Error bars represent the SEM. Due to the small SEM for congruent trials (.004, .003, and .004 for sessions 1–3, respectively, for both high and low spans) the error bars were not distinguishable from the line of data.

three-way interaction among span, congruency, and session ($F[2, 202] = .42$, $p < .66$).

Discussion

As predicted, the Simon warning experiment revealed differences between high and low spans in accuracy but not in RT. These accuracy differences were found exclusively in the incongruent trials and did not vary across the three experimental sessions (see Figure 5). This data pattern was expected and is very similar to Kane and Engle's (2003) Stroop task findings where high spans, when given warning instructions, outperformed low spans on accuracy for incongruent trials in the context of a high congruency task. However, it is not clear if the span differences we observed here are due specifically to the warnings we included or a more global difference in controlled processing between high and low spans that do not require prompting from such forceful instructions with regard to the presence of distracting, congruent trials.

Preliminary Experiment 2

To examine whether the warning instructions made a difference in the performance of high and low spans, we conducted a second experiment identical to the first, except for one critical variation. In the second experiment we did not warn participants about how the prepotent aspects of congruent trials might cause them to perform poorly on the important incongruent trials. Instead, we merely encouraged participants to respond to the arrow direction and to ignore the spatial location while being as quick and accurate as possible (i.e., standard speed-accuracy instructions). We predicted that if high spans are better at maintaining the task goal without need of such forceful instructions to implement control, they would not be reliant on experimenter-provided warning instructions to maintain more accurate performance than low spans. In other words, due to a greater baseline level of control, high spans may naturally and spontaneously exert more control than low spans, leading to more accurate performance than low spans on incongruent trials with or without a warning (i.e., the exertion hypothesis). This would be evidenced by a similar pattern of data to the warning experiment as reported above (i.e., greater accuracy on incongruent trials for high spans with no group differences observed in RT). Alternatively, based on previously cited data (e.g., Watson et al., 2005) where no span differences were found in a no warning experiment, we also predicted to find no difference between high and low spans on incongruent trials. If this is the case, it may be that high spans are withholding control, perhaps even strategically in order to conserve limited-capacity cognitive resources since a majority of the trials are congruent and can be resolved using automatic processing (i.e., the withdrawal hypothesis). Based on the withdrawal hypothesis, we expected to see no significant difference in accuracy between high and low spans on incongruent trials. In contrast, we predicted potential differences in RT, with high spans withdrawing from some controlled aspects of the task, making them faster on incongruent (and perhaps even congruent) trials compared with low spans. This withdrawal pattern and greater automation for high spans might be exaggerated with additional experimental sessions as participants have an increased opportunity to learn the high congruency trial proportions that characterize this experiment.

Method

Participants

University of Utah undergraduates (*N* = 66; 33 high spans, 33 low spans) were given research participation credit for their time in this experiment.

Procedure

Participants in the experiment were first given the OSPAN task and then completed three sessions of a high-congruency Simon task where they were given the following instructions:

> In this experiment you will be presented with an arrow pointing to either the left or right on the computer screen. The arrow could appear on the left half or right half or center of the screen. Please ignore the location of the arrow and simply respond based on the direction of the arrow by pressing a key on either the left or right side of the keyboard corresponding to the direction of the arrow. If the direction of the arrow is left, press the "q" key. If the direction of the arrow is right, press the "p" key. Please respond as quickly and accurately as possible.

A 5-minute break was given between each session.

Tasks

OSPAN was conducted exactly the same as in Experiment 1. The Simon task was also exactly the same as Experiment 1 except for the removal of the warning instructions (modified instructions provided above), potentially causing less emphasis to be placed on both the distracting properties of congruent trials and the importance of participants' performance on the incongruent trials in the current experiment (i.e., standard speed-accuracy instructions alone were now used).

Results

RT and accuracy data were analyzed using a 2 (span group; high v. low) X 2 (congruency; congruent v. incongruent) X 3 (session) ANOVA. Data were corrected using Greenhouse-Geisser. Because the correction did not change the significance or nonsignificance of uncorrected analyses, we present uncorrected degrees of freedom, for ease of reading. Trials with RTs <50 ms or >150 ms were excluded from all analyses reported below (removing <1% of data).

Similar to the RT data from the warning experiment, we found a main effect of congruency (*F*[1,64] = 1010.12, $p < .001$) with congruent trials significantly faster (*M* = 388.90) than incongruent trials (*M* = 514.63), as well as a main effect of session (*F*[2, 128] = 96.52, $p <.001$) with trials getting progressively faster from session one (*M* = 480.77) to session two (*M* = 443.87) to session three (*M* = 430.67; see Figure 6). In addition, the interaction between session and congruency which was not significant for the warning experiment, was also not significant for the no warning experiment (*F*[2, 128] = .03, $p = .97$) with congruent trials getting progressively faster across the three sessions (*M* = 418.01, 381.20, and 367.49, respectively), as well as incongruent trials (*M* = 543.52, 506.53, and 493.84, respectively).

However, unlike the warning experiment, there was a significant main effect of span in the RT analyses (*F*[1, 64] = 4.26, $p = .04$), where high spans (*M* = 439.18) were faster overall than low spans (*M* = 464.35). There was also a significant interaction with span and congruency (*F*[1, 64] = 4.96, $p = .03$) where high spans were faster than low spans on both congruent (*M* = 380.72 vs. 397.09) and incongruent (*M* = 497.64 vs. 531.62) trials, but particularly so on incongruent trials. However, the two-way interaction between span and session was not significant (*F*[2,128] = 2.32, $p = .10$) with high (*M* = 496.80, 452.02, and 444.24) and low (464.74, 435.71, and 417.09) spans showing similar decreases in their RTs across the three sessions. In addition, the three-way interaction among congruency, session, and span was moderately significant (*F*[2, 128] = 2.68, $p = .087$) suggesting there was a trend toward different performance between high and low spans across the three sessions, based on the congruency condition, but it did not reach significance.

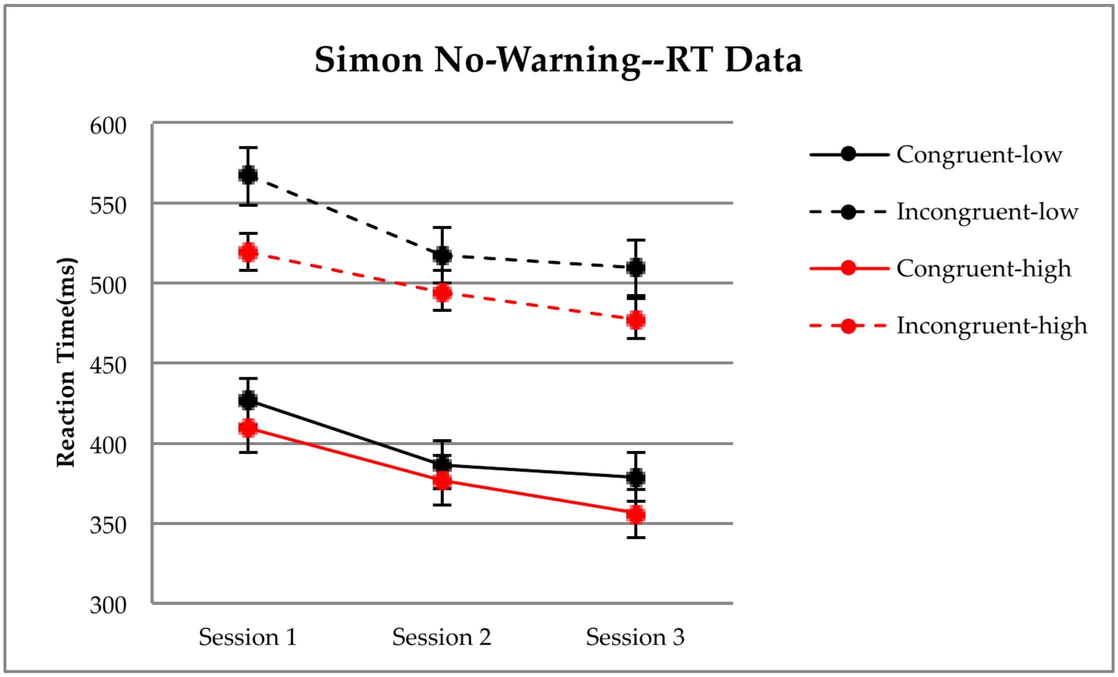

Figure 6. Simon No Warning: RT Data. RT means for high and low spans, plotted as a function of session for congruent and incongruent trials. Error bars represent the SEM.

Similar to the warning experiment, the no warning experiment showed main effects of congruency in accuracy (*F*[1, 64] = 216.46, $p < .001$; see Figure 7) where congruent trials (*M* = 99.35) were more accurate overall than incongruent trials (*M* = 70.45), as well as a main effect of session (*F*[2, 128] = 18.61, $p < .001$) where session one trials (*M* = 87.83) were more accurate than session two trials (*M* = 85.22) than session three trials (*M* = 81.66). In addition, the congruency by session interaction was also significant, (*F*[2, 128] = 18.08, $p < .001$), where congruent trials showed no change across the three sessions (*M* = 99.42, 99.39, 99.25, respectively), whereas incongruent trials showed an overall decline across the three sessions (76.24, 71.04, and 64.06, respectively).

Consistent with the withdrawal hypothesis, the no warning experiment produced no significant effects of span in accuracy. Specifically, there was no main effect of span (*F*[1, 64] = .20, $p = .66$) with high (84.45) and low (85.35) spans performing at the same level. Also, unlike the warning experiment, we did not find a congruency by span interaction (*F*[1, 64] = .16, $p = .69$). Neither the session by span interaction (*F*[2, 128] = .16, $p = .69$) nor the three-way interaction of congruency by session by span (*F*[2, 128] = .82, $p = .44$) was significant.

Discussion

In the Simon no warning experiment, we found evidence to support the withdrawal hypothesis. Specifically, across all three sessions, there was no significant accuracy difference between high and low spans on congruent and incongruent trials. Further support of the withdrawal hypothesis was found in the congruency by span interaction in RT. High spans were faster than low spans on both congruent and

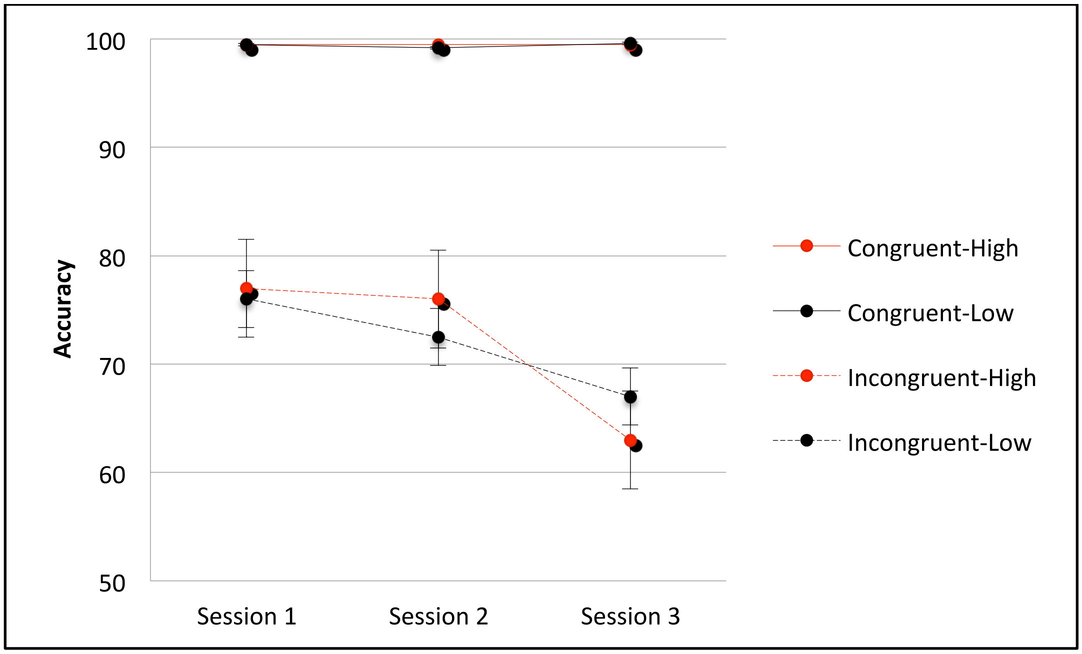

Figure 7. Simon No Warning Task: Accuracy Data. Accuracy means for high and low spans, plotted as a function of session for congruent and incongruent trials. Error bars represent SEM. Due to the small SEM for congruent trials (.004, .003, and .002 for sessions 1–3, respectively, for both high and low spans) the error bars were not distinguishable from the line of data.

incongruent trials, with this difference being most pronounced for incongruent trials. Taken together, these results suggest high spans may have strategically withdrawn control that resulted in an overall decrease in their RTs while increasing their error rate, where the latter is most noticeable in that high spans no longer have an accuracy advantage for incongruent trials, a contrasting pattern of results to those we obtained previously with the inclusion of a warning.

Preliminary Studies: General Discussion

It is intriguing that a group of participants (i.e., the high spans), who have repeatedly been shown to have greater baseline of cognitive control showed diminished performance by a simple change in the task instructions. While accuracy performance between high and low spans during the no warning experiment was statistically the same, it may be that high spans strategically chose this pattern of behavior, while low spans had less ability to control their performance between Simon experiments. The strongest evidence is the difference in performance by high spans between Simon conditions. High spans, who showed significantly higher accuracy on incongruent trials when warned appeared to spontaneously and flexibly shift to emphasizing speed on the no warning experiment, even though they had been explicitly instructed to be both fast and accurate (i.e., standard speed-accuracy instructions). In this way, high spans appear to have ignored the experimentally provided instructions, assessed the situation, determined the optimal way to respond, and then implemented speed over accuracy, allowing them to flexibly withdraw the control they have for the sake of automaticity. This conclusion fits with the ideas of the control dilemma wherein high spans, when not given an explicit warning, will sacrifice control for the sake of automation. Based on the high proportion of congruent trials, this is an efficient strategy since relying on the automatic, spatial cues will allow a person to be correct on 75% of trials. In contrast, low spans show a similar pattern of behavior across the two Simon conditions for RT and accuracy (compare Figures 4 & 5 to Figures 6 & 7, respectively) suggesting they are not able (or not as easily able) to choose a strategy. This may be due to more rigid processing by low spans, which does not allow them to quickly switch out of automatic processing to control, or vice-versa, when necessary.

Based on the Activation-Suppression model, moving from direct to indirect route processing requires suppression of the direct route that is brought about by switching into controlled processing. This transition requires additional processing time that may be completed more rapidly by high spans. Further, based on the horse race model, it may be that high spans have a faster control horse than low spans, which grants high spans greater flexibility in adopting controlled processing when they choose to exert it. For example, high and low spans might be assuming nearly the same strategy on the majority of trials, leading to their similar RTs, but high spans can be more accurate with warning instructions because they have greater flexibility in activating the controlled processing necessitated (i.e., a faster control horse that can beat out their automatic horse) by the rare incongruent trials. If this is the case, it may be rigid, middling transitions that cause low spans to perform less accurately than high spans. However, low spans may be capable of achieving similar levels of control to high spans if they are not forced to spontaneously settle on when to respond. Having a more rigid task structure may actually aid low spans in overall task performance. Based on this theory, could it be that the key difference between high and low spans is not the amount of control they are capable of exerting (or withholding), but rather high spans' natural efficiency in flexibly moving between automatic and controlled processing? In other words, are high spans more efficient at resolving the control dilemma through flexible configuration and allocation of the relative amount of controlled *and* automatic processing in response to particular task demands?

CHAPTER 3

DISSERTATION EXPERIMENTS: SPEED-BLOCKED SIMON EXPERIMENTS

The dissertation studies addressed this question by examining how individuals with varying levels of cognitive control resolve the control dilemma. Given the dilemma is the tension between exerting controlled processing and the development of automaticity, understanding how high and low spans navigate this transition is key. To examine this transition, the first two studies had high and low span participants once again participate in three sessions of a high-congruency Simon task that contained warning or no warning instructions. In addition, we adapted the first two studies to Heitz and Engle's (2007) speed-blocked task so that responding had to occur within an experimentally controlled timeframe. We believed forcing participants into a range of response deadlines might allow us to manipulate control (Gratton et al., 1988). Specifically, the earliest response deadlines (e.g., 200 ms) allowed little or no time for participants to exert the control necessary to accurately respond to incongruent trials, causing accuracy to be at or below chance. However, in blocks with longer time allowances, participants had more time to exert control and ultimately bring accuracy to asymptote.

In order to examine transitions in control during the Speed-blocked Simon task, we used conditional accuracy functions (CAFs) where the RT data was divided into bins, and accuracy was plotted as a function of those bins. Temporal changes in accuracy evident in the CAF are thought to reflect the amount of implemented control (Coles, Gratton, Bashore, Eriksen, & Donchin, 1985; Gratton et al., 1988; Heitz & Engle, 2007). For example, Gratton and colleagues (1988) had participants perform thousands of flanker task trials to then divide all of the trials into CAFs. In general, they found with very fast latencies, accuracy on congruent and incongruent trials did not differ significantly. That is, they were responding before controlled processing could activate, causing performance to be at, or below, chance. However, with longer latencies, participants were able to implement control, which led to greater accuracy and eventually to equivalent performance on congruent and incongruent trials. Gratton, Donchin, and Coles (1992) refer to this change in accuracy over time as a two phase process: first, all elements in the visual field are processed in parallel (e.g., the arrow direction and its spatial location) followed by a second, focused phase, where participants select a certain aspect of the visual field to focus on for further processing. It is only during the second phase of processing that a participant is able to inhibit distracting information in order to select for the task relevant response information. With greater inhibition, the rate of accuracy also increases, as does the time necessary to activate greater control. In this way, the rates of accuracy improvement evidenced by CAFs allow researchers to observe transitions in control.

Lohman (1989) considered the latency of control a response criterion or speed-accuracy tradeoff that indicates a participant's willingness (or ability) to commit more errors for the sake of faster reaction times (or vice-versa with a willingness to go more slowly in order to commit fewer errors, depending on the task demands). The more a participant is willing or able to give up or trade speed for the sake of greater accuracy implies the exertion of control or the changing of the response criterion (where the opposite, trading accuracy for speed, might imply the strategic withdrawal of control). As such, tracking the full range of responses via CAFs and knowing the highest rate of accuracy (i.e., asymptote) of each group allowed us to examine changes to the response criterion that might have differed between span groups based on task instructions.

In the first two dissertation experiments, we wanted to replicate and extend Heitz and Engle's findings as a way to explore span differences in resolving the control dilemma. Specifically, because span has been shown to be proxy of a participant's baseline of cognitive control, we believed time-course analyses could differentiate span groups through the rate of their transitions from automatic to controlled processing and/or the highest amount of control they were able or willing to exert at asymptote. Based on the results of the preliminary studies, we believed group differences in rate and asymptote might also be influenced by the differential control exerted, given the warning or no warning instructions. As an organizing framework for exploring these ideas, we based our predictions for the first two dissertation studies on similar or different performance between span groups in rate of transition and asymptote (see Table 1). As suggested by Gratton, Donchin, and Coles (1992), we believed group differences in rate would provide evidence of differences in the transition to asymptotic control and differences in asymptote, as suggested by Lohman (1989), would provide us evidence of each group's response criterion. Taken together, these two prediction measures served as a simple way to predict differences and similarities in the resolution of the control dilemma. We focused our predictions primarily on incongruent accuracy as these are the critical trials that are most indicative of shifts in the response criterion (Heitz & Engle, 2007; Lohman, 1989). In addition, we limited the predictions to the first session, even though we

Table 1. Prediction Matrix for Dissertation Experiments 1 and 2

	Difference in rate	Same rate
Difference in asymptote	Experiment 2: Prediction 2b	Experiment 2: Prediction 2a
Same Asymptote	Experiment 1	Experiment 2: Prediction 1

Note. Predictions for the two dissertation studies completed a 2 by 2 matrix of possible performance differences and similarities in rate and asymptote. Through the comprehensiveness of the predictions, we were able to account for different performance patterns that could be expected given the results of the preliminary studies and other relevant research discussed in this dissertation.

administered three sessions, as we expected the relative performance differences (or similarities) between span groups to remain relatively stable across sessions 1–3 as they did in the preliminary studies.

The first prediction is for Dissertation Experiment 1, where participants had explicit warning instructions. Due to previous work done by Engle and colleagues (e.g., Kane & Engle 2003) where explicit warning instructions were given to participants, we assumed Heitz and Engle (2007) had also given warning instructions since no specific instructions were provided in their paper. Based on this assumption, we expected a similar pattern of results in Dissertation Experiment 1 as found by Heitz and Engle. As seen in Table 1, we predicted a difference in rate, but the same asymptote that would be evidenced by an interaction between span and bin in the CAFs, suggesting that high spans' transition to asymptotic accuracy would differ from low spans', with high spans reaching their asymptote quicker than low spans, but given enough time, low spans would also reach the same asymptotic accuracy level.

In Dissertation Experiment 2, the predictions were not quite as clear and required two alternative accounts based on different approaches to resolving the control dilemma. According to the first set of predictions, in the absence of explicit warning instructions, high and low span groups would resolve the control dilemma by withdrawing control from the task in a similar manner as Preliminary Study 2. If so, this behavior would fit the same rate/same asymptote prediction cell and would be revealed through no significant differences in span (see Table 1). Given this pattern of data, we also expected a lower asymptote for both groups, suggesting they adopted a more automatic form of processing given a task environment that de-emphasized the exertion of controlled processing.

Our second set of predictions for Dissertation Experiment 2 suggested other implicit performance cues (e.g., the speed deadlines) within the Speed-blocked Simon task would prevent high spans from adopting the automatic speed strategy found in Preliminary Study 2. In Preliminary Study 2, high spans were able to adapt their task performance to an automatic strategy without feedback or other environmental cues discouraging this approach. In the dissertation experiments, manipulating speed through deadlines created a rigid task structure, purposefully aimed at reducing differences in RT performance, thus allowing performance to be based on the exertion of control instead of criterion shifts toward speed/automated performance. In this way, preventing the development of a speed strategy for high spans might have also provided a scaffolding by which control was maintained without explicit warning instructions. Based on this assumption, we predicted high spans would use the implicit warnings in the task environment (e.g., changing deadlines) to increase control and perform similarly to their warning performance.

In contrast, we believed low spans might have interpreted the no warning task environment as a chance to lessen or maintain their level of control (as compared to their predicted performance on the warning condition). As such, we did not expect low spans to be able to use the implicit warnings in the task environment to the same degree as high span, which would be evidenced in a lower asymptote (see Prediction 2a and 2b). However, it was not clear if there would be differences or similarities in the rate of transition to control. As seen in Table 1, Prediction 2a, if low spans were able to use some aspects of the task environment to improve performance, we predicted their rate of transition to control would be the same as high spans. Alternatively, if low spans did not use the implicit warning cues as a way to implement control, then we expected their rate would not be similar to high spans (see Prediction 2b).

Through the comprehensiveness of our 2 x 2 prediction matrix, we were able to account for different performance patterns that could be expected given the results of the preliminary studies and other relevant research discussed in this dissertation (e.g., Gratton et al., 1988; Gratton, Donchin, & Coles, 1992; Heitz & Engle, 2007). In what follows, we provide results that do and do not support the predicted possibilities found in this matrix. However, based on the way we have organized our predictions, we were able to use the similarities and differences to help us understand the specific contribution of our experiments. In particular, we suggest the results provide intriguing insights concerning the important roles of flexibility and goal maintenance as a way of balancing the demands of control dilemma.

Dissertation Experiment 1

In Dissertation Experiment 1, we replicated the design of Heitz and Engle's (2007) study but used the Simon task instead of the Eriksen flanker and added two additional sessions. Similar to Preliminary Study 1 and what we believed to be Heitz and Engle's study, we gave participants warning instructions thought to encourage the use of greater control in high spans. As just discussed (see Table 1), we predicted an interaction between span and bin on the accuracy rate of incongruent trials. Specifically, just like Heitz and Engle's results, high spans' rate of transition from automatic to controlled processing would be faster, but the attained asymptote would not differ between groups. If we find this predicted performance pattern, we would again have evidence that low spans can asymptote at a level of control consistent with the performance of high spans.

This would suggest the response deadlines did encourage the maintenance of control, so given the additional time afforded by the longest deadline blocks, their more sluggish controlled processes were able to evolve, particularly when these deadlines were coupled with strict warnings against the automation of responses. We predicted these span differences would remain stable across the three sessions, similar to Preliminary Study 1.

Method

Participants

Eighty University of Utah undergraduates (42 high span, 38 low span) were given 2 hours research participation credit for their time. All participants were fluent in English and between the ages of 18–33.

Procedure

Participants completed all tasks autonomously, but were tested in a room with up to four other people. Each participant completed written, informed consent before starting the experiment. After consent, participants completed the OSPAN task (see *Tasks* section below). After completing the OSPAN, participants were given a 3-minute break in the lab waiting area while a researcher recorded their performance. Following the break, participants completed three sessions of the Speed-Blocked Simon task (again, see *Tasks* section below), with a 3-minute break between each session. After completing all three sessions, participants were given an end of study questionnaire and a written debriefing form.

Tasks

OSPAN. See Preliminary Experiment 1 for details on the version of the OSPAN used in the current experiment.

Speed-blocked Simon task. We modified the high-congruency (75% congruent; 25% incongruent) arrow-direction Simon task (see *Tasks* in Preliminary Experiment 1) to include a similar experimental manipulation used by Heitz and Engle (2007), where Simon task trials were blocked into response deadlines. Heitz and Engle used these deadlines to evenly distribute responses throughout the RT distribution. The first deadline block began at 700 ms, and was always followed by blocks with deadlines at 600, 500, 400, 300, and 200 ms. Every trial equaled the same total duration (i.e., 1100 ms), but the time allocation on each screen differed by speed block (see Figure 8). Each of the 6 blocks had 80 randomly presented trials: 60 congruent, 20 incongruent, and there were no neutral trials. A 30-second break separated each of the speed deadline blocks.

For each trial, first, a white fixation cross appeared centrally on a black background for 100 ms, followed by a blank, black prestimulus screen that appeared for 100 ms. Next, the arrow stimulus appeared and remained on the screen for 100 ms. Following the arrow stimulus, two identical blank, black screens appeared, where the first was the response screen, followed by the postdeadline response screen. Together, the stimulus screen and these two response screens always equaled 800 ms, but the time spent on the two response screens depended on the speed block (see Figure 8). For example, on the 300 ms response deadline block, the stimulus appeared for 100 ms, the response screen appeared for 200 ms, and the postdeadline response screen appeared for 500 ms. The intertrial interval blank screen was 100 ms, yielding the total trial duration of 1100 ms, as noted above. Because participants were unable to detect the change between the

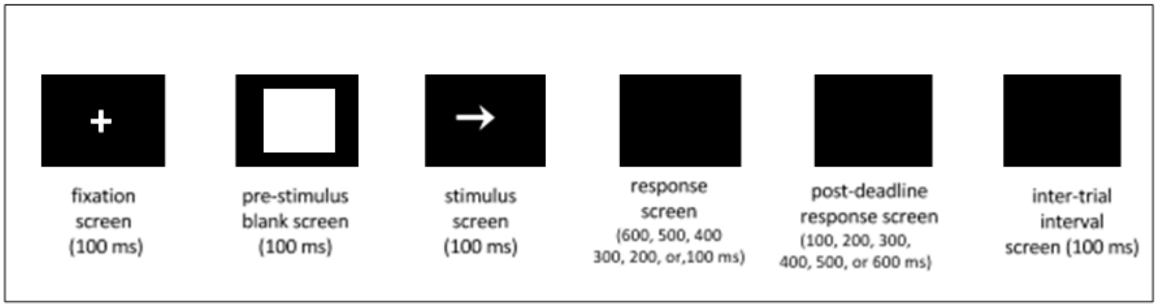

Figure 8. A Single Trial, With an Incongruent Stimulus, on the Speed-Blocked Simon Task. Time intervals for the response screen and postdeadline response screen were contingent on which response deadline block participants completed. All time intervals on the two response screens within a single response deadline block were exactly the same.

two response screens, they did not know if they missed the deadline until each trial was completed after 1100 ms. If a response was not made in time, participants received a message saying "Deadline Missed. Faster!" In addition, the program tracked the number of missed deadlines within 20 trial segments of each speed deadline block. When more than 25% (5 trials within 20) were missed, a black screen with red writing appeared saying, "You are missing too many deadlines. It is important each deadline is met, even if errors result."

Before beginning the series of six response deadline blocks, participants received instructions modeled directly from Preliminary Experiment 1, of how to complete the task, as well as an explicit warning about the high congruency proportions. Based on Preliminary Experiment 1, when participants are warned about high congruency proportions, high spans are better able to use the warning to improve performance, particularly on rare incongruent trials. In addition, after each block of response deadline trials, participants received a reminder warning that said,

> This next block of arrows will require you respond even faster than the last block. Please do so while also responding as accurately as possible.
>
> Remember it is extremely important that you ALWAYS ignore the spatial location of the arrow and focus instead on the direction the arrow is pointing.

Results

To compute the CAFs, we first removed the first 20 presented trials from each speed block to ensure we were measuring real differences in transitions to control that were not confounded by any given participant's variable adjustment to the new speed deadline (Heitz & Engle, 2007). We next determined 10 Vincentized *n*tiles on each person's rank-ordered RTs separately for congruent and incongruent trials within each of the three sessions. Each bin of responses was 10% of a participant's total RTs in the congruent or incongruent condition. For example, bin 1 reflected the fastest 10% of RTs, bin 2 the next 10%, and so on to 100% of total RTs within the 10 bins. Analyses only included trials where a response was made, even if the response was past the deadline (i.e., analyzing responses made on either the stimulus screen or one of the two response screens as shown in Figure 8). Based on Heitz and Engle's (2007) rationale, a missed deadline psychologically feels the same whether one responds in time or not since no immediate feedback is given.

Following the quantitative design of Heitz and Engle (2007), congruent and incongruent trials for each of the three sessions were analyzed separately.[2] RTs were examined first, as it was important to establish if there were span differences in RT before examining potential span differences in accuracy. If there were span differences in RT, caution would be necessary in interpreting the subsequent accuracy analysis as the results could be artifacts of the RT binning process, not veritable differences in performance. RT means for each bin were compared separately in a 2 (span) X 10 (bin) repeated measures ANOVA. On congruent trials in session one, there was no main effect of span, $F(1, 78) = .52$, $p = .47$, nor was there a significant span by bin interaction in RT, $F(9, 702) = .38$, $p = .67$ (see Figure 9). On incongruent trials there was also no main effect of span, $F(1, 78) = .76$, $p = .39$), nor a span by bin interaction, $F(9, 702) = 2.19$, $p = .11$.

To ensure we were only examining differences in accuracy that were due to the implementation of control, we conducted the accuracy ANOVA on bins where the mean

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[2] We only present the analyses of session one in the body of the paper as a way to more closely compare our predictions and findings with Heitz and Engle's work. However, important findings from these session analyses will be discussed in the body of the paper. We refer the interested reader to the Appendix for all of these analyses and related figures and tables.

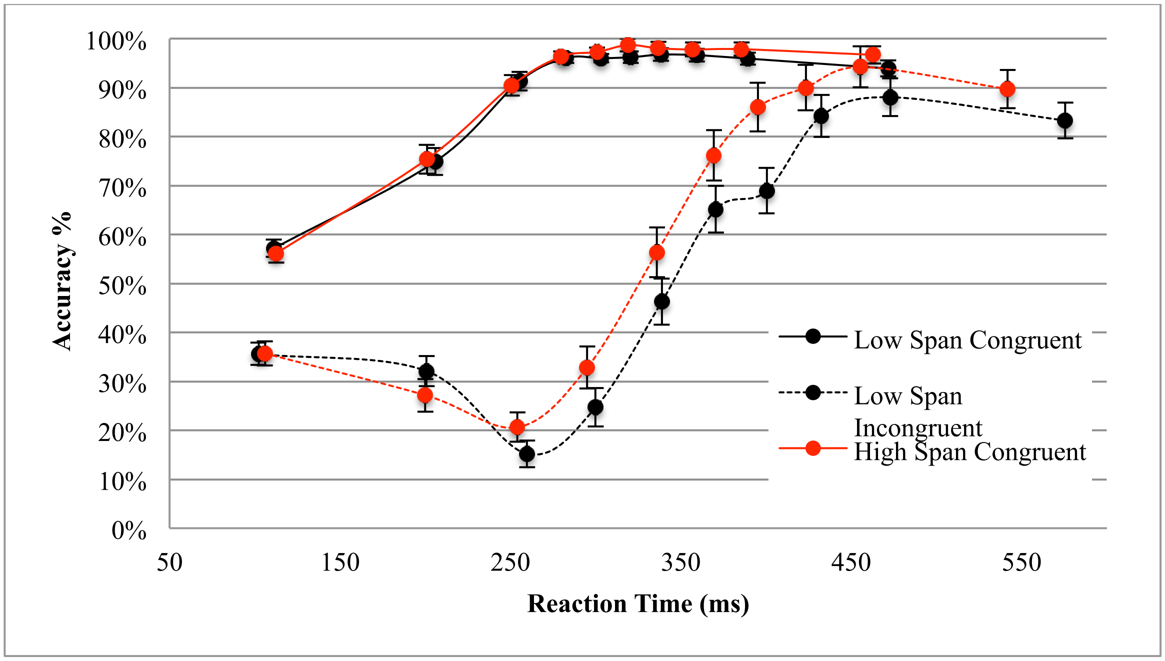

Figure 9. Speed-Blocked Simon Task, Warning: Session 1. CAFs for congruent and incongruent trials by span group. There were no group differences in RT for either trial type, nor was there a span difference in accuracy on congruent trials. However, as seen in the separation between the lines representing high and low spans' performance on incongruent trials, there was a significant main effect accuracy, with high spans outperforming low spans, but the predicted interaction between span and bin was not. The sequential *t* tests revealed no span difference in rate or asymptote on congruent trials, but low spans rate of transition was a bin before high spans on incongruent trials (Bin 8 vs. Bin 9, respectively), but high spans had a higher asymptote. Error bars represent the standard error of the mean for accuracy.

accuracy was at or above 50% (Heitz & Engle, 2007; Norman & Bobrow, 1975). All congruent bins in session one were above chance performance, leading to a 2 (span) X 10 (bin) repeated measures ANOVA. This analysis revealed no main effect of span, *F*(1, 78) = .30, *p* = .59, or span by bin interaction, *F*(9, 702) = .44, *p* = .69, suggesting congruent trial performance did not distinguish between span groups, as expected. On incongruent trials in session one, both groups started below chance (*M* = 35.21) and decreased in accuracy reaching a mean of 16% accuracy in bin 3 before starting their steady increase in accuracy. This dip in accuracy found in the earliest bins is also seen in both Heitz and Engle's and Gratton, Donchin, and Cole's (1992) studies and is often attributed to participants making a choice without fully processing any meaningful information (Heitz & Engle, 2007). As a result, these responses show the strong influence of the prepotent spatial information that is instinctually processed (Stins, Polderman, Boomsma, & de Geus, 2007) and the previous trial's congruency (Gratton et al., 1992). Because the trials were randomized, the unpredictable nature of response was also an additional factor adding to the low rates of accuracy in the earliest latency bins (Eriksen & Hoffman, 1974; Gratton et al., 1992). For session one accuracy, above chance performance occurred at bin 5, resulting in a 2 (span) X 6 (bin) repeated measures ANOVA. There was a significant main effect of span, *F*(1, 78) = 4.34, *p* = .04, with high spans more accurate overall than low spans (*M* = 82.1 vs. 73.2, respectively), but the span by bin interaction was not significant, *F*(5, 390) = .77, *p* = .58. Together, the main effect suggests span groups improved accuracy at a similar rate, but the nonsignificant interaction between span and bin suggests low spans never reached the same level of accuracy as high spans.

Next, we explored group differences in rate of transitioning to control by performing successive *t* tests on the accuracy within each latency bin across the three sessions (see Appendix A, for details on sessions two and three). Following the logic of Gratton, Coles, and Donchin (1992), understanding the transition from automatic to controlled processing (i.e., phase one to phase two processing) allowed us to examine how the task instructions might have influenced the resolution of control dilemma for each span group. Assuming accuracy was highest in bin 10, we conducted sequential *t* tests on the bin where above chance accuracy was achieved thru to bin 10 until we found the bin where accuracy was not significantly different[3] from bin 10. At this bin, accuracy performance was equivalent to bin 10, so asymptote had been reached. For example, if there were significant differences in accuracy comparing bin 10 to bin 4, but not when comparing to bin 5, we would know bin 5 was the bin of asymptote. Following the statistical reporting of Heitz and Engle (2007), we provide the last significant bin comparison before asymptote.

Each group's bin of asymptote told us the point at which they reached their highest accuracy performance in that condition and session, but it was also important to compare this level of accuracy within the bin of asymptote between groups. For example, if high and low spans had the same bin of asymptote, but their peak performance were significantly different, it would imply different response criterions based on the exerted level of control. To compare the rate of asymptotic accuracy between groups, we conducted an independent samples *t* test for each session and congruency condition.

The sequential *t* tests for congruent trials in session one revealed bin 5 (see Figure 9) was the bin of asymptote for low spans (bin 4 vs. bin 8 significant), $t(37) = 3.71$, $p <$

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[3] Some *t* tests analyses revealed an earlier bin was significantly more accurate than bin 10. In these situations, we used the bin of highest accuracy as the comparator bin for the sequential *t* test analysis.

.001, and high spans (bin 4 vs. bin 8 significant), *t*(41) = 1.85, *p* = .04. The accuracy level at the respective bin of asymptote for high and low spans was not significantly different *t*(78) = 1.40*, p* = .09, with high (*M* = 97.28) and low spans (*M* = 94.73) reaching similarly high levels of accuracy. For incongruent trials, the sequential *t* tests in session one (see Figure 9), revealed low spans' asymptote occurred at bin 8 (bin 7 vs. bin 10 significant), *t*(37) = 2.83, *p* < .001, and high spans' asymptote occurred at bin 9 (bin 9 significantly higher accuracy than all other bins), *t*(41) = -1.81, *p* = .04. The accuracy level within the bin of asymptote was significantly higher for high spans (*M* = 94.21) than low spans (*M* = 84.26), *t*(78) = 2.60, *p* < .01.

Discussion

Based on the assumption that Heitz and Engle (2007) used warning instructions in their study, we predicted to have the same pattern of different rate/same asymptote given the warning instructions in our current study (see Table 1). We suggested this would replicate the evidence that low spans could reach the accuracy level of high spans, if given more time for their more sluggish control to evolve. However, our findings did not support these predictions. Instead of our predicted interaction between span and bin, our analysis revealed a main effect of span, indicating similar rates of transition between high and low spans, albeit with high spans having an overall level of greater accuracy on the incongruent trials than low spans. In addition, the *t* tests revealed that low spans reached their asymptote at an earlier bin, but did not reach the same level of accuracy as high spans within that bin of asymptote.

Returning to the prediction matrix in Table 1, our results instead fit within the same rate/different asymptote pattern of performance cell. It is compelling that this cell was our predicted pattern of behavior for the no warning study that we suggested would occur if high and low spans used the implicit performance cues to aid them in implementing differential levels of control. Specifically, we suggested this use of the implicit cue would allow span groups to transition at a similar rate, but low spans would not be able to use the cues as efficiently, resulting in lower overall accuracy. By finding these results in the warning study, we can similarly suggest that something in the task environment, whether it was the implicit task structure or the explicit warning (or both) gave both groups the ability to implement control, but low spans were not able to implement it at the same level as high spans, leading to lower overall accuracy. However, it is important to note that without the results of Dissertation Experiment 2, we were cautious not to attribute performance to either the implicit or explicit aspects of the task, as there was no measure within the task that could dissociate the contribution of these two potential performance cues.

Based on the data previously discussed, we see similarities between session one performance and Preliminary Experiment 1 in that high spans had an accuracy, but not reaction time advantage over low spans. In Preliminary Study 1, this difference in performance remained constant across sessions, but in the current study, we found evidence of high and low spans both withdrawing control on sessions two and three, resulting in no difference in rate or asymptote by session three (see Appendix A). With the elimination of these span differences, what started as the resolution of the control dilemma through the exertion of control in session one quickly transitioned to the resolution of the control dilemma through the withdrawal of control for both span groups. In this way, high spans may have started the experiment with a similar pattern of data as found in in Preliminary Study 1, but they ended with a performance more similar to Preliminary Study 2, where span differences in accuracy were eliminated due to the automating of performance.

Dissertation Experiment 2

Due to the surprising findings in Dissertation Experiment 1, it was important to further explore the role of warnings as an accuracy performance cue by omitting them from the instructions to see if performance would change (or stay the same). In general, we predicted that if accuracy performance without the warning instructions was lower, this would suggest the warning instructions supported greater use of control. However, if accuracy performance was the same, it could either suggest span groups never used the warning instructions to implement control, or they used the explicit warning in Dissertation Experiment 1, and then, in its absence, relied on the more implicit cues to maintain the same level of performance.

As a recap of the specific predictions discussed in detail above (see Table 1), we suggested if high and low spans had the same relative performance as found in Preliminary Experiment 2, their rate of transition and their asymptotic accuracy would be the same (see Table 1). However, based on previous research (e.g., Watson et al., 2005), where high spans, but not low spans, are able to improve baseline performance given a warning, we alternatively predicted that high spans might be able to use implicit performance cues in the task environment in a similar manner as the warning. If this prediction was correct, we expected span differences to emerge in rate and asymptote based on low spans' propensity to use performance cues from the task environment to implement control. Specifically, if low spans were able to use the cues to implement control, we predicted they would have a similar rate of transition as high spans, but we did not believe they would be able to use the cues as efficiently as high spans resulting in lower asymptote. However, given the similar rate/different asymptote pattern of behavior, it might be the case that low spans were more influenced by the removal of the warnings, hence magnifying group differences in asymptote. Alternatively, if low spans were not able (or willing) to use the performance cues in the environment or were more influenced by the explicit warning instructions (or both), we expected them to have a different rate and different asymptote than high spans.

Method

Participants

University of Utah undergraduates (*N* = 104; 52 high span, 48 low span) were given two hours research participation credit for their time in this experiment. All participants were fluent in English and between the ages of 18–35.

Procedure

The current experiment utilized the same experimental design as Dissertation Experiment 1, with a separate group of participants. The critical experimental variation was the instructions given to participants at the start of each session and in between each block of trials did not have an explicit warning. Instead, instructions indicated participants should be as fast and accurate as possible. The instructions given at the beginning of each session were taken directly from Preliminary Experiment 2. In addition, after each block of response deadline trials, participants received reminder instructions without a warning about the high congruency proportions. These instructions said,

This next block of arrows will require you respond even faster than the last block.

Please do so while also responding as accurately as possible.

Results

The same performance screening procedure used in Dissertation Experiment 1, where trials were only removed if no response was made, was also used to exclude trials in the current study. This resulted in removing less than 2% of total trials. In addition, we again removed the first 20 trials from each speed block as a way to lessen the variability associated with transitioning to the new deadline (Heitz & Engle, 2007).

RTs for each latency bin were analyzed separately in a 2 (span) X 10 (bin) repeated measures ANOVA, conducted separately for each session (see Figure 10 for session one results and see Appendix B for results from sessions two and three). RTs for congruent trials in session one revealed a significant span by bin interaction, *F*(9, 918) = 3.09, *p* = .05, but no main effect of span, *F*(1, 102) = 1.66, *p* = .20. RTs for incongruent trials in session one also revealed a significant span by bin interaction, *F*(9, 918) = 5.48, *p* = .01, but no main effect of span, *F*(1, 102) = .53, *p* = .47. Due to this significant interaction with span, caution is necessary when analyzing and interpreting the accuracy data to ensure accuracy differences are due to veritable differences between groups and not an artifact of the RT binning process.

Accuracy rates within the latency bins for congruent trials in session one were all above 50%, so a 2 (span) X 10 (bin) repeated measures ANOVA was conducted and revealed no span by bin interaction, *F*(9, 918) = .92, *p* = .42, or main effect of span, *F*(1, 102) = 3.38, *p* = .07, with high and low spans performing equivalently overall (90.5 vs. 89.5, respectively). Incongruent trials did not reach a mean accuracy rate of 50% until bin 6, so a 2 (span) X 5 (bin) repeated measures ANOVA was conducted and revealed no

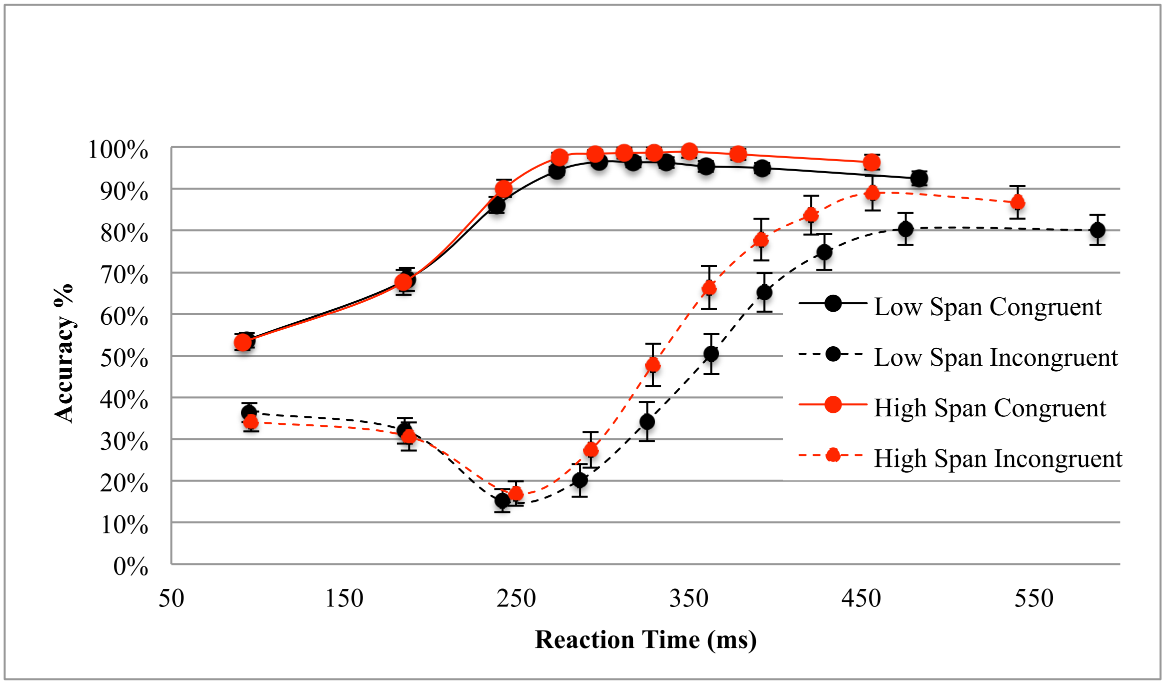

Figure 10. Speed-Blocked Simon Task, No Warning: Session 1. CAFs for congruent and incongruent trials by span group. A significant span by bin interaction in RT was significant on congruent and incongruent trials. In addition, accuracy differences were found in the repeated mesaures ANOVA for congruent trials; however, the sequential *t* test revealed high spans asymptoted a bin earlier than low spans (i.e, bin 4 vs. bin 5, respectively) and at a higher rate. Incongruent trial accuracy revealed a significant main effect of span, with high spans overall more accurate than low spans. This main effect is seen in the consistent separation between the lines representing performance by high and low spans. Sequential *t* tests revealed low spans reached asymptotic accuracy quicker than high spans on incongruent trials (Bin 8 vs. Bin 9, respectively), but high spans had higher accuracy at asymptote. Error bars represent the standard error of the mean for accuracy.

span by bin interaction, *F*(4, 408) = 1.22, *p* = .30, but there was a main effect of span, *F*(1, 102) = 5.13, *p* = .03, with high spans more accurate overall than low spans (80.7 vs. 70.2, respectively).

Given the significant span differences found in RT, we felt the main effect of span in accuracy on incongruent trials must be examined using other statistical tests. Heitz and Engle (2007) also had span differences in RT (in a later study in their 2007 paper, that also used CAFs), and they suggested the sequential *t* tests and bin of asymptote comparisons are appropriate ways to explore and potentially validate the accuracy findings in the ANOVA, as these comparisons are not directly influenced by the RT distribution. In session one (see Figure 10), bin 4 was the bin of asymptote for low spans (bin 3 vs. bin 9 significant), *t*(51) = 3.71, p < .01, as well as high spans (bin 3 vs. bin 10 significant), *t*(51) = 2.88, p < .001. The accuracy level at the respective bin of asymptote for high (*M* = 97.58) and low spans (*M* = 94.32) was significantly different, *t*(102) = 2.62, p < .01. On incongruent trials, bin 8 was asymptote for low spans in session one (bin 7 vs. bin 10 significant), *t*(51) = 3.33, *p* = .001, compared to bin 7 (bin 6 vs. bin 10 significant), *t*(51) = 1.29, *p* < .01, for high spans. The accuracy level at the respective bin of asymptote for high (*M* = 83.67) and low spans (*M* = 74.81) was significantly different, *t*(102) = 5.47, *p* < .01.

Discussion

Results from the current study fit our same rate/different asymptote prediction cell in Table 1 and suggests both groups used the implicit performance cues to aid them in their transition to control. Specifically, the results revealed a main effect of span in the accuracy of incongruent trials suggesting, just like in Dissertation Experiment 1, where both span groups could transition to control at a similar rate. The sequential *t* tests revealed high spans reached asymptote a bin earlier than low spans, and again had higher accuracy at asymptote. Finding the same pattern of results (i.e., same rate/different asymptote) in Dissertation Experiment 1 suggests relative group differences did not differ based on task instructions.

While the pattern of incongruent accuracy fit the same pattern as Dissertation Experiment 1, the RT results did not. We expected span differences in RT to be modulated by the response deadlines, as suggested by Heitz and Engle (2007). However, when making these predictions we were unaware of research suggesting the spatial location of the Simon task stimuli, combined with their simplicity allows for faster processing (and by extension responding) than the flanker task (Stins, Polderman, Boomsma, & de Geus, 2007). This difference in processing time is small, but may have been enough to allow for more automation, especially in combination with the no warning task where speed is commonly chosen over accuracy. Evidence of this automation is seen strongly in sessions two and three (see Appendix B) where low spans become significantly faster than high spans in most RT bins. However, in session one a series of independent *t* tests comparing span groups' RT performance within each bin revealed the interaction was driven by similar RT performance on trials until bin 9, $t(102) = .73$, $p = .05$, and bin 10, $t(102) = 2.18$, $p < .01$, when high spans actually became significantly *faster* than low spans. These results in combination with the initial accuracy ANOVA and *t* tests (suggested by Heitz and Engle) that indicated high spans were more accurate overall and at asymptote than low spans make us confident the differences in accuracy are veritable and not due to an artifact of the RT binning process.

Returning then to the accuracy performance, we suggest that the groups having the same pattern of data across experiments (i.e., same rate/different asymptote) does not necessarily mean each group performed the same, only that the relative differences were the same. It may be that both groups are performing significantly worse on the no warning experiment, but the span differences are stable causing us to only see the general pattern. It was important to examine if groups changed as a function of experiment, especially in terms of the critical variable: accuracy on the incongruent trials. To examine cross-experiment performance, we again determined the bin where mean accuracy performance across experiments was at or above chance. In session one this was bin 5, resulting in a 2 (experiment) X 6 (bin) repeated-measures ANOVA conducted separately for each group. Results from this analysis revealed a significant main effect of experiment for low spans, $F(1, 88) = 3.72$, $p = .05$, as they were more accurate with warning instructions ($M = 73.2$), than without ($M = 64.2$), but no experiment by bin interaction, $F(5, 440) = 1.32$, $p = .27$. For high spans the analysis revealed neither a main effect of experiment, $F(1, 92) = 2.43$, $p = .12$, nor an interaction between experiment and bin, $F(5, 460) = .49$, $p = .65$. Due to the differences in RT across experiments, we also wanted to compare accuracy at the bin of asymptote for each group. For low spans, they reached asymptote at bin 8 in both experiments, but they were significantly more accurate at asymptote in the warning, than no warning experiment, $t(88) = 1.78$, $p = .04$. High spans reached asymptote in bin 7 on the warning condition, but not until bin 9 in the no warning condition. Even though the ANOVA did not reveal accuracy differences between experiments for high spans, the bin of asymptote analysis showed a significant effect of experiment, $t(92) = 3.34$, $p < .01$, with high spans' asymptotic accuracy reaching higher accuracy in the warning than no warning experiment.

Through the cross-experiment analyses we found strong evidence that low spans' needed the warnings to exert greater control, which lead to greater accuracy as a function of the task instructions. This is an intriguing finding as low spans do not generally change performance based on explicit task instructions. In addition, returning to the rate/asymptote framework we found low spans across experiments had the same rate, but different asymptote. This pattern of data was the same for both experiments, and we similarly interpret these findings to suggest that they had a similar rate of transition, but accuracy at the bin of asymptote suggests it was far lower in the absence of an explicit warning. For high spans, the cross-experiment ANOVA did not reveal differences in accuracy across experiments, suggesting that overall, the accuracy was relatively stable across experiments. However, comparing the bin of asymptote revealed a different rate/different asymptote pattern of behavior, as high spans were faster and more accurate with warning instructions. Taken together, the ANOVA and *t* tests offer an interesting pattern of data that suggests high spans used the warning (i.e., the faster rate and higher level of asymptote), but were not reliant on it to implement control (i.e., the nonsignificant accuracy differences from the ANOVA). In this critical way, high and low spans differ in their ability to exert control in the absence of the warning.

It is important to also consider the results from the speed-blocked Simon task in comparison to the preliminary studies. Low spans appear to benefit from having the warning instructions, relative to their own baseline levels of control, but only in combination of the rigid structure provided by the speed-blocks. In this way, low spans appear rigid in exerting control and require a fair amount of environmental support.

However, even with the benefit to performance from the combination of deadlines and warning instructions, low spans were unable to reach the same level of accuracy as high spans on incongruent trials. In contrast, we found high spans benefitted from the warnings with or without the deadlines, but the improvement was more dramatic without the deadlines. Specifically, without deadlines or a warning (i.e., Preliminary Experiment 2), high spans accuracy was at or below that of low spans, but with the addition of the warning (i.e., Preliminary Experiment 1), high spans exert greater control leading to significantly higher accuracy than low spans. With the speed-deadlines, we found high spans did not automate performance in the absence of a warning, but instead maintained the same relative accuracy. However, with a warning they did benefit through an increase in asymptotic accuracy, which was reached at a faster rate. Taken together, across all four Simon studies reported here, we have evidence that highs can use either deadline or warning instructions as cues to implement control and outperform low spans. This suggests they have greater flexibility in balancing the need for automatic and controlled processes. When these deadline and warning cues are removed (i.e., Preliminary Study 2), high spans are flexible yet again as they appeared to automate their performance.

Speed-Blocked Simon Studies: General Discussion

When making the predictions about span differences and similarities, seen in Table 1, we expected Dissertation Experiment 1 to replicate the different rate/same asymptote finding of Heitz and Engle (2007) as we assumed, based on their previous research (e.g., Kane & Engle, 2003) they had also used an explicit warning in their study. It was only recently that we learned from the first author, Richard Heitz (i.e., through personal communication via e-mail February 11, 2014) their instructions were closer to our no warning instructions, as both emphasized speed and accuracy equally. Knowing our no warning, deadline procedures in Dissertation Experiment 2 are more similar to their experimental paradigm, we still did not replicate their pattern of results. So why did we get the *opposite* pattern of data, same rate but different asymptote across span groups, as opposed to the different rate but same asymptote finding of Heitz and Engle (2007), despite having the same speed deadlines and similar instructions?

To answer this question, we focused on the difference in selected task, as this was the primary difference between our studies. Specifically, we believed the differences between span groups was likely the same across experiments, suggesting the differences observed were most likely due to the extent to which the stimuli within each task differentially engaged automatic and controlled processing. The variation of the flanker task used by Heitz and Engle (2007), participants saw an array of letters and had to respond based on whether the middle letter was similar or different from the other letters in the array. This combination of stimuli would have been novel to participants, so the ability to respond appropriately to the target while ignoring the distracting flankers would not benefit from any prior knowledge or experience. Based on Gratton and collegue's (1989) distinction of the two phases of processing, we suggest the level of attention needed to interpret letters, in addition to the control necessary to narrow focus and inhibit distraction, was likely only available after the transition to phase two. In comparison, the variation of the Simon task we used required people simply respond to the direction of an arrow that was presented on the left or right side of the computer screen. Neither the arrow-direction or spatial location would have been novel stimuli to participants as both are preexperimentally learned stimulus-response associations. However, electrophysiological (EEG) evidence suggests that spatial cues have a particularly strong stimulus-response association that automatically activates a response (Luck, Woodman, & Vogel, 2000). As a result, EEG research from our laboratory suggests, participants can become reliant on the spatial cues in the Simon task, especially in high-congruency tasks when they serve as a valid response cue on 75% of trials (Miller, Watson, & Strayer, 2012). Even if participants were correctly ignoring the spatial cues and responding to the arrow location, we still believe responding to the Simon task was faster than the flanker task as a result of the known response-stimulus association and the simpler stimulus (Stins, Polderman, Boomsma, & de Geus, 2007). This difference in latency is critical as the deadlines were given to force responding and increase the need for control. As a result, there was likely more flexibility than we had expected in the Simon task, which may have allowed time to deactivate and activate control on a trial-to-trial basis. In contrast, the flanker task required control to stay highly active to narrow focus and inhibit distraction before the deadline had past (Bari & Robbins, 2013; Heitz & Engle, 2007). Based on these interpretations of the critical task differences, we suggest span differences in Heitz and Engle's study were due to the exertion of control, while span differences in our dissertation studies were due to the withholding of control. As a result, we suggest the dissertation studies allowed for greater variability in performance and therefore were a better measure of how each span group may have balanced the maintenance of control with the push to automate (i.e., the control dilemma). This benefit of our task selection was ideal as Goschke (2000) suggested the best resolution of the control dilemma is finding a balance between automatic and controlled processing, as opposed to relying completely on one form or the other.

Dissertation Experiment 3

Results from Dissertation Experiments 1 and 2 suggest high spans were better at balancing the automatic and controlled aspects of the speed-blocked Simon task by flexibly updating the salient performance cues and actively maintaining the task goal. In light of these results that offer initial evidence of a beneficial role for automatic processes, we felt it was important to further test these ideas using a different task paradigm where automatic processes had equal role in successful task completion. For example, we thought it might be possible our interpretations of the results thus far were due to the large role controlled processing served in task completion that played to high spans' strength in controlled processing, not low spans' strength in automaticity. If given tasks with important roles for both controlled and automatic processes, would we find low spans able to optimize automatic processes in order to improve overall task performance, while high spans may still show heavy use of control, even when not task appropriate? If this is the case, then those with greater control might be better at one aspect of processing, as elucidated by studies relying on opponent processing tasks, but inefficient at withdrawing that control when automatic processing would be more appropriate.

An ideal task to test these ideas was the stop-signal paradigm, as it required participants to complete two distinct tasks primarily using automatic or controlled processing (Logan, 1994; Logan & Cowan, 1984). For successful task completion, each participant had to strike a balance between the quick response to a visual stimulus (i.e., where "go" trials were operationalized as the automatic task) with accurately withholding a response when indicated by random auditory cues (i.e., where stop-signal trials were operationalized as the controlled task). Critical to performance in the stop-signal paradigm is balancing the need to quickly and accurately complete the go trials with accurately withholding a response when a stop signal is heard (Bissett & Logan, 2011). In this way, the stop signal serves as a multitasking variant of traditional opponent processing tasks; while there are still times where automaticity and control are in direct conflict, there are also beneficial and distinct roles for each of these processes.

In the third dissertation study, we administered the stop-signal paradigm as a way to explore the ideas of cognitive balance and flexibility beyond the Simon task to other oppositional logic tasks. Specifically, all trials started the same, with no indication it would be a go or stop signal trial until the auditory cue was heard, so participants had to tolerate the building automaticity associated with the response while still maintaining controlled processes, if the stop signal was heard. In this way, a high level of cognitive flexibility was needed to efficiently complete each trial, allowing us to examine span differences in tolerating automatic processing. The term tolerating is our proposed explanation for how automatic and controlled processes are kept in a balanced, active state when successfully resolving the control dilemma, without automaticity inappropriately overriding control (Colzato, Pratt, & Hommel, 2010; Goschke, 2000). We suggest an individual’s ability to tolerate and appropriately balance automaticity is directly dependent on their inhibitory control (Logan, 1994). In addition, we suggest tolerance may be the root of cognitive flexibility. As a result, we expected individual differences in tolerance due to the previously cited span differences in inhibition. To examine this prediction, the stop-signal paradigm would determine a person’s point of no return or the latency at which it was equally probable a participant would withhold or respond, given a signal to stop. As such, we believed a person’s point of no return was a direct measure of their tolerance of automaticity. We predicted high spans would perform at the same level as low spans on automatic, go trials, but would have a longer point of no return due in part to inhibitory control, which would aid them appropriately stopping more than low spans on the controlled, stop trials.

Method

Participants

University of Utah undergraduates (*N* = 58; 28 low; 30 high) were recruited through the Psychology Participant Pool and received 1 hour of course credit as compensation for their time. All participants were between 18–31 years of age and fluent in English.

Procedure

Participants completed all tasks individually, but were tested in groups of up to six. Each participant completed written, informed consent before starting the experiment. After consent, participants completed the OSPAN and then took a 3-minute break. Following the break, participants completed one session of the stop-signal paradigm (see *Tasks* below for details). After completing the stop-signal paradigm, participants were given an end of study questionnaire and then verbal and/or written debriefing.

Tasks

OSPAN. See Preliminary Experiment 1 for details on the version of the OSPAN we used in this experiment.

Stop-signal paradigm. The primary task in the stop-signal paradigm (Verbruggen, Logan, & Stevens, 2008) was to make a shape judgment by pressing a button on the left (for squares) or right (for circles) as they appeared centrally on the computer screen. On go trials, only the primary task stimulus was presented, but on stop signal trials, after the primary task stimulus is presented, the participant then heard the auditory cue indicating they should withhold their shape judgment response for that trial. The two trial conditions were randomly presented, so a participant had no idea if they would need to inhibit a response before the stop signal. Similar to the Simon task, we administered a high-congruency version of the stop-signal paradigm where 75 % of the trials were go trials and 25 % were stop trials.

Each trial began with a white fixation cross in the center of a black screen for 250 ms (see Figure 11). The fixation point was then replaced by the primary task stimulus of a circle or square that remained on the screen until a response was made or 1,250 ms (the maximum RT) had elapsed. Between each trial a blank black screen was presented for 2,000 ms. On stop signal trials, the auditory stop signal was variable, based on participant performance that varied throughout the entire task. stop signal trials where responses were successfully inhibited increased the stop signal delay (SSD) by 50 ms. stop signal trials where responses were not successfully inhibited decreased the SSD by 50 ms. In the stop-signal paradigm, participants first received task instructions encouraging them to be as quick and accurate as possible. Next, participants completed a practice block consisting of 32 trials. After the practice block, participants completed 3 blocks of 64 trials. Between the 3 blocks of trials, participants were given a 10-second break. During these breaks, the screen provided performance feedback on the previous block, including the number of incorrect responses on go trials, the number of missed responses on go trials, the mean RT on go trials, and the percentage of correctly suppressed trials.

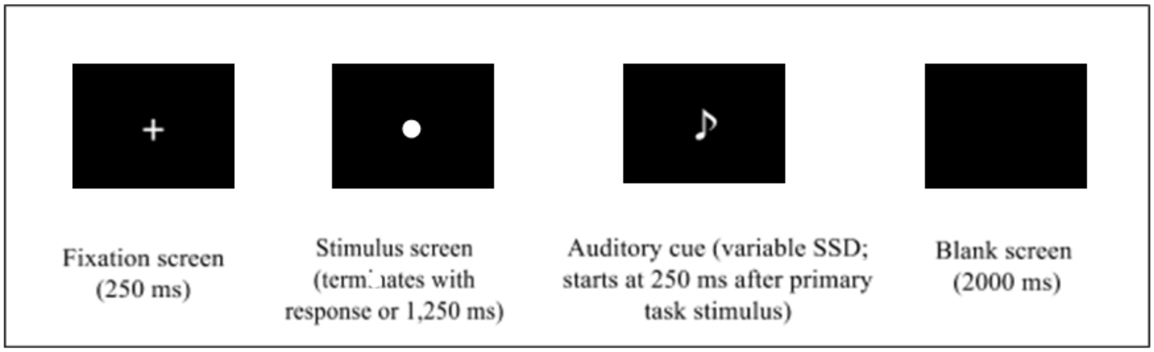

Figure 11. A Single Stop-Signal Trial in the Stop-Signal Paradigm. In this example, a circle appears on the screen and based on the instructions, participants should be preparing to press a button on the right. However, at some point in the response selection and execution, an auditory stop signal cue is given, indicating to a participant they should withhold their response (i.e., the right button press) for this trial. Successful completion of this trial would increase the variable SSD by 50 ms.

Quantitative Method

Before discussing the statistical methods involved in the stop-signal paradigm, it is essential to understand how the dependent measures were acquired. Calculating the covert latency associated with successfully inhibiting a go response, given a stop signal, requires estimation based on the primary task RT distribution (Logan & Cowan, 1984; Verbruggen & Logan, 2009). Figure 11 is an illustration of the concept behind these calculations. The figure is derived from the statistical processes proposed in the horse-race model, which evaluates the probability of making a response to the go task (automatic processes) or probability a participant will inhibit a response given the stop signal [*p*(inhibit|signal)] or PRS is represented on the left side of the distribution, while the probability a participant will inhibit a response given the stop signal [*p*(inhibit|signal)] is represented on the right side of the distribution. By knowing each participant's PRS and their go RT average, an experimenter can estimate when the internal response to the stop signal would begin (RTir; see Figure 12). This is important in calculating the latency of successful inhibition. Also important to this calculation is knowing a participant's SSD. The STOP-IT task (Verbruggen, Logan, & Stevens, 2008) we administered adjusted the SSD until the latency at which a person was equally likely to respond or inhibit given a stop signal [i.e., p(respond|signal) = .5]. This SSD was subtracted from the RTir to give us the SSRT, which indicates how long it takes a person to suppress their go response, given the stop signal.

Together the SSD and SSRT represent two important aspects of control. The SSD represents the level of tolerance a participant has for the automatic aspects of the task. For

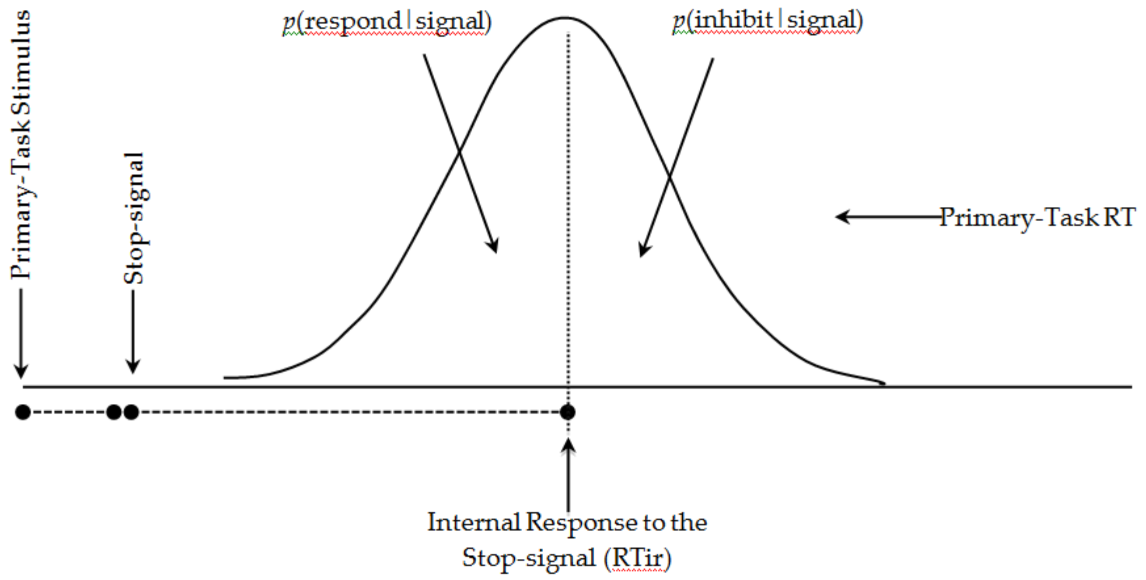

Figure 12. Illustration of the Probabilities of Responding, Based on the Horse-Race Model (Logan, Cowan & Davis, 1984), Given the Distribution of No-Signal RTs (Primary-Task RT), the Stop-Signal Delay (SSD), and the Internal Response RT (RTir).

example, a participant who can allow the primary task response to activate for a longer period of time and still successfully withhold that response shows greater tolerance of automatic processes through a flexible adaptation of control. The SSRT represents the speed and power of the inhibitory process for each participant. For example, a participant who has a short SSD and a long SSRT cannot tolerate high levels of automaticity, and they respond quickly after a stimulus is presented and are not as capable of withholding a response when a stop signal is given. This pattern of results has been found in populations with inhibitory control deficits like older adults (Kramer, Humphrey, Larish, Logan, & Strayer, 1994) and impulsive people (Logan, Schachar, & Tannock, 1997). When these populations were able to inhibit a response, a long SSRT (compared to matched controls) suggested their inhibitory processes took longer to shut down the automatically activated response. In contrast, participants who have a long SSD and a short SSRT can likely tolerate greater automaticity and stop a response to the stimulus (given the stop signal) far into the activation and response process. Their short SSRT suggests their inhibitory processes can quickly shut down the automatic response activation.

The dependent measures discussed thus far provide ways researchers can explore the contribution of different aspects of controlled processing. However, a critical piece of this dissertation is also examining the balance between control and automatic processing. To better examine this aspect of the data, we must take into account the go task RT distribution. Combined with SSD and SSRT, it indicates the level of balance struck between controlled and automatic features of the task. A participant who can maintain relatively quick speed on the go trials while also successfully discriminating the correct object (via button response) shows a high level of automatic skill, but this is only half of the task requirements. If that same participant concurrently performs poorly in inhibiting stop signal trials, one could make the argument they chose to focus on the automatic go trials, causing their stop signal performance to suffer. In contrast, a participant who had very long primary-task RTs may have been slowing down all responses in order to be more accurate on the stop signal trials. In this situation, they chose to focus on the stop signal portion of the task without balancing quick response to the primary task. Ideal performance is a participant who can maintain high levels of accuracy and quick RTs on go trials while also efficiently inhibiting on stop signal trials. In this way, both the controlled and automatic dependent variables are important to consider when understanding the overall efficiency of both span groups.

Based on the previously presented data, we anticipated high spans would demonstrate greater flexibility and efficiency in completing the stop-signal paradigm than low spans. Specifically, we anticipated high spans would have a shorter SSRT and longer SSD, indicating stronger response control. In addition, we anticipated this greater control would not come at the sacrifice of poorer performance on the primary task. We believed high spans would also be able to complete the primary task at the same level, or perhaps even marginally better, than low spans. Based on these predictions, we would see evidence, outside of the Simon task, for high spans having greater flexibility in the configuration of both controlled *and* automatic processing that leads to better overall cognitive processing.

Results

Dependent measures were derived using the ANALYZE-IT program, which is a companion to the STOP-IT task available online (Verbruggen, Logan, & Stevens, 2008). Using the formulas originally defined in Cowan and Logan’s 1984 paper, and then further specified by Logan et al. (1997), the ANALYZE-IT program calculated all dependent measures of interest for each participant. Once calculated by the ANALYZE-IT program, the dependent measures were output into a text file allowing for simple transfer to SPSS.

Descriptive statistics showing the means and standard deviations of all dependent measures of interest are shown in Table 2. Independent *t* tests by span group were conducted on all dependent measures. First, we analyzed performance on go trials and found no span differences. Specifically, there was no span difference in RT on go trials, $t(56) = -1.33$, $p = .10$. The percentage of correct responses on go trials was not significant, $t(56) = .43$, $p = .33$, nor was the percentage of missed responses, $t(56) = -.52$, $p = .30$ (see Table 2).

In contrast, an analysis of the dependent measures indicative of stop signal performance all had span differences except the PRS, $t(56) = 1.59$, $p = .11$. We did not expect a span difference in PRS as this was a measure, manipulated by the STOP-IT program, which kept each participant's ability to respond, given a signal, close to 50%. However, as predicted, there was a significant difference in SSD, $t(56) = -1.81$, $p = .03$. As seen in Table 2, this difference was due to a significantly longer point of no return for high spans compared with low spans. In addition, a significant difference in SSRT, $t(56) = 2.66$, $p < .01$, was due to high spans being significantly faster than low spans at inhibiting the primary task response (see Table 2).

Discussion

The results from Dissertation Study 3 suggest high spans were better at balancing the signal and go trials in the stop-signal paradigm. Specifically, high spans were able to tolerate high levels of automatic response activation, as evidenced by their longer SSD

Table 2. Stop Signal Paradigm Performance

Variable	*M*	*SD*
	Go trial	
RT		
Low	679.01	135.52
High	724.63	164.09
Accuracy		
Low	97.84	3.77
High	95.91	9.14
	stop signal trial	
SSD		
Low	406.95	139.74
High	479.78	180.76
SSRT		
Low	271.93	37.07
High	244.71	40.76
PRS		
Low	46.27	3.80
High	44.52	4.48

Note. Performance means and standard deviations for most dependent measures derived by the ANALYZE-IT program. RT, SSD, and SSRT are presented in milliseconds; accuracy and PRS are percentages out of 100. High and low spans had similar means on measures associated with performance on go trials (i.e., RT and accuracy), but had different means on trials associated with inhibiting a response on stop signal trials (i.e., SSD and SSRT). There was not a significant span difference in the PRS, suggesting both groups actively completed both tasks.

and, upon hearing the stop signal, high spans were quicker than low spans at arresting the response, as evidenced by their shorter SSRT. When responding to go trials, high spans were just as likely as low spans to respond quickly and accurately, suggesting they did not give up performance on the go trials in order to enhance performance on stop signal trials. Instead, they were able to tolerate the need to respond to the object discrimination on go trials, yet still effectively withhold their response on occasional stop signal trials, thus balancing the demands of automatic and controlled processing. In contrast, low spans were not able to use the more flexible task environment of the stop-signal paradigm to decrease span differences on the stop signal trials or to outperform high spans on the automatic aspects of the task on the go trials.

Taken together, our results replicate and extend research using stop-signal paradigm with other populations to include individual differences in cognitive control. Just as populations with inhibitory deficits showed a shorter SSD and longer SSRT, so too did the low spans compared to high spans. This interpretation of the stop-signal data converges with theories like the Activation-Suppression Model and research from the opponent processing literature suggesting span differences in inhibition is the most (Hasher & Zacks, 1988; Lustig, Hasher, & May, 2001; May, Hasher, & Kane, 1999) or one of the most critical factors that determine successful performance on a number of higher order tasks (e.g., Redick, Calvo, Gay, & Engle, 2011; Kane & Engle 2003; Unsworth, Schrock, & Engle, 2004), but the stop signal results from our experiment extend the role of inhibition to also supporting the use of automatic processing and suggest highs' spans greater cognitive abilities are made possible through control, but made efficient through their reliance on automatic processing.

The results of the current study also support the findings of the preliminary studies and Dissertation Experiments 1 and 2, which suggest high spans are able to exert more control than low spans and they are equally able to withdraw that control and use automatic processes in a more balanced manner than low spans. Far from being rigidly confined to controlled processes, these research studies all support the idea that high spans have a highly flexibly cognitive system that allows them to strategically adapt automatic and controlled processes for highly efficient performance. Specifically, it appears a key to high spans' flexibility is their superior inhibitory processing, represented in their significantly faster SSRT and their higher likelihood to withhold a response on stop signal trials. Without this greater inhibition high spans would not be able to tolerate as much activated automaticity, leading to a longer SSD.

CHAPTER 4

GENERAL DISCUSSION

Cognitive researchers have largely been interested in examining differences in controlled processing between groups and individuals without fully considering the role of automaticity. In the present set of five studies, we sought to bridge that gap of knowledge by administering tasks wherein automatic processing could more naturally be used. However, because all the tasks in this dissertation (and the work of Heitz and Engle, 2007) fit within the broad category of opponent processing, it is important to consider how the implementation of control differed between tasks and, by extension, how this may have influenced the use of automatic processes.

Most broadly, it is widely believed that the primary function of control in opponent processing tasks is inhibition (Friedman & Miyake, 2004; Miyake et al., 2000). However, the potential function(s) of inhibition are an ongoing matter of debate (e.g., Friedman & Miyake, 2004; Harnishfeger; 1995; Nee, Wager, & Jonides, 2007; Nigg; 2000; Redick, Heitz, & Engle, 2007). We organize our task analysis using the categorical distinctions made by Miyake and colleagues (Miyake et al., 2000; Friedman and Miyake, 2004), as their thoughtful and concise categorization of inhibitory processes is a commonly used taxonomy. They suggested prepotent response inhibition, resistance to distractor interference, and resistance to proactive interference are the major functions of inhibitory control used in opponent processing tasks (Friedman & Miyake, 2004). For the purposes of our task analysis, we focus on prepotent response inhibition and resistance to distractor interference categories, as the opponent processing tasks used in this dissertation have been specifically identified as fitting into one of these two categories(Friedman & Miyake, 2004; Miyake et al., 2000; Redick, Heitz, & Engle, 2007).

Prepotent response inhibition is defined as the ability to deliberately suppress dominant, automatic, or prepotent responses (Friedman & Miyake, 2004; Nigg, 2000). Further, Redick, Heitz, and Engle (2004) suggest it is the inhibitory function most directly associated with cognitive control. Based on this general description, we agree with other researchers who categorize the stop-signal paradigm and Simon task within this category of inhibitory control (Friedman & Miyake, 2004; Miyake et al., 2000). Specifically, in the Simon task, the spatial location of the arrow was highly prepotent and had to be actively suppressed until a behavior could be executed. Adding to this desire to respond to the spatial information was the large proportion of trials (i.e., 75%) where relying on the spatial information resulted in a correct response. Friedman and Miyake (2004) also categorized the stop-signal paradigm as a prepotent response inhibition task because the desire to respond to the go trial, while not prepotent, nonetheless activated a far more dominant response than the desire to stop a response, given the stop signal. The dominance of this response is partly due to the high proportion of go trials where responding to the go trial was the correct action (Logan, 1994). In addition, selecting the response was purposefully very simple, allowing it to be done with little cognitive effort (Verbruggen & Logan, 2009).

The other inhibitory control category of interest, resistance to distractor interference, is described as the ability to resist or resolve interference from information in the external environment that is irrelevant to the task at hand (Friedman & Miyake, 2000; Harnishfeger, 1995). We again agree with researchers who suggest the Eriksen flanker fits within this category of inhibitory control (Friedman & Miyake, 2004; Redick, Heitz, & Engle, 2007). Specifically, the function of inhibition in this task is a gating mechanism that focuses attention away from the flanking distractors and onto the central letter. Heitz and Engle (2007) refer to this gating process as a "spotlight of attention" that allows attention to narrow in on the relevant task information (e.g., the central letter).

A critical distinction between these two inhibitory control categories is the point at which conflict occurs on critical trials (Friedman & Miyake, 2004). In the prepotent response category, conflict does not occur until a behavioral response is being made (Friedman & Miyake, 2004; Nigg, 2000), while in the resistance to distractor interference category, the conflict occurs earlier, as a stimulus is being processed (Friedman & Miyake; Harnishfeger, 1995). The conflict that is generated in both tasks is due to a dimensional overlap between the relevant and irrelevant features of the stimulus. For different reasons, the Simon task and stop-signal paradigm bypass stimulus processing because a response is automatically activated by the irrelevant features of the stimulus. In the Simon task, this is the spatial location, and in the stop-signal paradigm, this is the proportion of trials where a response to the go stimulus is an appropriate response. It is only after this irrelevant stimulus activates a response that conflict monitoring triggers the activation inhibitory control (Botvinik, et al., 2001; Verbruggen, Liefooghe, Notebaer, & Vandierendonck, 2005). The version of the Eriksen flanker task used by Heitz and Engle had letters as the relevant and irrelevant stimulus features. On incongruent trials, this dimensional overlap created conflict as both stimulus features initially activated at a similar level (e.g., phase one processing). To resolve this conflict, inhibitory control had to suppress the irrelevant flanking letters, allowing attention to narrow in on the relevant, central letter (Chen, Tang, & Chen, 2013; Kornblum, 1994; Kornblum, Hasbroucq, & Osman, 1990). Only after this narrowing of attention occurred could an appropriate response be selected and executed. This difference in the stage of processing where conflict occurred generally leads to latency differences in the time it takes to complete a critical trial. Prepotent response inhibition is characterized as deliberate and rapid (Logan, 1994; Kok et al., 2004), as the automatically generated response must be suppressed quickly, while resistance to distractor interference is characterized as “a dynamic process that requires time” (Heitz & Engle, 2007, p. 220) as the relevant and irrelevant portions of the task must be processed fully before a response selection can be made.

Beyond differences in the function or latencies of inhibitory control, these categorical distinctions may also provide different latitude for the use of automatic processes. The stage of processing where automatic features of the task are suppressed might suggest different levels of tolerance that would be strategically appropriate. In the Simon task and stop-signal paradigm, automatic processes were active until the behavioral response stage, while in the flanker task, automatic processes were suppressed during the processing of the stimulus. As a result, automatic processes were able to have a much larger role in the prepotent response category than the resistance to distractor interference category. In terms of the tolerance hypothesis, the larger role of automatic processes in the Simon task and stop-signal paradigm required greater balance between the two processes for the most effective task completion. The Eriksen flanker task, in contrast, had a more limited role for automatic processes, causing there to be little or no strategic advantage to tolerating an active baseline of automaticity.

These differences in the use of automaticity may provide insight to a recent five-session training study (Chen, Tang, & Chen, 2013) where repeated practice on a Stroop task (also categorized as a prepotent response inhibition task) gradually improved congruent and incongruent trial performance, while no such gains occurred for the same participants on the Eriksen flanker task. In fact, they found that over the five sessions the stimulus conflict actually grew stronger with practice, causing greater conflict in narrowing in on the relevant stimulus. The researchers interpreted the findings, in part, as evidence of the benefit of an automatically generated response, but suggested that given different trial proportions, where the irrelevant task features did not reliably lead to a correct response on the majority of trials, the Stroop task may have had a modulated benefit from practice. We similarly recognize that all tasks compared in this dissertation were high congruent at a 3:1 ratio. Given inverse trial proportions on the Simon task or stop-signal paradigm, automatic processing of the stimulus would not reliably produce a correct response on most trials, so keeping it activated in a manner suggested in the tolerance hypothesis would not be strategically advantageous. Similarly, we suggest the warning instructions in Preliminary Experiment 2 and Dissertation Experiment 2 may have modulated the level of tolerance for automaticity for high spans, causing more control to be exerted (and performance to be improved). Finally, we also recognize that the speed blocks may have had an influence on the tolerance of automatic processes through implicit task cues that might have encouraged greater use of control (as discussed previously). The clearest evidence of this is the greater accuracy performance from high spans on the no warning dissertation study, compared to the no warning preliminary study.

In summary, the importance of this task analysis was to identify a potential role for automatic processes in each task. Since all tasks had the same proportion of congruent trials, we believe the differences between the use of automatic processing was a function of the stage of processing where inhibition occurred, the instructions (i.e, warning/no warning in Simon and flanker; explicit distinction of two stop and go tasks in the stop-signal paradigm), and the absence or presence of speed blocks. It is intriguing that were we to put the tasks along a continuum, based on the relative ability to use automatic processes, the tasks where the smallest amount of automatic processing is appropriate (i.e., the Eriksen flanker and Speed-blocked Simon with a warning), low spans have their best overall performance. Specifically, their performance on the Eriksen flanker task was arguably the best of that noted here as they were able to catch up to high spans, given enough time, and their performance on the speed-blocked Simon with a warning was greater than other Simon task performance as they had a similar rate of transition to control and were significantly better than their performance without a warning. High spans performance does not fit as cleanly along this continuum. They seem less influenced by the implicit aspects of the task that force control than the explicit warnings that encourage greater use of control. We found this in comparing their accuracy performance on the preliminary and dissertation studies with and without warning instructions. Because performance in all situations is better than low spans, it may be that high spans have already exerted the level of control necessitated by the implicit cues, so the explicit cues offer an additional source of control. Or, it could also be that less tolerance of automatic processing is given when explicit cues warn against the irrelevant features of the task. Future studies could test these ideas by giving a warning on stop-signal paradigm to see how that influences the dependent measures associated with automatic and controlled processes.

Future Directions

Within this dissertation we have asserted many theoretical ideas that require further scrutiny. Due to the novel nature of our task paradigms, we recognize that replicating and extending these ideas will be our primary goal for immediate future research. In what follows, we briefly offer several next steps for extending our ideas.

Returning to the 2 X 2 matrix, we want to use what we have learned from the dissertation studies to manipulate the *same* research paradigms to find results in the remaining cells (i.e., same rate, same asymptope and different rate, different asymptote). As suggested previously, to find the same rate and same asymptote, we need a task where performance is the same for both span groups, either due to both exerting greater control or due to both relinquishing that control to the same degree. Since we are more interested in times where the exertion of control is similar, we suggest a way to see similar effects in control is to continue to add rigidity to the task structure. Kane and Engle (2003) were able to largely eliminate span differences by reversing the congruency proportions on the Stroop task. In a similar way, we predict that if we were to give participants a low congruency version of the stop-signal paradigm, the task environment would so forcefully demand control that high and low spans would perfrom at a similar level with or without a warning. For the different rate, different asymptote prediction cell, we need the opposite task environment, where high spans will exert control at a faster rate and maintain that control, resulting in overall greater accuracy. Based on our suggestion that high spans naturally use implicit cues, but low spans only do when forced by the environment, in a follow-up study with no warning instructions, we could maintain the implicit cues provided by the speed blocks, but remove the forced exertion of control brought about by the shortest latency blocks. If our suggestion is correct, we would expect high spans to still be able to exert a similar level of control as the dissertation studies, while low spans might withdrawal more control than in Dissertation Experiment 2, which could result in rate and asymptote differences between span groups.

Next, we believe it is important to extend our 2 X 2 matrix to *different* research paradigms where we can explore a larger role for automatic processes while also offering converging evidence for our ideas. We would like to first examine other tasks categorized as fitting in the prepotent response inhibition category. For example, beyond the stop-signal paradigm, Friedman and Miyake (2004) highlighted the Stroop and antisaccade tasks as similarly eliciting a prepotent response that had to be suppressed on incongruent trials at the behavioral response. In the Stroop task, the prepotent but irrelevant response is reading the word, but the task relevant response is naming the color of the presented word. In the antisaccade task, participants must suppress the prepotent urge to look at a visual target that appears suddenly in the peripheral visual field (prosaccade) and must instead look away from the target in the opposite direction (antisaccade). Previous research investigations have found span differences in both paradigms (Kane & Engle, 2003; Unsworth, Schrock, & Engle, 2004), with high spans similarly showing a greater ability to suppress the prepotent response activation for the task relevant response.

However, these paradigms have left little room for automatic processes to play a role in task performance. By varying the use of automatic and controlled processes through the use of task instructions, speed deadlines and congruency proportions we would like to manipulate the ability to use automatic processing.

We are also interested in continuing research using the stop-signal paradigm and building the tolerance hypothesis. As suggested previously, by adding warning instructions we may gain greater insight to how explicit instructions influence the allocation of automatic and controlled processes. For example, if the warning instructions lead to a shorter SSRT for a span group, compared to their no warning performance, we could suggest they were likely exerting greater inhibition when given a warning. However, if we also saw a shorter SSD, we would have to alter the SSRT interpretation to suggest that group used the warnings to limit the amount of tolerance they would exert, causing their point of no return to be significantly earlier. In this way, the stop-signal paradigm allows us several ways to explore what happens to automatic and controlled behavior when a warning is given and, to a greater extent than tasks like the Simon, *how* this may be occurring.

Practical Implications

The entirety of this dissertation has thus far been a theoretical investigation into the role of automaticity in higher order processing. We feel our new ideas could be improved and extended by also considering practical implications with applied research. To start, a natural application of the current findings is skill acquisition research, where automatic processing has long been recognized as essential to the development of expertise (Logan, 1988). In contrast to the largely pejorative understanding of automaticity within opponent processing research, researchers in skill acquisition suggest a combination of automaticity and control greatly *improve* skilled performance by allowing for greater flexibility of the task environment (Salthouse, 1986). Specifically, experts are faster than novices and can respond more quickly to changing input, suggesting better control (Salthouse, 1986). However, experts are also better than novices at time-sharing and show fewer performance decrements while performing concurrent tasks. Together these findings suggest experts can exert greater levels of control, but know more reliably when to automate for the sake of efficiency and greater complex task performance (Logan, 1988).

In a similar way, we have shown high spans can exert greater levels of control while also knowing more reliably than low spans when to automate for the sake of efficiency. In this way, high spans' baseline is to behave in a similar pattern as experts, even in novel tasks. These natural abilities may provide high spans an early advantage when developing new skills. Research examining individual differences in skill acquisition supports this idea, as they have found highly intelligent people[4] (as measured by the intelligent quotient [IQ] test) have an advantage in the first phase of learning new complex skills (Carroll, 1993). However, their research has been less clear as to why this may occur (Boyle & Ackerman, 2004). The ideas we have just aligned with their research concerning cognitive flexibility may aid future research investigations regarding this

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[4] Research exploring span differences has found performance on complex span tasks significantly correlated with performance on measures of intelligence like IQ (i.e. Wechsler Intelligence Scale; Engle, Tuholski, Laughlin, & Conway, 1999) and general fluid intelligence (Oberauer, Schulze, Wilhelm, & Sub, 2005). While we believe there are important differences between working memory span and intelligence measures, the associations made between the two general constructs in this paper are for the sake of comparing disparate research literatures, not to claim they are the same construct. We believe it is out of the scope of this paper to compare the two constructs, so we interchangeably refer to them for the ease of reading.

advantage.

Our understanding of low spans can also benefit from the converging of our current research with skill acquisition. As discussed previously, we have initial evidence that the combination of the highly structured speed-blocked Simon task with the explicit warning instructions improved low spans exertion of control. Given these results, providing low spans with highly structured environments where task objectives are made explicit might improve their baseline performance. This application of our results is again supported by skill acquisition research that suggests those lower in intelligence (based again on IQ tests) benefit more from highly structured learning and training experiences than those with higher intelligence (Snow & Yallow, 1982). Similar research has suggested an underlying cause for this disparity may be lower intelligence people become frustrated by a lack of structure as they search unsuccessfully for strategies that will aid them in accomplishing a new task (Boyle & Ackerman, 2004). In contrast, for higher intelligence people a highly structured environment may be boring when they have better ideas and strategies on how to complete a task. These findings are an intriguing approach to thinking about the current studies. For example, it may be low spans try to assess salient performance cues like high spans, but are less able to determine what is most appropriate. This may also suggest that low spans could use performance cues when they are made explicit and given frequently to improve their development of skills.

This distinction between each span group’s abilities is further supported by research that suggests the ability to learn a skill is based on the total resource capacity, more than an appropriate allocation of that capacity (Kanfer & Ackerman, 1989). Based on Kahneman’s (1973) classic model of attention, we have a finite amount of attention to devote to a task, especially a resource demanding one like learning a complex skill. Kanfer and Ackerman's research has given them evidence that those with lower intelligence have fewer attentional resources available to them, so they can either devote all available attention to learning the skill, which would cause rigid cognition due to no remaining resources to help them flexibly think about strategies for learning the skill faster or implementing different steps efficiently, or they will only allocate a portion of their resources to learning the task which will results in slower understanding of the different aspects of the skill due to highly distractible attention. By extension, Kanfer and Ackerman suggest the highly intelligent have a greater attentional pool to draw from, so they will likely not need to give all of their attention to learning a new complex skill, allowing remaining attention to figure out faster ways to learn the steps or how to flexibly adapt this skill to what they already know.

This research from Kanfer and Ackerman (1989), in combination with Kahneman's model of attention (1973), offers insight about why the low spans were not able to balance the demands of automatic and controlled processing. As suggested previously, we see their similar rate of transition as evidence that low spans were seeking balance at the same level as high spans, but their fewer resources rigidly confined them from strategically seeking out ways (e.g., implicit task cues) to exert greater control. When given a warning, low spans used that as additional structure to build control and improve performance. Based on this interpretation of low spans' performance, they appear highly reliant on their task environment to enforce control, but if given that structure (e.g., Heitz & Engle, 2007), they can more efficiently allocate the limited attention they have available.

Research exploring learning in primary and secondary education builds on the ideas from skill acquisition and offers further insights about our current findings. A simple dichotomization of classroom environments often used in this area of research are teacher- or studen*t*-centered (Rogers & Frieberg, 1994). Learning in a teacher-centered classroom by its nature is generally more structured than studen*t*-centered classroom environments. Research exploring academically "low achievers" (often defined as students scoring in the 75th percentile and below on standardized tests) suggests low achievers benefit from the structure provided by teacher-centered classrooms, as these students tend to lack the strategic learning abilities and organization of ideas on their own (Glaeser & Millikan, 2009). In contrast, high achievers tend to do better in a studen*t*-centered classroom where they are able to learn at their own pace and determine the best strategy to complete a task (Colangelo, Assouline, & Gross, 2004).

Conclusions

Through this dissertation we have presented initial evidence of a more complete way for opponent processing researchers to conceptualize and study cognitive control, which provides an important and often constructive role for automatic processes. We have suggested due to the finite nature of our attention, we have to make choices about the relative amount of control needed in a task. By recognizing the essential role of automatic processes in making this choice, we have gained greater insight into how each span group is able to resolve the tension caused by need to exert control with the push toward automation (i.e., the control dilemma; Goschke, 2000). We have suggested, in a similar way as Goschke, that the ideal way to resolve the control dilemma is through the balance of automatic and controlled processes. Results from our studies suggest high spans are more likely to balance the demands of these two processes, unless they do not interpret one process demanding its use. In our dissertation experiment, this latter situation occurred through automating task performance when the task environment required far less control. When the need to balance cognitive processes is necessary, we have proposed high spans can more efficiently reach that balance through a tolerance of automaticity brought about by inhibition. As a result, we posit that the same control that is characteristically implemented by high spans in oppositional logic research is also used as a way to activate more automatic processing. In this way, high spans can more efficiently balance a full spectrum of cognitive processing and resolve the tension of the control dilemma.

The importance of these ideas in understanding the full nature of individual differences in resolving the control dilemma now falls to future research that will, no doubt, refine and extend the intial theories and ideas suggested in this dissertation. No matter the outcome of these future research investigations, we believe our area of research will be improved by being more mindful of the full scope of human cognition when interpreting opponent processing tasks. This balanced approach would better reflect individual differences in cognitive control based on the flexible use of automatic and controlled processing.

APPENDIX A

REPORT OF ALL SESSIONS IN DISSERTATION EXPERIMENT 1

Congruent Trials

Following the quantitative design of Heitz and Engle (2007), congruent and incongruent trials for each of the three sessions were analyzed separately. We first tested the mean RTs from each latency bin with a 2 (span) X 10 (bin) repeated measures ANOVA. There were no main effects of span in session one, $F(1, 78) = .52$, $p = .47$, $p = .67$, two, $F(1, 78) = .64$, $p = .43$, or three, $F(1, 78) = .14$, $p = .71$. Nor was there a significant span by bin interaction in session one, $F(9, 702) = .38$, two, $F(9, 702) = .97$, $p = .67$, or three, $F(9, 702) = .36$, $p = .74$ (see Figure A1). To ensure we were only examining differences in accuracy that were due to the implementation of control, we ran the accuracy ANOVA on bins where the mean accuracy was at or above 50% (Heitz & Engle, 2007; Norman, 1975). Congruent bins in all three sessions were above chance performance, leading to a 2 (span) X 10 (bin) repeated measures ANOVA that resulted in no main effects in session one, $F(1, 78) = .30$, $p = .59$, two, $F(1, 78) = .04$, $p = .85$, or three, $F(1, 78) = .05$, $p = .82$, and no interactions between span and bin in session one, $F(9, 702) = .44$, $p = .69$, two, $F(9, 702) = .36$, $p = .74$, or three, $F(9, 702) = .66$, $p = .62$.

Span differences and similarities in the sequential *t* tests and bin of asymptote analyses are presented in Table A1. In session one (see Figure A1), bin 5 was the bin of asymptote for low spans (bin 4 vs. bin 8 significant), $t(37) = 3.71$, $p < .001$, and high

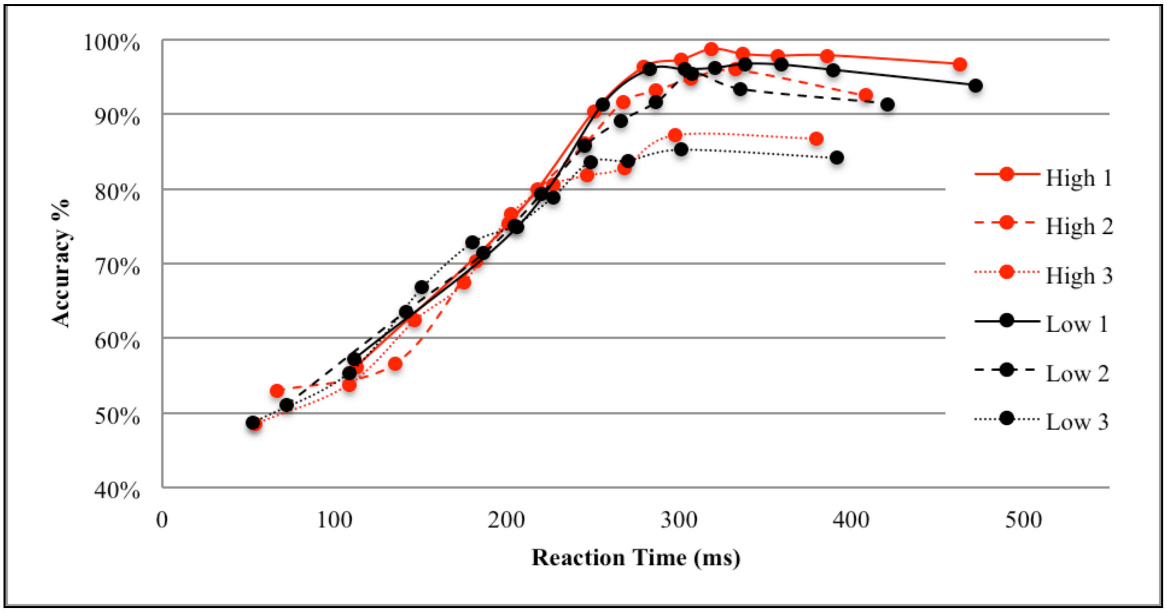

Figure A1. Speed-Blocked Simon Task, Warning: Congruent Trials. Congruent trial CAFs for high and low spans across all three sessions. There were no main effects or interactions with span in RT or accuracy. Span groups transitioned at the same rate and reached the same asymptote in all sessions, except session 3 when low spans reached asymptote a bin earlier than high spans (see Table A1).

Table A1. Dissertation Experiment 1: Congruent Trials

Session	Rate	Asymptote
1	Same	Same
2	Same	Same
3	Different (low spans)	Same

Note. Span differences or similarities in the rate of reaching asymptote (see rate column) and the level of accuracy at asymptote (see asymptote column) are presented here in an abbreviated form. In cells with differences, the word “different” is followed by the span group with the faster rate or higher accuracy, respectively. In cells with no span differences, only the word “same” is provided. The table provides a snapshot of the data revealed in the sequential *t* test and bin of asymptote analyses.

spans (bin 4 vs. bin 8 significant), *t*(41) = 1.85, *p* = .04. The accuracy rate at the respective bin of asymptote for high and low spans was not significantly different, *t*(78) = 1.40 *p* = .09, with high (*M* = 97.28) and low spans (*M* = 94.73) reaching similarly high rates of accuracy.The bin of asymptote shifted for both span groups in session two, as low spans did not asymptote until bin 8 (bin 8 significantly was higher than all other bins, including 10 shown here), *t*(37) = 1.81 *p* = .04, nor did the high spans asymptote until bin 8 (bin 7 vs. bin 9 significant), *t*(41) = 1.78, *p* = .04. There was no significant difference between high and low span groups in their accuracy for their session two bin of asymptote (*M* = 94.72 vs. 93.01, respectively), *t*(78) = .682, *p* = .25. In session three, asymptote occurred at bin 7 (bin 6 vs. bin 10 significant), *t*(37) = 1.66, *p* = .05, for low spans, and bin 8 (bin 7 vs. bin 10 significant), *t*(41) = 2.17, *p* = .02, for high spans. Again, there was no significant difference between high and low spans in their accuracy for their respective bins of asymptote (*M* = 86.75 vs. 81.29, respectively), *t*(78) = 1.45, *p* = .08.

Incongruent Trials

RTs for each latency bin were analyzed in a 2 (span) X 10 (bin) repeated measures ANOVA. A separate repeated measures ANOVA was conducted for each session (see Figure A2). In session one, the span by bin interaction was not significant, *F*(9, 702) = 2.19, *p* = .11, nor was there a significant main effect of span, *F*(1, 78) = .76, *p* = .39). In session two, there was also no span by bin interaction, *F*(9, 702) = .59, *p* = .61, nor was there a main effect of span, *F*(1, 78) = .52, *p* = .48. The same pattern continued for session three, with no span by bin interaction, *F*(9, 702) = . 1.42, *p* = .24) or main effect of span, *F*(1, 78) = .20, *p* = .66.

Accuracy rates for each latency bin were also analyzed based on the bin where

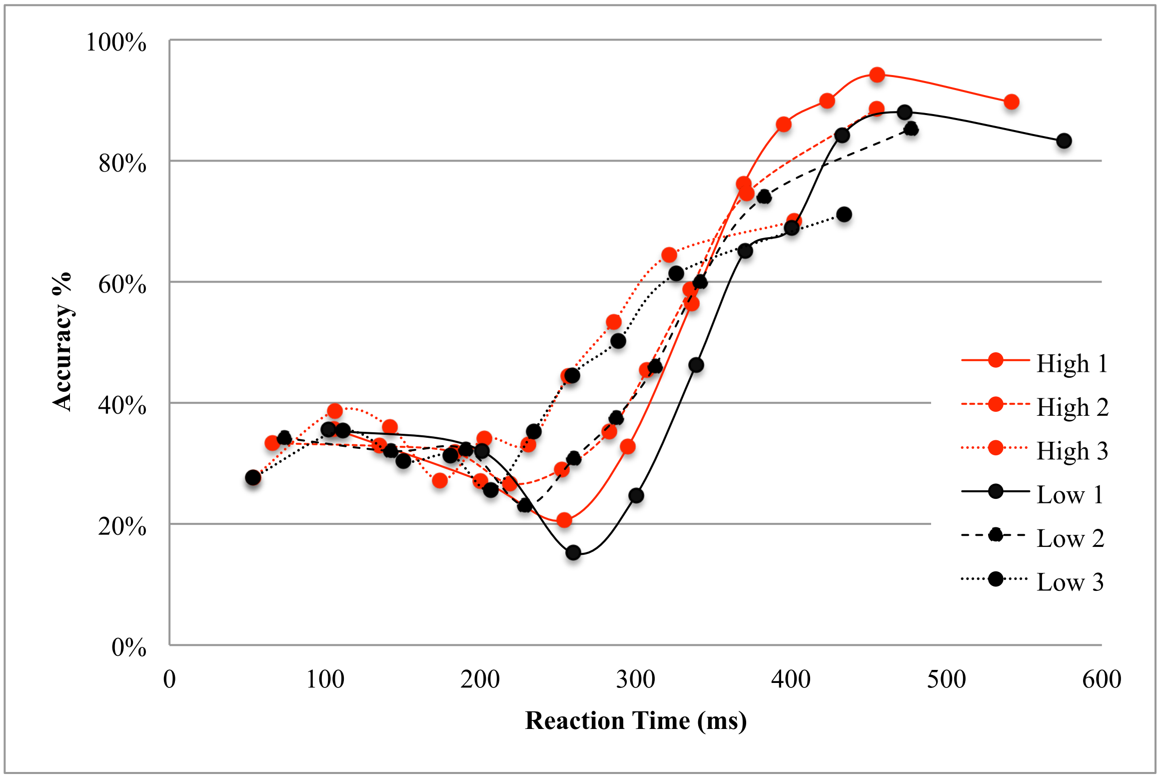

Figure A2. Speed-Blocked Simon Task, Warning: Incongruent Trials. Incongruent trial CAFs for high and low spans across all three sessions. There were no main effects or interactions with span in RT. A main effect of span was significant in session one, with high spans having a similar rate, but higher asymptote that low spans. No other main effects or interactions in accuracy were significant. The rate of transition and level of asymptote favored high spans in session one, but no other span differences were found in sessions two or three (see Table A2).

above chance performance began. In session one, above chance performance occurred at bin 5, resulting in a 2 (span) X 6 (bin) repeated measures ANOVA. There was a significant main effect of span, *F*(1, 78) = 4.34, *p* = .04, with high spans more accurate overall than low spans (*M* = 82.1 vs. 73.2, respectively), but the span by bin interaction was not significant, *F*(5, 390) = .77, *p* = .58. Session two accuracy did not reach above chance performance until Bin 8, so in a 2 (span) X 3 (bin) repeated measures ANOVA was run and revealed no main effect, *F*(1, 78) = .002, *p* = .96, or span by bin interaction, *F*(2, 156) = .10, *p* = .87. In session three, bin 8 was again where performance reached above chance performance, leading to a 2 (span) X 3 (bin) repeated measures ANOVA. The main effect was not significant, *F*(1, 78) = .09, *p* = .77, nor was the span by bin interaction, *F*(2, 156) = .25, *p* = .74.

A summary of span differences and similarities in the sequential *t* tests and bin of asymptote analyses are presented in Table A2. The sequential *t* tests in session one (see Figure A2), revealed low spans' asymptote occurred at bin 8 (bin 7 vs. bin 10 significant), *t*(37) = 2.83, *p* < .001, and high spans' asymptote occurred at bin 9 (bin 9 significantly higher accuracy than all other bins), *t*(41) = -1.81, *p* = .04. Accuracy within the bin of asymptote was significantly higher for high spans (*M* = 94.21) than low spans (*M* = 82.66), *t*(78) = 2.60, *p* < .01. In session two, bin 10 was asymptote for low spans as there were significant differences in the accuracy in all other bins (e.g., bin 9: *t*[37] = 2.37, *p* < .001). The same was true for high spans' asymptote as there were significant differences in the means up until bin 10 (e.g., versus bin 9: *t*[41] = 3.78, *p* < .001). There was no significant span difference in accuracy at the bin of asymptote for high (*M* = 88.59) and low spans (*M* = 82.46), *t*(78) = .57, *p* = .29. Finally, in session three, bin 9 was asymptote for low spans (bin 8 vs. bin 10 significant), *t*(37) = 4.08, *p* < .001, and high spans (bin 8

Table A2. Dissertation Experiment 1: Incongruent Trials

Session	Rate	Asymptote
1	Different (low spans)	Different (high spans)
2	Same	Same
3	Same	Same

Note. Span differences or similarities in the rate of reaching asymptote (see rate column) and the level of accuracy at asymptote (see asymptote column) are presented here in an abbreviated form. In cells with differences, the word “different” is followed by the span group with the faster rate or higher accuracy, respectively. In cells with no span differences, only the word “same” is provided. The table provides a snapshot of the data revealed in the sequential *t* test and bin of asymptote analyses.

vs. bin 10 significant), $t(41) = 2.99$, $p < .001$. Once again, there was no significant difference in accuracy between high ($M = 64.47$) and low spans ($M = 61.91$) in the bin of asymptote, $t(78) = .35$ $p = .37$.

APPENDIX B

DISSERTATION EXPERIMENT 2: GENERAL RESULTS FOR ALL SESSIONS

Following the quantitative design of Heitz and Engle (2007), congruent and incongruent trials for each of the three sessions were analyzed separately. The only screening criteria was no response trials. All statistics from the ANOVAs were corrected using Greenhouse-Geisser, but we report the uncorrected degrees of freedom for ease of reading.

Congruent Trials

RTs for each latency bin were analyzed in a 2 (span) X 10 (bin) repeated measures ANOVA, which were run separately for each session (see Figure B1). In session one the span by bin interaction was significant, $F(9, 918) = 3.09$, $p = .05$, but there was no main effect of span, $F(1, 102) = 1.66$, $p = .20$. In session two, there was also a significant span by bin interaction, $F(9, 918) = 6.25$, $p < .01$, and a main effect of span, $F(1, 102) = 4.65$, $p = .03$. The span by bin interaction in session three was significant, $F(9, 918) = .2.17$, $p < .01$, but just like session one, there was no main effect of span, $F(1, 102) = 2.75$, $p = .10$.

Accuracy rates for each latency bin were analyzed based on when span groups attained above chance accuracy. Across all three sessions, mean accuracy was above chance in all congruent bins allowing us to run a 2 (span) X 10 (bin) repeated measures

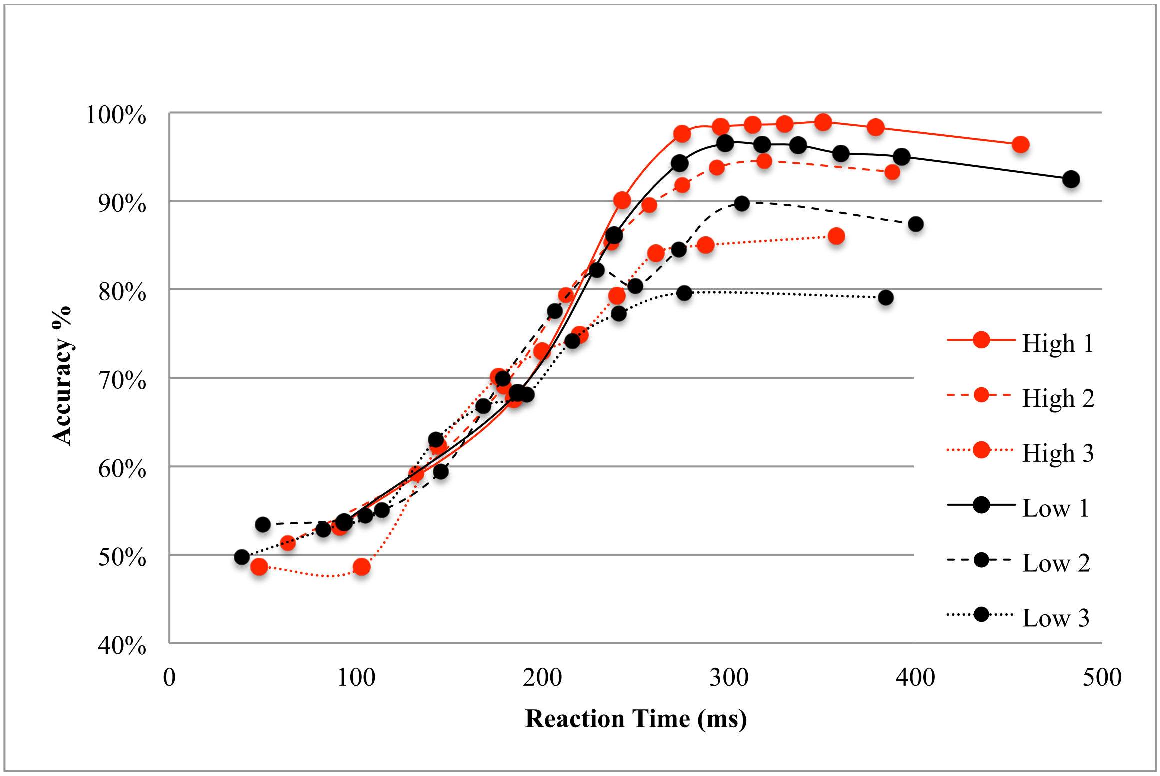

Figure B1. Speed-Blocked Simon Task, No Warning: Congruent Trials. Congruent trial CAFs for high and low spans across all three sessions. RT analyses revealed main effects of span in session two and an interaction with span in all three sessions. A significant main effect and interaction of accuracy with span was found only in session two. As illustrated in this figure, high spans reached a higher asymptote on all sessions, but span differences in the rate of transition was mixed (see Table B1).

ANOVA for each session (see Figure B1). In session one there was no span by bin interaction, *F*(9, 918) = .92, *p* = .42), nor was there a main effect of span, *F*(1, 102) = 3.38, *p* = .07), with high and low spans performing equivalently overall (90.5 vs. 89.5, respectively). In session two, both a span by bin interaction, *F*(9, 918) = 2.49, *p* = .04), and a main effect of span, *F*(1, 102) = .8.31, *p* < .01, emerged, with low spans performing far less accurately than high spans (73.9 vs. 80.7, respectively), but this went away in session three where neither the span by bin interaction, *F*(9, 918) = 2.11, *p* = .07 , or main effect were significant, *F*(1, 102) = 2.70, *p* = .10.

Span differences and similarities in the sequential *t* tests and bin of asymptote analyses are presented in Table B1. In session one (see Figure B1), bin 4 was the bin of asymptote for low spans (bin 3 vs. bin 9 significant), *t*(51) = 3.71, *p* < .01, as well as high spans (bin 3 vs. bin 10 significant), *t*(51) = 2.88, p < .001. The accuracy rate at the respective bin of asymptote for high (*M* = 97.58) and low spans (*M* = 94.32) was significantly different, *t*(102) = 2.62, *p* < .01. In session two, low spans did not asymptote until bin 9 (bin 9 significantly higher than all other bins), *t*(51) = 2.93, *p* < .01, and high spans at bin 8 (bin 7 vs. bin 9 significant), *t*(51) = 2.07, *p* = .02. There was a significant difference between high and low span groups in the bin of asymptote (*M* = 93.83 vs. 89.65, respectively), *t*(102) = 1.73, *p* = .04. In session three, asymptote occurred at bin 8 (bin 7 vs. bin 10 significant), *t*(51) = 2.12, *p* = .02, for low spans, as well as bin 8 (bin 7 vs. bin 10 significant), *t*(51) = 2.93, *p* < .01, for high spans. Once again there was a significant difference between high and low spans in the bin of asymptote (*M* = 84.13 vs. 77.32, respectively), *t*(102) = 1.65, *p* = .05, with high spans still maintaining greater accuracy in the bin of asymptote.

Table B1. Dissertation Experiment 2: Congruent Trials

Session	Rate	Asymptote
1	Different (low spans)	Different (high spans)
2	Different (high spans)	Different (high spans)
3	Same	Different (high spans)

Note. Span differences or similarities in the rate of reaching asymptote (see rate column) and the level of accuracy at asymptote (see asymptote column) are presented here in an abbreviated form. In cells with differences the word “different” is followed by the span group with the faster rate or higher accuracy, respectively. In cells with no span differences, only the word “same” is provided. The table provides a snapshot of the data revealed in the sequential *t* test and bin of asymptote analyses.

Incongruent Trials

RTs for each latency bin were analyzed in a 2 (span) X 10 (bin) repeated measures ANOVA. A separate repeated-measures ANOVA was run for each session. In session one (see Figure B2), the span by bin interaction was significant, *F*(9, 918) = 5.48, *p* = .01, but there was no main effect of span, *F*(1, 102) = .53, *p* = .47. In session two, the span by bin interaction was not significant, *F*(9, 918) = 1.58, *p* = .21, but there was a main effect of span, *F*(1, 102) = 3.97, *p* = .05. The results flipped again in session three (see Figure 12), with a significant span by bin interaction, *F*(9, 918) = 4.35, *p* = .01, but no main effect of span, *F*(1, 102) = 3.12, *p* = .08.

Accuracy rates for each latency bin were analyzed based on when the mean accuracy rate was above chance. In session one, a mean accuracy rate of 50% did not occur until bin 6, so a 2 (span) X 5 (bin) repeated measures ANOVA was run and revealed no span by bin interaction, *F*(4, 408) = 1.22, *p* = .30, but there was a main effect of span, *F*(1, 102) = 5.13, *p* = .03, with high spans more accurate overall than low spans (80.7 vs. 70.2, respectively). For session two above chance accuracy was not achieved until bin 9 (*M* = 62.25), leading to a 2 (span) X 2 (bin) repeated measures ANOVA with a significant main effect of span, *F*(1, 102) = 6.04, *p* = .02, but a nonsignificant interaction between span and bin, *F*(1, 102) < .01, *p* = .96. In session three, above chance accuracy again did not occur until bin 9, resulting in another 2 (span) X 2 (bin) repeated measures ANOVA. The main effect was no longer significant, *F*(1, 102) = 2.55 *p* = .11, and the interaction between span and bin remained nonsignificant, *F*(1, 102) = .31, *p* = .58.

A summary of span differences and similarities in the sequential *t* tests and bin of asymptote analyses are presented in Table B2. In session one (see Figure B2), bin 8 was the bin of asymptote for low spans (bin 7 vs. bin 10 significant), *t*(51) = 3.33, *p* = .001,

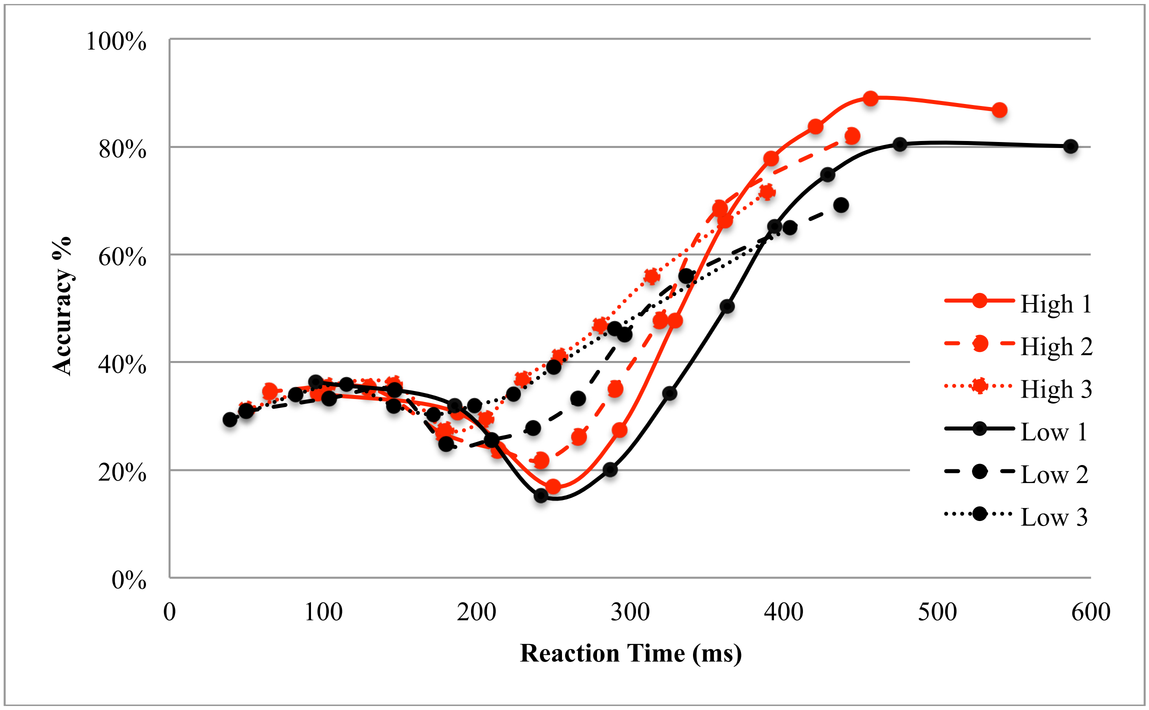

Figure B2. Speed-Blocked Simon Task, No Warning: Incongruent Trials. Incongruent trial CAFs for high and low spans across all three sessions. RT analyses revealed a main effects of span in session two and an interaction with span in session two and three. A significant main effect of accuracy was found in session one, but no other main effects or interactions were significant. As illustrated in this figure, high and low spans had a similar rate of transition in sessions one and two, but high spans had higher overall accuracy. In session three they had the same rate and same asymptope (see Table B2).

Table B2. Dissertation Experiment 2: Incongruent Trials

Session	Rate	Asymptote
1	Different (high spans)	Different (high spans)
2	Same	Different (high spans)
3	Same	Same

Note. Span differences or similarities in the rate of reaching asymptote (see rate column) and the level of accuracy at asymptote (see asymptote column) are presented here in an abbreviated form. In cells with differences the word “different” is followed by the span group with the faster rate or higher accuracy, respectively. In cells with no span differences, only the word “same” is provided. The table provides a snapshot of the data revealed in the sequential *t* test and bin of asymptote analyses.

compared to bin 7 (bin 6 vs. bin 10 significant), $t(51) = 1.29$, $p < .01$, for high spans. The accuracy rate at the respective bin of asymptote for high ($M = 77.81$) and low spans ($M = 74.81$) was significantly different, $t(102) = 5.47$, $p < .01$. Bin 10 was the asymptote for low spans (10 significantly higher accuracy than all other bins), $t(51) = 3.76$, $p < .001$, and high spans, $t(51) = 4.31$, $p < .001$, for session two (see Figure 12), but high spans ($M = 68.46$) were more accurate than low spans ($M = 55.85$), $t(102) = 2.61$, $p < .01$, within that bin. In session three, bin 10 was once again the point of asymptote for low, $t(51) = 4.86$, $p < .001$, and high spans, $t(51) = 3.91$, $p < .001$, but despite a large difference in mean accuracy, there was no significant difference in asymptotic accuracy between the high and low spans ($M = 71.63$ and 65.02, respectively), $t(102) = 1.21$, $p = .11$.

APPENDIX C

CROSS-EXPERIMENT COMPARISONS FOR ALL SESSIONS

Accuracy on incongruent trials was compared for each span group across experiments, based on when the mean accuracy was above chance. In session one, both span groups reached above chance accuracy at bin 5, resulting in a 2 (experiment) X 6 (bin) repeated-measures ANOVA run separately for each group. Results from this analysis revealed a significant main effect of experiment for low spans, $F(1, 88) = 3.72$, $p = .05$, as they were more accurate with warning instructions ($M = 73.2$) than without ($M = 64.2$), but no span by bin interaction, $F(5, 440) = 1.32$, $p = .27$. For high spans the analysis revealed neither a main effect of span, $F(1, 92) = 2.43$, $p = .12$, or an interaction between span and bin, $F(5, 460) = .49$, $p = .65$. In session two, both groups reached above chance accuracy at bin 9 resulting in a 2 (experiment) X 2 (bin) repeated-measures ANOVA. For low spans, there was a main effect of experiment, $F(1, 88) = 14.43$, $p < .001$, but not a significant experiment by bin interaction, $F(1, 88) = .13$, $p = .72$. High spans had neither a main effect of experiment, $F(1, 92) = 1.46$, $p = .23$, or an interaction between experiment and span, $F(1, 92) = .01$, $p = .92$. For session three, the same pattern continued for both span groups. Both high and low spans mean accuracy was again bin 9, resulting in a 2 (experiment) X 2 (bin) repeated-measures ANOVA. For low spans there was again a main effect of experiment, $F(1, 88) = 4.21$, $p = .04$, but not a significant experiment by bin interaction, $F(1, 88) = 2.71$, $p = .10$. While high spans again had neither a main effect of experiment, *F*(1, 92) = .34, *p* = .56, or an interaction between experiment and span, *F*(1, 92) = 3.39, *p* = .07.

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