VARIABILITY IN THE SIMON EFFECT

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Abstract

The automatic-controlled distinction provides one way to explore movement disorders such as apraxia. For such a population it would be useful to have a simple task and measure to distinguish automatic from controlled movements. The Simon task, which compares performance on congruent versus noncongruent tasks, is thought to have both automatic and controlled components. As a measure, Segalowitz and colleagues (Gilbert & Shallice, 2002; Norman, 1968, 1981; Norman & Shallice, 1986; Shallice, 1994) suggested the coefficient of variation (CV); responses resulting from controlled processing are thought to have more variability than those resulting from automatic processes. Two experiments evaluated the use of the CV as an indicator of automatic versus controlled processing in right-handed WSU kinesiology students, using a one-handed Simon task. It was predicted that noncongruent Simon trials would require more controlled processing than congruent trials, and thus would be more variable as measured by CVs. Experiment 1 (N=42) revealed the expected Simon effect of faster reaction time for congruent trials as opposed to noncongruent trials occurred. However, congruent trials were *more* variable than noncongruent trials when evaluated with distributional analysis, and were more positively skewed, indicating that the congruent trials require more

processes than noncongruent trials. Experiment 2 (N = 58) used a dual task procedure to validate conclusions based on CVs in Experiment 1. When a resource demanding counting task was added to the Simon task, congruent trials slowed more than noncongruent trials, although congruent trials remained faster than noncongruent trials. This result confirmed the CV results and indicated that congruent trials require more resources and thus more controlled processing than noncongruent trials.

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Dedication

This dissertation is dedicated to my parents, Bruce and Jean Nelson, who taught me to love learning; to my husband Greg who is my best friend and chief cook and dog walker; and to my three girls, Elizabeth, Nicole, and Emily, who turned out better than any dissertation ever could.

CHAPTER ONE: INTRODUCTION

Human performance is characterized by actions that result primarily from deliberate, conscious processing of stimulus information, as well as actions that seem to be primarily reflexive, automatic responses. Posner (1978) defined automatic processes as those which occur without conscious awareness, apart from deliberate intention, and which do not interfere with simultaneous processes or tasks. By contrast, controlled processing is that which is under conscious control, is intentional, and requires attentional resources and thus may detract from the performance of concurrent tasks. Recent research has demonstrated the importance of the distinction between automatic and controlled processing in highlighting the processing characteristics of persons with Attention Deficit Disorder (ADD), schizophrenia, Parkinson's and Huntington's Diseases and people with disorders resulting from head injury or vascular trauma, as compared with unaffected individuals (Cooper, 2002; Cooper & Shallice, 2000; Rumiati, Zanini, Vorano, & Shallice, 2001; Saling & Phillips, 2007; Southwood & Dagenais, 2001; Vakil & Tweedy, 1994) For example, persons with ADD, or who are otherwise characterized as impulsive, are more inclined than normal individuals to produce reflexive responses even in situations where these responses are inappropriate: they fail to inhibit word reading in the Stroop task even when asked to ignore the word and name text color (Kirkeby & Robinson, 2005). Persons with apraxia often exhibit what is termed an automatic-voluntary dissociation (Gravenhorst & Walter, 2007): while they cannot produce movements on command during testing, they are able to generate the same movements within a real-life context, in the presence of appropriate environmental cues. Also, certain laboratory tasks can elicit an apparent

automatic-voluntary dissociation in normal participants. For example, when instructed to respond to color or other stimulus attribute which is not related to stimulus location, people respond faster when stimulus and response locations correspond (see Lu & Proctor, 1995, for a review). The explanation is that the spatial stimulus-response correspondence may automatically trigger the spatially compatible response and thus decrease response time. Clearly, the distinction between automatic and controlled processing is practically significant and can potentially help to understand disorders and/or provide rehabilitation options for various patient populations, as well as contribute to our understanding of normal performance. The purpose of this research was to explore and quantify performance variability as a potential measure of the degree of automatic versus controlled processing in a task with a spatial compatibility component.

Automatic Versus Controlled Processing

Shiffrin and Schneider (Schneider & Shiffrin, 1977; 1977) provided seminal research on automatic versus controlled methods of processing. Their work was based on studies of consistent and varied mapping between stimulus and response sets in visual search tasks. In Shiffrin and Schneider's prototypical task, participants learned a memory set of targets, e.g. consonants. Then, they viewed a series of stimuli that could include elements from the target set or from a set of distracters (e.g., numbers), or both, and were asked to determine as quickly as possible whether a stimulus included a target element. Consistent mapping involved direct and exclusive mapping between stimuli and responses: targets were always from one set while distracters were always from another set. By contrast, in varied mapping target and distracter stimuli could be from the same set, i.e., a target in one trial could be a distracter in another trial..

Size of the target set was also varied; early in practice of both consistent and varied mapping conditions, participants were slower to respond as set size increased. However, after extensive practice in the consistent mapping condition, performance no longer depended on the size of the memory set. Participants could respond as quickly when the set was large as when it contained only a few elements, mapping conditions. Further, under consistent mapping conditions, participants became faster and more accurate and reported less conscious control of their processing. Response time decreased after thousands of practice trials until reaching asymptotic performance levels, and this was interpreted as indicative of automaticity. By contrast, in varied mapping situations, even after extended practice, participants never became automatic in their processing. The set size effect did not diminish nor did performance reach asymptotes. As originally conceived by Shiffrin and Schneider (Posner & Snyder, 1975; Schneider & Chein, 2003) these pattern differences relate to the diminished role of attention after sufficient practice in the consistent mapping condition. Based on their results, Shiffrin and Schneider described automatic processing as behavior that occurs "without the necessity of active control or attention by the subject" (p. 155-156), while controlled processes demand a share of limited processing capacity, and are intentional and modifiable.

Until recently, most views of the automatic versus controlled distinction were that tasks are either automatic or controlled in nature. Compared with controlled processing, automatic processing is considered to require few if any processing resources, and to be unintentional, ballistic (in the sense that once started, it is difficult to stop), and even unconditional so that a stimulus invariably produces some sort of automatic response (Saling & Phillips, 2007).

Another proposed characteristic of automaticity is that automatic performance is less variable than controlled performance (Povel & Collard, 1982; Wascher, Schatz, Kuder, & Verleger, 2001; Zhang & Kornblum, 1998). Also different types of automaticity may be possible (Saling & Phillips, 2007). For example, Logan associates automaticity only with changes that occur as a task is learned (2005); however, there is a possibility that there are natural stimulus-response associations that may result in automatic processing, such as spatial stimulus response compatibility (Hommel, 2000). Current, more nuanced views are that tasks are generally a combination of processes which are more or less automatic versus controlled (Bargh, 1992; Bargh & Chartrand, 2000; Bargh & Ferguson, 2000; Hommel, 2000). Task processing may be comprised of a mixture of automatic and controlled processes or a variety of different controlled processes.

While it is often inferred that speedier performance under automatic processing conditions is due to more efficient processing, research suggests that automatic processing may be qualitatively different than controlled processing (Saling & Phillips, 2007). For example, Nakahara, Doya and Hikosaka (1977) reported neurological evidence that with practice, parallel processing can replace serial processing. In Logan's conceptualization (2001), early in learning (i.e., during the "controlled" stage), performance is governed by rule systems, while later in learning it switches to a more automatic memory search to match stimulus with response. Use of the rule system is a slower, more effortful process than using memory search. Rogers and Monsell (1985) differentiate behavior triggered automatically (e.g., by stimulus characteristics such as spatial location) from behavior triggered internally, by intention. Automatically

triggered behavior requires few resources, while internally triggered behavior involves the function of the resource demanding Supervisory Attentional System, according to Rogers and Monsell. In spite of differences in the various explanations, accounts concur that controlled processing operates more slowly and requires more cognitive resources than automatic processing.

Research using brain scan and electroencephalography (EEG) techniques that monitor brain activation during laboratory testing also supports the notion of qualitative differences between controlled and automatic processing. Toni, Krams, Turner, and Passsingham (2005) showed that automatic performances are correlated with activity primarily in posterior cortex, while performances characterized as controlled use prefrontal brain areas. In evaluating changes that occur with task learning, Jansma, Ramsey, Slagter, and Kahn (1998) found no shift of activity with automatization but rather a reduction of prefrontal brain activity, which is associated with reduced working memory task involvement. Other researchers report that brain activity shifts from prefrontal cortical to mid level and subcortical regions as behavior becomes more automatic. For example, the basal ganglia become particularly active in automatic behavior (see Saling & Phillips, 2007 for a review). Further evidence confirming the importance of prefrontal cortex in controlled processing comes from research on various disorders such as schizophrenia and attention deficit disorder, which are known to affect prefrontal areas and result in controlled processing deficits (Holroyd, Nieuwenhuis, Mars, & Coles, 2004; Ridderinkhof, Scheres, Oosterlaan, & Sergeant, 2005; Ridderinkhof, van den Wildenberg, Wijnen, & Burle, 2004). Apraxia results from damage to a wide range of cortical and subcortical areas, but there is

agreement that most of these areas are components of the fronto-parietal loops that are involved in controlled processing (Gravenhorst & Walter, 2007). Thus, there is evidence that both behavioral and neurological changes signal a qualitative difference between controlled and automatic processing.

Measurement of Automaticity

Several different task paradigms have been used to evaluate whether controlled or automatic processing underlies performance (Saling & Phillips, 2007). One is Shiffrin and Schneider's method (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977), as described previously. Automatization of behavior is assumed, if performance reaches a plateau with practice, and does not change in spite of increases in set size. If increasing set size does degrade performance, then the task is considered to rely on controlled processing. Another method is to analyze reaction times (RTs) for well learned versus novel keypress sequences. For example, Sternberg, Monsell, Knoll & Wright (1978) compared production of well learned sequences, such as the days of the week repeated in order, with novel sequences of the same length, such as days of the week in random order. The well learned sequences were produced with a shorter RT than novel sequences, suggesting that the familiar sequences have become a unit and can be produced more automatically. If familiar sequences are not readily available this method would require extensive practice, similar to the Shiffrin and Schneider paradigm. For a quick measure of potential deficits in automatic versus controlled processing in a patient population, extensive practice would be a drawback. Further, both of these methods analyze how response speed changes in with practice, rather than evaluating already existing automatic versus controlled

processing. Also, asymptotic performance, which has been interpreted as a signal of automatic performance, can also be interpreted as a floor or ceiling effect. Finally, the focus on speed of response alone does not necessarily signal a qualitatively different type of processing and therefore might not represent a change in processing style (Saling & Phillips, 2007; N. Segalowitz, Poulsen, & Segalowitz, 1999; N. Segalowitz & Segalowitz, 1993).

A more complex, dual task methodology for assessment of automaticity involves comparing a single task versus the same task paired with a resource demanding task. This dual task methodology requires the assumption of an attention resource system with fixed limits (Kahneman, 1973) and the assumption that controlled processing demands more resources than automatic processing. An automatic task will deteriorate little when combined with a second, resource demanding task or will not affect performance of the second task when compared with performance of the second task alone. On the other hand, tasks which require controlled processing will be slowed and/or more prone to error in the dual task condition or will similarly disrupt the second task. A primary drawback of dual task methodology is the time-demanding and complex design and difficulty for patients of performing the primary and secondary tasks at the same time.

A less frequently used, but potentially simpler, method for determining whether performance is characterized by automatic or controlled processing involves analysis of variability. This methodology requires the assumption that automaticity is characterized by more consistent performance, i.e., reduced variability. Typically the standard deviation of a system parameter, for example, RT, is taken as the representation of variability for a sample of data. For

example, Jansma et al. (2001) evaluated the mean RTs and standard deviations of participants performing a Sternberg task, and compared a practiced task with a novel task. Analysis showed that the practiced task had both faster mean RTs and lower standard deviations than the novel task, and the authors concluded that learning results in lower response variability. Povel and Collard (1982) studied interresponse variability in keypress sequences, and found that variability between keypresses within a subset, or chunk, of a sequence was smaller than that between chunks. They concluded that subsets of movement sequences can become automatic and will be produced as if they were one response, or motor program, with increased consistency between sequence components. Kirkeby and Robinson (2005) used standard deviations to compare performance of more impulsive versus less impulsive people on Stroop test responses. Participants who scored higher on impulsivity performed the Stroop test with less variability overall, although there was no effect of impulsivity on overall speed or errors. The researchers attributed their results to the possibility that impulsive people are more reliant on automatic routines rather than on effortful, and thus more variable, controlled stimulus-response mapping.

However, there are difficulties with the use of standard deviations in behavioral analysis of RTs. Newell and Corcos (1993) remind us that the standard deviation is only a reasonable descriptor of data with a normal distribution. Also, if there are trial to trial relationships that are of interest, they can be masked by the standard deviation. For example, a sine wave and white noise may have the same standard deviation, but the sine wave involves trial to trial dependencies yielding complete predictability, while the white noise is random from trial to trial (Slifkin & Newell, 1998). Further, for RT experiments, variability (as measured by standard

deviations) is correlated with mean RT, such that as the mean RT increases, standard deviations increase (this is Weber's Law: see for reviews Gibbon, Malapani, Dale, & Gallistel, 1997; Ratikin, 2005). As an alternative, the coefficient of variation (CV), computed as standard deviation of the RTs divided by the mean of the RTs, has often been used to correct for the correlation between mean and standard deviation, so that variability can be evaluated as a separate dependent variable.

Segalowitz and colleagues (Poulsen & Segalowitz, 2000; N. Segalowitz, O'Brien, & Poulsen, 1998; N. Segalowitz et al., 1999; N. Segalowitz & Segalowitz, 1993; N. Segalowitz, Segalowitz, & Wood, 1998; S. J. Segalowitz, 2000) explored CV analysis as a way to identify changes in variability that occur with increased automaticity. Basic to their approach is that there are two ways to account for an increase in performance speed. One way is for the *type* of processing to remain the same but simply to speed up, resulting in a decreased mean RT and a proportional decrease in the standard deviation. Thus the decreased mean RT would *not* be accompanied by a change in CV. For example, people simply get better at the controlled processing required for a task, rather than changing to a new strategy (i.e. reducing the number of controlled processes or changing completely to automatic processing). A second way to improve performance speed is for a reorganization to occur, resulting in faster mean RTs. The reorganization is presumed by Segalowitz and colleagues to be a reduction in the number of controlled processes or a switch to automatic processing, yielding an increase in performance stability. In such a situation the standard deviation would decrease more than proportionately with the mean RT, resulting in reduced CV for the less controlled, or automatic, relative to the

more controlled processing task. Mathematically, since a reduction in mean RT with a disproportionate reduction in standard deviation results in decreased CV, a positive correlation between CVs and mean RTs would result. Thus, the general approach involves the following predictions: the magnitude of the CV decreases when a task is speeded due to reorganization (decreased number of controlled processes) but not when a decrease of mean RT is due to simply "general speed-up" of existing processes. The correlation between CV and RT will be at or near zero when performance remains controlled by qualitatively similar processes, while the correlation between CV and the mean will be positive when task performance switches to a qualitatively different process.

There is some evidence for the ability of CV to distinguish between performance changes due to speed-up versus due to reorganization of the task. Segalowitz and colleagues (N. Segalowitz & Segalowitz, 1993; N. Segalowitz, Segalowitz et al., 1998) compared RT variability in first versus second language stimuli, presuming that the second language tasks would be less automatic. As expected, CVs were smaller for first language tasks. Continuing in this vein, Segalowitz, Segalowitz and Wood (1998) explored changes that occur with learning a second language. Experienced language students had smaller CVs with a positive correlation between RT and CV. In contrast, beginners started with higher CVs and with no correlation between RT and CV; but after practice, CVs decreased and the positive RT-CV correlation became evident (see also Rickard, 1997, for pseudoarithmetic task).

Extending this work from language acquisition to an attention switching task, Segalowitz, Poulsen, and Segalowitz (1999) replicated Rogers and Monsell's (1995) task set switching

paradigm, but analyzed CVs in addition to mean RTs. For this type of task, CV magnitude predictions are relevant, but unlike in learning designs, the prediction of correlation is inappropriate. Participants had to switch attention from digit to letter decisions on every second trial of a reaction time task. Segalowitz et al. claimed that the repetition, or nonswitch, trials could be performed in an automatic or less controlled basis, while the switch trials required a controlled process for task reconfiguration. The processing mode manipulation thus contrasted qualitatively different processes. A task difficulty manipulation was also included: changes in task difficulty were not presumed to change processing qualitatively. Segalowitz et al. observed a main effect of processing mode on *both* RT and CV, such that both were decreased for the nonswitch trials compared with the switch trials. In addition, they found a main effect of task difficulty for RT but not for CV such that easier tasks were faster but not less variable. Segalowitz et al. concluded that the CV effects matched their designation of the switch trials as controlled and the repetition trials as automatic. Thus there is evidence that variability changes can dissociate types of processing. However, while some authors use variability to distinguish controlled from automatic processing, as described, others simply claim that more variability represents more processes (Wascher et al., 2001; Yap & Balota, 2007; Yap, Balota, Cortese, & Watson, 2006; Zhang & Kornblum, 1997).

As previously stated, deficiencies in automatic or controlled processing have been proposed to be related to deficits in a variety of patient populations ((Christensen et al., 2005; Hart, Giovannetti, Montgomery, & Schwartz, 1998; Rumiati et al., 2001). To determine whether automatic or controlled processing is compromised in such populations, it is important to use a

relatively simple and robust RT task that is thought to include trials which differ in the level of automatic and controlled processing required (MacDonald, 2008). Such a task can then be evaluated with a measure that can discriminate between automatic and controlled responses; the CV is a candidate for this measure. Some tasks that are considered to have both automatic and controlled components include Hayling's A and B (Bouquet, Bonnaud, & Gil, 2003; Burgess & Shallice, 1996), flanker tasks (Mattler, 2005) priming tasks, and tasks with spatial compatibility components (e.g., Stroop and Simon tasks, see Lu & Proctor, 1995, for a review). In these tasks, the automatic and controlled processing may result in conflicting response activation which slows response time in noncongruent trials. In general conflict in a task entails competition between a more or less automatically primed response to an irrelevant stimulus dimension and a more controlled, intentional response to a stimulus dimension specified by instructions. Resolving the conflict requires that responses to irrelevant stimulus dimensions are inhibited by a top down, attention demanding process (Burle, van den Wildenberg, & Ridderinkhof, 2005). Band and van Boxtel (1999) reported that this inhibitory control is executed by the prefrontal, resource demanding system (see also Botvinick, Cohen, & Carter, 2004; MacLeod & MacDonald, 2000). In contrast, trials in which the automatic and controlled processing results in activation of the same response are faster, possibly because at least some of these trials escape some of the controlled processes required to resolve conflict (Burle et al., 2005). I have chosen to use the Simon task for this research because it is simple, does not require a linguistic response, the size of the effect increases in aging participants, it is robust in a one-handed format, and

because spatial aspects of motor tasks are often disrupted in apraxia, so an automatic spatial-response compatibility effect seems most appropriate.

Simon Task

The classic Simon task (Simon & Rudell, 1967) is a two-choice RT task in which participants identify the color of a stimulus, e.g., red or green, presented on a computer screen, and respond by pushing a corresponding response key, e.g., right key for red and left key for green (for a review, see Lu & Proctor, 1995). The relevant color stimulus can occur on the monitor to the right or left side of body center. In congruent trials, the stimulus occurs on the same side of the CRT display as the response key and limb designated by the color cue, such that the stimulus, correct response key, and correct response limb are all on the same side of the body. Thus, the relevant and nonrelevant stimulus dimensions both prime the same response. In noncongruent trials, the stimulus appears on the side of the display opposite the response key and limb designated by the relevant color cue, such that the stimulus and correct response are on opposite sides of the body. This results in a conflict between the relevant and irrelevant dimensions. Research shows that participants consistently respond 20-30 msec slower (Lu & Proctor, 1995) and less accurately for noncongruent trials than for congruent trials due to the conflict between dimensions (Lu & Proctor, 1995). This pattern of response has become known as the Simon effect, and is sensitive enough to be observed with as few as 48 trials in a block. It is a robust effect, does not disappear with practice, and occurs in both visual and auditory tasks (Simon, 1990) and with both unimanual and bimanual responses (Cho & Proctor, 2003; Heister, Schroeder-Heister, & Ehrenstein, 1990; Katz, 1981).

Simon contended that people respond automatically first to the directional component of a stimulus as opposed to its meaning (1990). Accordingly, Kornblum and colleagues (Kornblum, Hasbroucq, & Osman, 1990; Kornblum & Lee, 1995; Zhang & Kornblum, 1997) and De Jong and colleagues (De Jong, Liang, & Lauber, 1994) proposed dual route explanations of the Simon effect, each incorporating the automatic spatial priming component, described by Simon, in conjunction with additional controlled processes. For example, De Jong et al.'s model consists of a direct route involving unconditional automatic priming by the irrelevant dimension (stimulus location), and an indirect, conditional route, which processes the relevant dimension (color). Both routes are "automatic" and are activated on all trials: the slower performance for noncongruent trials arises from conflict between the direct route and the indirect route. According to this model, the congruent trials would be comprised of the two automatic processes while noncongruent trials add a conflict resolution process. However, Kornblum et al. (1990) and other more recent characterizations of the dual route hypothesis consider the indirect route to be a controlled process. Thus, in this view, congruent *and* noncongruent trials have both the automatic and controlled activation components, and noncongruent trials add the conflict resolution component. A component of the conflict resolution process, active suppression of the automatic, spatially primed direct route response, may be involved in both congruent and noncongruent trials (Ridderinkhof, 2002). Either way, the dual route hypotheses suggest that the noncongruent trials have an additional controlled component, and thus should require more processing resources.

It is relatively certain that the direct route spatial priming has at least an automatic component. For example, Burle, Possamai, Vidal, Bonnet, and Hasbroucq (Burle, Possamai, Vidal, Bonnet, & Hasbroucq, 2002) use electromyography to show that even in correctly completed incongruent Simon trials, the irrelevant stimulus elicits a degree of activation in the limb which would produce an incorrect response. Interspersing trials of a secondary task between Simon trials has also provided evidence for automaticity of spatial priming (see Caessens et al., 2005, for review). Thus there is debate over the types of automatic versus controlled processes involved in the congruent and noncongruent components of the task (Abrahamse & Van der Lubbe, 2008; Hommel & Milliken, 2007; Musseler, Koch, & Wuhr, 2005); however, relatively few studies have directly tested the contributions of automaticity versus controlled processing in Simon task congruent and noncongruent trials (Musseler et al., 2005).

The purpose of the present study was to determine whether the CV reflects differences in the amount of controlled processing in congruent versus noncongruent trials in a one-handed Simon task, since a one-handed task would be required to test apraxic participants. To achieve this goal, two experiments were conducted. Experiment 1 examined whether there was a difference in CVs between congruent and noncongruent trials as a potential means of detecting qualitative differences in processing. Since variability has been interpreted either as an indicator of the *number* of processes as well as differences between controlled and automatic processes, the second experiment utilized the dual task method to validate qualitative processing differences suggested by the CV results obtained in Experiment 1.

CHAPTER TWO: EXPERIMENT ONE

Experiment 1

The purpose of Experiment 1 was to explore consistency as a measure of the amount of controlled processing in one-handed Simon task congruent versus noncongruent trials in normal participants. If consistency is a sensitive measure of resource demands in the Simon task, and if more resources are required to overcome the incorrect automatic activation of the spatially cued response in noncongruent trials, then CVs should be larger for the noncongruent condition than for the congruent condition.

Method

Participants

Forty-two right-handed undergraduate students from WSU kinesiology classes participated in this experiment in exchange for optional extra credit in a kinesiology course. Participants, by self-report, had no upper limb motor control deficits. They had normal reading visual acuity and color vision, as tested by a standard Snellen chart and online screening test for color vision ("Isahara Color Blind Test,").

Task and Procedure

Participants performed a classic Simon task on a laptop computer. DirectRT software was used to control the experiments and collect data. Participants were seated with body center positioned at screen center, with eyes approximately 60 cm from the screen. Stimuli consisted of 30 mm squares presented 10 cm to the left or right of screen center. Square color was the

relevant stimulus while location was the irrelevant stimulus. Participants were asked to respond, as quickly and accurately as possible, based on the color of the square. Responses were made with an index or middle finger of the right hand, responding with the index finger for a green square and middle finger for a red square and ignoring the stimulus spatial location. Note that when the green square occurred on the left and when the red square occurred on the right, the condition was congruent, as the spatial location of finger matched the location of the square on the screen. In each block of 48 trials congruent and noncongruent trials occurred in random order. Red was chosen as the mapping for the right side finger (middle finger) while green signaled a left response. While this mapping was the same for all participants, it resulted in equal numbers of right and left responses, right versus left stimuli locations, and green versus red stimulus colors for both congruent and noncongruent trials. Further this configuration was easier for participants to learn, using "r" as the mnemonic device, i.e., "red is right", than the reversed (green for right and red for left).[1]

Instructions for each block were presented on the laptop screen and were read aloud to the participant for the first trial block. Participants indicated readiness to begin by pressing either response key. A white X, used as a warning stimulus and means of centering the participant's attention between trials, was presented at center screen for 1000 msec after which a red or green square was presented to the right or left of center yielding an interstimulus interval (ISI) of 1000 msec. The stimulus remained on the screen until a response was made. In the event of an error, participants received an error message stating "red is right and green is left", after which they

pressed the correct key in order to continue with trials. Participants also received a message if they responded slower than 1000 msec ("please try to respond faster") or faster than 150 msec ("please wait for the stimulus"). The white X ready signal was presented immediately after the participant's response to the previous trial. Feedback on average response time and number of errors was given after each block and participants were encouraged to maintain error rates at or below five percent for each block. Each participant completed 12 blocks of 48 trials with a rest period of approximately one minute between blocks.

Results and Discussion

For all analyses, alpha levels were set at .05, and were controlled for familywise error rate in post hoc testing, using the Holm's sequential Bonferroni procedure. Error trials and trials after errors were removed from analysis; however, since variability was a measure of interest, no trials were eliminated because they exceeded an arbitrary cut-off point, either on the fast or the slow end of the distribution. Trials from all blocks were included in analysis, since the Simon effect appears without practice, and does not disappear with even extended practice (Lu & Proctor, 1995; Simon, 1990). A 12 blocks by trial type (congruent versus noncongruent) ANOVA confirmed the lack of block effect or interaction on correct RTs ($p > .10$); there were not enough errors per block to analyze. Two-way within subjects ANOVAs were conducted separately on percent errors and remaining correct RTs. Within subject factors were trial type (congruent versus noncongruent) and trial contingency (trials following congruent trials versus trials following noncongruent trials), and error trials and trials after errors were removed from

RT analysis. Trial contingency was included as a factor since many Simon effect studies have demonstrated that the Simon effect is eliminated after noncongruent trials (Praamstra, Kleine, & Schnitzler, 1999; Stürmer, Leuthold, Soetens, Schröter, & Sommer, 2002; Valle-Inclán, Hackley, & de Labra, 2002).

Overall Simon Effect (RTs and Errors)

Mean correct RTs and percent errors for trial contingency and trial type are presented in Figure 1 (p. 59). For RTs, there was a significant main effect for both trial type [$F(1, 41) = 107$, $p < .001$, partial $\eta^2 = .723$] and trial contingency [$F(1, 41) = 21.4$, $p < .001$, partial $\eta^2 = .343$]. Also, the interaction between trial type and trial contingency was significant [$F(1,41) = 83.3$, $p < .001$, partial $\eta^2 = .670$]. Noncongruent trials were 56 msec slower than congruent trials when they followed congruent trials [$t(41) = -13.17$, $p < .001$, $d = 1.14$], but following noncongruent trials, there was an insignificant noncongruent-congruent difference of 3 msec [$t(41) = .847$, $p = .40$]. Error results were consistent with RT results. Percent error analysis revealed a main effect of trial type [$F(1,41) = 23.34$, $p < .001$, partial $\eta^2 = .363$] and of trial contingency [$F(1,41) = 5.411$, $p = .025$, partial $\eta^2 = .117$]. Also, the interaction between trial type and trial contingency was significant [$F(1,41) = 50.68$, $p < .001$, partial $\eta^2 = .553$]. For trials following congruent trials, percent error was significantly less for congruent (1.36%) versus noncongruent (4.53%) trials [$t(41) = -7.17$, $p < .001$, $d = 1.42$]. However, following noncongruent trials, percent error was not significantly different between congruent (2.67%) and noncongruent trials (2.09%), [$t(41) = 1.98$, $p > .05$]. Thus, statistical analysis confirmed a Simon effect consistent with

previous research: RT and errors were larger for noncongruent trials than for congruent trials, but only for trials following congruent trials.

Consistency in the Simon Task

Having demonstrated a typical Simon effect, consistency of congruent versus noncongruent trials was evaluated. CVs were calculated by dividing the standard deviations of correct RTs for each condition for each participant by its corresponding mean. A two-way within subjects ANOVA was conducted on CVs, with trial type (congruent versus noncongruent) and trial contingency (trials following congruent trials versus trials following noncongruent trials) as factors. Figure 2 (p. 60) shows CVs for correct trials by trial type and trial contingency. There were no significant effects: trial type [$F(1, 41) = 3.18$, $p = .082$]; trial contingency [$F(1, 41) = 1.94$, $p = .171$]; interaction between trial type and trial contingency [$F(1,41) = .907$, $p = .347$]. Thus noncongruent trials were not more variable than congruent trials, even when considering trial contingencies. In fact, the trend toward main effect of trial type is in the reverse of the predicted direction: congruent trials (CV = 0.2347) tended toward being *more* variable than noncongruent trials (CV = 0.2164).

However, statistical differences between means, standard deviations or CVs of entire congruent and noncongruent RT distributions may not reflect the qualitative differences in processing between these trial types, whereas distributional analysis may be more useful. De Jong et al. and others (Burle et al., 2002; Burle et al., 2005; De Jong et al., 1994; Ridderinkhof, 2002; Wascher et al., 2001) showed that, in the Simon task, congruent trial RTs may be distributed over a wider range than noncongruent trials (see Zhang & Kornblum, 1998, who

attest that this is not true for all studies). If this is true for a set of data, the congruent trial distribution will have larger variability than the noncongruent distribution simply by virtue of the statistical properties of distributions, even though mean RT is smaller for the congruent trials. In the present experiment, for trials after congruent trials, the range for congruent trial RTs (775 msec) was larger than the range for noncongruent trials (687 msec), consistent with other research. While this was not a significant difference (t = 1.25, p = .219, d = .25), the lack of power due to large between-participant variability is likely the cause of failure to reach significance. Some researchers (e.g., Wascher et al., 2001) view increased range and correspondingly increased variability for the congruent trials as evidence that more processes are involved in these trials. Additionally, congruent distributions are generally more positively skewed than noncongruent distributions: the Simon effect is usually strongest at the faster end of the RT distributions (Burle et al., 2002; Burle et al., 2005; De Jong et al., 1994). Heathcote, Popiel, and Mewhort (1991) used the ex-Gaussian three parameter distributional analysis model to distinguish conflict from nonconflict trials in the Stroop task, claiming that the more positively skewed distributions for the conflict trials signaled additional processing in these trials. Thus, distributional differences may indicate changes in numbers of processes involved, or as previously discussed, may distinguish controlled from automatic processing (N. Segalowitz et al., 1999; N. Segalowitz & Segalowitz, 1993; N. Segalowitz, Segalowitz et al., 1998).

Vincentizing procedures, which divide distributions into quantiles, can elucidate differences between congruent and noncongruent trials at specific points in the distribution, in addition to distributional skew. For example, Ridderinkhof et al. (2002; 2005; 2004) used

distributional analysis to support an activation-suppression hypothesis: since suppression of the direct, automatic spatial priming builds up over time, the difference between congruent and noncongruent trials will be smaller at the slower end of the distributions. Also, when comparing congruent and noncongruent trial RTs, analysis by bin allows comparisons between fast congruent and fast noncongruent trials (Yap & Balota, 2007; Yap et al., 2006). Burle et al. (2002) claim that fast correct congruent responses may escape controlled processing, as opposed to slower correct congruent responses. Thus it is possible the distribution of congruent RTs may represent some fast, mostly automatic trials, while the slower trials may utilize controlled processing. This mix of trials may produce the observed variability.

The previous examples of distributional analysis compared RTs of corresponding bins in order to evaluate differences between congruent and noncongruent trials. However, the CV of each bin may provide additional information. Since there was a trend for congruent trials to be more variable than noncongruent trials, distributional analysis may indicate why this trend was nonsignificant. In addition, a comparison of the CVs for corresponding bins of congruent and noncongruent trials may highlight differences in skew between the distributions. For example, if the congruent distribution is more positively skewed than the noncongruent distribution, the fastest bin of the congruent distribution will have smaller CVs than the fastest bin of the noncongruent distribution. Thus both mean RTs and CVs were compared for congruent versus noncongruent trials at the different quantiles of the RT distributions.

Distributional Analysis (RTs and CVs)

Because the Simon effect was only observed for trials following congruent trials, only these correct trial RT distributions were analyzed. In order to evaluate differences between correct congruent and noncongruent RTs at different quantiles of the RT distributions, correct RTs for each participant were numerically ordered and 20% cutoff points calculated to create five bins. Within each bin, for each participant, mean correct RTs and CVs were calculated. Because of the extreme variability of the fifth bin across all conditions and participants, and because the largest effects were more likely for the faster RTs bins, the slowest fifth bin was removed from analysis (Wascher et al., 2001). A two way repeated measures ANOVA was conducted to separately evaluate mean correct RTs and CVs. Within subject factors included trial type (congruent versus noncongruent) and bin (1 through 4).

RTs. Figure 3 (p. 61) illustrates correct RT results for congruent and noncongruent trial types following congruent trials at each of the four RT bins. The ANOVA revealed a significant trial type main effect [$F(1, 41) = 435.7$, $p < .001$, partial $\eta^2 = .914$] and a significant bin main effect [$F(3,39) = 369.5$, $p < .001$, partial $\eta^2 = .966$]. The interaction between trial type and bin was also significant [$F(3, 39) = 13.3$, $p < .001$, partial $\eta^2 = .506$]. To evaluate the interaction, differences between congruent and noncongruent trials were calculated for each bin separately. Post hoc comparisons indicated that the difference between congruent and noncongruent trials at bin 1 (57 msec) was significantly smaller than the bin 2 difference [65 msec, $t(41) = -3.89$, $p < .001$], but the bin 1 difference was not significantly different from the bin 3 (65 msec) and bin 4 (43 msec) differences (p values >.05). Also, the difference between bin 2 congruent and

noncongruent RTs was similar to bin 3 (65 msec) and 4 (43 msec) differences (p values >.05). Finally, the difference between congruent and noncongruent RTs in bin 3 (65 msec) was larger than the bin 4 difference (43 msec) [$t(41) = 3.02$, $p = .004$]. Thus, while previous research has shown generally a larger difference between congruent and noncongruent trials at the fastest end of the distribution, this was not found. RT results provided the foundation for the analysis of variability within each bin.

CVs CVs were calculated, as previously described, for each of the bins for each participant and condition, and entered into a two trial types by four bins repeated measures ANOVA. Figure 4 (p. 62) illustrates the changes in congruent and noncongruent CVs across four bins.

The trial type main effect [$F(1, 41) = 4.56$, $p = .039$, partial $\eta^2 = .100$], bin main effect [$F(1,41) = 305.7$, $p < .001$, partial $\eta^2 = .96$] and interaction [$F(3, 39) = 10.32$, $p < .001$, partial $\eta^2 = .443$] were all significant. Post hoc testing for simple main effects revealed that in bin 1, noncongruent trials had larger CVs (.0586) than congruent trials [.0519; $t(41) = -2.91$, $p = .006$]. However, in bins 2, 3 and 4, congruent trials had larger CVs than noncongruent trials. In bin 2 congruent trials CV averaged .0227 and noncongruent trials CV averaged .0201 [$t(41) = 2.384$, $p = .022$]. Bin 3 congruent trials' CV was .023 and noncongruent trials' CV was .0181 [$t(41) = 4.62$, $p < .001$] and in bin 4 congruent trials' CV was .0314 and noncongruent trials' CV was .024 [$t(42) = 4.61$, $p < .001$].[2] The interaction explains the non-significance of the overall trial type effect for CVs discussed previously (congruent trials were slightly more variable than

noncongruent trials): throughout most of the distribution the bin CVs were larger for congruent trials than for noncongruent trials, with the exception of bin 1 which showed larger CVs for noncongruent versus congruent trials.

Thus, the distributional CV analysis showed that for most of the bins, CVs were larger for congruent trials than for noncongruent trials. This finding provides two important pieces of information. First, although the overall mean CV for congruent trials was not significantly larger than for the noncongruent trials, *most* of the congruent distribution is in fact more variable than the noncongruent trials, confirming the trend in overall CV main effect. Second, the result indicates a more positive skew for the congruent trials than for the noncongruent trials. Greater skew combined with the larger range and overall larger variability for the congruent distribution support the possibility that the congruent trials actually require more controlled processing than the noncongruent trials. This result was unexpected given that congruent trials are performed faster than noncongruent trials, since controlled processing is thought to require more time. Also, as previously mentioned, research on Stroop conflict trials suggests that the noncongruent Stroop RT distributions are actually skewed more than the congruent Stroop RT distributions, and thus the noncongruent trials require more controlled processing. This result is in direct conflict with our findings that CVs are higher and more skewed for the congruent trial distribution. One possible explanation is that the overall trend for congruent trials to be more variable than noncongruent trials is the result of trial contingency effects. As shown in Figure 1, congruent trial performance after noncongruent trials is 38 msec slower than after congruent trials. By contrast, noncongruent trial performance decreases by 18 msec after noncongruent

trials when compared with performance after congruent trials. This difference in trial contingency effect is significant ($t(41) = 10.2$, $p < .001$, $d = .96$) and may result in the increased variability observed for congruent trials. However, the CV distributional analysis was performed only on trials after congruent trials, and the variability effect was stronger than in the combined analysis. According to Segalowitz et al., this finding suggests that more controlled processing is involved in the *congruent* trials. For the Simon task, therefore, it may be that the congruent trials are performed faster *because* of the larger amount of controlled processing resources invested in their performance, that simply more processes are involved in congruent trial performance than in noncongruent trial performance, or that there are a mix of trials in the congruent distribution. For example, fast congruent trials may be more automatic, while slower congruent trials may involve the addition of one or more controlled processes to the automatic spatial priming process. Experiment 2 used dual task methodology to determine whether congruent trials actually require more resources than noncongruent trials and therefore that all or some of these trials may require more controlled processing than noncongruent trials. If this is the case, it will validate the use of the CV measure to compare the amount of controlled versus automatic processing in two or more tasks.

CHAPTER THREE: EXPERIMENT TWO

Experiment 2 utilized a dual task methodology to compare the resource demands of congruent and noncongruent Simon task trials: Simon task performance alone was compared with Simon task performance combined with a continuous counting task. Experiment 1 results showed that congruent Simon trials, except for the fastest ones, are *more* variable than noncongruent trials. This suggests, according to Segalowitz et al., that congruent trials require *more* controlled processing than noncongruent trials. If this is true, adding a resource demanding secondary task should result in a larger increase in Simon task RTs and percent error for the congruent trials than for the noncongruent trials.

Method

Participants

Sixty right-handed undergraduate students from the WSU kinesiology classes participated in this experiment in exchange for optional course points; none had participated in Experiment 1. Participants were screened as in Experiment 1. One participant was dropped from the study because he did not complete the seventh block of dual task trials and a second because of an extremely high error rate.

Task and Procedure

Simon Task. The Simon task used in Experiment 2 was the same as described in Experiment 1. Also, the blocks of 48 trials were configured in the same way as in Experiment 1.

Secondary task: Backwards counting. In this experiment, backwards counting (Peterson, Peterson, & Miller, 1961) was performed with along with the Simon task[3]. Counting back by ones at a self-determined rate resulted in a combined task with a moderate (200-300 msec) increase in RT, while errors and variability also increased. Analysis of counting performance showed that counting rate for different participants ranged from an average of 51 to 178 numbers counted per Simon task block. Blocks ranged from two to five minutes in duration; thus, counting rate averaged approximately one number per two seconds. Although the counting rate range was quite large there was no evidence that faster versus slower counters were putting more or less effort into the tasks. [4]

Procedure: All participants completed the Simon task alone first, then the Simon task with the counting task. This order was necessary because of the difficulty that pilot participants had combining the Simon task with other tasks; participants needed to first learn the Simon task before adding a second task. Thus, all participants first completed seven blocks of 48 Simon trials, as described in Experiment 1. Next, participants established a preferred backwards counting rate, which they were encouraged to maintain throughout the dual task blocks. The arithmetic difference between the first and last number spoken for each trial block was recorded as the counting score, and served to confirm that the same counting rate was maintained for all dual task blocks (no block effect, $p > .05$). Participants completed seven blocks of the Simon task concurrently with the counting task. As participants started each block of 48 Simon trials,

they began counting backwards from a randomly generated three digit number between 300 and 1000. All participants were encouraged to focus on the counting task as the primary task, and to maintain the steady counting rate throughout each block.

Results and Discussion

Because Experiment 1 confirmed that the Simon effect occurred only after congruent trials, the trials following noncongruent trials were eliminated from data analysis. For all analyses, alpha levels were set at .05, and were controlled for familywise error rate in post hoc testing, using the Holm's sequential Bonferroni procedure. Data were treated as in Experiment 1.

Initial Analysis of Simon Effect (RTs and Errors)

To determine whether drawing resources from the Simon task affects congruent versus noncongruent trials differently, RTs and percent errors were compared for congruent versus noncongruent trials in single versus dual tasks. Results are shown in Figure 5 (p. 63). Two-way repeated measures ANOVAs for RTs and errors included task condition (single versus dual) and trial type (congruent versus noncongruent) factors. For correct RTs, the main effects of task condition [$F(1,57) = 142.7$, $p < .001$, partial $\eta^2 = .711$] and trial type [$F(1,57) = 129.7$, $p < .001$, partial $\eta^2 = .691$] were significant. RTs were slower overall for noncongruent versus congruent trials, and the addition of the secondary task increased RTs for both congruent and noncongruent

trials. Moreover, the interaction between task condition and trial type was also significant [$F(1,57) = 6.91$, p = .011, partial $\eta^2 = .711$].

As is shown in Figure 5, addition of the resource demanding counting task increased RTs for both congruent trials and noncongruent trials, but the effect on congruent trials (254 msec) was *greater* than the effect on noncongruent trials [228 msec; $t(58) = 2.63$, $p = .011$]. Thus, drawing resources from the Simon task was overall *more* detrimental for congruent than for noncongruent trials. This result is consistent with results from Experiment 1's CV distributional analysis, suggesting that congruent trials may actually require more controlled processing than noncongruent trials.

Error results were consistent with RT interpretations. The lower panel of Figure 5 depicts the error data, showing errors for congruent and noncongruent trials in both single and dual task conditions. Although the task condition main effect was not significant [$F(57 = .733$, $p = .395$], there was a significant trial type main effect [$F(57) = 80.73$, $p < .001$, partial $\eta^2 = .578$] and the task condition by trial type interaction [$F(57) = 5.41$, $p = .023$, partial $\eta^2 = .084$]. Overall more errors were committed for noncongruent trials than for congruent trials. Furthermore, post hoc testing of the interaction indicated that for congruent trials, percent error in the single task condition was 1.17 and increased to 2.36 in the dual task condition [$t(57) = -2.15$, $p = .016$]. However, the addition of the secondary task had no effect on error for the noncongruent trials [single noncongruent percent error was 8.33 while dual noncongruent percent error was 7.92; $t(57) = .646$, $p = .521$].

Distributional Analysis

Evidence that noncongruent RTs increased significantly less than congruent RTs in the dual task condition strengthens the inference that the noncongruent trials were in fact *less* affected than congruent trials by combination with a resource demanding secondary task. To determine whether these effects are consistent throughout the RT distributions, the congruent and noncongruent RT distributions were Vincentized as in Experiment 1, for single and dual tasks separately, and mean RTs and CVs for each bin were compared.

Figure 6 (p. 64) illustrates the RT distributional analysis, showing congruent and noncongruent means for four bins in the single task and dual task conditions. A three way repeated measures ANOVA (two task conditions by two trial types by four bins) evaluated the relationships between factors for RTs and CVs. All main effects and interactions were significant (see Table 1). An inspection of Figure 6 shows that the increase in correct congruent RTs in the dual task relative to the single task condition was greater than that found for the noncongruent trials in all but the first RT bin [bin 2, 33 msec greater: $t = 5.51$, $p < .001$; bin 3, 59 msec greater: $t = 4.77$, $p < .001$; bin 4, 55 msec greater: $t = 4.29$, $p < .001$]. In the first bin there was no significant difference between the effects of the dual task on congruent versus noncongruent trials [10 msec difference: $t\ (58) = 1.76$, $p = .08$]. The bin 1 RT trend, although not significant, is consistent with the pattern above for RT bins 2 through 4. Thus, within Experiment 2, results of the RT distributional analysis are consistent with overall RT results, suggesting that congruent trials are actually more resource demanding than the noncongruent. Further, these results are consistent with Experiment 1 CV analysis in which the overall CV was

larger for congruent trials throughout most of the distribution and positive skew was greater than for noncongruent trials. It appears that, overall, congruent trials require more processing resources than noncongruent trials and thus involve more controlled processing.

CVs. CVs were calculated as for Experiment 1 and were entered into a three way repeated measures ANOVA with task condition (single and dual), trial type (congruent and noncongruent) and bin (one through four) factors. Figure 7 (p. 65) shows CVs for congruent and noncongruent trials in the single and dual task conditions for four bins, and Table 2 shows results for CV bin analysis. The task condition and bin main effects were significant but the trial type main effect was nonsignificant. The two way interaction between condition and bin and the interaction between condition and type were significant However, the interaction between trial type and bin was not significant, nor was the three way interaction.

Paired comparisons clarified these interactions. Replicating Experiment 1 results, for the single task, at bin 1, congruent CVs (.0578) were smaller than noncongruent CVs [.07; $t(58) = -2.446$]. At the second, third, and fourth bin this reversed so that noncongruent CVs were smaller. In bin 2 noncongruent CVs averaged .0217 while congruent CVs averaged .0255 [$t(58) = 3.05$, $p = .005$]. Similarly, in bin 3 noncongruent trials' CVs (.0201) were less than congruent [.2373; $t(58) = 2.91$, $p = .0050$] and in bin 4 noncongruent CV was .0296 while congruent CV was .034 [$t(58) = 2.03$, $p = .047$]. In the dual task condition, noncongruent CVs were always less than congruent CVs. The respective differences for bins 1 through 4 were: 0 .0067; 0.0115; 0.0077; 0.0040 (all p values < .001).

Overall the results of Experiment 2 were in agreement with the results of Experiment 1. The CV analysis in Experiment 1 revealed greater variability and larger positive skew for congruent trials, suggesting that these trials utilize more resources and therefore more controlled processing than noncongruent trials. The dual task manipulation confirmed that congruent trials require more processing resources than noncongruent trials. Interestingly, the addition of the resource demanding counting task reversed the consistency difference between congruent and noncongruent trials at the fastest RT bin: in the dual task condition *all* congruent trial bins had larger CVs than their corresponding noncongruent trial bins. This result confirms that congruent trials are overall more variable than noncongruent trials but also that there was a change in distributional skew: in the dual task condition, the congruent distribution was no longer more positively skewed than the noncongruent bin. If positive skew indicates more controlled processing, it appears that in the dual task condition skew no longer differentiates the congruent and noncongruent trials in terms of their respective processing types. It is likely that the dual task condition imposed an additional controlled process which had its strongest effect on variability in the fastest congruent trial bin.

It should be noted that the experimental procedure used for the dual task in Experiment 2 may have some limitations. It was impossible to tell, for example, what kind of decrement occurred in the counting task when combined with the Simon task. Counting backwards by ones is an easy task when done on its own, and any measurement of this task alone would likely have been subject to a ceiling effect. It was clear from observing the participants that the counting task degraded in the dual task condition, although conditions did not allow measurement of

counting timing characteristics, such as pausing to allow a Simon task response. However, participants were able to maintain consistent performance on the counting task across blocks, indicating that they were conscious of the necessity to maintain some consistency in the counting performance.

CHAPTER FOUR: GENERAL DISCUSSION

Two experiments were conducted to explore whether the coefficient of variation (CV) can identify qualitative processing differences in congruent versus noncongruent Simon task trials. Experiment 1 showed the expected Simon effect of an RT advantage for congruent trials compared with noncongruent trials. More importantly, distributional analysis revealed that variability as measured by CV was larger for congruent trials than for noncongruent trials for all but the fastest RT bin, in opposition to the predicted direction of effect. In accordance with Segalowitz et al. (Poulsen & Segalowitz, 2000; N. Segalowitz et al., 1999; N. Segalowitz, Segalowitz et al., 1998), larger CVs for congruent trials indicate that these trials involve more controlled processing than noncongruent trials. Distributional CV analysis revealed that the congruent trial RT distribution was more positively skewed than the noncongruent distribution, further evidence that more controlled processing is required for congruent trials. Results from Experiment 2 validated this interpretation. In a dual task condition, congruent trials were affected more by the addition of a secondary task than were noncongruent trials, compared with a single task condition: RTs were increased more across the entire congruent distribution than in the noncongruent distribution, although the difference between the increases for congruent and noncongruent trials was not significant in the first bin. The CV results indicated that in the dual task condition, *all* congruent bins were more variable than their corresponding noncongruent bins. Overall, both CV analysis and dual task results identified the congruent trials as requiring more controlled processing than the noncongruent trials. These results indicate that CV analysis

in a simple task like the Simon task identified differences in the degree of controlled processing between the two trial types.

While the results of the distributional analyses in the two experiments are consistent in suggesting that congruent trials require more controlled processing than noncongruent trials, Experiment 1's overall CV main effect was nonsignificant. The CV differences between congruent and noncongruent trials were evident only in the distributional analysis; thus the analysis of CVs must go beyond simple analysis of central tendency in order to be meaningful. A variety of distributional analyses exist, some more complex than others. The Vincentizing procedure used in these experiments is a method in which RT means for corresponding bins are compared between conditions to determine differences between distributions which may be masked by measures of central tendency. In the present research, the Vincentizing procedure provided indication of RT differences between corresponding bins, and in addition, CVs were calculated and compared for all bins. When bin RTs are combined with a measure of variability for each bin, an estimation of the distribution's skew results. For example, at the fast end of the positively skewed distribution, where the slope of the distribution is steep, the variability of a bin will be small, compared with the center or more spread out slower tail of the distribution.

Ex-Gaussian analysis is another statistical method which provides information about distributional skew, but involves more complex statistical analysis and special software. Heathcote, Popiel, and Mewhort (1991) piloted the use of ex-Gaussian analysis for Stroop task RT distributions. Normally distributions are described by two parameters, the mean and variance. The ex-Gaussian method uses a third parameter which identifies the degree of positive

skew in the distribution. Thus, computing the variability of each bin during a Vincentizing procedure will produce roughly the same information as ex-Gaussian analysis but can be completed without the necessity for specialized software or training (see also Rouder & Speckman, 2004, for a description and analysis of using Vincentizing procedures with parameter estimation). A computationally simple and easily understood method for evaluating skew is useful since skew differences are critical when evaluating qualitative processing between conditions (Heathcote et al., 1991; Zhang & Kornblum, 1997).

In the present experiments, the distributional CV analysis indicated more variability and a greater skew for congruent than for noncongruent trials in single task conditions; this result, combined with the dual task finding that congruent trials require more processing resources, can be taken as evidence that comparing the skew of distributions does in fact provide information about qualitative processing differences. It is generally accepted that the Simon task trials represent a heterogeneous mixture of processing requirements rather than a clear automatic-controlled distinction between congruent and noncongruent trials. The larger variability and skew for correct congruent trials indicates that these trials may involve a more complex mix of processes than noncongruent trials. Automatic processes may be primary for some congruent trials and controlled processes may be primary for other congruent trials. For example, distributional CV analysis in Experiment 1 suggested that only the fast correct congruent trials may benefit primarily from the automatic spatial priming process (congruent CVs were significantly less than noncongruent CVs for this bin only; in all other bins the result was reversed). This interpretation is in accord with Burle et al.'s claim that fast congruent trials

escape controlled processing (Burle et al., 2002), and Ridderinkhof et al.'s suggestion that controlled suppression takes longer to develop and thus will not affect correct fast congruent trials (Ridderinkhof, 2002; Ridderinkhof et al., 2005). An analysis of congruent and noncongruent error trials in the present experiments supports these contentions. Automatic spatial priming will result in fast correct responses for congruent trials but in fast errors in noncongruent trials. Thus, noncongruent error trials should be faster than congruent error trials. Experiment 1 had low error rates; however, for the 24 out of 40 participants who had error values in each cell, a two-way repeated measures ANOVA was conducted on error RTs, with trial type and trial contingency as factors. The trial type main effect was the only significant effect: noncongruent error RTs (496 msec) were faster than congruent error RTs (595 msec) [$F(1,23) = 21.06$, $p < .001$]. Noncongruent error RTs were 42 msec faster than correct congruent trials overall, and 25 msec faster than the congruent trials that occur after congruent trials.[5]

Experiment 1's distributional analysis showed that the fast congruent bin had less variability than slower congruent and all noncongruent bins, and the previous discussion relates this finding to the possibility that fast correct congruent trials are primarily automatic in nature. The increased variability of the slower congruent bins and all of the noncongruent bins suggests, in contrast, that these slower trials involve controlled processes in addition to the direct spatial priming. This conclusion is compatible with Ridderinkhof's activation-suppression hypothesis (Ridderinkhof, 2002). In his model, direct route activation from automatic spatial priming is thought to start immediately on stimulus presentation, as per Jong et al. (1994), and then decay

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gradually, while indirect route activation related to the relevant stimulus characteristic starts somewhat later, as does controlled suppression of the direct route activation. When the suppression process is strong it may enter into the task earlier than when it is weaker; the strength of suppression can be varied by changing task parameters such as the probability of a congruent response, or by interference from a secondary task as in Experiment 2. It should also be noted that suppression is expected to be stronger for noncongruent trials more than congruent trials (Ridderinkhof, 2002). Specific predictions can be made based on the activation-suppression hypothesis, for both RTs and errors under strong and weak suppression. For noncongruent trials, with strong suppression to prevent the direct route spatial priming from creating an overt response, differences between congruent and noncongruent trial RTs will decrease from the fast to the slow end of the distributions, while in weak suppression (dual task) the differences will increase. Also, for strong suppression, there should be fewer fast errors than when suppression is weakened. At the slower end of the distribution there should be a smaller difference between numbers of errors in single and dual task conditions than the fast end of the distribution. The Experiment 2 data are in agreement with Ridderinkhof's activation-suppression model (see Appendix B) and also with the connection of increased variability and increased processes in correct congruent Simon task performance.

The results of the present experiments are consistent with other Simon effect research describing a mix of automatic and controlled processing in Simon trials which potentially result in increased correct congruent variability. However, the finding in dual task conditions that even the fast congruent trials require more controlled processing than noncongruent trials, as

confirmed by dual task results, was not expected based on many descriptions of behavior in the Simon task. First, as described in the introduction, automatic processing is considered to be faster than controlled processing; correct congruent trials are performed faster than correct noncongruent trials. Brain activation studies of conflict tasks indicate increases in anterior cingulate and prefrontal cortex activity during conflict trials (e.g., noncongruent trials) compared with nonconflict trials. Activation is reduced after congruent trials and increased after noncongruent (conflict) trials, and this activation difference is considered to be the basis for the reduction or disappearance of the Simon effect after noncongruent trials (Kerns, 2006). The distributional CV analyses in Experiment 1 and 2 included only trials after *congruent* trials, so the influence of these controlled processing brain areas should be minimized. Despite this manipulation, both variability measures and dual task procedures implicate more controlled processing in the congruent trials. Why do even the fastest congruent trials appear to require more controlled processing than fast noncongruent trials?

One possibility for this is that participants put more effort into congruent trial performance. Increased effort would result in more fast correct trials and thus a more positive skew. It is also possible that, while fast correct congruent trials are performed more automatically in the single task condition, in a dual task condition a controlled process is added which increases the variability of the fast congruent trials. Another explanation could be that the verbal responses in the dual task conditions may delay the Simon task responses enough that the direct route automatic spatial priming decays, usually after only several hundred msec (De Jong et al., 1994; Roswarski & Proctor, 1996; Simon, Acosta, Mewaldt, & Spiedel, 1976; Zhang

& Johnson, 2004). In Experiment 2, with the addition of the secondary task congruent trial mean RT increased almost 300 msec, supporting the possibility that decay of the spatial priming may affect performance within a single trial.

Another possibility is that additional controlled processing operating in congruent trials actually speeds performance. Wascher et al. (Wascher et al., 2001; Wiegand & Wascher, 2005). compared anatomically mapped Simon tasks with crossed-hands Simon tasks, and proposed that there are two spatial activation processes in the Simon task. One is based on anatomical correspondence with the stimulus orientation (visuomotor facilitation) and results in activation of the spatially corresponding response effector. This process occurs only with anatomical positioning (does not occur in the crossed hands condition) and only in the visual Simon effect, implicating the dorsal stream and visually linked grasping system as the source. The second process is a more cognitive spatial correspondence effect, based on the more natural tendency to respond with right limb to stimuli on the right. The authors claim that in the congruent trials the added visuomotor activation process, while increasing the variability of the congruent distribution, does not add time to the congruent task but rather speeds it (apparently the anatomical activation process is not allowed to unfold in noncongruent trials). Wascher et al. suggest that activation of succeeding stages such as response programming may result from this visuospatial priming, which accelerates processing in those stages and facilitates the congruent trial response. The present experiments utilized a body-centered, one-handed Simon task, so the parallel with Wascher et al. is not direct. However, Experiment 1 showed the typical larger Simon effect for stimuli on the right side compared with the effect when stimuli were on the left

side (see Appendix 1). Thus a visuomotor activation effect that is not necessarily restricted to the body's hemispace may contribute to the congruent trial variability in the present experiments.

Another possible facilitating process in the correct congruent trials is repetition effects as a result of trial to trial similarities between stimuli and/or responses. Recall that the Simon effect occurred only after congruent trials. When congruent trials followed congruent trials, for half of these pairings the stimulus for the second congruent trial was the same color and in the same location as the stimulus for the first trial and required the same side response. In the other half of congruent trials the second stimulus did not share any characteristics with the first stimulus and required the opposite side response. By contrast, for all noncongruent stimuli following congruent stimuli, either the stimulus was a different color *or* in a different position. In these noncongruent trials, depending on the stimulus characteristic configuration, the second required response was either the same or opposite from that required by the first trial. Previous research has shown that both complete *alternations* as well as complete *repetitions* benefit response times (see Wuhr & Ansorge, 2005, for a discussion of arguments relating to trial contingencies in the Simon effect). It is possible that the process underlying these repetition effects could be resource demanding, and yet facilitate congruent trials. However, the trial to trial modulations cannot explain increased congruent trial variability, since both types of repetition effects for congruent trial-congruent trial pairings are facilitatory. Based on Wascher et al. and Wurh and Ansorge's research, adding a control process may not always be time consuming, and may actually reduce response time if the process can prime, bias, or partially activate the correct response.

Ridderinkhof et al.'s delta plot analyses, Wascher et al.'s proposal of a controlled process which speeds performance, and the anterior cingulate research shed light on possible responses of patient populations in the Simon task, but also demonstrate the complexity of analysis required to understand the contributions of various processes to Simon task performance. Patients with controlled processing difficulty may have reduced controlled suppression, as occurred with the addition of the secondary task in Experiment 2. They may also have slower congruent trial responses combined with *less* variability of the congruent distribution, if Wascher et al. are correct in their hypothesis of a facilitating controlled process. If the contribution of the anterior cingulate is compromised in these patients, they should have more errors and slower RTs in noncongruent trials, but also perhaps slower congruent RTs if MacLeod and MacDonald are correct that congruent trials are faster because of more anterior cingulate activity. In any event, analysis must go beyond simple measures of central tendency and variability to elucidate controlled and automatic processing contributions to Simon task congruent and noncongruent trials.

In conclusion, the coefficient of variation detected a processing difference between congruent and noncongruent trials that was verified by dual task methodology. The increased variability of congruent trial distributions, and the larger increase in RT for congruent trials compared with noncongruent trials when adding a secondary task, suggests that the congruent trials *overall* are more effortful and/or require a greater number of processes than noncongruent trials. However, the difference between congruent and noncongruent trials is not simply that one

is more automatic than the other. Only the fastest congruent trials, which could be elicited by direct spatial priming due to correspondence between stimulus and response location may be primarily automatic in nature. Thus, for the Simon task, increased CVs appear to signal that the correct congruent trials may have a more complex mix of automatic and controlled processes than the noncongruent trials. Distributional analysis is required in order to separate the more automatic faster congruent trials from the noncongruent and slower congruent trials. Despite the complex analysis, Simon task performance is relatively simple for participants, and the CV analysis yields identifiable differences in processing between congruent and noncongruent trials. Therefore, the use of CV analysis combined with the Simon task is potentially a useful tool to explore controlled versus automatic processing.

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Appendix A
Side of Stimulus and Side of Response Effects

Experiment 1

Figure A1 (p. 66) shows RTs for congruent and noncongruent trial types when stimuli appear on the right versus left of the screen. When the stimulus is on the right and the trial is congruent, the response side is also on the right. Left sided stimulus values can be interpreted in the same way; thus these results can be interpreted both for stimulus side and response side. A trial type by stimulus side repeated measures ANOVA indicated a main effect of trial type [$F(1, 41) = 111.14$, $p < .001$, partial $\eta^2 = .726$] and a significant trial type by stimulus side interaction [$F(1, 41) = 11.09$, $p = .001$, partial $\eta^2 = .221$]. Post hoc testing indicated that the Simon effect was larger for right sided stimuli (36 msec advantage for congruent trials) than for left (16 msec advantage for congruent trials, $t(41) = 3.45$, $p = .001$, $d = .79$). Although there was a difference in Simon effect size, effects for right and left stimuli were strong and in the same direction.

Experiment 2

Figure A2 (p. 67) shows correct RT results for stimulus and response sides for both trial types in single and dual task conditions. Again, data for stimulus side can be reinterpreted for response side; hence only stimulus side data was analyzed. Repeated measures ANOVA indicated a significant trial type main effect such that congruent trials were faster [$F(1, 57) = 153.58$, $p < .001$, partial $\eta^2 = .722$]. There was also a significant task condition main effect: single task was faster [$F(1, 57) = 163.7$, $p < .001$, partial $\eta^2 = .735$], and a significant trial type by task condition interaction [$F(1, 57) = 19.17$, $p = .001$, partial $\eta^2 = .245$]. . The important

information for the purposes of this analysis is that there was no significant effect of stimulus side, nor any interaction involving stimulus side (*p* values > .10).

Appendix B

Delta Plot From Experiment 1

Figure B1 (p. 68) depicts delta plots comparing congruent and noncongruent RTs and percent errors for four RT bins.

Footnotes

[1] Tagliabue et al. (2007) suggest that response and stimulus side should be considered as separate factors in Simon task experiments, since a typical finding is that for stimuli and responses on the right side, the Simon effect is greater than on the left side, and the left side effect may even be reversed. However, they argued that where the Simon effect is in the same direction, and significant, for both right and left sides, data may be collapsed over side. This was true for both Experiment 1 and 2. In Experiment 1, while there was an interaction of response side and trial type (congruent versus noncongruent), the Simon effect was strong and in the same direction for both right and left responses. In Experiment 2 there was no interaction of stimulus side or response side with trial type or condition (single or dual task). Using right hand only and one color-response mapping simplified a potentially complex design necessitated by distributional analysis. See Appendix A for analysis of mapping effect results. The critical factors (trial type and trial contingency) are mapped equally to right and left finger responses (Wascher et al., 2001)

[2] It should be noted that the U-shape of the CV quantile plots is to be expected for RT distributions: the range of RT values included in the fastest and slowest bins will be larger than the range in the center of the distribution, because of the generally normal (although skewed) shape of the distribution.

[3] Experiment 2 was first attempted using random number generation in time with a metronome as the secondary task. Participants found this combination difficult and it resulted in an increase in Simon task RTs of over 2000 msec, with individual trial RTs ranging up to 4000 msec. Counting tasks were chosen next (Peterson et al., 1961). Pilot work using this task started with counting back by threes, which was also shown to be too difficult when combined with the Simon task: pilot participants' RTs increased by more than 800 msec from single to dual task, and errors and variability increased dramatically. Further, any counting task with a metronome was determined to be too difficult for participants.

[4] There was a significant *negative* correlation between counting score and RT for dual task noncongruent trials (r = -.452, p = .02, N = 58) while a negative correlation was marginally significant for dual task congruent trials and CS (r = -.35 p = .08, N = 58). It appears that faster counters were also faster at responding to Simon task trials. Similarly, CS's were significantly negatively correlated with the difference between single and dual congruent mean RTs (r = -.397, p = .045, N = 58) and with the difference between single and dual noncongruent RTs (r = -.479, p = .013, N = 58). The effects of the dual task were thus *reduced* for the faster counting participants compared with the slower counting participants.

[5] Because of the difference in numbers of trials between correct responses and error responses, statistical analysis is inappropriate.

Table 1

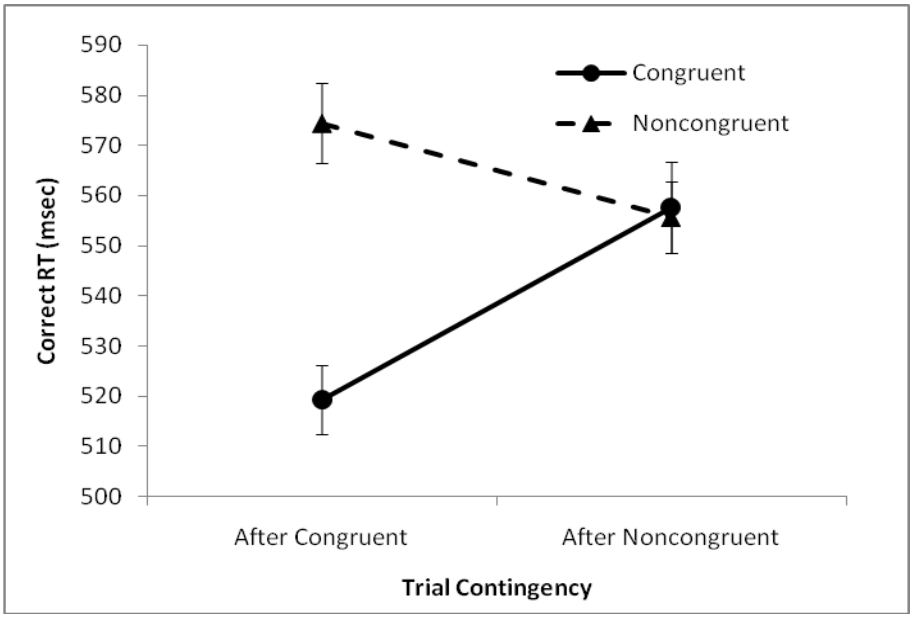
Experiment 2 RT analysis

Source	Statistic
Condition (C)	$F(1,57) = 110.2$, $p < .001$, partial $\eta^2 = .655$
Type (T)	$F(1,57) = 238.6$, $p < .001$, partial $\eta^2 = .804$
Bin (B)	$F(3,55) = 229.2$, $p < .001$, partial $\eta^2 = .925$
C x T	$F(1,57) = 24.18$, $p < .001$, partial $\eta^2 = .294$
C x B	$F(3,55) = 33.59$, $p < .001$, partial $\eta^2 = .643$
T x B	$F(3,55) = 5.05$, $p = .004$, partial $\eta^2 = .213$
C x T x B	$F(3,56) = 10.51$, $p < .001$, partial $\eta^2 = .36$

Table 2

Experiment 2 CV analysis

Source	Statistic
Condition (C)	$F(1,58) = 55.94$, $p < .001$, partial $\eta^2 = .491$
Type (T)	$F(1,58) = .323$, $p > .10$]
Bin (B)	$F(3,56) = 86.95$, $p < .001$, partial $\eta^2 = .823$
C x T	$F(1,58) = 5.93$, $p = .018$, partial $\eta^2 = .093$
C x B	$F(3,56) = 12.52$, $p < .001$, partial $\eta^2 = .402$
T x B	$F(3,56) = 1.02$, $p = .393$
C x T x B	$F(3,56) = 2.63$, $p = .059$



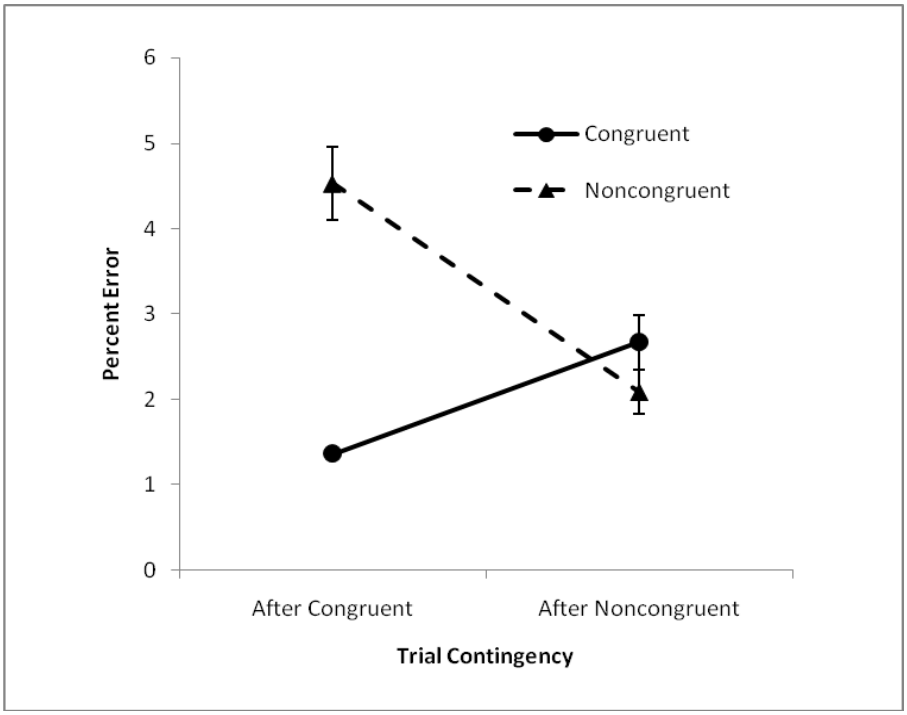


Figure 1. Experiment 1 RTs and percent error as a function of trial contingency (after congruent versus after noncongruent) and trial type (congruent versus noncongruent). Error bars denote standard error.

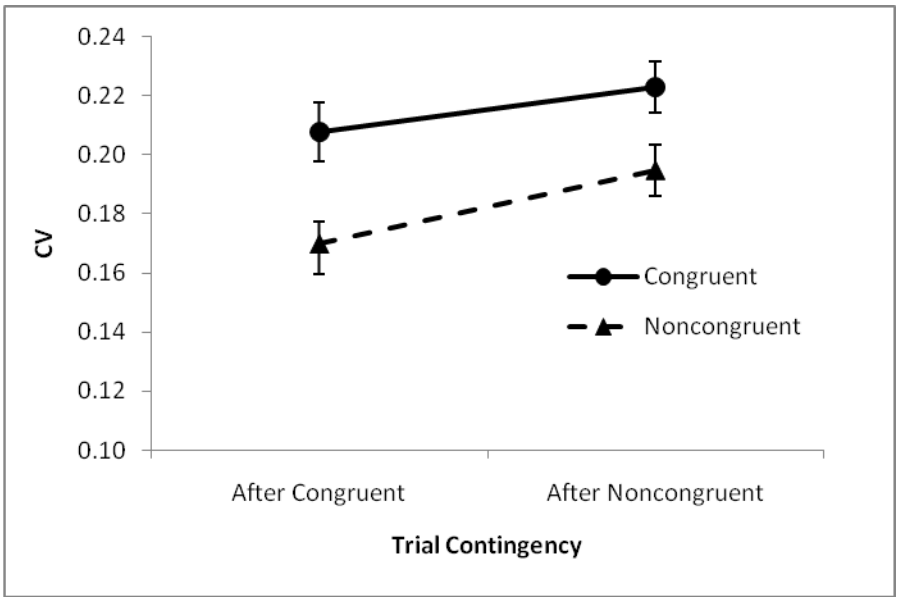


Figure 2. Experiment 1 CVs as a function of trial contingency (after congruent versus after noncongruent) and trial type (congruent versus noncongruent). Error bars denote standard error.

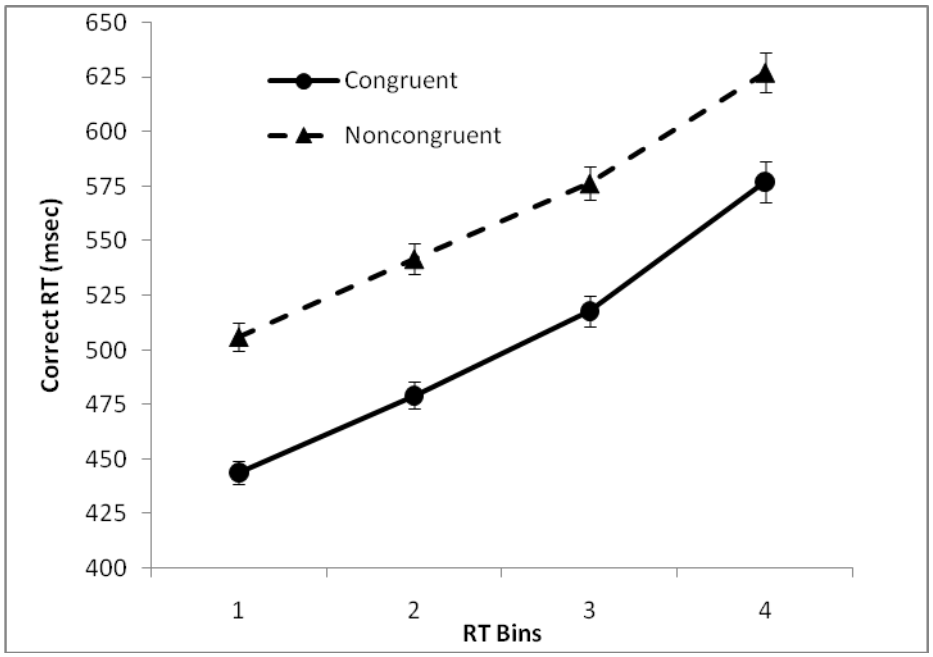


Figure 3. Experiment 1 RTs from trials after congruent trials as a function of RT bin and trial type (congruent versus noncongruent). Error bars denote standard error.

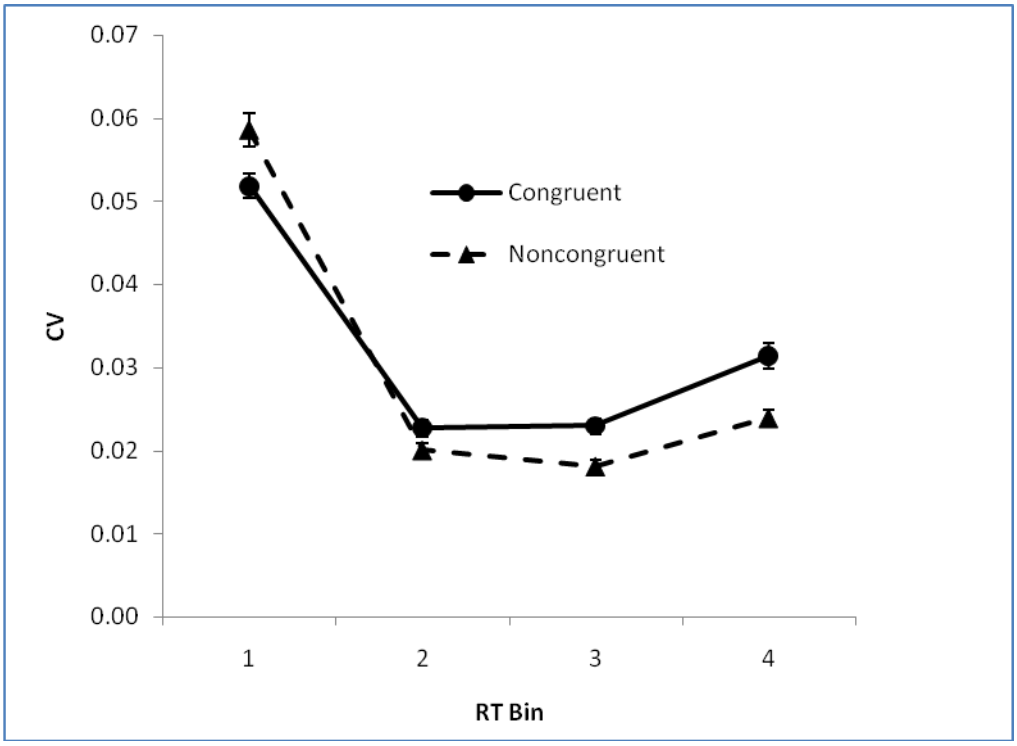


Figure 4. Experiment 1 CVs from trials after congruent trials as a function of RT bin and trial type (congruent versus noncongruent). Error bars denote standard error.

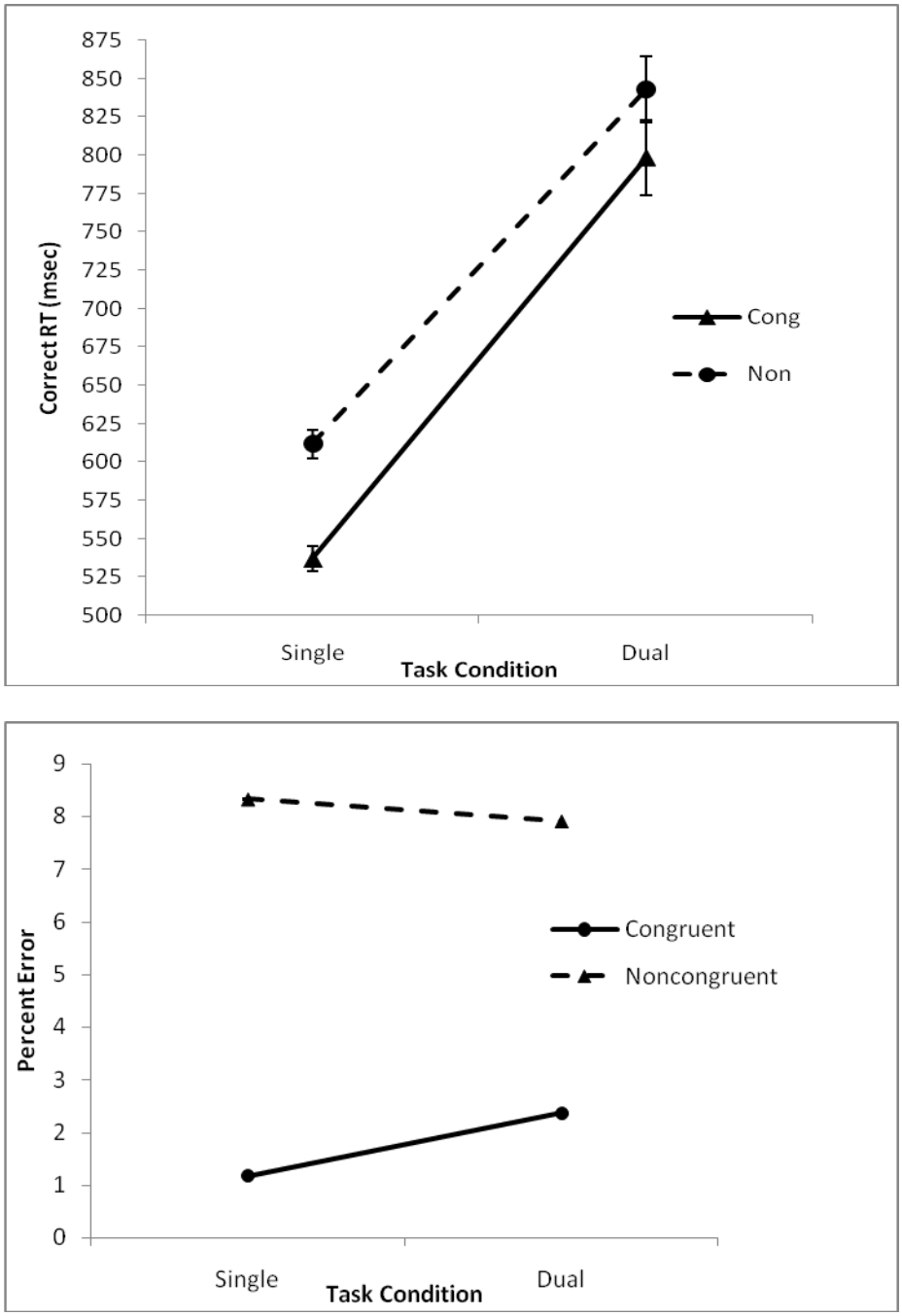


Figure 5. Experiment 2 mean RTs and percent errors from trials after congruent trials as a function of task condition (single versus dual) and trial type (congruent versus noncongruent). Error bars denote standard error. Standard error for percent error is too small to be pictured.

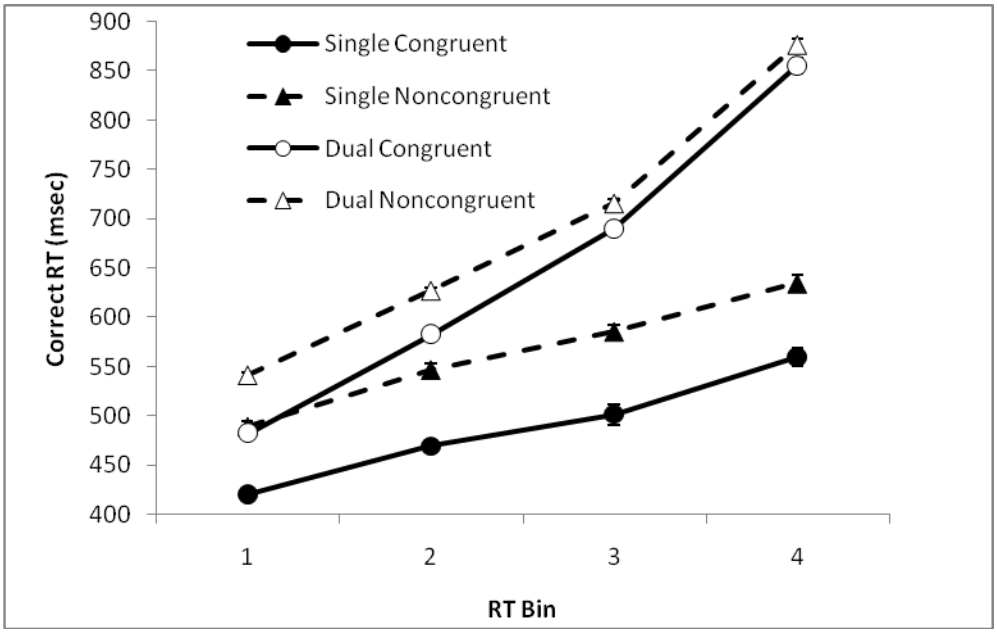


Figure 6. Experiment 2 mean RTs from trials after congruent trials as a function of task condition (single versus dual), trial type (congruent versus noncongruent), and RT bin. Error bars, where visible, denote standard error.

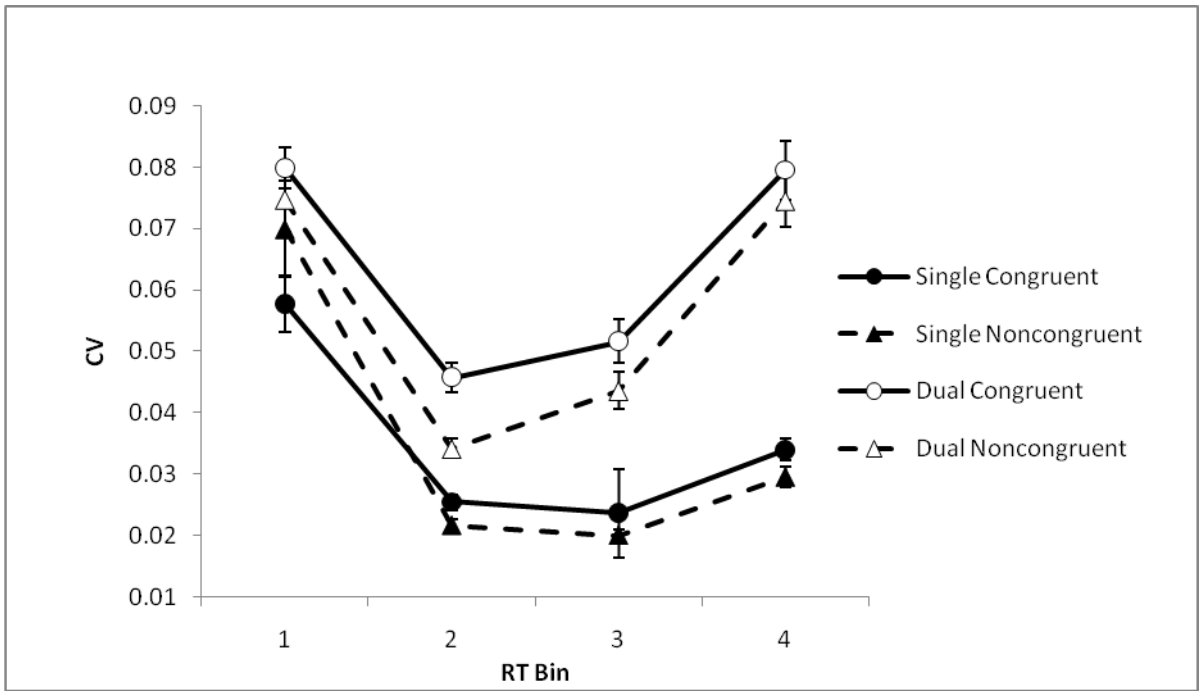


Figure 7. Experiment 2 mean CVs from trials after congruent trials as a function of task condition (single versus dual), trial type (congruent versus noncongruent), and RT bin. Error bars denote standard error.

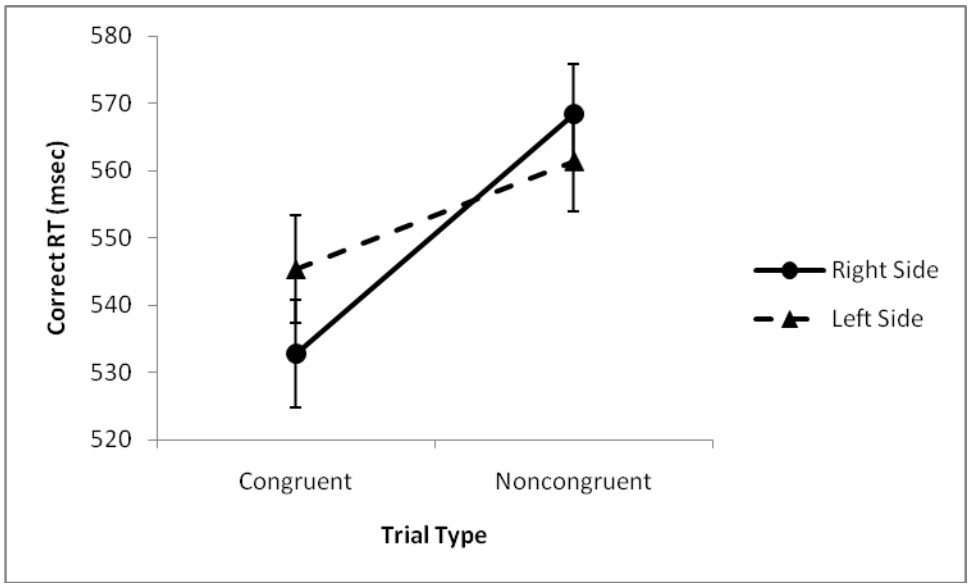


Figure A1. Correct RTs in msec for congruent versus noncongruent trial types when stimuli occur on the right versus left of the screen. Error bars denote standard error.

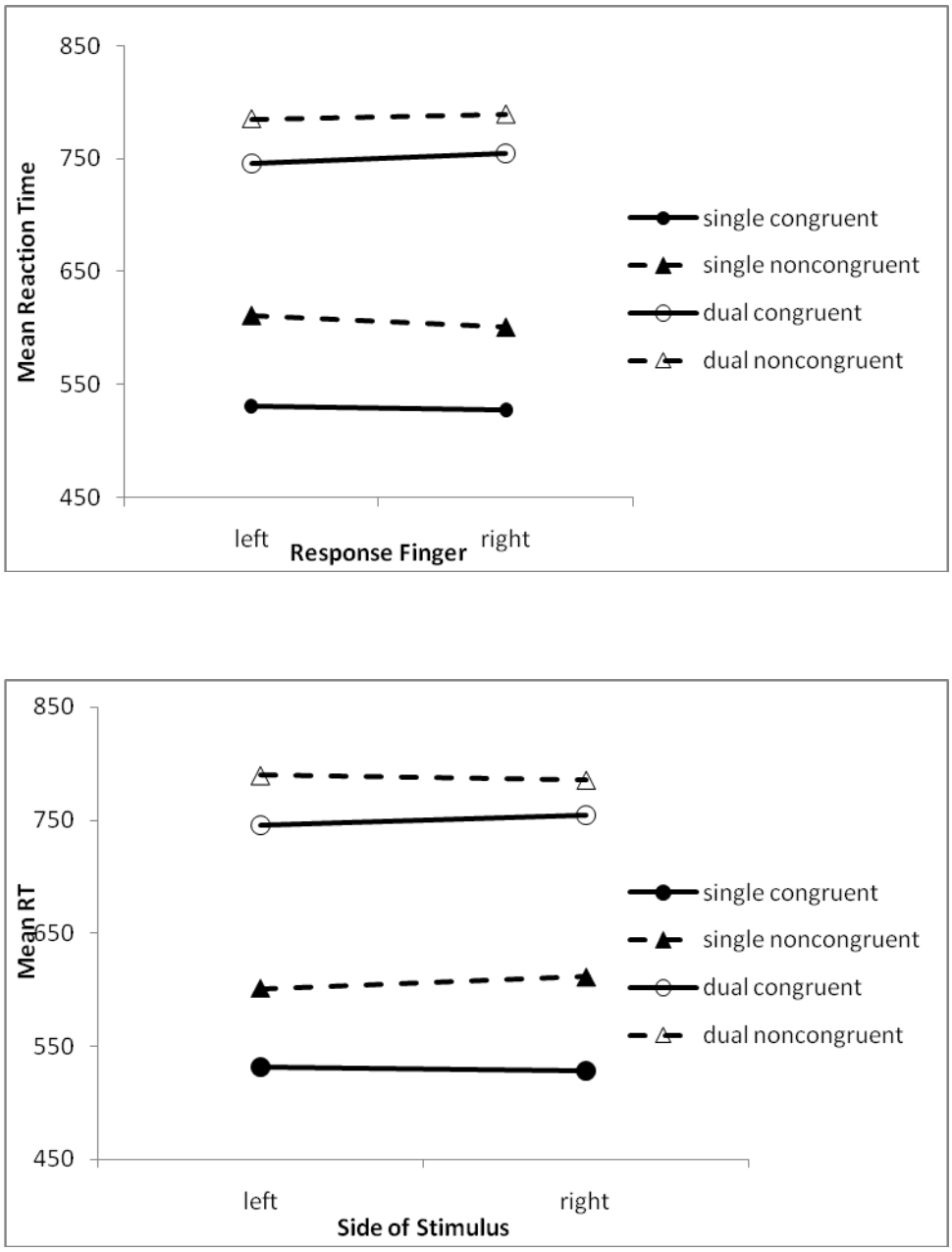


Figure A2. Experiment 2 mean reaction times for congruent and noncongruent trials in both single and dual task conditions, for response finger in the top frame, and for side of stimulus in the lower frame.

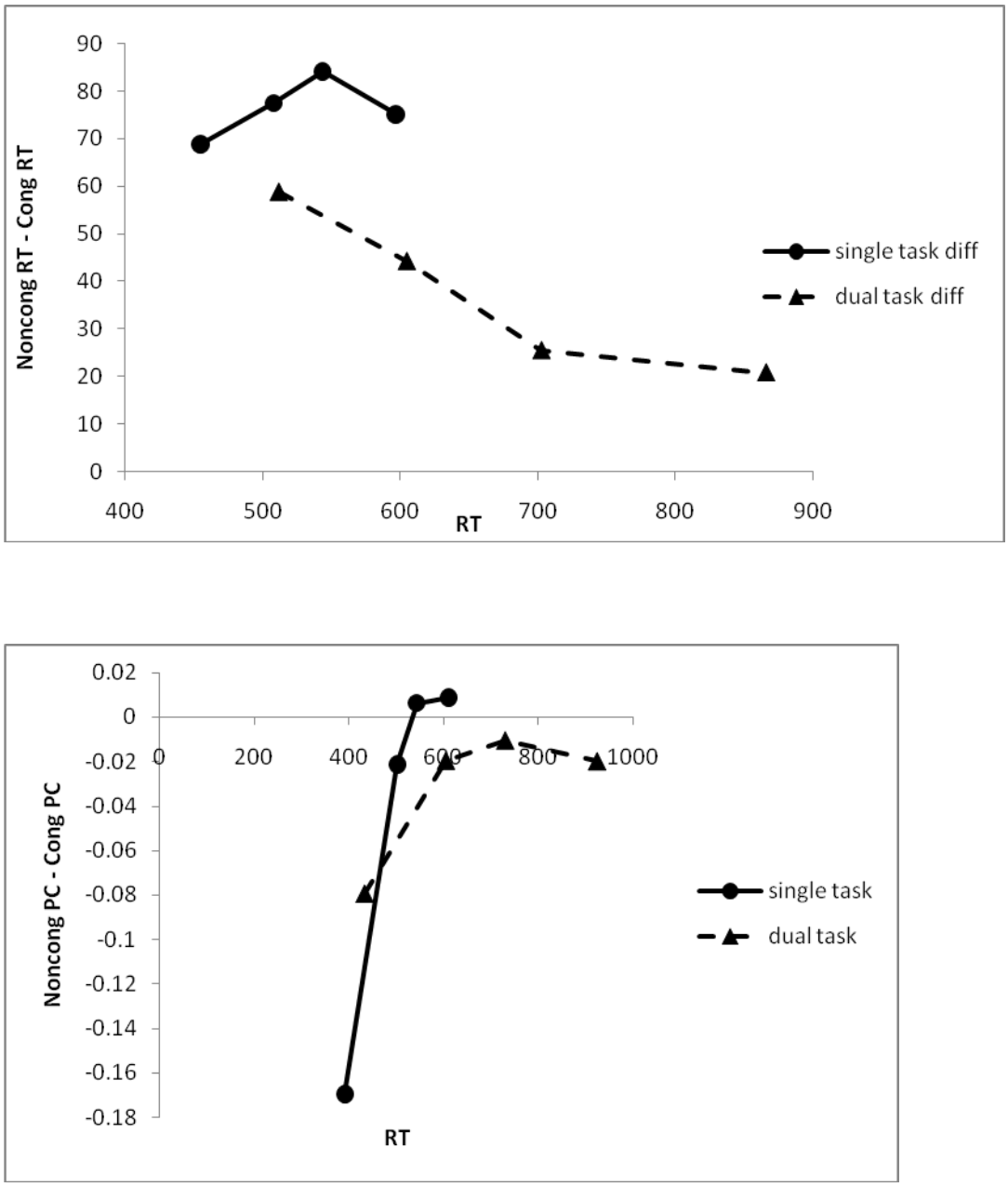


Figure B1. Delta plots showing the differences between noncongruent and congruent RTs (top panel) and percent correct (PC: lower panel) from Experiment 2.