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EVALUATING THE ROLE OF PROCESSING EFFICIENCY IN ADHD-RELATED WORKING MEMORY DEFICITS

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ABSTRACT

Theoretical models of working memory state that basic processing speed may drive individual differences in this ability. In addition, recent research suggests that working memory deficits in ADHD, a key feature of the disorder, can also be attributed slower processing speed. However, research on this relationship has relied mainly on correlational methods, and thus a causal relationship between speed and working memory ability has not been established. The current study uses a novel working memory paradigm, in which the processing speed of the distractor items can be manipulated within subjects, to determine whether slowing speed reduces working memory recall in children with ADHD and typically developing children. Findings indicate that working memory recall is causally driven by processing speed in both groups, indicating that processing speed is a plausible cause of individual differences in the ability of children and ADHD-related deficits.

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Introduction

Children identified as having attention deficit hyperactivity disorder (ADHD) have been found to face substantial barriers to academic success. ADHD, which is estimated to affect around 7.7% of children aged 4 to 17 nationwide, is one of the most common mental health diagnoses occurring during children's school-aged years in the United States (Fulton et al., 2009). The behavioral syndrome of ADHD is marked by inattentive behavior, inability to sustain attention or effort on tasks, disorganization, impulsive choices or actions, and excessive levels of activity (*Diagnostic and Statistical Manual of Mental Disorders* (4th ed., text rev.; DSM-IV-TR; American Psychiatric Association, 2000). For a diagnosis of ADHD to be determined, these behaviors must occur across different contexts (often in both home and educational settings) and an individual must experience substantial impairment in social, academic or work-related functioning. Not surprisingly, academic underachievement has been frequently and consistently identified in children diagnosed with ADHD (Bussing et al., 2012; Loe & Feldman, 2007) and has been predicted by this diagnosis over and above other externalizing behavior problems (Frick et al., 1991). Children diagnosed with ADHD have been found to score significantly lower on tests of reading and math achievement relative to their same-age peers, with a large, robust effect size (d=.71) across studies (Frazier, Youngstrom, Glutting & Watkins, 2007). Academic impairment contributes to an estimated annual cost of $15 to $20 billion for educational interventions alone for children with ADHD in the United States (Doshi et al., 2012), highlighting the need for further clarification of the causes of these children's academic difficulties.

Cognitive neuroscience research investigating the underlying causes of the observed impairment in ADHD has led to theoretical models that point to both abnormalities in the functioning of sub-cortical dopaminergic systems, leading to problems with motivation, reward, and temporal processing, as well as the disruption of higher-order cognitive functions mediated by the prefrontal cortex, such as executive attention, inhibitory control and working memory (Coghill, Nigg, Rothenberger, Sonuga-Barke & Tannock, 2005; Castellanos & Tannock, 2002). Deficits in working memory, in particular, present a highly plausible explanation for the academic difficulties faced by children with ADHD. Working memory (WM) is a multifaceted capacity that allows an individual to maintain, store and concurrently process information (Miyake and Shah, 1999) such as maintaining number values while executing a math problem or keeping relevant knowledge on line while reading a passage. Thus, it has been shown to be critical for a variety of skills necessary for academic success (Engle, Kane & Tuholski, 1999; Engle, Tuholski, Laughlin & Conway, 1999; Gathercole and Pickering, 2000). WM impairment has been identified and consistently replicated in group comparisons of children and adults with ADHD and non-ADHD counterparts (Kasper, Alderson, & Hudec, 2012; Schoechlin & Engle, 2005) and working memory deficits have, in fact, been linked to both academic and classroom behavioral problems in both ADHD and non-ADHD populations (Alloway, Gathercole, Kirkwood, & Elliott, 2009; Alloway, Gathercole, Holmes, Place, Elliott, Hilton, 2009; Gathercole and Pickering, 2000; Gremillion & Martel, 2012; Miller et al., 2013).

Yet, since WM involves a multitude of other more basic cognitive abilities, such as selective attention (Cowan, 1988), general executive functioning ability (Unsworth & Engle, 2007), long term memory retrieval (Lewandowsky, Geiger, Morrell & Oberauer, 2010; Shipstead & Engle, 2012), and the efficient processing of tasks that are completed concurrent with memory maintenance (Unsworth, Redick, Heitz, Broadway & Engle, 2009), individual differences in any of these sub-components of WM could drive individual differences in children’s overall WM capacity.

Recently, a strong link between basic processing speed, or the general efficiency with which a given individual can successfully execute cognitive tasks (Kail & Salthouse, 1994), and WM ability has been established in findings on developmental (Fry & Hale, 2000; Bayliss, Jarrold, Baddeley, Gunn and Leigh, 2004), individual (Schmiedek et al., 2007), and ADHD-related (Karalunas & Huang-Pollock, 2013) differences in WM ability. As children with ADHD generally display less efficient processing overall (Karalunas, Huang-Pollock & Nigg, 2012; Metin, Roeyers, Wiersema, van der Meere, Thompson & Sonuga-Barke, 2013), these findings suggest that deficits in processing speed may be largely responsible for WM deficits in ADHD, and, ultimately, academic impairment. However, the hypothesis that processing speed drives individual differences in WM ability has thus far been supported mainly by correlational evidence, and has not been explicitly experimentally investigated. Equally plausible is the intuitive hypothesis that executive function deficits, for which ADHD is largely known, prevent children with ADHD from optimally utilizing controlled attention to maintain memory items, as would be predicted by the model of WM as executive attention (Engle, 2002).

The current study seeks to establish a causal account of the relationship between slower processing speed and lower WM ability, and to determine whether the relationship between speed and WM ability is the same in children with ADHD and typically-developing children. To meet these goals, a WM task in which processing speed can be experimentally manipulated will be designed. There are two key challenges in doing so. First, processing speed has traditionally been operationalized as mean reaction time (Hale & Jansen, 1994). However, any experimental manipulation that speeds or slows reaction time (RT) must also control for the presence of speed-accuracy trade-offs. That is, when an individual takes time to fully process a stimulus in a speeded task, prioritizing accuracy over speed, he or she will on average respond more slowly than another individual who does the reverse. In this example, it is easy to see why concluding that the second individual is able to process information more quickly than the first ignores critical information. A method is needed to integrate both speed and accuracy to obtain a single estimate of performance. The Ratcliff diffusion model (Ratcliff & McKoon, 2008) is one way to do so. The diffusion model is a computational model for two-choice decision tasks and derives its parameters from RT distributions from both error and correct responses. Specifically, the model's parameter of drift rate (*v*) serves as an index of processing efficiency that is independent of speed-accuracy trade off settings.

Second, any experimental manipulation that degrades or improves the speed of processing in the context of a working memory paradigm must also control for the confounding effects of time-based decay of memory. That is, manipulations that slow or speed response times also alter overall task length, confounding processing speed with the amount of time that items must be remembered (Towse & Hitch, 1995). Correcting this confound requires that the amount of time memory items must be maintained between conditions be controlled as well. Therefore, to experimentally determine whether individual differences in processing speed drive individual differences in WM ability, the speed at which a component of a WM measure can be processed (as indexed by *v*) will be manipulated in the following study, while controlling for the amount of time memory items must be maintained.

To outline the background and theoretical implications of the current study, WM's basic features and importance for academic competence in both typically-developing children and children with ADHD will be reviewed. Following this, two major explanations for WM variation, that of executive attention and that of basic processing speed, will be explored in detail. The evidence for both views and the relevance of each theory to understanding WM deficits in ADHD will be highlighted. Finally, the current study's design, as a way to explicitly test the explanation the processing speed causes individual differences in WM ability in both typically developing children and children with

ADHD will be outlined, and the implications of possible patterns of results for both major theories will be discussed.

I. Working memory, its measurement and function

While theoretical models of WM posit different structural components and causes of individual variation, there are some general agreements within the field on the broad definition of the construct and its functional role in human cognitive performance. Working memory is generally conceptualized as the ability to encode items, such as numbers, letters, or words, into a limited-capacity memory store and to retain these items during concurrent processing, which may either involve completing an unrelated secondary task (e.g., reading a sentence or making a perceptual decision) or the manipulation of the encoded information (Baddeley, 2012; Miyaki & Shah, 1999; Oberauer, Lewandosky, Farrell, Jarrold & Greaves, 2012; Unsworth & Engle, 2007). In this way, major models of WM distinguish this ability from that of short term memory, in which recently encoded information is retained, but without any concurrent processing demands other than simple maintenance of the memory items (Baddeley 2012; Lewandosky, Geiger, Morrell & Oberauer, 2010; Unsworth & Engle, 2007). WM allows for the manipulation of information in addition to its retention, and the separation of these two constructs is warranted by psychometric findings that WM appears to be uniquely associated with reasoning ability and higher-order cognition; WM, but not short term memory, has been strongly and reliably linked to reasoning ability and general fluid intelligence, appearing to be a domain-general function of the prefrontal cortex (Engle, Tuholski, Laughlin & Conway, 1999; Conway, Cowan, Bunting, Therriault & Minkoff, 2002), while short term memory storage ability is generally linked to other abilities within the domains (e.g., verbal, spatial) of the memory items (Baddeley, 2012).

The theoretical distinction between working memory and short term memory is explicitly operationalized in one of the most commonly used and empirically validated measures of working memory ability, the complex span paradigm (Conway, Kane, Bunting, Hambrick, Wilhelm & Engle, 2005; Daneman & Carpenter, 1980). This category of measures, first created by Daneman and Carpenter (1980), involves the presentation of memory items that are interspersed with attention-demanding tasks designed to tax WM. While a “simple span” task only involves the presentation of memory items, such as words or numbers, and thus indexes short term storage ability, the “secondary processing” task in complex span paradigms fulfills the construct’s requirement that a WM measure involve concurrent processing of information (Conway et al., 2005). Daneman and Carpenter’s (1980) reading span task requires participants to remember words while reading and comprehending sentences that are interspersed between the to-be-remembered items. In another commonly used variant, the operation span task (Turner and Engle, 1989), participants solve basic math problems while attempting to remember words. Generally, the processing task is completed prior to the presentation of each item in the set to be remembered.

Complex span tasks are not the only WM measures commonly used in research. WM updating tasks such as the n-back, in which participants must modify or manipulate memory items after they are presented, are also widely used and have been demonstrated to index the same construct (Schmiedek, Hildebrandt, Lovden, Wilhelm & Lindenberger, 2009). Though updating tasks present alternative operational definitions of WM, major research efforts investigating causes of individual variation in the construct (e.g., see Unsworth & Engle, 2007; Barrouillet & Camos, 2012; Bayliss et al., 2004; Schmiedek et al., 2007) utilize complex span or paradigms derived from it. Furthermore, the complex span paradigm's construct validity and reliability has been repeatedly demonstrated (Broadway & Engle, 2010; Redick et al., 2012) and, likely because of its strong validity, complex span has become the most common WM measure to be used in applied fields outside of cognitive psychology (Conway et al., 2005).

A second general consensus in the research literature on WM is the function that it serves in human cognitive performance. Because WM allows individuals to not only remember information, but *utilize* that information in the service of ongoing cognitive processes, it has been theorized that this capacity is what allows humans to execute complex cognitive functions like reading and math (Baddeley & Hitch, 1974). Indeed, WM capacity has been shown to predict reading comprehension over and above comparable short term memory tasks (Daneman & Merikle, 1996) and has been linked to complex cognitive skills as diverse as spatial ability (Miyake, Friedman, Rettinger, Shah & Hegarty, 2001), mathematical competency (Nyroos & Wiklund-Hornqvist, 2012: Geary, Hoard, Byrd-Craven, Nugent, & Numtee, 2007), verbal ability (Alloway, Gathercole, Kirkwood, & Elliott, 2009), general capacity for reasoning (Kyllonen & Christal, 1990), and overall academic achievement (Gathercole & Pickering, 2000). A robust relationship between WM ability and general intelligence has also been established and replicated in a number of studies (Engle, Tuholski, Laughlin & Conway, 1999; Engle, Kane & Tuholski, 1999; Unsworth et al., 2006), underscoring the importance of WM as a key underpinning of both domain-general capacities and more specific academic skills.

Indeed, WM deficits (which have been consistently established in ADHD; Kasper et al., 2012; Schoechlin & Engle, 2005) both mediate the relationship between ADHD status and mathematics achievement (Gremillion & Martel, 2012), and are strongly related to children with ADHD's ability to detect the central theme of reading passages, a key skill for reading comprehension (Miller et al., 2013). Children with ADHD also show greater difficulty developing automatic, skilled performance on a cognitive task with high WM load, but not on a task with lower WM demands (Huang-Pollock & Karalunas, 2010). Though there is strong evidence that WM deficits substantially drive academic problems seen among children with ADHD, what drives individual differences in WM deficits is not clear. However, basic research on individual differences in executive attention and global processing speed provides two likely explanations.

II. Models of WM and competing theories of individual variation: Attention

Working memory's architecture has been debated since the construct was first defined, and thus, so too have the causes underlying its variation across individuals. The first major model of working memory, known as the multiple-components model, was proposed by Baddeley and Hitch (1974) as an improvement on prior models of short term memory. This model posits that WM is a multi-component system comprised of a "central executive" control mechanism and two "slave systems" that, based on the demands of this executive, maintain and execute processing demands within their domain. The first of the two systems, the phonological loop, maintains verbal memory representations (letter, numbers, words) through memory rehearsal processes, while the second, the visuospatial sketchpad, is comprised of a passive store for visuospatal memory representations and another active maintenance mechanism similar to the rehearsal process in the phonological loop (Baddeley and Logie, 1999). In both short term stores, memory items that are not actively maintained are lost to decay. The role of the central executive is to control these two systems, (thus the "slave" term) optimally in the service of ongoing cognitive processes. In this conceptualization, working memory variation occurs chiefly because of limitations within the slave system's capacity for maintaining memory items, and thus protecting them from decay (Baddeley and Logie, 1999).

Despite the empirical support that has accumulated for the multiple-component model since its initial proposal (reviewed in Baddeley, 2012), newer, alternative models posit a single capacity of controlled attention as a limiting factor for WM, rather than separate short term stores for different types of representations. Cowan's (1999) embedded process model laid the framework for these theories by presenting evidence of a single, domain-general memory store (assumed to be long term memory), within which exists a limited-capacity "focus of attention". This focus of attention can only hold a limited number of items, determined to be about 4 (Oberauer & Kliegl, 2006; Cowan, 2001), and "activates" a further subset of items in WM by temporarily moving them in and out of the focus, which serves to maintain them for WM's access, but which is subject to temporal decay (Cowan, 2001). This structural model of WM has also received strong support from neuroimaging investigations of WM's components that contrast it with the multiple-component model (e.g., Chein & Fiez, 2010).

A preeminent model that incorporates the assumptions of a long term memory store and capacity-limited focus of attention and that makes explicit predictions about the cause of individual differences is the theory of working memory as executive attention (Engle, 2002; Unsworth and Engle, 2007). Engle (2002) developed this theory of individual variation based on an accumulation of evidence suggesting that WM ability is strongly correlated with functions of the prefrontal cortex and the ability to effortfully control attention, in particular. In this view, WM ability reflects an individual's capacity to voluntarily control attention in the service of retaining memory items, and is thus related to individuals' general capacity for executing goal-directed behavior.

Unsworth and Engle (2007) further elaborated the theory by proposing a structural model of working memory that distinguishes between primary memory (PM), or the store of items held within the focus of attention, and secondary memory (SM). In SM, WM items that have been displaced from the conscious focus of attention are transferred to the larger, long term memory store. As in the original embedded process model, PM's capacity is limited to a small number of items, so additional items displace original items to the long term store. Concurrent processing tasks, which compete for the focus of attention, further displace memory items from PM, and all items that are displaced must be retrieved back into PM from long term memory when recall is required. This model is supported by findings that memory tasks, which involve concurrent processing, involve recruitment of the medial temporal lobe, implicated in long term memory, while tasks that do not involve concurrent processing demands do not, theoretically because, in these tasks, items are not displaced from the focus of attention to the same degree (Chein, Moore & Conway, 2011). Therefore, Unsworth and Engle (2007) argue that WM capacity reflects an individual's ability to actively maintain items within the focus of attention (PM) and, when they are displaced by novel items or concurrent processing, to conduct a controlled search for the displaced items within the long term store (SM). Both components of WM ability, in theory, require executive functioning, or the general capacity to utilize controlled cognitive processes in the service of meeting a goal (i.e., maintaining memory items during processing).

Support for the theory that WM variation occurs because of variation in individuals' capacity for voluntarily controlling attention, and thus, depends on the functioning of the prefrontal cortex (Kane & Engle, 2002), has come from studies that involve comparing high- and low-WM capacity individuals' in other indices of cognitive control. High-WM individuals are faster to shift attention to a target in antisaccade tasks, where one must resist the automatic tendency to shift attention to a distracting stimulus that always appears on the opposite side of the target in a display, while WM ability is not related to performance an prosaccade trials, which require only the automatic response (Kane, Bleckley, Conway & Engle, 2001). WM ability has also been strongly linked to performance on the Stroop task, a measure that requires one to voluntarily ignore an automatic response in favor of a conscious goal (Kane & Engle, 2003; Meier & Kane, 2013). Additionally, studies with diverse methodologies that have found high-WM capacity individuals tend to be more adept at maintaining task goals than their low-WM capacity counterparts (Marcovitch, Boseovshi, Knapp & Kane, 2010; Redick & Engle, 2011).

Impairment in executive attention provides an intuitive account of WM deficits in ADHD, as it is a disorder that, perhaps more than any other, is strongly associated with executive dysfunction (Castellanos & Tannock, 2002; Coghill et al., 2005). Thought to result from dysregulation of dopaminergic loops between the striatum and prefrontal cortex (Castellanos & Tannock, 2002), children with

ADHD have been found to have considerable deficits in executive attention and other related neuropsychological functions. Willcutt, Doyle, Nigg, Faraone and Pennington (2005), in a meta-analytic review of studies investigating the role of executive deficits in ADHD, determined that, while executive function deficits are not uniformly present in children with ADHD, executive functions from various domains have been consistently found to be impaired. The executive attention processes outlined by Engle (2002) have also explicitly been shown to be affected in ADHD; ADHD status and symptoms are negatively related to both antisaccade performance (Carr, Nigg & Henderson, 2006; Goto et al., 2010; Nigg, Butler, Huang-Pollock & Henderson, 2002) and stroop task performance (Barkley, Grodzinsky & Dupaul, 1992; Ikeda, Okuzumi & Kokubun, 2013), suggesting that, if executive attention is a main contributor to WM ability, ADHD-related WM deficits could be related to problems with this function. This claim has, in fact been made by several ADHD researchers (Alderson, Hudec, Patros & Kasper, 2013; Rapport et al., 2008)

While this line of research demonstrates the considerable amount of support that the theory of WM as executive attention has received, and the plausibility of the application of this model to explain WM deficits in ADHD, empirical research on the causes of developmental differences in WM ability has provided another potential explanation for ADHD-related deficits in WM.

III. Models of WM and competing theories of individual variation: Speed

Several developmental studies have documented the relationship between WM maturation and perhaps the most basic psychometric construct that exists: simple speed of processing. Processing speed, or the general efficiency with which a given individual can successfully execute cognitive tasks, is typically defined as the reaction time to complete simple tasks that involve minimal contributions from higher cognitive functions (Fry & Hale, 2000). The speed with which an individual completes simple cognitive tasks from diverse domains (e.g., letter classification and mental rotation) tends to be highly correlated (Hale & Jansen, 1994), suggesting that processing speed is a domain-general function. This global or general processing speed improves exponentially during childhood and throughout mid adolescence (Hale, 1990; Kail, 1993).

In the case of WM, a strong correlation between developmental improvements in processing speed and WM capacity has been established and replicated by several research groups. Kail and Park (1994), using a large cross-national sample of Korean and North American children, ages, 7 to 14, found that age-related improvements in processing speed were directly related to both speed of articulation – itself a determinant of short term and working memory span – and working memory span. Fry and Hale (2000), in a review of prior research on links between speed, working memory, and general intelligence found that the vast majority of variance in WM ability accounted for by age – all but 3% – was variance shared with processing speed. These analyses strongly suggest that global processing speed mediates the relationship between age and WM ability (Fry & Hale, 2000), a relationship that has been demonstrated to be independent of whether speed of processing is measured in a visual or verbal domain (Bayliss, Jarrold, Baddeley, Gunn and Leigh, 2005).

The time-based resource-sharing (TBRS) model creates a structural framework to explain these findings. This model posits that items in WM decay unless they are constantly refreshed by a capacity-limited attentional focus (i.e., attentional "bottleneck"), that secondary tasks prevent refreshing, and, thus, that memory recall on complex span tasks is directly related to the ratio of available refreshing time to time spent distracted by the secondary task (Portrat, Camos & Barrouillet et al., 2009). Support for this account comes from studies in which both the difficulty of and time available for secondary tasks is manipulated. When either the amount of time available for processing of the secondary task is increased, or the difficulty of the secondary task is decreased, both of which provide more free time for the refreshing of the memory items, memory recall improves (Barrouillet & Camos, 2012). For example, Gaillard, Barrouillet, Jarrold, & Camos (2011) demonstrated that when 11-year old children are given a more difficult distractor task than 9-year-old children (adding 2 to a digit in each interval rather than adding 1), effectively equating the time spent completing the distractor for both age groups, age-based differences in memory recall are greatly reduced. This finding provides a convincing explanation for processing speed's influence on memory span: older children can process distractor tasks in shorter amounts of time, which allows them more free time for refreshing and in turn prevents the decay of memory items.

However, in these experimental manipulations, relatively long intervals (in some conditions as much as 1940 ms) are left between the end of the distractor task and presentation of the next item (Gaillard et al., 2011). Typical complex span tasks, by contrast, leave little, if any, time explicitly free for refreshing or articulatory rehearsal beyond the time during the presentation of memory items (Redick et al., 2012). Thus, in studies that support TBRS (e.g, Gaillard et al., 2011; Barrouillet, Bernardin & Camos, 2004), it is not clear whether such results would be replicated under more typical complex span conditions. Because of this difference, the TBRS paradigm may reflect short term memory rather than working memory in some conditions, as there are very low demands for concurrent processing, which most major WM theories posit as a fundamental characteristic of the construct (Baddeley 2012; Lewandosky, Geiger, Morrell & Oberauer, 2010; Unsworth & Engle, 2007). In addition, the empirical studies supporting the model have thus far used mean RTs as an index of how long individuals spend processing secondary tasks relative to refreshing memory items. However, RT lengths are affected by multiple processes in addition to the task processing component, including motor preparation, other cognitive processes that may take place between the stimulus onset and the decision, and speed/accuracy trade-offs (Ratcliff & McKoon, 2008). Despite these limitations in the current literature testing TBRS, the model provides a causal framework to explain why differences in processing speed exert a strong influence on WM ability.

IV. Capturing differences in speed: reaction time components and individual differences in WM

The relationship between processing speed and WM ability in the individual, rather than developmental, differences literature underscores the need for precise formal definitions of the construct of processing speed. Individual difference studies using mean reaction time data from traditional psychometric measures of speed have failed to find results consistent with the hypothesis that individual variation in speed drives individual variation in adults' WM ability (Redick, Unsworth, Kelly & Engle, 2012). However, using mean reaction time data collapses an index of cognitive processing speed with a multitude of indices of other processes, such as motor response time, lower level perceptual processes, and response conservatism (Ratcliff & McKoon, 2008). Doing so can obscure the relationship between processing speed and other variables, such as WM ability, because of the influence of these extraneous factors on RT. A more detailed review of computational methods used to index the speed of cognitive processing is necessary to frame the findings of individual difference studies on the relationship between speed and WM.

The use of mathematical models to explain inter- and intra-individual variability in reaction times has contributed to research on both neural processes underlying simple decision making and human processing efficiency on simple decision tasks (Smith & Ratcliff, 2004). These models generally share a set of biologically-validated assumptions about how humans make simple decisions: 1) quantitative evidence for each possible response in the decision task accumulates over time in some manner, which, as animal research has suggested, reflects an increase in neural firing within areas corresponding to that response (Schall, 2003), until a *response threshold* of activation, predetermined by the individual, is reached by one of the response accumulators and that response is chosen, 2) this evidence gathering process is inherently noisy, so between- and/or within-trial variability in the accumulation process must be used to account for the substantial within-condition and within-subject variability in reaction times, 3) evidence for one decision decreases activity in the accumulators of opposing decisions, presumably through lateral inhibition processes and 4) reaction times contain a “nondecision” component, which comprises of lower-level perceptual and motor processes unrelated to the cognitive processing of the decision (Smith & Ratcliff, 2004). These models can both explain the basic processes that underlie simple decision making and be used to index individual differences in these processes when fit to empirical data.

Traditional accumulator models, such as the leaky competing accumulator model (LCA: Usher & McClelland, 2001), have framed decision processes as competitions between discrete accumulators. In the LCA, each response accumulator gains activation as evidence for that response is acquired, but loses activation both to time-based decay and lateral inhibition from other accumulators. Eventually, in trials where error variance has not pushed an incorrect accumulator higher than the correct accumulator, the accumulator for the correct response reaches the response threshold first. An individual’s drift rate, or the rate at which evidence accumulates for the correct response accumulator (Usher & McClelland, 2001) indexes, depending on the dependent variable of interest, the quality of the stimuli in the decision (i.e., difficulty of the decision) or the efficiency with which an individual can correctly execute a simple decision (Ratcliff & McKoon, 2008). Using the assumptions of lateral inhibition, time-based decay and variability in both, the LCA accounts for what amount to two key goalposts of decision-making models: the ubiquitous positive skew of human reaction time distributions and the phenomenon of fast errors under conditions that stress speed and slow errors in conditions that stress accuracy (Smith & Ratliff, 2004).

A model that simplifies some assumptions of the LCA while still explaining these reaction time phenomena adequately, and one that has been used extensively outside of the field of mathematical psychology, is the Ratcliff drift diffusion model (Ratcliff & McKoon, 2008). This model frames a two-choice decision as a single evidence accumulation process that drifts between two response boundaries (correct and incorrect) until a response is generated by contact with one (See Figure 1). In this way, the model accounts for lateral inhibition implicitly; evidence for one decision degrades evidence for the other automatically as the single diffusion process drifts away from the latter boundary. The drift rate (v) is the average rate at which the process moves toward the correct boundary, and errors occur when within-trial variability (captured in a drift variability parameter) causes the drift process to terminate at the incorrect boundary. Drift rate of the diffusion process to the correct response varies with both experimental manipulations, in which more difficult tasks slow drift rate relative to easier tasks, and with individual differences in speed of processing, as faster drift rates being associated with generally faster populations (Ratliff & McKoon, 2008). Consistent with the idea that drift rate provides an index of global processing efficiency, this parameter has also been shown to increase with maturation (Ratcliff, Love, Thompson & Opfer, 2012). The parameter indexing the distance between the correct and error response boundaries, boundary separation (*a*), accounts for speed-accuracy tradeoffs; individuals who seek less confirmatory evidence before initiating a decision have narrower boundaries, allowing the diffusion process to terminate at a boundary sooner, but leading to more terminations at the incorrect boundary from noise. As in all decision models (Smith & Ratcliff, 2004), the model also includes a parameter that indexes the time spent completing processes not associated with cognitive processing, nondecision time (*Ter*).

Fitting the diffusion model to empirical data and using the parameter value of drift rate to index cognitive speed as a means of operationalizing processing efficiency has several key advantages over the analysis of mean reaction times. First, the *a* parameter controls for possible confounds related to individuals' speed-accuracy trade-off settings which, if not considered, may weaken relationships between speed and other measures. In one example, with all other parameters equal, individuals with narrow boundaries will have faster reaction times. Under the traditional mean reaction time mode of analysis, they could then be assumed to have high speed, despite the fact that their error rates are much higher than those with wider boundaries. The diffusion model accounts for both speed of response and accuracy of response within a single framework, preventing contradictory or deceptive results where speed and accuracy data do not align, and utilizing information from incorrect trials which are typically disregarded, providing a more advanced index of processing efficiency than simple analysis of mean or median reaction times. In a related empirical example, older adults have been found to display longer reaction times not because of slower drift rates, but because of conservative responding (wider boundaries) (Ratcliff, Thapar & McKoon, 2004).

Secondly, factoring out components of reaction time not related to the processing of the decision (i.e., *Ter*) isolates cognitive efficiency from portions of RT related to extraneous factors. These non-decisional components are assumed to include the encoding of stimuli and motor preparation processes, but in theory, *Ter* should account for all processes, cognitive, perceptual or otherwise, occurring during the reaction time that are not directly involved in the decision process (Ratcliff & McKoon, 2008). In the case of a secondary task within a complex span WM measure (in which little to no time is left to explicitly refresh memory items), *Ter* would also include the component of the RT during which an individual refreshes memory items, either before or after the decision is made (Figure 1B). Within the TBRS model, then, *Ter* would represent the portion of RT during which the attentional bottleneck is not taken up by the distractor decision and could be used for refreshing. Thus, along with *v*, *Ter* should be related to memory recall; greater observed *Ter* during the RT to distractor tasks should correspond to greater memory retention, as the participant has more time to refresh relative to the amount of time that is spent processing the distractor task.

Advocates of diffusion model analysis of human cognitive data have demonstrated the benefits of using drift rate as an index of cognitive efficiency over traditional analysis (Ratcliff & McKoon, 2008; Ratcliff, Thapar & McKoon, 2004), and, in turn, have spurred the investigation of how individuals' drift rate relates to WM ability. For example, Schmiedek and colleagues (2007) fit 135 adult participants' reaction time and accuracy data from a battery of these tasks to the diffusion model. Schmiedek et al. (2007) formed a latent variable on to which estimates of individuals' drift rate on each simple task were loaded and used structural equation modeling to investigate the relationship between drift rate, the other diffusion model parameters, and individuals WM capacity. Their findings, that over 42% of the variance in WM capacity was explained uniquely by individuals' drift rate (the most out of all model parameters) strongly suggests that individual differences in WM ability, as in the developmental literature, can be attributed to simple efficiency of processing. This work both demonstrates how the use of alternative techniques for operationalizing cognitive speed may provide a more nuanced measure of the construct and underscores findings from the study of WM development that suggest that WM variation depends largely on basic processing speed.

V. Using diffusion modeling to understand the role of speed in individual differences and ADHD-related WM impairment

In addition to deficits in executive processes, less efficient global processing of information has also been a common finding in children with ADHD. Reaction times of children with ADHD on a variety of tasks are characteristically slower and more variable than those of typically-developing children, and responses are more likely to be inaccurate (Castellanos et al., 2005; Hervey et al., 2006; Klimkeit, Mattingly, Sheppard, Lee & Bradshaw, 2005). Studies of children with ADHD's reaction times to simple tasks have found evidence for reduced speed (Holdnack, Moberg, Arnold, Gur & Gur, 1995; Katz, Brown, Roth & Beers, 2011; Shanahan et al., 2006), suggesting that this phenomenon may be due to lower overall processing efficiency.

However, alternative explanations for slow and variable reaction time include the theory that children with ADHD have slowed motor responses. Children with ADHD have been consistently identified as having problems with the coordination of movement (Pitcher, Piek, & Hay, 2003; Rommelse et al., 2009), suggesting that slowed and variable responding may occur due to problems in the execution of motor responses rather than the slowing of the cognitive processes that precede them. As problems with motor coordination and preparation would also lead longer reaction times through increased time spent on responding (i.e., longer *Ter*), this explanation makes similar predictions about the mean reaction times of children with ADHD as the theory that they have lower processing efficiency, highlighting the need for a methodology that can distinguish between the unique contributions of cognitive and motor processes to reaction time.

Similarly to the assessment of speed in aging populations, speed-accuracy tradeoffs may also be a concern when assessing speed of processing in ADHD. Consistent findings of response inhibition deficits in children with ADHD (Wilcutt et al., 2005) suggest that children with ADHD may display more “impulsive” processing, or, in the context of the diffusion model, narrower boundaries. In light of the alternative explanation of motor coordination problems as the cause of slowed RTs and the possible confound of speed-accuracy trade-offs in ADHD, the utility of using alternative techniques for analyzing reaction times in this population, such as that used by Schmiedek et al. (2007), is clear.

The application of mathematical models for reaction time analysis, and the drift diffusion model (Ratcliff & McKoon, 2008) in particular, has largely supported the view that ADHD effects on reaction time speed and variability are due to less efficient processing overall. Karalunas, Huang-Pollock and Nigg (2012) found evidence of slower drift rates on a two-choice decision task in two independent and geographically distinct samples of children with ADHD and age-matched controls, while other components of reaction time distributions did not display reliable group differences. The finding of slowed drift rate in ADHD has since been replicated in another study using different two-choice tasks (Metin et al., 2013), indicating that inefficient processing appears to be a robust, general cause of ADHD-related performance deficits. Furthermore, a meta-analysis of ADHD individuals’ reaction times to continuous performance tasks (CPTs) using the EZ-diffusion model (Wagenmakers, van der Maas & Grasman, 2007), a closely related variant, also found that performance deficits on CPTs, which are often assumed to index attentional focus, could be attributed to slowed drift rate instead (Huang-Pollock, Karalunas, Tam & Moore, 2012). As this evidence suggests that children with ADHD have slower drift rates in general, and drift rate has been found to be strongly linked to individual differences in WM capacity (Schmiedek et al., 2007), an alternative to the executive attention account of WM deficits in ADHD appears to be possible; less efficient information processing in ADHD, indexed by slower drift rates, impairs WM ability in this population.

Evidence for this account has, in fact, been identified. Karalunas and Huang-Pollock (2013) found that drift rate partially mediated the relationship between ADHD status and WM performance. The similarity of this study's results with the findings of Schmiedek et al. (2007) strongly suggests that efficiency of processing on simple cognitive tasks is highly predictive of WM ability and indicates that observed inefficiency of processing in ADHD may be a cause of WM deficits.

However, as most studies linking efficiency of processing to WM ability in ADHD and in other individual differences (e.g., Karalunas & Huang-Pollock, 2013; Schmiedek et al., 2007; Bayliss et al., 2005) thus far have been entirely correlational, a causal relationship has not yet been established between speed and span. Since the causal direction of this relationship is not yet clear, proponents of the model of WM as executive attention have posited that the link between drift rate on simple tasks and WM ability may, at least partially, be an artifact of inconsistent attention or "mind wandering" during simple tasks in individuals with poor attentional control (McVay & Kane, 2012). The experimental literature on the TBRS model has provided some evidence that processing speed differences cause WM ability differences by limiting the amount of time one has to refresh memory items, but studies that support this model are limited by two factors. First, tasks used in studies supporting the TBRS model (Gaillard et al., 2011; Barrouillet, Bernardin & Camos, 2004) leave more time available for refreshing than typical complex span tasks. Second, these studies have indexed speed as mean reaction times, rather than utilizing a formal model, such as the diffusion model, that takes latency of responses, accuracy of responses, and other sub-components of RT into account. Furthermore, there have not been experimental attempts to demonstrate the causal relationship between speed and WM in ADHD, limiting this model's ability to explain WM deficits specific to this population. The current study is designed to address these limitations and gaps in the literature by directly testing whether manipulating processing speed, as indexed by drift rate in the diffusion model, causally influences WM ability in children with ADHD in a manner consistent with the TBRS model.

VI. Current Study

While the theory of WM as executive attention provides a compelling framework with which to explain ADHD-related WM impairment (Alderson, Hudec, Patros & Kasper, 2013; Rapport et al., 2008), an alternative explanation holds that deficits in basic processing efficiency, as indexed by drift rate, are the cause of the maladaptive individual differences in WM ability often found in children with ADHD (Karalunas & Huang-Pollock, 2013). Therefore, while the role of processing efficiency in WM ability has not been causally determined, doing so may be vital to understanding the core causes of WM deficits in children with ADHD. The current study is designed to experimentally test the hypothesis that individual differences in processing efficiency, as indexed by drift rate, establishes limits on WM capacity and is the cause of ADHD-related WM deficits.

The study uses a newly designed WM measure; a modified version of a well-validated complex span task in which the drift rate of the secondary task ("numerosity task"; (Ratcliff & McKoon, 2008) can be easily manipulated by changing the difficulty of the secondary task. In this way, the efficiency with which the secondary task can be processed is increased or decreased, and the effects of this manipulation can be directly observed independently of speed-accuracy trade off effects. To control for task duration, which may influence memory recall by simply increasing or decreasing the amount of time items must be remembered (Towse & Hitch, 1995), the paradigm equates the time participants are given to complete the distractor tasks across difficulty conditions.

By allowing participants a limited amount of time to complete successive distractor trials, the task provides no free time for refreshing only, fulfilling the concurrent processing constraint of the construct not met by the common experimental paradigm used in research on the TBRS model.

In addition to controlling for speed-accuracy trade-offs and providing an advanced estimate of processing efficiency, diffusion modeling provides an estimation through *Ter* of the amount of time during the secondary task that is not directly spent on the decision process itself. Though most commonly interpreted as an index of stimulus encoding time and the time for motor preparation, *Ter* represents the proportion of RT that is not directly spent on the decision process, and so, in the context of a complex span task in which no time is left explicitly for the refreshing of memory items, could theoretically also represent the amount time spent refreshing (See Figure 1B). This becomes important because if drift rate is slowed in the difficult condition, the distractor decision would fill the attentional bottleneck for a greater amount of time, leaving less time available for refreshing between decision processes in the distractor block (See Figure 1C). A second way, if refreshing does occur during the *Ter* proportion of RT between decision processes, that decreases in drift could negatively impact memory recall in the context of the current task would be by decreasing the opportunities for refreshing in between decision processes; slower drift would lead to increased RT for each decision, so that during a time-limited block of distractor trials, there would be fewer opportunities between successive decision processes to refresh the to-be-recalled information (See Figure 1C/D).

Both possibilities are consistent with TBRS model, as both hold that the amount of refreshing an individual can engage in is reduced by decreases in drift rate and corresponding increases in the time it takes the attentional bottleneck to process distractor decisions. However, they produce distinct predictions. If reduced drift decreases the proportion of time during the distractor block that individuals are able to refresh, mean RTs would remain relatively similar between high and low drift rate conditions, but the proportion of RT spent on non-decision processes (i.e., *Ter*/RT) would decrease. If reduced drift rate instead reduces the number of opportunities between decision processes that individuals have to refresh, mean RT would be longer in the slow drift rate condition, but *Ter* would not change (see Figure 1 C/D). In either case, individuals may be able to compensate for increases in the time the decision process takes up by reducing response caution (*a*); as drift slows and the attentional bottleneck is increasingly occupied by time spent on the distractor task, this time could be reduced by lowering *a*. Thus, these patterns of parameter value differences between the difficulty conditions may further support the TBRS model's account of how speed influences WM ability.

If low processing efficiency is a plausible major factor that impairs WM ability in children with ADHD, children with ADHD will display a similar effect of processing speed on memory recall to typically-developing children. If the WM ability of children with ADHD is not majorly influenced by speed of processing and instead is due to executive attention, a smaller or non-significant effect in this group would be predicted.

Hypotheses

Hypothesis 1: There will be a main effect of difficulty on *v* in which difficult secondary tasks will result in slower *v* than easy secondary tasks.

Hypothesis 2: If processing speed (as indexed by *v*) is a causal factor in determining WM capacity, then WM span on blocks with easy secondary tasks (fast *v* condition) will be greater than memory recall on blocks with difficult secondary tasks (slow *v* condition). However, if speed is not a causal factor in determining WM capacity, this relationship would not be observed.

Hypothesis 3: If an association between drift and WM is seen, then the TBRS model of WM suggests that this relationship exists because slowed speed decreases the amount of time that attention can be devoted to memory refreshing. If this is true, in the current task, this could occur either because reduced drift rate decreases the proportion of time during the distractor block that can be spent refreshing, indexed by the ratio of *Ter* to mean RT, or by increasing RT, and thus reducing the number of opportunities for refreshing between decision processes. If the former explanation is correct, the proportion of RT taken up by nondecision processes (*Ter*/RT) will be lower in the difficult condition than the easy condition, and be lower in the group with slower drift rates (expected to be the ADHD group). If the latter is correct, the nondecision time is expected to remain constant, but the mean of RT is expected to be higher in the difficult condition and in the group with slower drift rates.

Hypothesis 4. It is expected that ADHD-related deficits in WM are determined by the same mechanism as individual differences in WM capacity. Therefore, both typically-developing children and children with ADHD will display a similar effect of *v* on WM, demonstrating that processing speed, rather than another factor (e.g., executive attention) drives WM ability in both groups.

Methods

Sample

Children, ages 8 through 12, were recruited from a community sample as part of an ongoing study on attention and learning processes in school-age children with and without ADHD. Children identified as having ADHD (*N*=72: 47 male) were required to meet DSM-IV criteria for ADHD including age of onset, duration, cross situational severity, and impairment as determined by a parental report on the Diagnostic Interview Schedule for Children version IV (DISC-IV) (Shaffer, Fisher, & Lucas, 1997). At least one parent and one teacher report of behavior on the Attention, Hyperactivity, or ADHD subscales of the Behavioral Assessment Scale for Children (BASC-2: Reynolds & Kamphaus, 2004) or the Conners' Rating Scales (Conners': Conners, 2001) was required to exceed the 85^{th} percentile (T-score>61) was also required. Children prescribed a psychostimulant medication were required to cease taking their medication at least 24 hours in advance of the day of testing.

Non-ADHD controls (*N*=27: 10 male) had never been diagnosed or treated for ADHD in the past. They did not meet criteria for ADHD on the DISC-IV and were below the 79^{th} percentile (T-score≤58) on all of the above listed rating scales. To equate IQ levels between the ADHD and control groups so that group differences could not be attributed to differences in general intelligence, potential non-ADHD controls with an estimated IQ>115 were excluded from participating in the study. In addition, children in both groups with an estimated IQ<80 were also excluded.

The presence of common childhood disorders, such as anxiety, depression, oppositional defiant disorder, and conduct disorder was assessed using the DISC-IV, but the presence of these conditions was not exclusionary. The sample demographics were as follows: (reflecting regional demographics): 72.7% Caucasian/non-Hispanic, 8.1% Caucasian/Hispanic, 2% other Hispanic, 7.1% African American, 1% Asian, 6.1% mixed and 3% unknown/missing.

Cognitive Screening Measures. A 2-subtest short form (Vocabulary, Matrix Reasoning) of the Wechsler Intelligence Scale for Children—IV (WISC-IV: Wechsler, 2003) provided an estimated IQ for participants. The correlation of the 2 subtest short form with the full 12-subtest battery is 0.87 (Sattler, 2008).

<u>Experimental Task</u> The experimental task used was a modified version of the symmetry span task obtained from Randall Engle and colleagues and modified for use in school aged children and for the particular goals of the task (Unsworth, Heitz, Schrock, & Engle, 2005). In order, children completed a short term visual spatial recall block, a numerosity decision block, and a complex span test block, described below.

Recall block. In the first block, children viewed a 4x4 grid in which one square at a time randomly turned red (the target) at a presentation time of 2000ms. Children were told to remember the location of the target, and the number of to-be-remembered targets varied from two to nine, with three trials presented at each set size in random order. The partial credit load scoring system, in which children receive 1 point for each target correctly recalled in the correct position (Conway et al., 2005) was used as an index of short term memory as a baseline measurement to ensure the effectiveness of the secondary distractor task in the complex span blocks of the task negatively impacts memory retention.

Numerosity decision block. Based on the numerosity decision task (Ratcliff & McKoon, 2008; Ratcliff, Love, Thompson & Opfer, 2012), in the second block participants were presented with arrays of asterisks (“candy”) on a 10 × 10 invisible grid within a square box (see example stimulus, Figure 2) and were asked to determine whether the arrays contained a “large” (>50) or “small” (<50) amount of candy. Children were shown examples of “large” (100 asterisks) and small (21 asterisks) “boxes of candy”, and were told to click the right button on the computer mouse if the box contains a small amount and the left mouse button if the box contains a large amount. Children were told to weight speed and accuracy of response equally, “It is very important that you get as many correct as you can and also make your decisions as fast as you can”.

One hundred arrays were presented sequentially, in random order, and no arrays are repeated. Fifty trials in the sequence were from the difficult (slow *v*) condition, with half containing 41-45 asterisks (small) and half containing 56-60 asterisks (large). The remaining 50 trials were from the easy (fast *v*) condition, with half containing 31-35 asterisks (small) and half containing 66-70 asterisks (large). The number of asterisks in each difficulty condition was adopted from prior research investigating the effect of task difficulty on drift rate in different age groups (Ratcliff et al., 2012).

Each individual trial began with a 400ms blank screen, used as a negative mask. Following the mask, the trial array is presented and remains the only item on the screen until a response was recorded. Immediately following the response, the word “Correct” or “Wrong” was presented in blue text below the stimulus array for 1000ms.

Complex span block. In the final block, items in the memory recall task were interleaved with rounds of numerosity discrimination tasks. Before the presentation of each memory item, participants were given 3 seconds to complete as many numerosity discrimination trials (which were selected at random) as possible. After each decision, the array was followed by a blank screen for 100ms. The next array then appeared, and the process is repeated until the 3 second cutoff point is reached. At the cutoff point, the next to-be-remembered visual spatial target was presented immediately, without allowing the participant to respond to the final array presented. The cutoff procedure was employed to ensure that all distractor rounds were of the same length, and specifically that difficult distractor rounds do not last longer than easy distractor rounds. In this way, the task controls for time spent completing the distractor task. No feedback was given on the numerosity decisions in this block because error feedback may be especially distracting. If there were more errors in one of the two experimental conditions, error feedback could become a confounding factor.

Participants completed four trials of each set size (ranging from two to seven memory items) in random order, making twenty four recall trials in all. Twelve of the trials presented were randomly selected to contain difficult numerosity distractor decisions while the remaining twelve contained easy distractor decisions. The partial credit load scoring system was also used as the dependent variable of memory recall. Response time and accuracy data from the trials in the distractor rounds were fit to the diffusion model (procedure described below) to obtain an estimate of drift rate for the secondary task in each condition. Prior to the experimental block, participants completed a practice block that contained three trials at a set size of two.

Procedure

In both age groups, participants completed the experimental paradigm and cognitive screening measures as part of a larger battery of cognitive tasks and neuropsychological tests that includes other measures of working memory. Children's parents were compensated with a gift card of at least $30 and children were allowed to choose a small toy (<$1) from a prize box.

Diffusion Model Fitting

After data collection, the response time and accuracy data from the secondary task were fit to the diffusion model to obtain estimates of the *v* parameter for each participant in each condition (easy/difficult) using the Fast-dm modeling program (Voss & Voss, 2007), downloaded from the authors' website: http://www.psychologie.uni-heidelberg.de/ae/meth/fast-dm. Fast-dm estimates diffusion model parameters by fitting a cumulative distribution function (CDF) of correct trials (represented as "RT") and errors (represented as "-RT") to a CDF predicted by the best-fitting set of diffusion model parameters for each condition. After initial parameter values are determined using the EZ-diffusion diffusion model program (Wagenmakers, Van Der Maas, & Grasman, 2007), Fast-dm uses a simplex-downhill method to fit the predicted and observed distributions in three successive attempts with increasingly strict fit criteria until the best possible model-fit (as indexed by p-value) is achieved. As Fast-dm was able to fit all participants' data to the model well (all ps>.16), no participants were excluded from analysis due to poor model fit.

Data Analysis Plan

Demographics. Initial analyses comparing the ADHD and control groups on parental education and income were conducted using one-way ANOVAs, with group membership as the independent variable and each demographic variable as a dependent variable. To compare the groups' race and ethnicity status, Chi Square tests were used.

Validation of the Measure. For the new complex span paradigm to be validated as working memory measure, rather than a measure of short term memory (which includes memory recall but not concurrent processing of secondary tasks) it must be determined that the secondary numerosity decision task degrades memory retention. To ensure that the secondary distractor task in the complex span block negatively impacts memory retention, individual's scores on the recall-only block of the task and on the complex span block were converted into percentages that reflect the amount of items remembered out of the total amount of items displayed. Following this, recall on the recall-only block and recall on the complex span block were compared using a repeated-measures ANOVA. If, as expected, participants remember a significantly greater percent of items in the recall-only block than on the complex span block, this would indicate that the numerosity decision task affects memory retention and lends support to the paradigm as a valid measure of working memory.

Hypothesis Testing. To test the main hypotheses and exploratory hypotheses of the study, four 2 × 2 (Difficulty × Group) repeated-measures ANOVAs were conducted on *v*, *a*, and *Ter* on the distractor task rounds and memory recall. All ANOVAs had Difficulty condition (2: easy/difficult) as a within-subjects factor and Group (2: ADHD/control) as a between-subjects factor.

For the first ANOVA (*v*), main effects of difficulty condition and ADHD status were expected, with participants displaying faster *v* in the easy condition than the difficult condition (supporting Hypothesis 1) and controls having significantly faster *v* than children with ADHD (supporting Hypothesis 4). No specific interaction effects on *v* were expected.

For *Ter*, no effects of Difficulty or Group were expected (Hypothesis 2A). For *a*, no effect of group was expected. However, in line with the TBRS model, a main effect of Difficulty was anticipated, in which participants strategically decrease *a* in the difficult condition to increase refreshing time (Hypothesis 2B).

For the ANOVA on memory recall, main effects of difficulty condition and ADHD status were expected. For the main effect of ADHD status, it was expected that typically-developing children would display greater memory recall than children with ADHD, supporting Hypothesis 4. For the main effect of difficulty condition, it was expected that memory recall in the easy condition would be greater than memory recall in the difficult condition. This would lend support to Hypothesis 3A, that increasing the difficulty and thus decreasing the processing efficiency of the secondary distractor task in a working memory measure, even when controlling for processing time, can decrease memory retention. Importantly, no Diagnosis × Group interaction was expected, supporting the prediction that processing speed is directly related to WM ability in both typically-developing children and children with ADHD (Hypothesis 5A).

An exploratory analysis investigating the independent effects of each diffusion model parameter on memory recall was also conducted. A multiple regression analysis was run in which individuals' *v*, *a*, and *Ter* (averaged across difficulty conditions) were entered as predictors and memory recall (also averaged) was entered as the dependent variable. It was anticipated that, as in prior research (e.g. Karalunas & Huang-Pollock, 2013), *v* and memory recall would be positively related. In line with the TBRS model, it was also expected that *a* would be negatively related to WM ability (as reduced *a* would increase opportunities for refreshing and thus memory recall ability) and *Ter* would be positively related to WM ability, as this would indicate greater time spent on refreshing processes during the secondary task block.

Results

Preliminary Group Analyses. Table 1 provides descriptive statistics. Comparisons of symptom counts indicated that children with ADHD displayed more inattentive, $F(2)=267.98, p<.001$, and hyperactive/impulsive, $F(2)=54.65, p<.001$, symptoms than controls. There were no statistically significant group differences in FSIQ, $F(2)=1.30, p=.275$, or age, $F(2)=1.31, p=.277$.

Validation of WM Measure. A Span Type (2: Simple/Complex) × Group (2: ADHD/Control) repeated measures ANOVA comparing the percentage of items recalled on the recall-only vs. complex span portions of the task confirmed that participants recalled fewer items while concurrently performing the numerosity-discrimination task, $F(1,97)=83.98, \eta^2=.46, p<.001$, thus validating this portion of the task as a measure of WM. A smaller interaction effect was also discovered, $F(1,97)=5.64, \eta^2=.06, p=.02$, in which children with ADHD displayed greater performance decrements when the secondary task was added than typically-developing children (see Figure 3). However, inspection of the post hoc analyses indicated that both children with ADHD, $F(1,71)=106.44, \eta^2=.60, p<.001$, and typically developing controls, $F(1,26)=26.43, \eta^2=.50, p<.001$, displayed performance decrements in the complex, relative to simple span block.

Practice Numerosity Decision Trials. RT, accuracy, and diffusion model parameter data from the numerosity practice block is displayed in Figure 4. Children were slower to respond on the practice trials in the difficult condition than those in the easy condition, $F(1,97)=35.18, \eta^2=.27, p<.001$, and children with

ADHD displayed slower RTs overall, $F(1,97)=9.21, \eta^2=.09, p=.003$. Children were also less accurate in the difficult condition, $F(1,97)=177.69, \eta^2=.65, p<.001$, and children with ADHD were less accurate overall, $F(1,97)=119.70, \eta^2=.10, p=.001$. While children with ADHD displayed more variable RTs overall, $F(1,97)=109.27, \eta^2=.09, p=.002$, there were no differences between, $F(1,97)=1.17, \eta^2=.01, p=.28$, or interactions with, $F(1,97)=.10, \eta^2<.01, p=.76$, difficulty condition. No interactions were detected in mean RT, $F(1,97)=.09, \eta^2<.01, p=.77$, or accuracy, $F(1,97)=1.73, \eta^2=.02, p=.19$.

Only 50 trials in each difficulty condition were presented during the practice block and thus only 50 trials per condition were entered into Fast-dm. Traditionally, diffusion model estimates are made when there are at least 80 trials available, although Fast-dm has been demonstrated to recover parameters well from as few as 20 RTs (Voss & Voss, 2007). Thus, some caution may be warranted because the lower trial numbers may have led to unstable estimates of parameters. Regardless, all fits appeared to be adequate (all $p > .45$). Diffusion model estimates in the practice block revealed that children displayed slower drift rate, $F(1,97)=57.63, \eta^2=.64, p<.001$, narrower boundary separation, $F(1,97)=29.36, \eta^2=.23, p<.001$, and longer nondecision times, $F(1,97)=23.18, \eta^2=.19, p<.001$, in the more difficult, relative to the easy condition. Children with ADHD displayed slower drift rate, $F(1,97)=18.68, \eta^2=.16, p<.001$, and wider boundary separation, $F(1,97)=7.74, \eta^2=.07, p=.006$, than controls, but did not differ in nondecision time, $F(1,97)=.10 \eta^2<.01, p=.75$. No significant interactions were identified (all *p*s>.056).

Comparison of diffusion model parameters in the practice block with those during the complex span task revealed that children displayed slower drift rate, $F(1,97)=288.44, \eta^2=.63, p<.001$, and shorter nondecision time, $F(1,97)=239.68, \eta^2=.71, p<.001$, in the complex span block. An interaction was detected, $F(1,97)=6.74, \eta^2=.07, p=.011$, in which children with ADHD lowered boundary separation in the complex span block, $F(1,72)=8.74, \eta^2=.11, p=.004$, but typically developing controls did not show a significant effect, $F(1,26)=2.72, \eta^2=.10, p=.11$.

Numerosity Decision during Complex Span Task. RT and accuracy data from the numerosity discrimination task when it was embedded in the complex span task are displayed in Table 2 and Figure 5. Children with ADHD were less accurate, $F(1,97)=13.62, \eta^2=.12, p<.001$, and had more variable RTs, $F(1,97)=5.71, \eta^2=.06, p=.019$, than controls. There were no effects of group in mean RT, $F(1,97)=.39, \eta^2=.004, p=.53$. Effects on all diffusion model parameters are displayed in Figure 6. As expected, children with ADHD displayed slower drift rates than their typically-developing counterparts, $F(1,97)=14.92, \eta^2=.13, p<.001$, though there were no significant group differences in boundary separation, $F(1,97)=.004, \eta^2<.001, p=.95$, or non-decision time, $F(1,97)=2.91, \eta^2=.03, p=.09$. Furthermore, as predicted by the TBRS model, the proportion of RT spent on non-decision processes (Prop*Ter*=*Ter*/mean RT) was diminished in the - lower drift rate - ADHD group relative to controls, $F(1,97)=4.60, \eta^2=.05, p=.035$ (see Figure 7).

Compared to the easy discrimination trials, the more difficult numerosity discriminations yielded increased error rates, $F(1,97)=384.41, \eta^2=.80, p<.001$, and RT variability, $F(1,97)=25.10, \eta^2=.21, p<.001$, but did not lengthen mean RT, $F(1,97)=3.07, \eta^2=.03, p=.08$. A condition x group interaction in accuracy, $F(1,97)=9.40, \eta^2=.09, p=.003$, revealed that differences between the groups in accuracy in the easy condition, $F(1,97)=16.73, \eta^2=.15, p<.001$, were larger than those in the difficult condition, $F(1,97)=7.45, \eta^2=.07, p=.008$. There were no interactions between group status and difficulty condition in RT, $F(1,97)=.82, \eta^2=.008, p=.37$, or RT variability, $F(1,97)=.15, \eta^2=.02, p=.149$.

The difficult, relative to the easy condition slowed drift rate, $F(1,97)=302.52, \eta^2=.76$, $p<.001$ and decreased boundary separation, $F(1,97)=31.41, \eta^2=.25, p<.001$, suggesting the presence of a strategic speed/accuracy trade-off effect to compensate for slower drift. There was no significant effect of condition on *Ter*, $F(1,97)=3.51, \eta^2=.04, p=.064$. However, the proportion of RT that could be spent on refreshing (i.e. Prop*Ter*) was much smaller in the difficult condition, $F(1,97)=9.52, \eta^2=.09, p=.003$, in line with the TBRS model's assertion that tasks requiring longer processing time decrease this ratio. An unexpected significant interaction with group was also detected in drift rate, $F(1,97)=13.52, \eta^2=.12, p<.001$, in which the group difference in drift rate in the easy condition, $F(1,97)=16.32, \eta^2=.14, p<.001$, was larger than in the difficult condition, $F(1,97)=9.33, \eta^2=.09, p=.003$. There were no comparable interactions with group in the boundary parameter, $F(1,97)=1.80, \eta^2=.02, p=.18$, in *Ter*, $F(1,97)=.068, \eta^2=.001, p=.80$, or in Prop*Ter*, $F(1,97)=.14, \eta^2=.001, p=.71$.

WM performance. Consistent with study hypotheses, a main effect of difficulty condition on WM performance was detected, $F(1,97)=6.52, \eta^2=.06, p=.012$, with children displaying poorer recall in the difficult condition (Figure 8). As expected, children with ADHD also displayed poorer recall overall than control children, $F(1,97)=23.77, \eta^2=.79, p<.001$. Crucially, no interaction between difficulty condition and group status was detected, $F(1,97)=.40, \eta^2=.004, p=.53$, suggesting that for both groups, working memory capacity was similarly affected by changes in processing efficiency.

Individual Differences Regression Analysis. To replicate the findings of Schmiedek et al. (2007) and Karalunas & Huang-Pollock (2013), who found strong associations between individual differences in drift rate on separate laboratory tasks and WM ability, a regression analysis was conducted using the diffusion model estimates of performance during the complex span task to predict memory recall on the same task. Table 3 displays the correlation matrix of all model parameters and WM performance, averaged between difficulty conditions. The regression model, in which all three model parameters of interest were entered as predictors of WM, explained a significant portion of variance in WM ability, $F(3,98)=5.68, R^2=.15, p=.012$. However, only drift rate was a significant predictor, $b=.40, t(98)=4.06$, $p<.001$, while boundary separation, $b=.04, t(98)=.38$ $p=.71$, and nondecision time, $b=-.11, t(98)=-1.07$, $p=.29$, had no effect on WM.

Discussion

Past correlational research has suggested that ADHD-related WM impairment is driven by slower processing speed in individuals in ADHD (Karalunas & Huang-Pollock, 2013). The current study sought to experimentally test the hypotheses that manipulating processing speed, as operationalized by drift rate in an evidence accumulation model framework, causally impacts WM performance, and that this relationship is similar in children with ADHD and typically developing children. As expected, an experimental manipulation that slowed processing speed within subjects also decreased WM recall, a relationship that was present both in children with ADHD and their typically-developing counterparts. This pattern of results provides experimental support for theories of individual and ADHD-related differences in WM ability that emphasize the causal role of basic processing efficiency (e.g., Barrouillet & Camos, 2012; Fry & Hale, 2000; Karalunas & Huang-Pollock, 2013; Schmiedek et al., 2007). The study also sought to clarify *how* slowed processing efficiency on simple tasks may causally impact WM ability in both groups. The Time-Based Resource-Sharing model (Portrat et al., 2009), which posits that WM ability is constrained by the speed with which an individual can complete secondary processing tasks, provides such a causal explanation; slower speed increases time that must be spent processing concurrent tasks, and thus leaves less time available for individuals to refresh memory items. This explanation was upheld by analyses demonstrating that the proportion of time available for refreshing, relative to the proportion of time that must be spent processing concurrent tasks, was reduced when processing speed was reduced.

In order to test these questions, a novel WM paradigm, based on prior “complex span” paradigms (Daneman & Carpenter, 1980; Conway et al., 2005), was created. Children were presented to-be-remembered visual targets interspersed with numerosity decision trials, which varied in difficulty. As expected, memory recall was strongly degraded when children completed the secondary task while maintaining the targets in short term memory storage, and this was seen regardless of diagnostic status. Furthermore, increasing the difficulty of the secondary task lead to decreased accuracy and slowed drift rates, indicative of decreased processing speed, on the distractor trials.

Consistent with predictions, manipulating the difficulty of the distractor task not only slowed processing efficiency on distractor trials, but also diminished WM performance on the separate recall component of the task. This finding demonstrates that processing efficiency can causally influence WM performance, and thus shows that processing efficiency is a plausible cause of WM capacity differences due to developmental immaturity (Bayliss et al., 2004: Fry & Hale, 2000), individual variability (Schmiedek et al., 2007), or ADHD-related impairment (Karalunas & Huang-Pollock, 2013). The finding that processing efficiency drives WM ability could not be attributed to increases in the absolute amount of time items must be held in WM, as earlier time-based models of WM would posit (e.g., Towse & Hitch, 1995), because an explicit control in the experimental design held this time constant.

Other models have suggested that it is instead the ability to control attention that drives individual differences in WM capacity (Engle, 2002; Unsworth and Engle, 2007). However, those models would not have predicted a direct effect of changes in processing efficiency/speed on recall. That is, proponents of the attentional control models of WM have suggested that the predictive relationship of speed to WM capacity is primarily driven by the long RTs at the extreme end of an individual's RT (which are prominent in the determination of drift rate), and which they attributed to the presence of attentional lapses (McVay & Kane, 2012). However, this particular interpretation of the long tail suggests that any manipulation that increases the difficulty of a task and slows RT (such as the one used in the current study) does so because that manipulation causes more frequent attentional lapses. Such a suggestion does not seem logically plausible. Instead, the current study demonstrates the presence of a causal link between cognitive processing speed (as indexed by drift rate) and WM performance, and thus does not support this model.

Another alternative account of this result from the perspective of executive attention theories of WM may posit that the more difficult distractor task taxed executive functions more or demanded greater attention than the easy distractor task. If this position is accurate, lower WM recall in the more difficult, slower processing efficiency, condition could be attributed to subjects displaying poorer attentional control while performing more difficult tasks. However, even if greater task difficulty somehow taxed attentional processes to a greater degree, this would be unlikely to affect memory recall on complex span tasks. A long-standing tenet of cognitive psychology, supported by a wealth of empirical tests, is that effortful, attentional processes are serial in nature (Shiffrin & Schnieder, 1977). This assumption is shared by TBRS (Portrat et al., 2011) and executive attention (Unsworth & Engle, 2007) theories of WM ability, which both hold that, during the completion of secondary processing tasks, all items in WM are removed from the focus of attention. Therefore, whether attentional control is taxed to a greater degree during the more difficult numerosity discrimination trials is irrelevant to memory, which occurs only after attention is re-directed to the memory items. Any effects of attentional control deficits related to task difficulty that remove memory items from this attentional focus would imply parallel processing – which is an unlikely possibility for attention-demanding tasks (Shiffrin & Schnieder, 1977) and which violates the assumptions of the executive attention theory of WM itself (Unsworth & Engle, 2007).

Specific to ADHD-related WM variation, it was predicted that the causal influence of speed would be similar between the group of typically-developing children and children with ADHD, and this was in fact the case. Accounts of ADHD-related WM deficits highlight the role of top-down executive control (Alderson, Hudec, Patros & Kasper, 2013; Rapport et al., 2008) and predict that the processing efficiency manipulation would have a marginal effect on WM performance in the clinical group, but this was not the case. Therefore, the current study confirms prior correlational research findings suggesting that efficiency of processing, when measured by drift rate in an evidence accumulation model framework, drives WM deficits in children with ADHD (Karalunas & Huang-Pollock, 2013).

Using the novel paradigm, the study was also able to test the validity of the TBRS model, in particular, for explaining *how* differences in drift rate may change WM performance, both in typically and atypically developing populations. In this model, items in WM are maintained by the process of returning them to an "all or none" serial focus of attention for brief "refreshing" periods in between the completion of concurrent processing tasks (Portrat et al., 2009). Individual differences in WM performance can then be understood in relation to the ratio of time individuals are able to spend refreshing relative to time spent completing concurrent tasks (Barrouillet & Camos, 2012). The model has been supported by prior experimental work (Portrat et al., 2009; Gaillard et al., 2011), though the previous work often allowed participants greater periods of time to refresh or rehearse memory items than is typical of WM paradigms (Conway et. Al., 2005) and did not operationalized processing efficiency with formal evidence accumulation models.

In the context of the current study, it was proposed that refreshing processes in between decisions on the numerosity task would be captured by the model parameter of *Ter*, as this parameter indexes the component of RT spent on any non-decision processes before and after simple decisions are made (Ratcliff & McKoon, 2008; see Figure 1B), and as no time was explicitly provided between trials for refreshing. Specifically, it was assumed that decreases in drift rate could impact WM recall in two ways. First, slowed drift rate could decrease the proportion of RT that was spent refreshing memory items, leaving RT length unaffected. If this was the case, then the manipulation would decrease the amount of time that the attentional bottleneck could be devoted to refreshing processes relative to the amount of time it could be focused on completing the distractor decisions (Figure 1C). A second possibility was that slower drift rate could result in increased RT, but the amount of time spent refreshing between decisions would not change (Figure 1D). This effect would reduce memory recall by limiting the number of opportunities an individual would have to refresh between decision processes. The former possibility predicted that RT would remain constant between difficulty conditions and groups that differed in drift rates (e.g., ADHD vs. control), but that the proportion of RT taken up by *Ter* would decrease with increasing difficulty, and be lower in the group with lower drift rate. The latter possibility predicted that RT would increase with difficulty and would be longer in the group with slower drift rate and lower WM ability.

To test these alternate possibilities, the proportion of time spent on non-decision processes (*Ter*) was divided by the total time spent responding to the distractor trials (mean RT) for each participant to obtain a rough estimate of the refreshing/decision-processing ratio ("Prop*Ter*"). As predicted by the first explanation, both groups displayed decreases in this parameter in the difficult condition, and children with ADHD, the group with slower drift rate and lower WM recall, displayed lower ratios overall. Furthermore, there were no differences in mean RT length between difficulty conditions or groups, making the second causal explanation unlikely. Thus, the results point to a single clear and testable explanation for how drift rate reductions affect WM maintenance that is consistent with the TBRS model.

Potentially relevant to this explanation, a speed/accuracy trade-off effect in the boundary separation parameter was also observed. Children in both groups reduced their caution in the difficult condition, an effect that typically decreases decision times at the cost of reduced accuracy (Ratcliff & McKoon, 2008). This decrease, in the context of the above explanation, can be seen as a strategic choice by participants to allow more time for refreshing; if participants notice that decreased processing efficiency in the difficult condition constrains the amount of time they have to refresh memory items, becoming less cautious at their decision-making, and thus shortening the amount of time they must spend processing the secondary task, would partially counteract this effect. While it has been argued by some groups (e.g., Conway et al., 2005) that individuals do not "trade off" between processing and storage functions in complex span tasks (for example, accepting poor performance on the distractor trials in favor of putting more effort into memory maintenance), these results suggest that the opposite is true. Conway et al. (2005) point to individual differences studies finding that individuals who perform well on the secondary task also perform well in memory recall as evidence for a lack of trade-offs. However, this relationship could be explained equally well be the pattern of findings in the current study; individuals who are faster at the secondary tasks would have improved memory recall simply because they are better able to refresh memory items, though within-subjects trade-offs in secondary task performance may very well occur.

Beyond questions of WM ability and task strategy, the boundary separation findings are also relevant to recent work on speed/accuracy trade-offs in ADHD. Multiple groups have found evidence that children with ADHD display difficulty implementing controlled speed/accuracy trade-offs when explicit (Mulder et al., 2010) or implicit (Weigard & Huang-Pollock, 2014) task demands value either a cautious or speed-emphasizing mode of responding. However, the current results demonstrate that, at least in the context of the study task, individuals with ADHD were able to respond to task demands, which valued shorter decisions allowing more time for refreshing, by implementing speed/accuracy trade-offs to the same degree as their typically-developing peers. Future research on this process in ADHD should seek to clarify which situations create difficulty for individuals with ADHD to implement the process, and why these situations differ from those in which impairment is observed.

The analysis of Prop*Ter*, despite being a direct test of the TBRS model's ability to account for the data, is nonetheless limited by the fact that the model parameter *Ter* has never before been interpreted as an index of refreshing time. In the context of the current task, theoretically, any time spent refreshing between distractor trials should theoretically be picked up by *Ter*, this parameter has traditionally been seen as an index of other nondecision processes present in RT, including stimulus encoding and motor preparation (Ratcliff & McKoon, 2008). Future research that integrates evidence accumulation models like the diffusion model with resource-sharing accounts of WM should attempt specific, falsifiable tests of this explanation before it can be accepted.

These data also replicate several effects from prior literature and displays a handful of unexpected, but relevant, findings. First, the regression analysis conducted in which diffusion model parameters were allowed to predict WM ability replicates prior studies that have linked individual differences in drift rate to those in WM (Karalunas & Huang-Pollock, 2013; Schmiedek et al., 2007), and thus provides additional evidence for the link between these individual-difference constructs. Second, the main effects of ADHD status on drift rate and WM ability replicate two now well-established findings from prior literature on the disorder; that individuals with ADHD display substantial impairment in WM (Kasper et al., 2012; Schoechlin & Engle, 2005), and display reduced drift rate relative to their typically-developing peers, indicative of abnormalities in basic information processing (Karalunas et al., 2012; 2014; Metin et al., 2013). In addition to providing more evidence in favor of these established findings, the results also indicate that the experimental task, while novel, provides valid measures of individuals' drift rate estimates and WM ability.

While not expected, tests to validate the measure as an index of WM revealed a significant interaction in which children with ADHD displayed greater reductions in WM performance when the secondary processing task was added than their typically-developing peers (though typically developing children also displayed large decrements). This interaction effect may simply indicate that children with ADHD display more difficulty remembering items when there are concurrent processing demands relative to when these demands are minimal (e.g., only refreshing/rehearsing memory items). This interpretation would be consistent with the related theories that WM tasks must involve both concurrent processing and storage components (Conway et al., 2005; Daneman & Carpenter, 1980) and that children with ADHD display primary deficits in WM rather than short term memory recall in general (Castellanos & Tannock, 2002; Willcutt et al., 2005). Another unexpected interaction indicated that drift rate differences between the groups were larger in the easy condition than the difficult condition. While this effect may simply reflect a floor effect in children with ADHD's scores in the difficult condition or could have emerged as a peculiarity of decision tasks completed during memory maintenance, it also could indicate that differences in drift rate between children with ADHD an their typically-developing peers could be somewhat dependent on task difficulty. Future research extending findings on the effects of ADHD or other neurocognitive disorders on diffusion model parameters may be advised manipulate task difficulty levels to further explore this possibility.

The primary finding of the study, that ADHD-related WM deficits can be attributed to basic processing efficiency, has practical implications beyond causal theoretical models of ADHD. As the substantial academic difficulty faced by children with ADHD (Frazier, Youngstrom, Glutting & Watkins, 2007) can be attributed in large part to WM impairment (Alloway et al., 2009; Gathercole and Pickering, 2000; Gremillion & Martel, 2012), targeted methods for addressing speed-related WM problems in the classroom may provide ways to help children with ADHD improve their academic competence. For instance, reasonable accommodations that reduce concurrent processing demands in children with

ADHD, such as external supports (e.g., pen and paper for note taking and math problems, sheets that contain reminders of concepts or formulas) and access to technology (e.g., calculators), may be particularly helpful for reducing the impact of WM impairment on achievement. In contrast, attempts to improve WM ability through the training of attention (e.g., Klingberg, 2010) may be less fruitful because they do no address processing speed, as a core determinant of WM ability.

In sum, the current study used novel methods to produce findings that have direct relevance to basic theories of WM, models of ADHD, and clinical practice with children displaying ADHD-related academic impairment. First, for theories of WM, the current study demonstrates that manipulating basic processing efficiency can causally alter WM performance, and thus validates theories denoting processing speed as the cause of individual and developmental differences in WM (Barrouillet & Camos, 2012; Fry & Hale, 2000; Karalunas & Huang-Pollock, 2013; Schmiedek et al., 2007). The findings also suggest a specific explanation for how speed drives WM ability, consistent with a major current model of WM (TBRS: Portrat et al., 2009), that highlights the crucial role of time-limited memory refreshing processes to WM maintenance. Second, the study demonstrates that, despite the intuitive nature of explanations attributing ADHD-related WM deficits to deficits in attention or other executive processes (Alderson et al., 2013; Rapport et al., 2005), a more likely possibility is that WM deficits in ADHD occur, at least in part, because of deficits in basic processing efficiency. Finally, by providing a coherent, causal account of WM deficits in

ADHD, the study can help inform clinical practice; clarification of the underlying mechanisms of this impairment may lead to novel accommodations and interventions that allow children with ADHD to succeed academically despite limitations in this crucial function.

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Appendix: Figures and Tables

Figure 1A. Schematic of the diffusion decision process (Ratcliff, 2002)

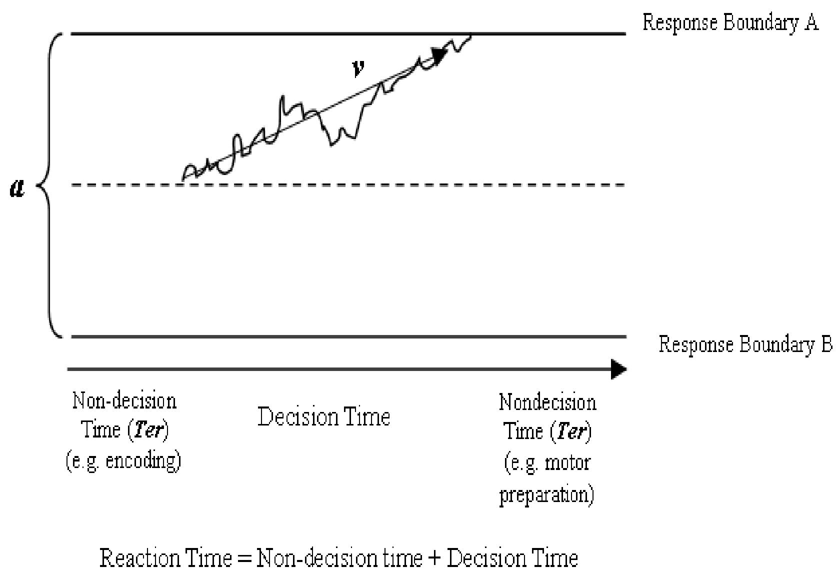

Figure 1B. Proposed components of nondecision time

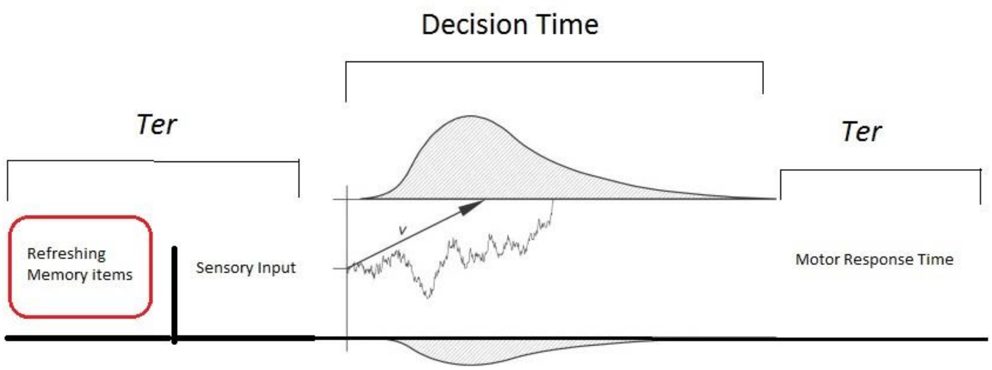

Figure 1C/D. Effect of reduced drift on time available for refreshing between decision processes for both TBRS explanations outlined in the text. *Explanation A*: Reduced drift rate decreases the amount of time available for refreshing between each decision process. Note that the same number of decisions are made in the block, and thus that there are equal numbers of opportunities for refreshing between conditions, but the length of these pauses between decisions is reduced, thus decreasing the total amount of time available for refreshing. *Explanation B*: Reduced drift increases total RT, providing fewer between-decision opportunities for refreshing. However, the amount of time available for refreshing in the pauses remains the same.

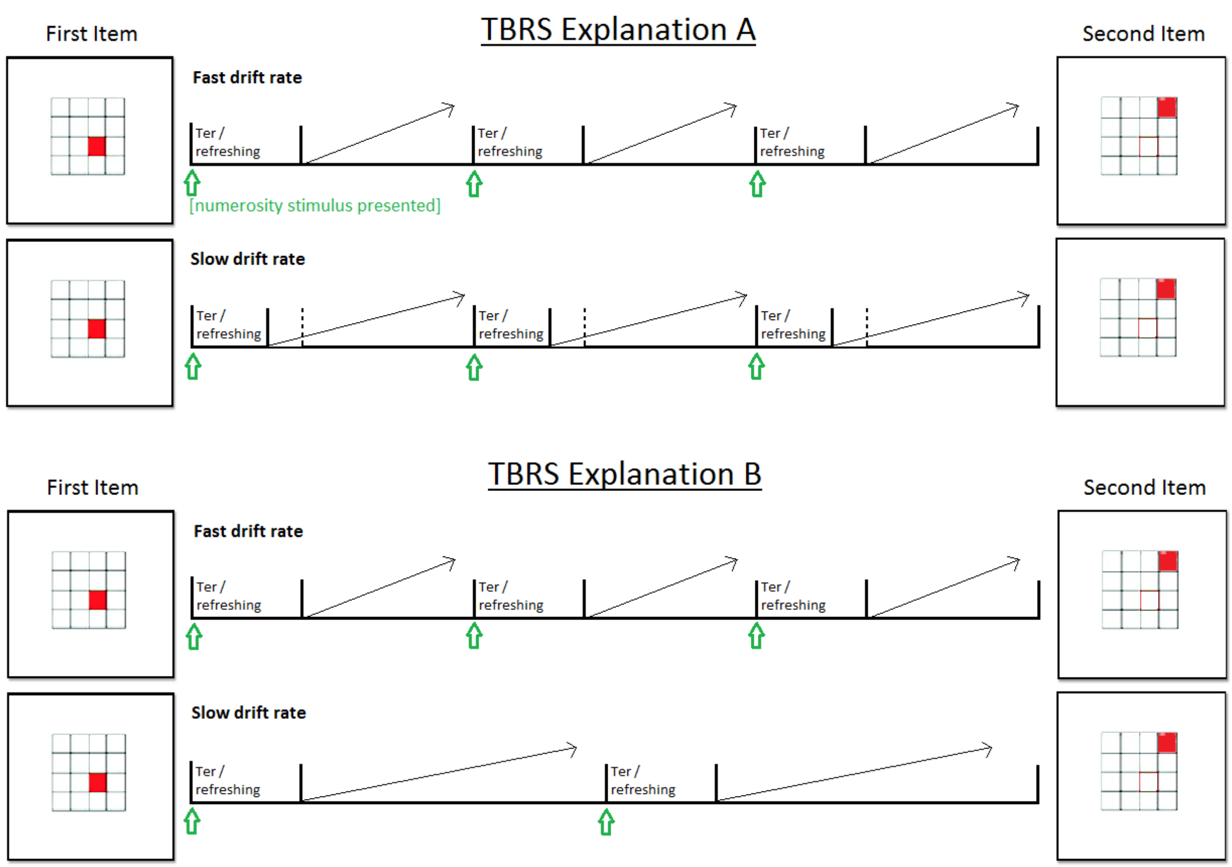

Figure 2. Example stimulus from numerosity discrimination task

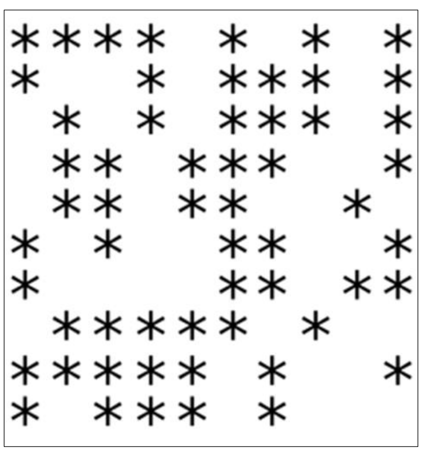

Figure 3. Differences between simple and complex span on the new measure in percentage of items correctly recalled (error bars reflect standard error of the mean); Control = dashed line, ADHD = solid line

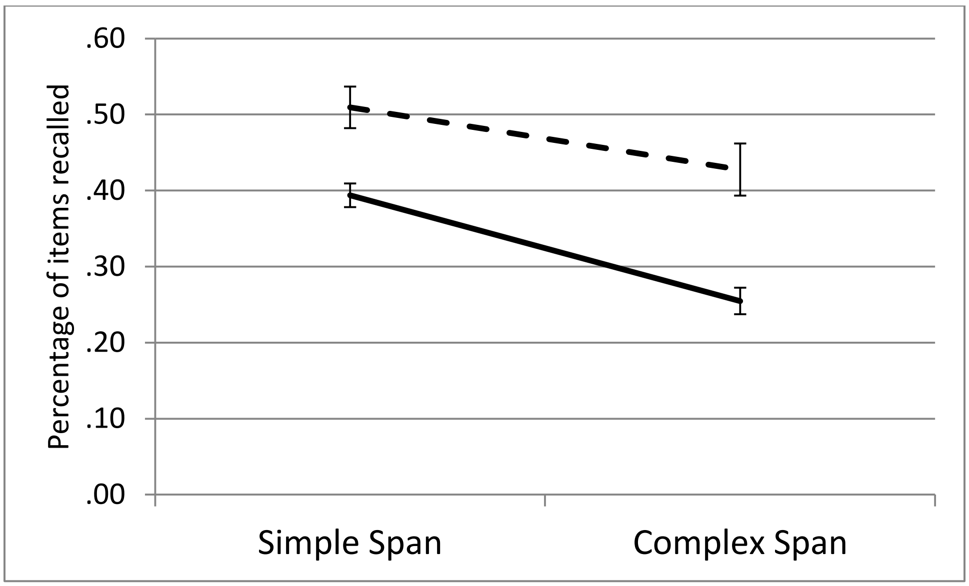

Figure 4. Effects of difficulty on traditional indices and diffusion model parameters in the practice block (error bars reflect standard error of the mean); Control = dashed line, ADHD = solid line

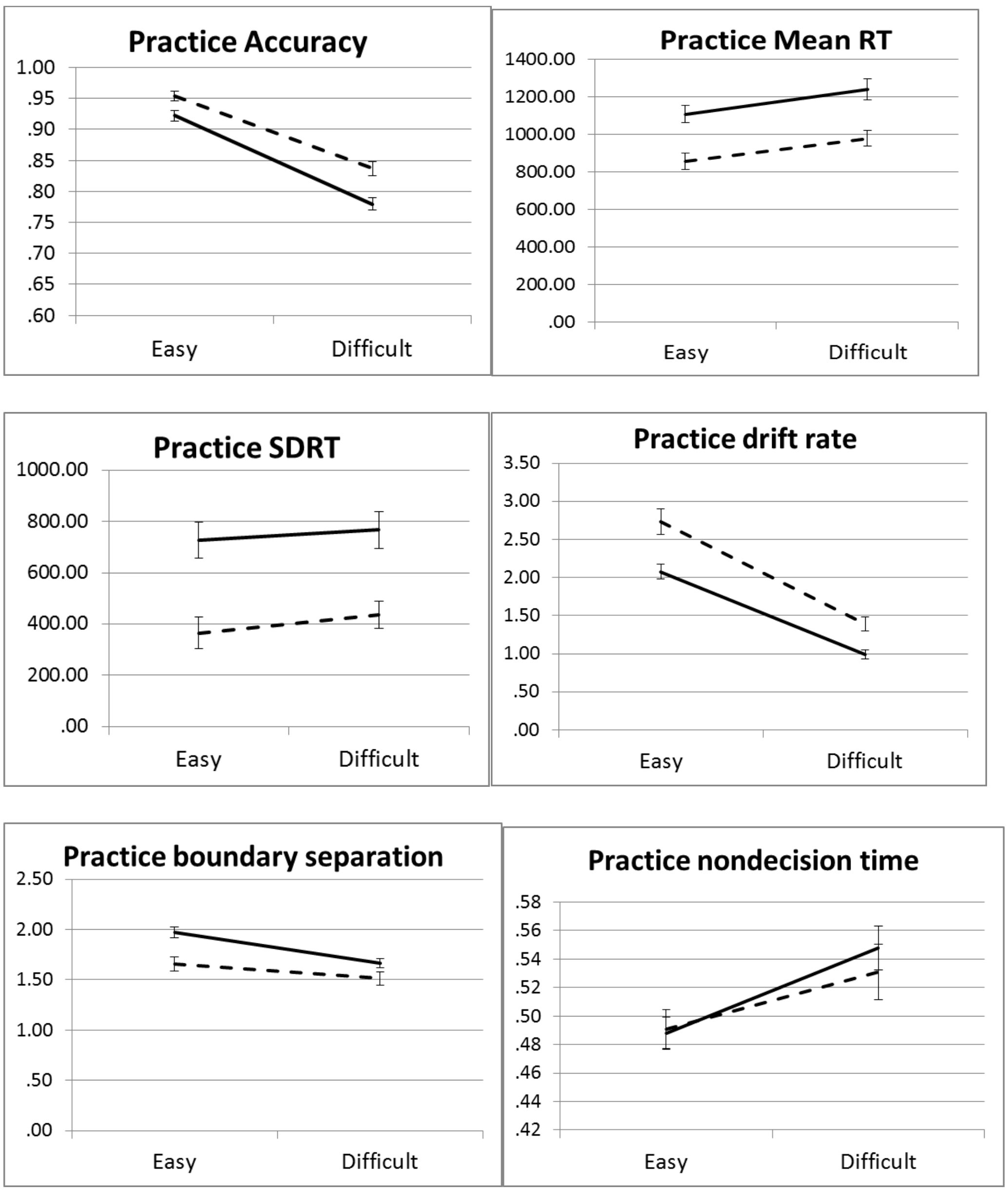

Figure 5. Effects of difficulty on traditional performance measures during the complex span task (error bars reflect standard error of the mean); Control = dashed line, ADHD = solid line

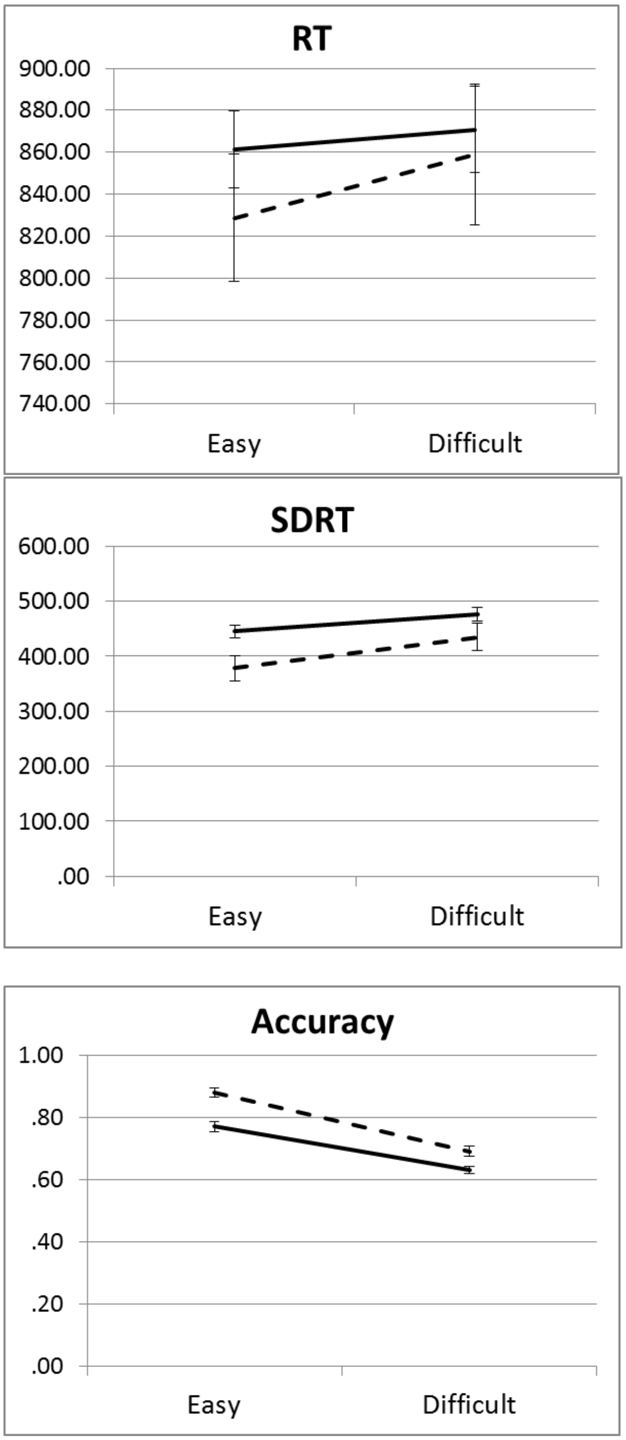

Figure 6. Effects of difficulty on diffusion model parameters during the complex span task (error bars reflect standard error of the mean); Control = dashed line, ADHD = solid line

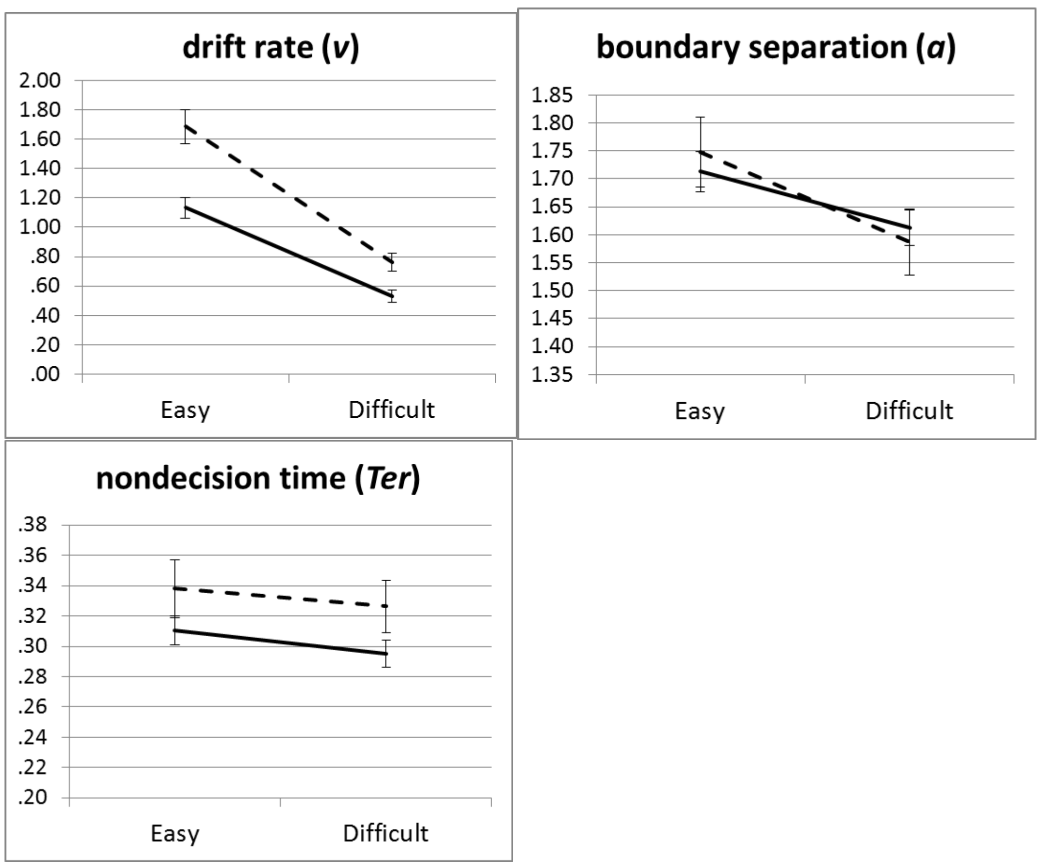

Figure 7. Effects of difficulty on the proportion of RT available for refreshing (error bars reflect standard error of the mean); Control = dashed line, ADHD = solid line

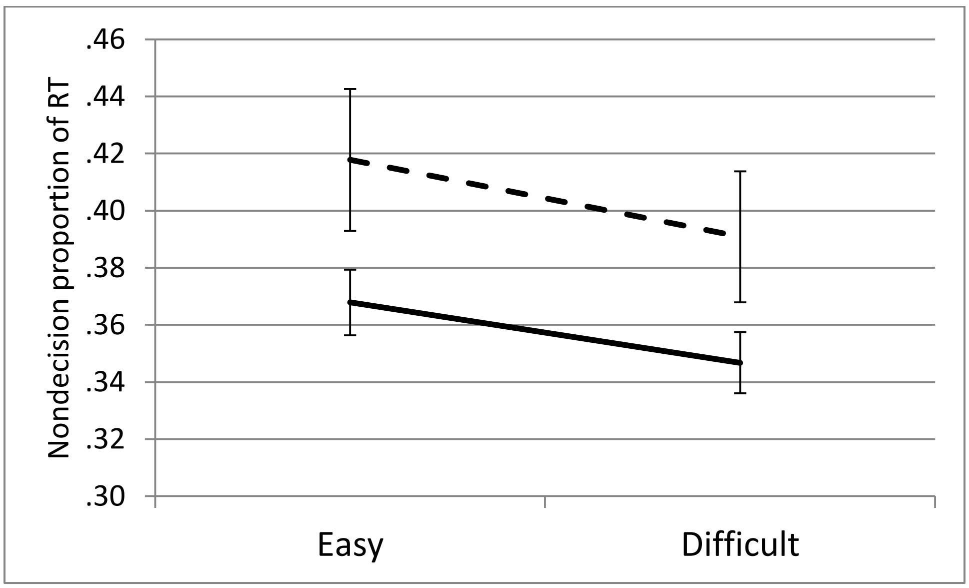

Figure 8. Effects of difficulty on WM performance (error bars reflect standard error of the mean); Control = dashed line, ADHD = solid line

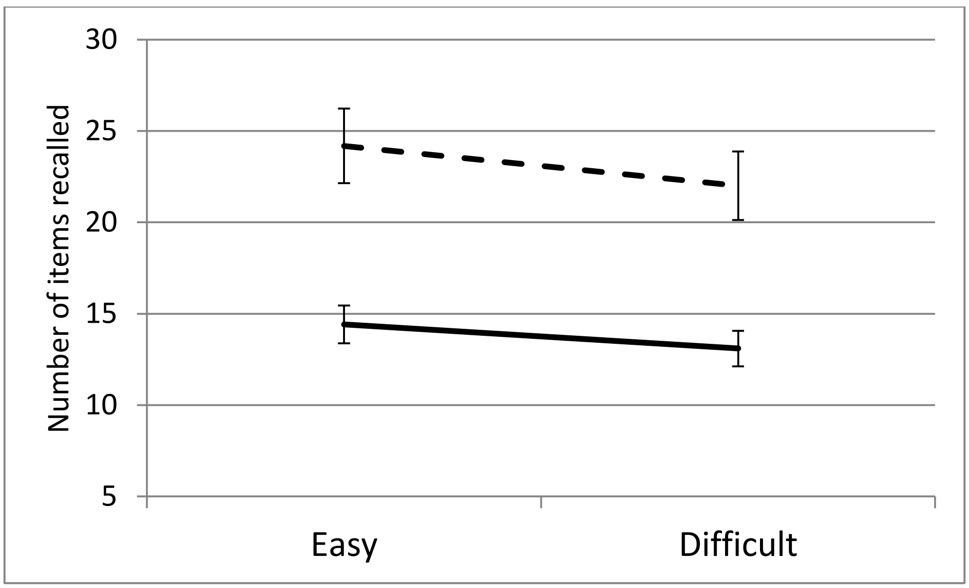

Table 1. Description of groups. Means, with standard deviation in parentheses. All ratings scales reported in T-scores.

	Control	***ADHD***
N(Males:Females)	27(10:17)	72(47:25)
#Subtypes (H,I,C)		2,31,39
Age	9.76(1.27)	9.94(1.76)
Estimated FSIQ	106.52(7.38)	102.66(13.50)
Hyperactivity/Impulsivity		
Total # of symptoms	0.30(.61)	5.68(2.64)***
Parent BASC-2	45.37(3.05)	66.83(13.46)***
Parent Conners	45.37(3.05)	68.06(14.28)***
Teacher BASC-2	43.19(2.75)	58.24(12.43)***
Teacher Conners	45.56(2.33)	56.92(11.40)***
Inattention		
Total # of symptoms	0.30(.47)	7.86(1.67)***
Parent BASC-2	42.70(6.97)	66.31(8.21)***
Parent Conners	46.48(3.59)	68.85(10.62)***
Teacher BASC-2	43.56(5.00)	60.32(7.33)***
Teacher Conners	47.22 (4.42)	57.17(10.56)***
Comorbidity (DISC: past year)		
MDD	0	4
GAD	0	5
ODD/CD	2/0	29/8

*p<.05, *** p<.001

Table 2. Mean RT (ms), accuracy rates, and standard deviations in both conditions and practice round. Standard deviations in parentheses reflect between-participant score variability, not within-participant RT variability.

	Control	***ADHD***
Practice Trials		
RT	1081(398.60)	1032(275.64)
Accuracy	.83(.17)	.78(.17)
SD-RT	379(166.02)	425(160.81)
Easy Trials		
RT	829(158.14)	861(156.08)
Accuracy	.88(.08)	.77(.13)***
SD-RT	378(117.77)	445(99.84)
Difficult Trials		
RT	859(173.60)	870(174.34)
Accuracy	.69(1.47)	.63(1.67)*
SD-RT	434(129.04)	476(103.73)*

*$p<.05$, *** $p<.001$

Table 3. Correlations of individuals' diffusion model parameters and WM ability

	v	***a***	***t0***	***WM***
drift rate (*v*)		.06	.30*	.374***
boundary separation (*a*)			-.085	.07
nondecision time (*t0*)				.01

*p<.05, *** p<.001