PROCESSING SPEED IN CHILDREN: EXAMINATION OF THE STRUCTURE IN MIDDLE CHILDHOOD AND ITS IMPACT ON READING

A Dissertation

Presented to

The Faculty of the Department

of Psychology

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Doctor of Philosophy

By

Elyssa H. Gerst

May, 2016

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ABSTRACT

The primary aim of this study was to examine the structure of processing speed (PS) in middle childhood by comparing five theoretically driven models of PS. The models consisted of two conceptual models (a unitary model, a complexity model) and three methodological models (a stimulus material model, an output modality model, and a timing modality model). A second aim was to evaluate the utility of these models for key reading skills (single word reading, fluency, and comprehension) relevant to this age group. Participants consisted of 844 children enrolled in urban public elementary schools. Average participant age was 9.92 (SD = 0.89) and students were enrolled in 3rd (n = 186), 4th (n = 482) and 5th (n = 176) grade. Sixteen variables from 12 tasks differing in their demand characteristics captured PS. Confirmatory factor analyses and regression equations evaluated hypotheses. A two-factor Timing model (Latency and Efficiency) was the strongest fit to the data and similarly structured two-factor Complexity model (Simple and Complex) was also a good fit to the data. Both models were examined as predictors of reading skills. Only the Efficiency/Complex factors were predictive of each key reading skill when considered alone and with relevant language and demographic variables, with the exception of single word reading, where both PS latent factors were predictive in the context of covariates. The structure of PS in middle childhood was found to form a two-factor structure, and separation was apparent between a simpler and more complex level of timed processing. Additionally, PS appears to be contributory to the prediction of word single word reading, reading fluency, and reading comprehension in the context of highly relevant predictors.

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Processing Speed in Children: Examination of the Structure in Middle Childhood and its Impact on Reading

Processing speed (PS) is a common term found in both the neuropsychological and cognitive literatures. PS has been implicated in a variety of neurological and developmental disorders including Multiple Sclerosis (Banwell & Anderson, 2005; Kail, 1997, 1998), traumatic brain injury (Anderson, Catroppa, Morse, Haritou, & Rosenfeld, 2005; Mathias & Wheaton, 2007), spina bifida and hydrocephalus (Anderson, Northam, & Wrennall, 2014), Attention-Deficit/Hyperactivity Disorder (Tannock, Martinussen, & Frijters, 2000), and learning disabilities (Shanahan et al., 2006; Wolf, Bowers, & Biddle, 2000). In school-aged children impaired PS can impact the rate of learning available and the acquisition of new skills (Marchman & Fernald, 2008).

While a precise, widely-agreed upon definition is elusive, the 'processing' of PS can be considered to be either perceptual or cognitive, and the 'speed' of PS can be assessed on the order of milliseconds or seconds, depending on the task. PS can be operationalized in many ways – as the time it takes someone to acknowledge the presence of a stimulus (push a button – or say "star" – when you see a "star"), as the time it takes a person to make a decision based on a single parameter (if arrow points left, press this left-sided button – or say "left"; if it points right, press this right-side button – or say "right"), or in more complex tasks which can either (a) increase the number or type of decision, (b) increase the number of parameters that must be tracked, or (c) that add time pressure to increase fluency or efficiency, some of which may subserve goal-directed behavior.

There are few models of PS available (particularly for school-aged children – see below), and few studies compare different models of PS (conceptual or methodological ones). It is also unclear how the structure accorded by these models translates to their use as specific, principal-driven predictors of function. Therefore, this study addresses these issues with two goals. The first and primary purpose of this study is to evaluate the latent structure of PS through a comparison of competing models. We will examine five competing models: two conceptual models (a unitary model, a complexity model) and three methodological models (a stimulus material model, an output modality model, and a timing modality model). Second, we evaluate the impact of these structural models in regard to reading skills, given its important role in the population studied here. Below, potential models of PS are reviewed, followed by a review of the role of PS in reading.

Models of Processing Speed

There are at least five dominant models of PS. Of these, two are conceptual in nature, and three are considered more methodological. We were unable to locate any study that has evaluated all models competitively.

Conceptual Models. At stake is whether PS is unitary, versus the extent to which it is differentiated according to the cognitive complexity of the task (all the way from simple response time, to tasks that could be considered to fall within more cognitively complex domains). Support for a unitary model comes from theory (Kail, 1991, 2000) and factor analytic studies (Barth, Catts, & Anthony, 2008; Schulte-Körne et al., 2007). Contrasting support for a "complexity" model also comes from theory (Babcock, Laguna, & Roesch, 1997; Tucker-Drob & Salthouse, 2008) and from other factor analytic studies (Chiaravalloti, Christodoulou, Demaree, & DeLuca, 2003; Salthouse, 1993). Of note, most of the cited studies above occurred in adults or a clinical sample; the present work will expand this literature to a non-clinical (though with at-risk characteristics) sample of children.

Unitary. The "global developmental trend" described by Kail (1991, 2000) proposes that PS develops in a uniform manner across the lifespan (Kail, 1991, 2000). This unitary construct view of PS has gained support in the literature though factor analyses that identify a single latent variable of PS among other latent variables of cognitive function (Barth et al., 2008; Schulte-Körne et al., 2007). For example, Peter, Matsushida, and Raskind (2011) found support for PS as a global construct as opposed to a domain-specific process in a large sample of children with dyslexia through an exploratory factor analysis of PS and language measures. Support for PS as a unitary construct suggests that a latent variable built from any kind of measurement of reaction time (RT) or speeded response would provide a strong fit to data across populations and ages, and that growth in PS should be uniform across various tasks in children independent of content or cognitive process (Fry & Hale, 1996; Kail, 2000; Span, Ridderinkhof, & van der Molen, 2004). Therefore, any comparison of models of PS must include a unitary factor as a rationale contender.

Complexity. Despite previous support for PS as a unitary construct, there is evidence to suggest that PS can be examined as separate factors, specifically in childhood. For example, while the "dedifferentiation hypothesis" has variable support in adults (Babcock et al., 1997; Tucker-Drob & Salthouse, 2008) and is poorly defined in children, the theory suggests that cognitive traits re-integrate in older age from differentiated factors present in late childhood/early adolescence. Other cognitive domains have found differentiation within construct structure in childhood as well; for example, executive function (EF) appears to be represented by a single identifiable factor in preschool children that may differentiate into separate but related processes as the child develops into adolescence/adulthood (Anderson, Anderson, Northam, Jacobs, & Catroppa, 2001; Lee, Bull, & Ho, 2014; Levin et al., 1991;

Miyake, Friedman, Emerson, Witzki, & Howerter, 2000). A link between EF and PS is supported by findings from a Miyake et al. study (2000) that found three separate but relatable factors of EF in college-aged adults, though four of the nine dependent measures were timed and therefore indexed PS to at least some degree. Further, these timed measures loaded onto two of the three factors, indicating that PS may be capable of being partitioned according to task characteristics. Huizinga, Dolan and van der Molen (2006) also invoked the relation between EF and PS when examining PS as a covariate in a latent variable analysis of EF. This type of result highlights the difficulty in distinguishing where PS "ends" and EF "begins". Taken together, the developmental trend of differentiation from a unitary construct to separable factors during middle childhood through adulthood across other cognitive functions (i.e., EFs) provides support for the examination of PS as a construct consisting of multiple related factors.

Additional support for PS as a componential rather than unitary construct comes from factor analytic studies that focus to varying extent on PS. In a study of adults, Salthouse (1993) distinguished two factors corresponding to simple (purely motor) PS tasks versus those with more cognitive complexity (e.g., WAIS-R Digit Symbol), although the PS factors were strongly related (r = .81). Chiaravalloti et al. (2003) also found 3 principal components to describe 11 measures of PS, attention, and working memory, in a mixed medical sample of adults: a simple speed/RT factor, a complex information PS factor, and a working memory factor. These studies indicate that examining PS according to the level of complexity of the measured tasks is a key contrast to a unitary model of PS, and may help clarify its relation to other domains (e.g., EF), and to functional outcomes (e.g., reading skills).

While previous studies have examined a two-factor model (simple vs complex PS), the complexity model in this study will examine three levels of PS, recognizing the potential overlap of PS with EFs. The simple level of PS will be operationalized as simple RT or latency captured by a speeded response requiring identification of the presence of a perceptual target, with no additional cognitive demands. The middle level of complexity will be operationalized as speed of response on a measure with minimal goal-directed demands. For example, in children, the Trail Making subtest from the DKEFS includes multiple subtests that capture PS at different levels of cognitive demands ranging from simple motor speed to number-letter sequencing (Delis, Kaplan, & Kramer, 2001). The number sequencing task from this subtest (Condition 2) exemplifies the middle level of PS operationalized by this study as it requires subjects to quickly scan a page in order to connect numbers in increasing order without the addition of higher-level cognitive demands. Variables included in the middle level latent factor will be those that require some sort of cognitive processing (i.e., counting, scanning, etc.) but will not capture traditional EF processes. The highest level of complexity in our processing speed hierarchy includes tasks that require goal-directed processing, balancing of speed and accuracy efficiency, or those that otherwise overlap with conceptualizations of EF. Again using the Trail Making subtest as an example, the number-letter sequencing task would represent the high level of complexity to be examined because of the added requirement of switching. The variables included in the highest level latent variable will be measures that include processing speed but also may capture EF.

Methodological Models. The conceptual models above can be compared to methodologically driven models that break down PS tasks according to stimulus material (verbal versus visual), output modality (oral versus manual), and by timing modality (latency, time-dependent or timed performance). Contrasting theoretical and methodological models has been conducted in other realms (see Wiebe, Espy, & Charak, 2008 for an example within the EF domain). Therefore, the comparison of the conceptual models of PS in relation to the methodological models will provide a greater understanding of the structure of PS in childhood. This is particularly true in the case of PS, where cognitive demands are typically minor relative to many other neuropsychological constructs.

Stimulus Material (Input). The stimuli presented in a task are influential in the measurement of PS. Task stimuli are often separated into two categories: alphanumeric (i.e., letters and words) and non-alphanumeric (i.e., shapes and colors). For example, Leonard et al. (2007) examined PS and working memory using confirmatory factor analysis in the prediction of a reading composite in 14 year old students and found that models differentiating between alphanumeric and non-alphanumeric dimensions of each process appropriately fit the data (Leonard et al., 2007). This alphanumeric and non-alphanumeric separation is also seen in models of working memory (Baddeley, 2003). Therefore, we also consider a stimulus-based (input) methods model of PS in our evaluation of model fit.

Output Modality. The process of collecting PS data is most often done via a motor speed task or a verbal-response speed task. Therefore, a model of PS that is dependent on the output modality of the measures may be particularly relevant for any studied population. Shanahan et al. (2006) examined the structure of PS in a sample of children and adolescents using a principal axis factor analysis and found that a two-factor model based on output (motor and verbal) fit such that the verbal factor accounted for 45.6% of the shared variance among the variables and the motor factor accounted for 12% of the shared variance among the variables in their sample of children with reading disability (RD) and/or Attention-Deficit/Hyperactivity Disorder (ADHD). The distinction between verbal and motor PS has been identified in clinical populations as well. For example, Mulder, Pitchford and Marlow (2010) found that verbal PS was a better predictor of teacher-rated English/Literacy performance than motor PS in very preterm children. Such contrasts offer additional support for the examination of PS with separate factors for verbal and motor output.

Timing Modality. Measurement of PS in adults is often based on capturing the timing associated with a basic cognitive function (i.e., RT) or the latency between a presentation of a stimulus and a correct response (Deary & Der, 2005; Salthouse, 2000). However, even the construct of RT (or response latency) can be examined in multiple ways. For example, Dennis et al. (2015) examined RT in three separate ways: simple, choice and cognitive. More generally, the operationalization of what is ‘cognitive’ and what is ‘processing’ is important to consider. Denney et al. (2011) operationalize their complex measures of PS as measures of “cognitive tempo” rather than “general processing speed” because they allowed participants to focus on accuracy rather than the time it takes to complete a task. Therefore, the accuracy of the total completed items on a time-dependent measure, where subjects are asked to complete a task in a set period of time (i.e., naming within a 60 second trial), may provide information regarding the rate cognitive processing. Additionally, the time it takes subjects to complete a total set of operations within a specific task (timed completion; i.e., how long it takes to draw a line connecting a set number of items) may be distinct from latency (or RT) and time-dependent performance. Therefore, a methodological model of PS that accounts for the different timing modalities used to examine PS (i.e., latency, time-dependent performance, and timed completion) may provide evidence for the differentiation of PS components in childhood. No known studies have directly examined PS in this manner, and therefore this alternative is more conjectural, but the distinction is readily apparent in clinical assessment.

Summary. This study will compare five theoretically-informed models of PS. Two of the models are conceptual in nature and examine the construct of PS as a unitary factor versus a construct that differs according to three levels of task complexity. These models will be compared to three models that are methodological in nature (based on stimulus-material, output-modality, and timing-modality). While we expect all of the models to be a reasonable fit to the data, we expect that the conceptual models will be a better fit than the methodological ones. Based on the findings from previous studies and factor analyses (Chiaravalloti et al., 2003; Salthouse, 1993) and the notion that PS may follow a differentiated developmental pattern, with separable processes emerging in late-childhood, among the conceptual models, we expect the complexity model to fit better than the unitary model.

Reading Skills and Processing Speed

Much of a child's life is spent in the classroom learning, so reading outcomes are a strong external validity target for the proposed PS models. Three reading skills will be examined in this study: single word reading, reading fluency, and reading comprehension. Word decoding (single word reading) is the process of identifying letter-sounds, blending the sounds to construct a word, and then identifying the word (Perfetti, 1984; Perfetti & Hogaboam, 1975; Stanovich, 1982). Reading fluency is the ability to efficiently and quickly identify and read words (Pikulski & Chard, 2005; Wolf & Katzir-Cohen, 2001). Reading comprehension utilizes the above skills, and also requires the ability to extract information and meaning from a sentence or passage (Cromley & Azevedo, 2007; Duke & Carlisle, 2010). In a normative population, all three processes develop simultaneously with a differential pattern of development, and by late elementary school are expected to be of functional use (Duke & Carlisle, 2010; Verhoeven & van Leeuwe, 2008).

Reading proficiency is dependent on the co-occurring development (or bi-directional influence, in terms of phonological awareness; Wagner, Torgesen, & Rashotte, 1994) of other cognitive processes. Well-defined cognitive constructs most commonly associated with reading include phonological awareness (PA; the ability to break a word down to its component parts) and rapid automatized naming (RAN; the ability to quickly and efficiently name alphanumeric stimuli). Both PA and RAN are considered to be very influential in the processes of decoding and fluency (Kirby, Parrila, & Pfeiffer, 2003; Norton & Wolf, 2012; Schatschneider, Fletcher, Francis, Carlson, & Foorman, 2004; Wagner, Torgesen, & Rashotte, 1994). For reading comprehension, word reading and listening comprehension are particularly important (Cutting & Scarborough, 2006; Gough & Tunmer, 1986).

Other non-language processes have also been related to reading, including working memory and other executive functions (the processes that enable engagement in goal directed behavior) (Fletcher et al., 1994; Kibby, Lee, & Dyer, 2014); strategy use (Cain, Oakhill, Barnes, & Bryant, 2001, p. 200; Oakhill & Cain, 2012); and background knowledge (Speece, Ritchey, Cooper, Roth, & Schatschneider, 2004; Whitehurst & Lonigan, 1998). EF has been most strongly related to reading comprehension, above decoding and fluency (Sesma, Mahone, Levine, Eason, & Cutting, 2009; St Clair-Thompson & Gathercole, 2006). PS is an additional, important, non-language cognitive process that has been implicated in reading, and will be focused on here. However, as reviewed above, the differentiation between PS and EF is difficult, as many EF tasks involve a speeded/efficiency component and the prediction of different reading processes may be influenced by the complexity of the PS tasks examined.

The relation between PS and reading has been examined specifically in the context of rapid naming, but also more generally in relation to timing and speed, as well as with regard to comorbidity. PS, specifically as it relates to the speeded naming of alphanumeric stimuli, has been thoroughly examined in relation to dyslexia and reading difficulties (Cutting & Denckla, 2001; Wolf et al., 2000). Wolf and Bowers (1993; 1999) proposed a 'dual deficit' model of reading disability that emphasizes the influence of a naming speed deficit as well as a phonological deficit as the core of the challenges for children with RD. Numerous studies have found support for the dual deficit model in the context of reading (Lovett, Steinbach, & Frijters, 2000; Norton & Wolf, 2012; Wolf et al., 2002). The most prominent operationalization of naming speed is the Rapid Automatized Naming (RAN) task (Neuhaus, Foorman, Francis, & Carlson, 2001; Norton & Wolf, 2012; Powell, Stainthorp, Stuart, Garwood, & Quinlan, 2007).

PS as timing impairments in reading difficulties and dyslexia have also found support in the literature, stating that slowed processing at the cellular and subcortical levels can disrupt the development of key language processes important for reading (Tallal et al, 1996; Tallal, 2004; Wolff, 2002). Children with a reading disability have been found to display more PS impairments compared to children with ADHD and controls (Shanahan et al., 2006). When PS was separated between verbal and motor factors, the effect size of the verbal factor for children with a RD compared to controls was d = 1.37 and the effect size of the motor factor was d = 1.55, providing support for the relation between PS and reading.

Finally, PS has been hypothesized to be a shared deficit among RD and ADHD in the multiple deficit model of development disorders (McGrath et al., 2011; Pennington, 2006), indicating that the construct of PS is separable from reading processes and, likely, a strong predictor of performance among different groups of children.

The above demonstrates the complicated way in which PS has been linked to reading; however, few known studies have evaluated the role of a theoretically-drive model of PS for reading. A key study by Christopher et al. (2012) found that WM and PS (the latter defined as a general construct measured by speeded matching of objects) were predictive of both word reading and reading comprehension (fluency was not examined in that study) above and beyond rapid naming (alphanumeric and non-alphanumeric stimuli) and inhibition in 8 to 16 year old children, providing support for the examination of PS and reading separate from RAN. Shaul and Nevo (2015) examined PS (defined as a general construct measured by the Visual Matching and Cross-Out tasks of the Woodcock-Johnson) and early reading skills development in 96 middle-class Israeli children between Kindergarten and 1st grade and found significant correlations between PS and reading, although the contribution of PS to reading is lost when controlling for IQ (as defined by the WISC-R General Knowledge and Block Design subtests) and rapid naming. Additionally, this study found that rates of PS were differentially predictive of reading, such that slow PS was a significant predictor of decoding and reading fluency and average PS was a significant predictor of decoding and reading comprehension (Shaul & Nevo, 2015). Catts, Gillispie, Leonard, Kail, and Miller (2002) examined the performance of 2nd through 4th grade children with specific language impairments across separate domains of PS (lexical, grammatical, phonological, motor and visual) and found that children with poor reading performance were slower in all examined domains relative to children with good reading performance.

Taken together, the results of the reviewed studies suggest that the construct of PS (separate from RAN) is a significant contributor to reading performance in children, but this is an area that will benefit from further investigation. A key advantage of this study is to extend the literature by defining PS as theoretically-driven latent variable constructs, and then to examine their predictive utility PS (separate from alphanumeric naming speed and other language skills), for multiple reading skills (single word reading, fluency, and comprehension), in late elementary-aged children.

Contextualizing PS and Reading in the Development of an At-Risk Sample

When evaluating the role of PS in reading skills performance, individual characteristics associated with the development of both cognitive functions requires consideration. The development of PS has been described as a “developmental cascade” as the rate of PS increases throughout the stages of development and slows at the end of life as a result of the advancement and loss of myelin and synaptogenesis within the brain (Fry & Hale, 1996; Kavé & Knafo-Noam, 2015; LaForte, McGrew, & Schrank, 2014). Changes in white matter and cortical development are also related to the development of reading skills in children (Deutsch et al., 2005; Schlaggar & McCandliss, 2007). Thus, examination of PS and reading outcomes across age cohorts likely introduces developmental-related variance. Despite the relatively small range of development included in this study (ages 8 to 11), performance across both PS and reading tasks may differ across the age groups and will be examined as a covariate in the predictive models.

The influence of environmental factors on PS and reading outcomes (and related language processes) must also be considered. For example, children from low SES families have been found to have delayed/stunted development of key cortical areas associated with both PS and reading, including the frontal lobe and left fusiform gyrus (Hackman & Farah, 2009; Hackman, Farah, & Meaney, 2010; Monzalvo, Fluss, Billard, Dehaene, & Dehaene-Lambertz, 2012) and there is variable support for impaired white matter integrity (Chiang et al., 2011; Jednoróg et al., 2012). Reading in a bilingual, low SES population has also been found to be impacted by external factors including limited access to educational resources, poor vocabulary development and even poor phonological development when children are not read to (Aikens & Barbarin, 2008; Bowey, 1995). Children from low SES, bilingual and/or minority-status families may even be considered to be at-risk for academic failure and identified by school systems as needing additional support. Additionally, level of English-language proficiency has been shown to impact performance on academic measures (Abedi, 2002; Lesaux, Crosson, Kieffer, & Pierce, 2010). These factors are particularly relevant to the sample chosen for this study as the students were recruited from urban school districts where the majority of students are identified as being from low SES, bilingual (mostly Spanish speaking) and minority-status backgrounds.

Finally, as should be apparent, beyond individual and family-level characteristics, individual differences in language must also be considered when evaluating reading performance. As was previously discussed, PA and RAN are well-known and strong predictors of reading single word reading and reading fluency (Schatschneider et al., 2004). Additionally, the simple view of reading (Gough & Tunmer, 1986; Hoover & Gough, 1990) posits reading comprehension to be the product of single word reading and listening comprehension; therefore, these will also be important covariates to consider.

Present Study

Structural Aim. The first aim of this study is to evaluate various means of modeling PS by directly comparing them to one another for the purpose of conceptual and measurement clarity. Five models will be examined: two conceptual and three methodological. For the conceptual models a Unitary PS model (based on Kail, 2000) and a Complexity model, separated by three levels of task complexity (Simple, Middle, and High) will be examined. These models will be compared to the three proposed methodological models consisting of a stimulus-material Input model (Alphanumeric vs Non-alphanumeric), an Output modality model (Verbal vs Motor; based on Shanahan et al., 2006) and a Timing component model (Latency vs Timed vs Time-dependent). The five predicted models are outlined by task in Table 1.

Hypothesis. While each model is expected to adequately represent the sample data, the conceptual models are expected to be better fits to the data than the methodological ones, and the Complexity model is expected to fit the data above and beyond the other models, based in part on previous principal component and factor analytic studies examining the structure of PS in different samples (Chiaravalloti et al., 2003; Salthouse, 1993).

Prediction Aim. The second aim of this study is to define the utility of each domain of processing in the prediction of performance in different reading outcomes (single word reading, reading fluency and reading comprehension), assuming that the three-level complexity model is the best fit to the data.

Hypotheses. The three factors of the Complexity model are expected to be uniquely predictive of each reading component. Given that fluency is a speeded skill, the PS factors in combination are expected to account for greater variance in reading fluency relative to other reading skills. Among the three Complexity PS factors, the High factor is expected to be more predictive of reading comprehension than are the Low or Middle factors, given the EF demands required in a reading comprehension task. This same general pattern is expected to hold when important demographic and language covariates are added, though with likely reduced unique PS contributions.

Method

Participants

The participants are 846 students enrolled in public elementary schools in urban school districts in Houston, TX and Austin, TX. Two students were missing data on all EF measures and were excluded from analyses, making the final number of participants 844. Data was collected as part of a larger data collection project and approved by the participating Institutional Review Board. Fourth grade students were recruited on the basis of low reading comprehension performance and were targeted for participation in a separate intervention study (Vaughn, Solís, Miciak, Taylor, & Fletcher, 2016). Average participant age was 9.98 (SD = 0. 91), students were enrolled in 3rd (n = 186), 4th (n = 482) and 5th (n = 176) grade. The majority of participants identified as Hispanic or multiple ethnicities (36%) or Black (29%) and 90% of students are eligible for free or reduced lunch. Additional demographic information is found in Table 2.

Procedures

Data was collected over a three month period of time with trained examiners. The larger study included many more measures, so in order to better facilitate testing procedures, students were randomly assigned to one of six data collection patterns, allowing for planned missing data within the entire sample (see Table 3 for measure-specific data patterns). The data patterns were designed so that at least 1/6 (~16%) of the total participants completed any pair of measures. Academic measures were collected in a group setting; all other measures were collected in individual testing settings over multiple sessions. Demographic data was collected at a school level.

Measures

Additional detailed information on data collection, reliability and validity for measures used in this study can be found at http://www.texasldcenter.org/projects/measures.

Processing Speed Measures. Variables were chosen from a variety of tasks with a timed component, despite their intended use in other settings. Support for the use of a traditional measure of EF to differentially capture the construct of PS is found in a study by Anderson, Anderson, Northam, Jacobs, and Catroppa (2001), who examined the development of PS and EF with separate components captured from the same measure and found differential developmental trends for each construct. Given that the complexity model is predicted to be the strongest fit, the following measures are presented in groups of complexity: Simple, Middle, and High.

Simple Level PS.

Go/No Go (Inquisit 3, 2003). The Go/No-Go is a computerized task designed to measure response inhibition in children and adults. Participants are asked to respond quickly to the display of a presented stimuli ("Go" trials) and to inhibit their response to other presented stimuli (“No Go” trials) by pressing a designated button on a keyboard. Each stimulus is presented for a short period of time (less than a second) and the latency to response for each “Go” and “No Go” trial is collected. Each presentation is randomized; therefore, item-level reliability for this measure is not reported. This version of the Go/No Go task has been found to have low (range $r = |.20 \text{ to } .21|$), but significant, correlations to other measures of RT (Stop Signal) and to a measure of reading comprehension (Gates MacGinitie Reading Comprehension; Miciak, Gerst, Cirino, Child, & Huston-Warren, 2016). The dependent measure will be the recorded latency (raw score in milliseconds) between stimuli presentation and response for all valid Go trials.

***Delis-Kaplan Executive Function System (D-KEFS); Trail Making Test* (TMT; Condition 5: Motor Speed;** Delis et al., 2001). The D-KEFS was designed to capture executive function processes in children and adults ages 8 to 89 through a battery of age-normed tests. The D-KEFS is a widely used measure and the validity and reliability of each subtest is known, with the reliability for all conditions of this measure ranging from .57 to .81 (Delis et al., 2001). To capture simple motor speed, the fifth condition (Motor Speed) of the TMT was collected. This condition requires the participant to quickly trace over a dotted line, making sure to touch each dot along the designated route. The dependent measure collected from this task is the total completion time (raw score in seconds).

N-Back Task (Shapes & Letters; Inquisit 3, 2003). The N-Back Task (based on the original developed by Kirchner, 1958) is a widely measure of working memory in children and adults. In the 0-back trials of this task sustained attention is captured by presenting participants with a series of stimuli on a screen (either shapes or letters) and asking them to respond every time they see a specific stimuli (i.e., press the space bar every time a ‘Z’ appears). The N-Back Letters version requires responses based on the presented of alphanumeric stimuli and the N-Back Shapes version requires responses based on non-alphanumeric stimuli. Both versions involve a motoric response. The dependent measure from N-Back Letters and N-Back Shapes will be the mean RT (raw score in milliseconds) for all valid 0-back trials.

Stop Signal (Inquisit 3, 2003). The Stop Signal task is a computerized measure of response inhibition. This task was modeled after the original Stop-Signal Paradigm (Logan & Cowan, 1984). In the *Inquisit* version of this task, participants are presented with an empty circle in the center of a computer screen. When an arrow appears in the circle, participants are instructed to press a key corresponding to the direction the arrow is pointing (go trials); however, the participants are instructed to withhold their response when the arrow is presented with a verbal beep (stop signal). The task consists of three blocks (each lasting about two minutes) with a 10 second pause between blocks, and the timing of the stop signal presentation follows the horse-race model (Band, van der Molen, & Logan, 2003). The coefficient alpha for this version of the *Inquisit* Stop Signal task is .99 (Miciak et al., 2016). While the mean RT for stop signal trials is typically evaluated from this measure (Logan & Cowan, 1984), the dependent measure used in this study will be the mean RT (raw score in milliseconds) for all valid go trials, which captures the latency to respond to a simple (go) command.

Middle Level PS.

Corsi Block-Tapping Task (Forward Condition; Inquisit 3, 2003). The *Inquisit* Corsi Block-Tapping Task is a computerized measure of visuospatial memory for use with children and adults. Participants are presented with a display of nine blocks that light up in various sequences, ranging from 2 to 7 blocks, and are asked to recall the sequences in the same order. There are 14 trials, with 2 presentations for each sequence length. Variability in the administration of this task leads to limited reporting of reliability and validity (Berch, Krikorian, & Huha, 1998; Pagulayan, Busch, Medina, Bartok, & Krikorian, 2006); however, Cronbach's alpha for this version of the measure was found to be .63 (Miciak et al., 2016). Additionally, this version of the Corsi Block-Tapping task was found to have a low (r = .21), but significant, correlation with the Gates MacGinitie Reading Comprehension measure (Miciak et al., 2016). The dependent measure will be the total completion time (raw score in milliseconds) for all correct trials.

***Delis-Kaplan Executive Function System (D-KEFS); Color Word Interference Test* (CWIT; Condition1: Color Naming;** Delis et al., 2001). The CWIT of the D-KEFS is designed to measure inhibition after the Stroop procedure (Stroop, 1935). The CWIT consists of four conditions of increasing complexity and the reliability for all conditions of this measure ranges from .62 to .86 (Delis et al., 2001). The first condition (Color Naming) will be examined in this study. In this condition, participants are presented with a page filled with patches of color and are asked to name the color of each with a maximum of 90 seconds. The dependent measure will be the total completion time (raw score in seconds) for the first condition of this measure.

***Delis-Kaplan Executive Function System (D-KEFS); Trail Making Test* (TMT; Condition 2: Number Sequencing;** Delis et al., 2001). The second condition of the TMT requires participants to connect a series of numbers on a page in order as quickly as they can. Participants are given up to 150 seconds to complete the task and are corrected if they connect the numbers incorrectly. This task requires manual manipulation to connect the items. The dependent measure from this condition will be the total completion time (raw score in seconds).

NEPSY-II; Visuomotor Precision (Korkman, Kirk, & Kemp, 2007). The NEPSY-II was developed as a battery of tasks designed to measure a variety of neuropsychological functions (i.e., attention, EF, language, memory, sensorimotor function, social perception, and visuospatial processing) in children and adolescents (Korkman et al., 2007). The Visuomotor Precision subtest measures graphomotor skills by having participants trace along a presented track as quickly and accurately as possible. Participants are timed and errors (pencil lifts and tracing outside of the line) are recorded. Average reliability coefficient for the total completion time between the ages of 7 to 12 years is $r = .75$, test-retest stability for total completion time is $r = .65$, and this task is moderately ($r = .38$) correlated with the Processing Speed Index of the WISC-IV (Korkman et al., 2007). The dependent measure will be the total completion time (raw score in seconds) for this measure.

Purdue Pegboard (Lafayette Instruments, 1999). The Purdue Pegboard, originally designed by Tiffin and Asher (1948), is a task of motor dexterity that assesses both gross and fine motor movements in children and adults. In this task, participants place cylindrical pegs into holes on a board separately with each hand, then with both hands simultaneously. The participants are given 30 seconds to complete the task and are assessed on how many pegs they place during that time. The test-retest reliability for a simple administration per trial ranges from .37 to .82 across ages for the normative population. The dependent measure will be the total number of pegs placed in the allotted time when using both hands simultaneously.

Woodcock-Johnson III Tests of Academic Achievement; Visual Matching (WJ-III; Woodcock, McGrew, & Mather, 2001). The WJ-III Visual Matching test is designed to measure PS in children and adults. The task asks participants to circle matching numbers aligned in a row of 6 numbers and are given 3 minutes to complete the task. Test-retest reliabilities for children between the ages of 8 to 13 range from .82-.88. Additionally, the visual matching subtest is hypothesized to measure the CHC broad ability of PS (G_s) (Woodcock et al., 2001). The dependent measure for this task will be the total number of correctly identified matches within the allotted time.

High Level PS.

Delis-Kaplan Executive Function System (D-KEFS); Verbal Fluency and Category Fluency (Delis et al., 2001). Verbal Fluency is a measure of speeded generation of words in multiple formats (Letter Fluency, Category Fluency, and Category Switching). In the Letter Fluency format, participants are asked to produce as many words as they can within a 60 second period that begin with a designated letter (F, A, S). In the Category Fluency format, participants are asked to produce as many semantically related words as they can within 60 seconds: categories include animals and boy’s names. Participants are awarded credit for words beginning with the designated letter within the bounds of the presented rules. The dependent measure for Letter Fluency condition is the total number of words across all three letters (i.e., the raw score is the number of words generated within 180 seconds). The dependent measure for the Category Fluency condition is the total number of words across both categories (i.e., the raw score is the number of words generated within 120 seconds).

***Delis-Kaplan Executive Function System (D-KEFS); Design Fluency* (Condition 2: Empty Dot;** Delis et al., 2001). The design fluency task consists of three conditions in which a participant is asked to quickly create designs within a 60 second time limit. Participants are presented with response boxes filled with both filled and empty circles. In the first condition (Filled Dot), participants are instructed to create unique designs within the response boxes by connecting a set number of the filled dots. The second condition (Empty Dot) differs from the first condition, in that it asks the participant to create designs in similar response boxes by connecting a set number of empty dots. The dependent measure that will be used is the total correct number of correct designs across the second condition (i.e., the raw score is the total number of correct designs within 120 seconds).

***Delis-Kaplan Executive Function System (D-KEFS); Trail Making Test* (TMT; Condition 4: Number-Letter Sequencing;** Delis et al., 2001). The fourth condition of the TMT asks participants to connect a series of numbers and letters in numerical and alphabetical order while switching between a number and a letter (e.g., 1-A-2-B) on a page in order as quickly as they can. Participants are given up to 150 seconds to complete the task and are corrected if they connect the numbers and letters incorrectly. This task requires manual manipulation to connect the items. The dependent measure from this condition will be the total completion time (raw score in seconds).

Tower of London Task (after Shallice, 1982; *Inquisit 3*, 2003). The Inquisit Tower Task is a computerized measure of planning in children and adults. Participants are presented with an initial configuration and are asked to make their model to match a goal model in as few moves as possible while obeying specific rules. The models consist of three different sized sticks and three different colored balls that can move between the rings. This measure is untimed and there are 13 problems to complete; two of the problems require a minimum of two moves, three require a minimum of three moves, four require a minimum of four moves and four require a minimum of five moves. The dependent measure for this study will be the mean latency time (raw score in milliseconds) to first move for all correct problems, rather than the traditionally used accuracy-based total score, in order to capture the specific speed-related processes of this task (Kaller, Unterrainer, Rahm, & Halsband, 2004).

Reading Measures.

Woodcock-Johnson III Tests of Academic Achievement; Letter-Word Identification (WJ-III; Woodcock, McGrew, & Mather, 2001). The Letter-Word Identification task is designed to measure single word reading skills by asking participants to read letter and real words out loud. The test-rest reliability for students between the ages of 8 to 13 ranges from .89 to .96. Within the geographically distributed sample, this task was found to measure the CHC narrow ability of reading decoding. The dependent measure will be total correct words reads.

The Test of Word Reading Efficiency – Second Edition; Sight Word Efficiency **(TOWRE-2;** Torgesen, Wagner, & Rashotte, 1999). The Sight Word Efficiency subtest is designed to measure the accuracy and speed of word reading. Participants are presented with a list of words with increasing complexity and are asked to read them aloud as quickly and accurately as possible within 45 seconds. Test-retest reliability for this subtest exceeds .90 within the normative sample. The dependent measure will be the raw number of total words read correctly aloud.

Gates MacGinitie Reading Tests – 4th Edition (GMRT); Passage Comprehension (MacGinitie, MacGinitie, Maria, Dreyer, & Hughes, 2000). The Gates-MacGinitie is a nationally normed, untimed test of reading comprehension abilities. Participants are asked to read 11 passages and provide multiple choice answers to 48 questions requiring inference making, summarization, main idea, literal questions and vocabulary. Reliability for this measure exceeds .90 for students in grades 3 to 5. The dependent measure will be the total correct score.

Language Covariates.

Woodcock-Johnson III Tests of Academic Achievement; Oral Comprehension (WJ-III; Woodcock, McGrew, & Mather, 2001). The Oral Comprehension task is an untimed measure of oral cloze procedure. Participants are asked to provide a single word response to complete a verbally presented passage. The median reliability for this subtest is .80 within the 5 to 19 age range. The raw total correct responses will be the dependent measure.

Comprehensive Test of Phonological Processing; Elision (CTOPP; Wagner, Torgesen, & Rashotte, 1999). The Elision task of the CTOPP is a norm referenced, untimed task of phonological segmentation. Participants are presented with a word and asked to repeat the word without a specified sound (e.g., remove the /p/ sound from the word “pat”). Each item is presented in order of increasing complexity. Within this age range, the average reliability ranges from .86 to .91. The dependent measure will be the total raw score from the task.

Comprehensive Test of Phonological Processing; Rapid Letter Naming (CTOPP; Wagner, Torgesen, & Rashotte, 1999). The CTOPP Rapid Letter Naming is designed to assess the speed with which a participate can name alphanumeric components of language, based off of the original RAN task (Denckla & Rudel, 1976). Participants are presented with four rows of six randomly arranged letters and are asked to read each letter aloud from right to left until the last letter is read. Performance is based on total completion time for forms A and B. The Cronbach alpha range for this measure is from .70 to .90. The dependent measure from this task will be the total time raw score for forms A and B.

Analyses

Preliminary analyses evaluated sample-based and model-based residual outliers prior to analyses of the models. Variable distributions were examined for normality parameters, including skewness and kurtosis. Outliers were identified in five variables. For the Go/No-Go, Purdue Pegboard and Corsi tasks unexplained performance observations (+/- 3 SD from the mean and at least half a SD from the next observation) were Winsorized and set to three standard deviations from the mean, maintaining original rank ordering. This applied to 20 observations. However, two of the five variables (Tower of London and RAN) displayed patterns of extreme skewness and required a log transformation to maintain a normal distribution.

Primary statistical analyses were conducted using the Mplus computer software (Muthén & Muthén, 2012) to evaluate Structural Aim hypotheses utilized confirmatory factor analysis (CFA). This approach was successfully used in other realms to examine latent factors of a complex construct (i.e., EF's; Miyake et al., 2000; Wiebe et al., 2008). The indicators within each model used raw scores (timed or raw totals/scaled scores). When raw timed data was not available, the indicators (raw totals and/or scaled scores) were scaled so that lower scores indicate better performance to allow for consistent comparison across

PS variables. A "weight" variable was included in the models to account for the large percentage students in the 4^{th} grade who were struggling readers, selected for their overlap with an intervention study (Vaughn et al., 2016). The criterion variable was the normal curve equivalent (NCE) score of the Passage Comprehension measure of the Gates MacGinitie Reading Comprehension Test (MacGinitie et al., 2000). The weight for the variable was calculated by dividing the percent of the 4^{th} grade sample who participated in this arm of the study (N = 846), against the percent of the entire 4^{th} grade screening sample (N = 2,200) who obtained that same score. The distribution of the "weight" variable was smoothed using PROC GENMOD, a log-linear smoothing technique (Holland & Thayer, 1987; Moses & von Davier, 2006). As a result, the weighted mean of this sample was similar to the raw mean of the entire screened sample. The Maximum Likelihood Robust (MLR) estimator was used to allow for examination of the data with a weighted variable (Muthén & Muthén, 2012).

Goodness of fit for the models were examined at both the global fit and local fit levels. Multiple global fit indices included: the model chi-square (χ^2) with non-significance indicative of fit; the Comparative Fit Index (CFI) and the Tucker-Lewis (non-normed fit) Index (TLI) with values between .90 and 1.00 indicative of good fit; the root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR) with values of < .08 indicative of good fit (Hu & Bentler, 1999; Kline, 2004; Wiebe et al., 2008). The Akaike information criterion (AIC) and the Bayes information criterion (BIC) within the models was examined, with smaller values across models indicative of having the best fit (Kline, 2004; Wiebe et al., 2008). Within each model, these measures compare covariance matrices and covariance residuals to a baseline (independence) model covariance matrix, with some accounting for parameters including, sample size and complexity of the model (Kline, 2004). The local fit levels examined parameters including correlations within the factors, beta weights, and factor loadings (Kline, 2004). Given that several models are nested, χ^2 comparisons were used to comparing these, as was done previously in other cognitive realms (see Wiebe et al., 2008); however, the alternate χ^2 difference test (Satorra-Bentler) was used because the sample was weighted and, therefore, the MLR estimation was used (Satorra & Bentler, 2001). Other fit indices were also evaluated, e.g., CFI change scores less than -0.01 are suggestive of significant differences between models (ΔCFI; Cheung & Rensvold, 2002).

Predictive Aim analyses were assessed using structural regressions. Potential covariates examined for inclusion in the regressions included: age, sex, English-language proficiency (as defined by Limited English Proficiency status; LEP), economic disadvantage status (as defined by Free-Lunch eligibility), phonological awareness (PA), Rapid Automatized Naming (RAN), and oral comprehension. Age, sex, LEP, and economic disadvantage status were all significantly related to the reading outcomes ($r < .05$). PA and RAN were examined in the single word reading and fluency models given their status as well-known and strong predictors of both reading processes (Schatschneider et al., 2004), whereas single word reading, oral comprehension, and RAN were examined in the comprehension model given the support from the simple view of reading (Gough & Tunmer, 1986; Hoover & Gough, 1990). Interrelationships between multiple covariates was examined to avoid redundancy and results are reviewed below.

Structural regression models were used to provide evidence for the predictive utility of the best fitting PS model (hypothesized to be the complexity model) above and beyond highly relevant covariates for single word reading, reading fluency, and reading comprehension. Two a priori models were evaluated for each of the three reading outcomes to address the hypotheses for the prediction aim. The first model for each reading outcome examined the PS model alone in the prediction of each reading outcome to examine the predictive utility of this model without the influence of highly relevant covariates. The second model included the PS model and all relevant covariates for the reading outcome in order to understand the predictive utility of the model when examined in the context of other empirically-supported predictors. Descriptive models including only relevant covariates without the latent PS constructs were also evaluated for each reading outcome to judge the added contribution of the PS factors.

Each structural regression model was examined in Mplus in order to test the impact of the latent variables on reading performance, rather than a derived factor score (Muthén, 2002). Statistical significance of the overall model and total model variance (R^2) was evaluated along with effect sizes for each predictor variable via the standardized beta weights. Examination at both levels allows for evaluation of overall model relevance and the contribution of each predictor above and beyond the contribution of all other predictors in the model (Fritz, Morris, & Richler, 2012). The R^2 change (ΔR^2) was used as an index of the added predictive value of the proposed PS model.

Results

Preliminary Results

Descriptive statistics for the PS measures, reading measures, and language measures are found in Table 3. All measures were appropriately distributed with TMT Number-Sequencing having the largest skew (1.35) and Purdue Pegboard having the highest kurtosis

(2.12). Correlations among indicators, outcomes and covariates using the weight variable are found in Tables 4, 5, and 6. Most PS variables were found to have significant small to medium correlations with each other (range r = |.03 to .52|), with reading outcomes (range r = |.02 to .43|), and with language covariates (range r = |.01 to .48|), with the exception of NEPSY Visuomotor Precision and TOL latency; these correlated significantly with nine and thirteen (of 21 possible) other measures, respectively.

Structural Aim Results

The two conceptual models were examined first. Model 1 (Unitary) was a single latent variable for the construct of PS using all 16 indicators. This model was a poor fit to the data (AIC = 78965.122, BIC = 79192.553, ABIC = 79040.120, χ^2 = 462.668, df = 104, RMSEA = .064, RMSEA CI 90% = .058 to .070, CFI = .744, TLI = .705, SRMR = .089). However, the D-KEFS Verbal Fluency variables (letters and category) were found to have strong correlated residuals (as identified by modification indices), which is conceptually appropriate, so this model (and all subsequent ones) was re-evaluated with this correlated residual. The model fit statistics for the Unitary model considered subsequently are reported in Table 7, and when compared with the values above demonstrate improved fit, though some values (e.g., CFI = .801) remain poor.

Model 2a (Complexity) was examined next and contained three latent variables: Simple, Middle, and High. Chi-square differences between the models and the Unitary (Model 1) were examined using the Satorra-Bentler scaled (mean-adjusted) chi-square formula (Satorra & Bentler, 2001). The model provided an adequate fit to the data and fit significantly better than the Unitary model (Model 1; p < .001, see Table 7. However, the Middle and High latent factors correlated greater than one (r = 1.05, p < .001). Therefore, Model 2a was collapsed into a two-factor model (Model 2b) with the same Simple factor and a new Complex factor consisting of the indicators from both the Middle and High factors of Model 2a. Indicator factor loadings for Model 2b are presented in Figure 1. Model 2b provided a similar fit to the data as Model 2a and was also significantly different from Model 1 (Unitary) in χ^2 difference comparisons. The correlation between the two factors (Simple and Complex) was moderate ($r = .46$, $p < .001$). While the χ^2 difference comparisons were unable to be examined for Model 2b and the subsequent models (due to having the same df), Model 2a was a significantly better fit than Model 3 (χ^2 difference = 149.886, $p < .001$) and Model 4 (χ^2 difference = 154.993, $p < .001$).

The three methodological models were examined next. Model 3 (Stimulus Input) contained the two latent factors of Alphanumeric and Non-Alphanumeric. Model 3 provided a poor fit to the data, although it was significantly better than (Unitary) Model 1 (based on χ^2 difference, p < .xxx). Additionally, the Alphanumeric and Non-Alphanumeric factors had a strong correlation ($r = .90$, $p < .001$), which may account for the poor model fit. Model 4 (Output Modality) contained the two response-based latent factors of Verbal and Motor. This model provided a poor fit to the data and did not differ from Model 1 in χ^2 difference comparisons. Additionally, the Verbal and Motor latent factors had a strong correlation ($r = .94$, $p < .001$).

Finally, the third exploratory methodological Timing model (Model 5a) was examined. Model 5a consisted of three factors (Latency – time to begin activity, Time-Dependent – complete an activity in a specified time, and Timed – total time to complete activity) and provided a strong fit to the data, with global indices exceeding those of all other models and significant χ^2 difference comparisons (see Table 7). However, the Time-

Dependent and Timed latent factors correlated was $r = 1.00$, $p < .001$, and therefore were collapsed into a single Efficiency factor in Model 5b. Model 5b provided a similar fit to the data as Model 5a. The correlation between the two factors (Latency and Efficiency) was moderate ($r = .44$, $p < .001$). Model 5a significantly differed from both Model 3 (χ^2 difference = 182.293, $p < .001$) and Model 4 (χ^2 difference = 187.400, $p < .001$).

Global fit indices indicate that Model 5b was the strongest fitting model. Relative to all other examined models, Model 5b met standard criteria for global fit indices (CFI/TLI > .90 and RMSEA/SRMR < .08; Hu & Bentler, 1999; Kline, 2004; Wiebe et al., 2008). Additionally, the χ^2 difference (188.407, $p < .001$) and ΔCFI (-0.133) from the Unitary model were more substantial for Model 5b than any other model. Additionally, while Models 5b and 2b (the next best fitting model) could not be compared against each other using χ^2 difference comparisons (due to having the same df), the global fit indices were all better for Model 5b; the CFI and TLI are larger, the AIC, BIC, and ABIC are lower, as are the RMSEA and SRMR. However, differentiating between Model 5b and Model 2b beyond statistical fit was a challenge, given that the structure of the latent factors within each model only differ by two indictors (TOL and DKEFS TMT Motor Speed) with similar factor loadings across models (see Figures 1 and 2). Additionally, since Model 5b was developed as an experimental comparison model, it is also important to consider the relevance of a theoretically-driven model that also provides a strong fit to the data (Model 2b). Therefore, while only a single model was hypothesized to be used as a predictor of reading skills, both the Complexity (Model 2b) and Timing (Model 5b) models were examined in the Predictive Aim of this study.

Predictive Aim Results

Covariates. Examination of relevant covariates was conducted using the SAS® software (SAS Institute Inc., 2012) prior to inclusion in the prediction models in Mplus. Demographic variables (grade, age, LEP, and economic disadvantage status) were examined as relevant covariates. Special education status was not considered as a covariate due to missing data for 393 observations. Additionally, student race/ethnicity was not significantly correlated with any reading outcome (ps > .050) and therefore was not considered as a covariate. For single word reading and reading fluency, related demographic variables included age, sex, grade, economic disadvantage and LEP ($p < .001$); however, when considered together economic disadvantage and LEP were found to be noncontributory. Therefore, the demographic covariates for the single word reading and reading fluency models included age, sex, and grade. Grade, LEP, and economic disadvantage status were all significantly related to reading comprehension ($p < .001$); however, when considered together economic disadvantage was noncontributory. Therefore, the demographic covariates for the reading comprehension model were grade and LEP. Theoretically relevant language variables were included in the models as well (phonological awareness and rapid naming for single word reading and fluency, and single word reading and oral comprehension for reading comprehension). Descriptions of final models are found below.

Single Word Reading. Regression statistics for single word reading with Model 2b and Model 5b are summarized in Tables 8a and 8b, respectively. Overall model fits for each predictive model are presented in Table 11. In order to better understand the contribution of PS to models, regressions with and without relevant demographic and language covariates were reviewed. This pattern was repeated for all examined reading outcomes (reading fluency and reading comprehension). When examined without covariates, the Complex factor of Model 2b was a significant predictor ($p < .001$) and the Simple factor was not (p = .175). The same pattern was found for Model 5b, with the Efficiency factor as a significant predictor ($p < .001$) but not the Latency factor (p = .113). Both PS models accounted for 25% of the variance in the prediction of single word reading.

As reviewed above, relevant covariates for single word reading included age, sex, grade, RAN and PA. When examined with Model 2b, the predictors accounted for 47% of the variance and the significant predictors included the Simple latent factor (p = .036), the Complex latent factor (p = .018), RAN ($p < .001$), PA ($p < .001$), age ($p < .001$), and grade ($p < .001$). Sex did not contribute to the prediction of single word reading (p = .095). Given that the accuracy measures of PS were reverse scored to support comparison with timed measures of PS, where lower scores indicate better performance, the negative direction of the relation between the PS factors and word reading is expected and would suggest that reading performance would improve with faster PS. Additionally, the direction of the relation between the covariates and word reading indicate that performance would be enhanced with faster RAN (a timed measure), better Elision, older age, and enrollment in a higher grade. The same pattern of results were found for Model 5b with the predictors also accounting for 47% of the variance. When models were examined without the PS latent factors, the included covariates accounted for 45% of the variance for both the Complexity (Model 2b) and Timing (Model 5b) models. The ΔR^2 value derived from examination of the models with and without the PS latent factors was .019 for the Complexity (Model 2b) model and .018 for the Timing (Model 5b) model.

Reading Fluency. Regression model statistics for reading fluency are summarized in Tables 9a and 9b. When examined without covariates, the Complex factor of Model 2b was a significant predictor ($p < .001$) and the Simple factor was not ($p = .529$). The same pattern was found for Model 5b, with the Efficiency factor as a significant predictor ($p < .001$) but not the Latency factor ($p = .753$). Model 2b accounted for 32% and Model 5b accounted for 31% of the variance in the prediction of reading fluency.

As reviewed above, relevant covariates for reading fluency included age, sex, grade, RAN and PA. When examined with Model 2b, the predictors accounted for 50% of the variance and the significant predictors included the Complex latent factor ($p < .001$), RAN ($p < .001$), PA ($p < .001$), age ($p < .001$), and grade ($p < .001$). The Simple latent factor ($p = .764$), and sex ($p = .105$) did not contribute to the prediction of reading fluency. Within this model, the negative direction of the relation between the Complex factor and word reading suggests that reading fluency would improve with faster PS. The direction of the relation between the covariates and reading fluency indicate that performance would be enhanced with faster RAN (a timed measure), better Elision, and enrollment in a higher grade. The same pattern of results were found for Model 5b with the predictors accounting for 50% of the variance. When models were examined without the PS latent factors, the included covariates accounted for 45% of the variance for both the Complexity (Model 2b) and Timing (Model 5b) models. The ΔR^2 value derived from examination of the models with and without the PS latent factors was .050 for the Complexity (Model 2b) model and .046 for the Timing (Model 5b) model.

Reading Comprehension. Regression model statistics for reading comprehension are summarized in Tables 10a and 10b. When examined without covariates, the Complex factor of Model 2b was a significant predictor ($p < .001$) and the Simple factor was not ($p = .491$). The same pattern was found for Model 5b, with the Efficiency factor as a significant predictor ($p < .001$) but not the Latency factor ($p = .529$). Both PS models accounted for 21% of the variance in the prediction of reading comprehension.

As reviewed above, relevant covariates for reading comprehension included sex, grade, LEP, oral comprehension and single word reading (to account for the Simple View of reading; Cutting & Scarborough, 2006; Gough & Tunmer, 1986) and RAN. When examined with Model 2b, the predictors accounted for 65% of the variance and the significant predictors included the Complex latent factor ($p < .001$), oral comprehension ($p < .001$), single word reading ($p < .001$), sex ($p = .034$), English language proficiency ($p < .001$), and grade (range $p < .005$). The Simple latent factor and RAN did not contribute to the prediction of reading comprehension ($p > .050$). As with the previously reviewed models, the negative direction of the relation between the Complex factor of PS and reading comprehension suggests that reading performance would improve with faster PS. As would be expected, there is a positive relation between the language covariates and reading comprehension. The results also suggest that children without a LEP status and girls are likely to perform better on the reading comprehension measure in this study. Additionally, given the unique constitution of this sample, with many 4th grade students having low reading comprehension, the negative direction of the relation between grade as a covariate and reading comprehension is not unexpected. The same patterns of results were found for Model 5b with the predictors accounting for 65% of the variance. When models were examined without the PS latent factors, the included covariates accounted for 63% of the variance for both the Complexity (Model 2b) and Timing (Model 5b) models. The ΔR^2 value derived from examination of the models with and without the PS latent factors was .022 for the Complexity (Model 2b) model and .021 for the Timing (Model 5b) model.

Discussion

This study had two aims: a Structural Aim to examine the structure of PS in late-elementary aged children, and a Predictive Aim to evaluate the utility of PS for three key reading skills (single word reading, reading fluency, and reading comprehension). PS was found to be dual-level construct with differentiation apparent between a simple and more complex level of PS. Two of the five proposed models (Complexity and Timing) provided adequate fits to the data and were examined as predictors of reading skills, specifically in the context of highly relevant covariates. The higher-level processing speed factor contributed uniquely to each reading skill examined, whereas the lower-level processing speed factor was only a unique predictor for single word reading.

Structural Aim Discussion

The latent structure of PS was examined in this study by comparing five different models – two conceptual (Unitary and Complexity) and three methodological (Stimulus Input, Output Modality, and Timing), with the conceptual models (specifically, a three-factor Complexity model) hypothesized to fit best relative to the others. However, the final two-factor version of the methodological Timing model was statistically the best fit to the data, relative to all other examined models; the final two-factor version of the Complexity model was also a good fit to the data. Both of these models *each* fit better than *either* the Unitary conceptual model, or methodological (Stimulus Input and Output Modality) models.

The similar strength of separate conceptual and methodological models is noteworthy. In particular, the Timing model was conjectural as there was little prior support. Denney et al. (2011) also found that tasks which capture speeded processing in different manners (covertly and explicitly, in their study) were separable in adults with multiple sclerosis, although their study did not examine the structure of PS in a factor-analytic approach and only examined PS with five computerized tasks. The Complexity model, a conceptual model with strong support from multiple domains (Chiaravalloti et al., 2003; Huizinga et al., 2006; Salthouse, 1993), was also found to be a good fit to the data, though less strong relative to the experimental Timing model. However, there were few differences between these models in terms of which indicators are included in each latent factor. Specifically, the factors only differ by two indicators (TMT Motor Speed and TOL) and all indicators retained the same pattern of loadings between the models (see Figures 1 and 2). In other words, there are strong similarities between the Latency (from the Timing model) and the Simple (from the Complexity model) factors, as well as between the Efficiency (from the Timing model) and the Complex (from the Complexity model) factors. Therefore, the dual-level structure of PS in this study can be viewed more broadly as incorporating a speed-based, less complex level of PS and an efficiency-based, more complex level of PS.

The findings of the current study provide support for PS as a dual-level construct in childhood (specifically between the ages of 8 to 11). Prior work has shown support for both PS as a unitary construct in the adult literature (Kail, 1991, 2000), as well as a dual-level process (Chiaravalloti et al., 2003; Salthouse, 1993). In children with a variety of neurodevelopmental or neurological disorders, PS is often examined via a single or composite variable in studies of cognitive processes (Mayes & Calhoun, 2007). The results of this study clearly support this dual-level in children within the examined age range and demographics of this sample. Future studies may benefit from examining this structure in a wider age range or longitudinally, and in a different sample of children (i.e., within clinical populations, or other regions/cultures).

Within the more complex, efficiency-based level of PS, one intention of the study was to provide a basis for an examination of where PS “ends” and EF “begins”, as overlap between the constructs can be seen in studies that have used PS as a control variable when examining the structure of EF (Huizinga et al., 2006). The proposed three-factor Complexity model attempted to separate PS in this manner by examining tasks on the level of cognition required in the task: Simple – RT, Middle – decisions made using simple parameters, and High – traditional EF processes. The Middle level of PS was intended to capture speeded responses that are separate from processes traditionally ascribed to EFs (planning, working memory, inhibition, shifting, etc.). However, the correlation between both cognitively-based factors (Middle and High) was very strong (r = 1.05), requiring the factors to be collapsed into a single ‘Complex’ latent factor. Furthermore, while the operational definition of the different Timing model factors does not involve the level of cognition required on a given measure, it so happened that most of the tasks included in the Efficiency factor (a combination of timed tasks and time-dependent tasks) were more cognitively complex than those included in the Latency factor. While differentiation between PS and EF was not evidenced in this study, a stronger test of this differentiation for future studies would include a systematic, a priori structure that uses measures capable of separating the timing mechanism from the cognitive parameters.

Similar to the Complexity Model, the Timing model also exhibited a dual-level structure. The construct of PS has been collected in a variety of ways in the literature, including pure response speed or RT to simple, low demand tasks (Deary & Der, 2005; Salthouse, 2000), as well as in a more complex manner as in the subtests of the Processing Speed Index of the Wechsler tests (Coding and Symbol Search; Wechsler, 2003; 2014). For this study, the Timing model latent factors were originally developed to capture three separate ways in which PS can be collected from a variety of speed-related tasks: Latency/RT, time-dependent tasks or how long it takes to complete a set number of items in a task, and timed tasks or how many items can be completed within a set period of time. However, the two latent factors related to more efficiency-based timing mechanisms were strongly related (r = 1.00), and were therefore combined into an "Efficiency" factor. The findings suggest that the construct of PS is separable by the way in which timed data is collected (i.e., pure speed vs. accuracy). Future studies may benefit from examination of a variety of speeded measures in conjunction with more strongly empirically supported measures of PS and RT.

The way in which we define each level of the dual-level of PS is critical and can impact interpretation of empirical results. For example, Deary and Ritchie recently defined PS tasks as those that capture "how efficiently people can complete mental tasks that, if there were no time pressure, would rarely be answered incorrectly" (p. 28, Deary & Ritchie, 2016). In contrast, other authors define PS tasks as those that capture information in a speeded manner that are free to vary on the level of cognitive demands placed on the examinee (Chiaravalloti et al., 2003; Shanahan et al., 2006). Although a precise definition of PS or the format in which it should be collected cannot be determined by this study alone, the results indicate a clear separation between low-cognitive demand, "pure speed" measures, and those that involve varying degrees of cognitive load. This separation was apparent even when the cognitive load was rather low. Additionally, while the predictive power of individual tasks may differ (e.g., NEPSY Visual Puzzles vs. DKEFS Verbal

Fluency), a strength of this study is that the use of latent variables provides a context for examining relationships that are less dependent on individual error variances.

Prediction Aim Discussion

While the Structural Aim of this study provided support for PS as a dual-level construct, the value of any model is also dependent on its predictive utility of relevant outcomes. The Predictive Aim of this study examined the contribution of PS as a key/unique predictor of three reading skills (single word reading, reading fluency, and reading comprehension). While the Complexity model was hypothesized to be the best fitting model, the results from the Structural Aim indicated that the Timing model was a better fit. Therefore, both models were run in the predictive aim, though the pattern of results was ultimately the same for each model.

The pattern of results for both the Timing and Complexity models support the proposed hypotheses that the more complex level of PS would be a greater predictor of single word reading, reading fluency, and reading comprehension. In the context of highly relevant language and demographic covariates, the Efficiency/Complex factor was contributory to all three examined reading skills, but the Latency/Simple factor was only contributory for single word reading. The hypothesis that PS would account for more variance (over strong demographic and language covariates) for the fluency outcome relative to other reading outcomes, was also supported (e.g., ~5% ΔR^2 relative to 2% for the other models). The total R^2 contribution between the examined models was similar, which would be expected given that each model ultimately included the same exact measures (all 16 PS indicators and relevant covariates). Therefore, any differences in R^2 contribution, although very small, must be due to the differential predictive utility of the latent variables despite being so similar.

The current findings suggest that the predictive power of PS may track with the level of cognitive processing required in the measures used to evaluate PS. The Efficiency/Complex factor was predictive of all three examined reading skills when PS was examined alone and in the context of demographic and language covariates. However, the Latency/Simple factor was only predictive for word decoding when in the context of covariates. The separable utility of these latent factors of PS is supported by a study by Wolff et al. (1990) who found that children with dyslexia show impairment on speeded motor tasks only when the task required more complex processing, and there were no differences between those children and controls on a simple motor RT task. Additionally, Nissan, Liewald and Deary (2013) examined the relation between different types of 'simple' and 'choice' RTs and intelligence and found that RT involving more cognitive processing was more strongly related to cognitive performance. Management of speed versus accuracy on more complex tasks may account for the differential predictive utility between the pure speed Latency/Simple factor and the duality of additional cognitive functions required in the Efficiency/Complex factors.

The predictive role of PS in the evaluation of key reading skills for 3rd through 5th grade children has been examined but with variable support in the literature (Catts et al., 2002; Christopher et al., 2012; Shaul & Nevo, 2015). For reading comprehension, the Efficiency/Complex latent factor remained significant in the context of oral comprehension and single word reading (covariates from the Simple View of Reading; Hoover & Gough, 1990). Additionally, for both word reading and reading fluency, the Efficiency/Complex latent factor remained contributory in the context of rapid naming and phonological awareness (covariates from the Dual Deficit model of dyslexia; Bowers & Wolf, 1993; Wolf & Bowers, 1999). Previous studies have found variable support for the role of PS as a separate predictor from RAN (Cutting & Denckla, 2001; Georgiou, Parrila, & Kirby, 2009), and this study provides evidence for PS as a separate (and predictive) construct. Taken together, the predictive utility of the more complex, efficiency-based level of PS, in the context of highly relevant and empirically supported language processes, provides support for PS (specifically the more cognitively complex level) as a unique contributor to reading skills in elementary-aged children.

The role of the Simple/Latency level of PS is more nuanced, specifically for single word reading. When PS alone was examined, only the Efficiency/Complex factor was predictive (similar to the other examined reading skills), but in the context of other highly relevant covariates, both the Simple/Latency and Efficiency/Complex factors were predictive. McGrath et al. (2011) also found that a PS latent factor (based on the Shanahan et al., 2006 study and most aligned with the Efficiency/Complex factors from this study) was predictive of both timed and untimed word reading, while a RAN-based latent factor was only predictive of timed reading. Additionally, the differential predictive utility of separate levels of PS has been found previously in a study that found that slow PS in Kindergarten predicts different reading skills than average PS, although word decoding was significantly predicted by both levels of PS (Shaul & Nevo, 2015). The strong relation between PS and word decoding is also supported by previous studies (Catts et al., 2002; Christopher et al., 2012; Shaul & Nevo, 2015) where single word reading (as captured by tasks ranging from non-word decoding to single word recognition) was consistently related to PS, no matter how PS was defined and captured in the various studies.

One potential explanation for the present findings is that the level of performance on each reading measure differed, such that participants performed within average levels on the single word reading (WJ LWID) task, but below average levels on both the reading fluency (TOWRE CWE) and reading comprehension (GMRT) tasks, despite the use of a weighting variable to account for the poor reading comprehension performance of the 4th grade students. Reading fluency and comprehension require multiple cognitive process to complete (i.e., EFs including shifting, inhibition and working memory; Gerst, Cirino, Fletcher, & Yoshida, 2015; Hudson, Pullen, Lane, & Torgesen, 2008; Savage, Cornish, Manly, & Hollis, 2006). However, single word reading may depend less on the higher level cognitive functions captured by the Efficiency/Complex level of PS, allowing for the Latency/Simple level of PS to display predictive power. However, given that the Latency/Simple level of PS was not predictive when covariates were *not* included, the need for additional examination of the role of this simple level of PS in different reading skills is apparent.

Christopher et al. (2012) also found support for the stronger predictive role of PS in word reading over comprehension (reading fluency was not examined), and suggested that the role of PS in word reading is to quickly retrieve learned words, while the context provided by a reading comprehension task lessens the need for quick word retrieval. Although the average single word reading performance in this sample was in the average range, this does not rule out that students in this study might be still be building their decoding skills. Given that the single word reading task involves the most decoding of the examined reading skills, it might be expected that the Latency/Simple level of PS would also be a significant predictor of tasks such as WJ Word Attack, where word decoding may be more strongly captured.

General Discussion

A definitive, multi-field, agreed upon definition of PS remains elusive. For example, in reviewing the labels commonly assigned to the construct of speeded cognitive processing in the literature, the Latency/Simple factor identified within this study may align best with the terms “reaction time,” “simple PS,” or “latency” and may be captured by the computerized, millisecond-based tasks that require very few cognitive requirements. The Efficiency/Complex factor identified within this study may align best with the terms “cognitive processing speed,” “cognitive tempo”, or “information processing” and may be captured by the paper-and-pencil, seconds-based tasks with requirements of cognitive processing to varying degrees. As such, the amount of “processing” required appears to differentiate the two factors of PS identified within this study.

Given the poor predictive utility of the Latency/Simple level of PS for highly relevant academic outcomes, even when examined only in the context of the other level of PS, one may ask, is the examination of the separate levels of PS worth it? The findings from this study suggest a nuanced interpretation of PS. The closer a measure gets to capturing pure and simple PS, predictive power may suffer (e.g., the poor predictive utility of the Latency/Simple factor), but the concept of speeded processing becomes more clear for such measures. On the other hand, the closer a measure gets to capturing a more complex level of PS, the more important the consideration of overlap with other cognitive processes becomes. The complex measures of PS in this study, or other common measures such as the Coding and Symbol Search from the Wechsler measures (Wechsler, 2003; 2014), require multiple types of "processing". Similarity between the more the cognitive demands of the PS measures and the outcomes may drive the observed correlation more than the underlying "speed".

Additional Future Directions. One area of interest in the literature appears to be the shared cognitive processes for comorbid disorders, such as reading disabilities (RD) and ADHD. Shanahan et al. (2006), previously examined the construct of PS as a shared risk factor among children with RD and ADHD and found a similar pattern of deficits between groups, with PS being worse in the RD group. However, PS was defined in a methodological manner (similar the Output model in this study) and was not compared against other theoretically driven models of PS. Given the predictive utility of PS for multiple reading skills identified in this study, future examination of the role of PS as a disorder-specific or more general neurodevelopmental deficit is warranted. Specifically, as children with RD and ADHD also share EF deficits, which may overlap with the more complex, efficiency-based level of PS identified in this study.

The results of this study also are relevant to clinicians who assess PS. For example, PS is often operationalized with subtests of the Wechsler IQ measures (Wechsler, 2003; 2014). PS can also be operationalized as slowed performance on other speeded measures of cognitive function like attention, EF, and motor skills tasks. When PS impairments are noted, recommendations for speed-based academic accommodations, including extended time on homework and tests, are expected. However, given the differential predictive utility of the dual-levels of PS identified in this study and additional causes of slowed performance including distractibility and anxiety, the benefit received from time-based accommodations may or may not be captured in a clinical evaluation, depending on the tasks chosen and how they are interpreted. Future studies may examine whether children differ on their level of PS (i.e., fast simple level and slow complex level) and whether their response to academic accommodations can be predicted by their performance on the different levels of PS, above and beyond other potential causes of slowed performance.

Limitations

One limitation of this study was that the tasks included were primarily chosen to capture EF performance in this population. However, many of the measures included in this study have been used in prior studies examining PS (Anderson et al., 2001; Shanahan et al., 2006). Additionally, this study did not use standard clinical measures of PS (i.e., Coding & Symbol Search; Wechsler, 2003; 2014). It would, however, be expected that such measures would load more on the Efficiency/Complex than Simple/Latency latent factors, as the demands of each task would be operationalized to be placed in the Efficiency and Complexity factors. For example, Coding and Symbol Search would likely load onto the Efficiency latent factor because both tasks require the subject to complete as many items as possible within a defined time limit (120 seconds), similar to the task demands of the other Efficiency factor indicators. Additionally, both tasks would likely load well onto the Complexity factor as they require the subjects to respond according to higher level demands (i.e. scanning for the Symbol Search task and working memory for the Coding task; (Wechsler, 2003; 2014). Replication of this model structure with the inclusion of standard clinical measures of PS would provide additional support for the separation of PS as a dual-level construct.

Other limitations include the level of performance for the reading skills among the students. As previously reviewed, the 4th grade participants were chosen for inclusion in a reading intervention study due to low reading comprehension performance. In order to address this discrepancy, a weighted variable was included in all analyses to address the low reading performance among the sample. Additionally, both grade-level and age were included as covariates in the prediction regressions and were found to be significant predictors for each reading skills, indicating that the findings may be dependent on level of reading skill development and/or cognitive development. For example, it could be suggested that younger children will likely have worse performance on reading tasks and slower PS (Fry & Hale, 1996; Georgiou, Papadopoulos, & Kaizer, 2014). Future studies may provide better insight through a longitudinal examination of a dual-level model of PS in relation to reading skills development.

Additionally, the demographic make-up of the sample is unique and the results must be examined of the context of the sample population. For example, that 90% of the overall sample was eligible for free or reduced lunch, a proxy for SES with variable support (Harwell & LeBeau, 2010; Ransdell, 2012), indicates that it is likely that the variable was not predictive as a covariate due to the limited variability of the sample. However, SES has been found to be an important influence on the development of reading skills and PS in other studies (Aikens & Barbarin, 2008; Bowey, 1995; Hackman & Farah, 2009). Also, given that the measures in this study were presented in English, and previous studies have shown that poor English proficiency can impact academic performance (Abedi, 2002; Lesaux et al., 2010), the role of LEP on the reading comprehension model may represent the impact of English proficiency on reading skills development in an urban sample of children.

However, in the present study, LEP was only found to be predictive of reading comprehension, likely due to the high overlap between 4th grade participants with poor reading comprehension and those who were also designated as LEP by the school. Thus, it appears to be appropriate that LEP would be more strongly related to reading comprehension. Taken altogether, the results of this study should be examined in the context of a low SES, urban sample from a variety of cultural backgrounds.

Conclusion

In conclusion, we compared five separate models of PS using CFA. Findings suggest that PS is a dual-level construct with a separation apparent between a simple, speed-based and more complex, efficiency-based level of cognitive processing. When examined as predictors of key reading skills for late elementary-aged children, the simpler level of PS was found to be a poor predictor of reading fluency and comprehension, while the more complex level of PS appears to have unique predictive utility for all three examined skills (single word reading, reading fluency and reading comprehension), even in the context of highly relevant demographic and language covariates.

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Table 1. Indicator Variables by Predicted Model

		Complexity Model			Output Model		Input Model		Timing Model		
Task Name	Unitary	Simple	Middle *(Complex)*	*High (Complex)*	Verbal	Motor	Alphanumeric	Non-Alphanumeric	Latency	Time-Dependent *(Efficiency)*	Timed *(Efficiency)*
VF L	X			X	X		X			X	
VF Ca	X			X	X		X			X	
DF	X			X		X		X		X	
TMT NLS	X			X		X	X				X
TOL	X			X		X		X	X		
CB	X		X			X		X			X
CWIT	X		X		X			X			X
TMT NS	X		X			X	X				X
VP	X		X			X		X			X
PP	X		X			X		X		X	
VM	X		X			X	X			X	
GNG	X	X				X		X	X		
TMT MS	X	X				X		X			X
NB L	X	X				X	X		X		
NB S	X	X				X		X	X		
SS	X	X				X		X	X		

Note: VF L = DKEFS Verbal Fluency: Letters, VF Ca = DKEFS Verbal Fluency: Categories, DF = DKFES Design Fluency: Empty Dots, TMT NLS = DKEFS TMT: Number-Letter Sequencing, TOL = Tower of London, CB = Corsi Blocks: Forward, CWIT = DKEFS CWIT: Color Naming, TMT NS = DKEFS TMT: Number Sequencing, VP = NEPSY Visuomotor Precision, PP = Purdue Pegboard, VM = WJ-III Visual Matching, GNG = Go/No-Go, TMT MS = DKEFS TMT: Motor Speed, NB L = N-Back: Letters, NB S = N-Back: Shapes, SS = Stop Signal

Table 2. Demographic Characteristics

	Category/Scale	**Grade 3**	**Grade 4**	**Grade 5**	**Total**
N		186	482	176	844
Sex					
	Female (%)	101 (54%)	225 (47%)	84 (48%)	410 (49%)
Age					
	Mean (SD)	8.94 (0.50)	9.92 (0.53)	11.22 (0.49)	9.98 (0.91)
Site					
	Houston (%)	91 (49%)	244 (51%)	86 (49%)	421 (50%)
Ethnicity					
	Hispanic (%)	42 (22%)	213 (44%)	50 (28%)	304 (36%)
	White (%)	46 (25%)	49 (10%)	45 (26%)	140 (17%)
	Black (%)	73 (39%)	121 (25%)	53 (30%)	247 (29%)
	Other (%)	26 (14%)	99 (21%)	28 (16%)	153 (18%)
Special education (N = 451)					
	Yes (%)	14 (8%)	47 (10%)	28 (16%)	89 (11%)
	No (%)	84 (45%)	211 (44%)	67 (38%)	362 (43%)
Economic disadvantage					
	Free/Reduced lunch (%)	162 (87%)	448 (93%)	149 (85%)	759 (90%)
	Not economically disadvantaged (%)	24 (13%)	34 (7%)	27 (15%)	85 (10%)
Limited English Proficiency (N = 830)					
	LEP (%)	0 (0%)	197 (41%)	0 (0%)	197 (23%)
	Non-LEP (%)	186 (100%)	280 (58%)	167 (95%)	633 (75%)

Table 3: Descriptive Statistics for Indicator, Outcome and Covariate Variables

Variable	N	Mean	SD	Skew-ness	Kurt-osis	Data Patterns 1	2	3	4	5	6
VF L						x	x	x	x	x	x
Total Raw Score	832	18.22	7.13	0.48	0.27						
Scaled Score	832	8.93	2.91	0.44	0.04						
VF Ca						x	x	x	x	x	x
Total Raw Score	832	24.52	6.78	0.37	0.15						
Scaled Score	832	9.20	2.68	0.25	0.07						
DF						x	x	x	x	x	x
Total Raw Score	827	5.85	2.30	0.36	-0.01						
Scaled Score	827	8.93	2.48	0.40	0.18						
TMT NLS						x	x	x			
Total Time (seconds)	410	159.26	58.96	0.05	-1.35						
Scaled Score	405	7.33	4.12	-0.13	-1.26						
TOL						x	x	x	x	x	x
Mean Latency to First Move (ms)	822	7.33	0.36	0.78	1.46						
CB						x	x	x	x	x	x
Total Time (ms)	826	1532.08	341.84	1.10	1.79						
CWIT								x		x	x
Total Time (seconds)	415	44.86	9.33	0.79	1.52						
Scaled Score	415	9.78	2.92	-0.51	0.04						
TMT NS						x	x	x			
Total Time (seconds)	410	62.09	27.93	1.35	1.35						
Scaled Score	410	6.95	4.12	-0.22	-1.31						
VP							x		x	x	x
Total Time (seconds)	563	120.44	45.46	0.96	1.00						
Scaled Score	563	9.26	3.02	-0.28	0.57						
PP						x		x	x	x	x
Total Pegs	685	9.94	2.03	0.78	2.12						
z-score	685	-0.73	1.30	0.78	2.61						
VM							x	x		x	x
Total Raw Score	565	35.23	6.14	-0.24	0.75						
Scaled Score	562	94.66	14.56	0.05	0.01						
GNG						x	x		x	x	
Mean Latency for Go Trials (ms)	563	508.80	69.37	0.58	0.47						
TMT MS						x	x	x			
Total Time (seconds)	410	57.78	26.46	1.26	1.76						
Scaled Score	410	8.00	3.42	-0.55	-0.53						
NB L						x		x	x		x

Mean RT (ms)	544	373.47	48.33	0.68	0.84						
NB S						x	x		x	x	
Mean RT (ms)	559	377.82	47.65	0.68	0.75						
SS						x	x	x	x		x
Mean RT (ms)	524	714.12	162.32	0.82	0.45						
WJ LWID						x	x	x	x	x	x
Total Raw Score	842	47.47	8.62	0.02	-0.19						
Standard Score	839	96.08	13.44	-0.09	0.29						
TOWRE						x	x	x	x	x	x
Total Raw Score	836	57.58	13.13	-0.56	0.56						
Standard Score	835	87.64	14.98	0.06	-0.11						
GMRT						x	x	x	x	x	x
Total Raw Score	835	20.29	10.63	0.69	-0.57						
Standard Score	835	89.03	15.01	0.62	0.01						
WJ Oral Comp						x	x	x	x	x	x
Total Raw Score	838	16.03	5.22	-0.33	0.09						
Standard Score	834	92.96	15.94	-0.45	0.49						
CTOPP Elision						x	x	x	x	x	x
Total Raw Score	837	11.31	4.80	0.23	-1.29						
Scaled Score	836	8.25	3.00	0.33	-0.56						
CTOPP RLN						x	x	x	x	x	x
Total Time (seconds)	838	3.73	0.27	0.80	1.40						
Scaled Score	837	8.86	2.39	0.19	-0.08						

Note: RT = Reaction Time, ms = Milliseconds, VF L = DKEFS Verbal Fluency: Letters, VF Ca = DKEFS Verbal Fluency: Categories, DF = DKFES Design Fluency: Empty Dots, TMT NLS = DKEFS TMT: Number-Letter Sequencing, TOL = Tower of London, CB = Corsi Blocks: Forward, CWIT = DKEFS CWIT: Color Naming, TMT NS = DKEFS TMT: Number Sequencing, VP = NEPSY Visuomotor Precision, PP = Purdue Pegboard, VM = WJ-III Visual Matching, GNG = Go/No-Go, TMT MS = DKEFS TMT: Motor Speed, NB L = N-Back: Letters, NB S = N-Back: Shapes, SS = Stop Signal, WJ LWID = WJ-III Letter-Word ID, TOWRE = TOWRE Sight Word Efficiency, GMRT = Gates MacGinitie Reading Tests, Reading Comprehension, WJ Oral Comp = WJ-III Oral Comprehension, CTOPP Elision = CTOPP Phoneme Elision, CTOPP RLN = CTOPP Rapid Letter Naming

Table 4: Correlations among Indicator Variables

	VF L	VF Ca	DF	TMT NLS	TOL	CB	CWIT	TMT NS	VP
VF L	-								
VF Ca	0.52**	-							
DF	0.29**	0.30**	-						
TMT NLS	-0.39**	-0.33**	-0.35**	-					
TOL	-0.11*	-0.04	-0.10*	0.14*	-				
CB	-0.23**	-0.23**	-0.27**	0.25**	0.23**	-			
CWIT	-0.29**	-0.33**	-0.26**	0.40**	0.13*	0.26**	-		
TMT NS	-0.24**	-0.29**	-0.36**	0.45**	0.09	0.26**	0.33*	-	
VP	-0.06	-0.09*	-0.16**	0.10	0.07	0.13*	0.19*	0.11	-
PP	0.20**	0.22**	0.26**	-0.28**	-0.13*	-0.26**	-0.26**	-0.29**	-0.13*
VM	0.42**	0.37**	0.32**	-0.51**	-0.18**	-0.32**	-0.38**	-0.27**	-0.07
GNG	-0.20**	-0.15**	-0.23**	0.23**	0.11*	0.28**	0.24*	0.18*	0.11*
TMT MS	-0.24**	-0.26**	-0.26**	0.34**	0.10*	0.16*	0.23**	0.39**	0.29*
NB L	-0.18**	-0.14*	-0.17**	0.29**	0.16**	0.25**	0.24**	0.24**	0.07
NB S	-0.23**	-0.17**	-0.21**	0.17*	0.09*	0.28**	0.39**	0.11	0.05
SS	-0.10*	-0.17**	-0.10*	0.10	0.30*	0.27**	0.27**	0.12*	0.12*

	PP	VM	GNG	TMT MS	NB L	NB S	SS
PP	-						
VM	0.31**	-					
GNG	-0.17**	-0.22**	-				
TMT MS	-0.31**	-0.12	0.16*	-			
NB L	-0.22**	-0.18*	0.53**	0.21**	-		
NB S	-0.24**	-0.20**	0.48**	0.03	0.77**	-	
SS	-0.07	-0.13*	0.30**	0.11	0.25**	0.27**	-

Note: $^{*}p < .05$, $^{**}p < .001$, All correlations included the weighted variable; VF L = DKEFS Verbal Fluency: Letters, VF Ca = DKEFS Verbal Fluency: Categories, DF = DKFES Design Fluency: Empty Dots, TMT NLS = DKEFS TMT: Number-Letter Sequencing, TOL = Tower of London, CB = Corsi Blocks: Forward, CWIT = DKEFS CWIT: Color Naming, TMT NS = DKEFS TMT: Number Sequencing, VP = NEPSY Visuomotor Precision, PP = Purdue Pegboard, VM = WJ-III Visual Matching, GNG = Go/No-Go, TMT MS = DKEFS TMT: Motor Speed, NB L = N-Back: Letters, NB S = N-Back: Shapes, SS = Stop Signal

Table 5: Correlations between Indicator Variables and Reading Measures

	WJ LWID	TOWRE CWE	GMRT
VF L	0.38**	0.41**	0.38**
VF Ca	0.29**	0.32**	0.29**
DF	0.20**	0.20**	0.20**
TMT NLS	-0.36**	-0.31**	-0.36**
TOL	-0.04	-0.09*	-0.04
CB	-0.22**	-0.29**	-0.22**
CWIT	-0.29**	-0.50**	-0.29**
TMT NS	-0.18**	-0.20**	-0.18**
VP	0.01	-0.08	0.02
PP	0.11*	0.18**	0.11*
VM	0.29**	0.43**	0.29**
GNG	-0.16**	-0.20**	-0.16**
TMT MS	-0.20**	-0.17*	-0.20**
NB L	-0.12*	-0.20**	-0.12*
NB S	-0.12**	-0.21**	-0.15**
SS	-0.12*	-0.11*	-0.12*

Note: *$p < .05$, **$p < .001$, All correlations included the weighted variable; VF L = DKEFS Verbal Fluency: Letters, VF Ca = DKEFS Verbal Fluency: Categories, DF = DKFES Design Fluency: Empty Dots, TMT NLS = DKEFS TMT: Number-Letter Sequencing, TOL = Tower of London, CB = Corsi Blocks: Forward, CWIT = DKEFS CWIT: Color Naming, TMT NS = DKEFS TMT: Number Sequencing, VP = NEPSY Visuomotor Precision, PP = Purdue Pegboard, VM = WJ-III Visual Matching, GNG = Go/No-Go, TMT MS = DKEFS TMT: Motor Speed, NB L = N-Back: Letters, NB S = N-Back: Shapes, SS = Stop Signal, WJ LWID = WJ-III Letter-Word ID, TOWRE = TOWRE Sight Word Efficiency, GMRT = Gates MacGinitie Reading Tests, Reading Comprehension

Table 6: Correlations between Indicator and Covariate Variables

	WJ Oral Comp	CTOPP Elision	CTOPP RLN
VF L	0.44**	0.29**	0.42**
VF Ca	0.38**	0.20**	0.33**
DF	0.28**	0.20**	0.26**
TMT NLS	0.39**	0.27**	0.24**
TOL	0.06	0.01	0.11*
CB	-0.21**	0.21**	0.30**
CWIT	-0.24**	-0.22**	0.48**
TMT NS	-0.23**	-0.10	0.19**
VP	<0.01	0.05	0.13*
PP	0.17**	0.09*	-0.21**
VM	0.25**	0.19**	-0.39**
GNG	-0.19**	-0.13*	0.24**
TMT MS	-0.31**	-0.14*	0.23**
NB L	-0.21**	-0.15**	0.27**
NB S	-0.25**	-0.09*	0.33**
SS	-0.23**	-0.05	0.16**

Note: *$p < .05$, **$p < .001$, All correlations included the weighted variable; VF L = DKEFS Verbal Fluency: Letters, VF Ca = DKEFS Verbal Fluency: Categories, DF = DKFES Design Fluency: Empty Dots, TMT NLS = DKEFS TMT: Number-Letter Sequencing, TOL = Tower of London, CB = Corsi Blocks: Forward, CWIT = DKEFS CWIT: Color Naming, TMT NS = DKEFS TMT: Number Sequencing, VP = NEPSY Visuomotor Precision, PP = Purdue Pegboard, VM = WJ-III Visual Matching, GNG = Go/No-Go, TMT MS = DKEFS TMT: Motor Speed, NB L = N-Back: Letters, NB S = N-Back: Shapes, SS = Stop Signal, WJ Oral Comp = WJ-III Oral Comprehension, CTOPP Elision = CTOPP Phoneme Elision, CTOPP RLN = CTOPP Rapid Letter Naming

Table 7: Structural Aim Model Fit Statistics

Model	AIC	BIC	ABIC	χ^2	*df*	RMSEA	90% RMSEA C.I.	CFI	TLI	SRMR	χ^2 diff	*p*
1. Unitary (1 factor)	78865.460	79097.630	78942.021	382.460	103	0.057	0.051 to 0.063	0.801	0.768	0.086		
2a. Complexity (3 factors)	78676.728	78923.112	78757.976	226.148	100	0.039	0.032 to 0.045	0.910	0.892	0.075	156.312	< 0.001
2b. Complexity (2 factors)	**78677.744**	**78914.652**	**78755.868**	**230.196**	**102**	**0.039**	**0.032 to 0.045**	**0.909**	**0.892**	**0.075**	**152.264**	**< 0.001**
3. Input (2 factors)	78857.933	79094.840	78936.056	376.034	102	0.056	0.050 to 0.063	0.805	0.770	0.085	6.426	0.016
4. Output (2 factors)	78866.234	79103.141	78944.357	381.141	102	0.057	0.051 to 0.063	0.801	0.766	0.085	1.319	0.298
5a. Timing (3 factors)	78636.274	78882.658	78717.523	193.741	100	0.033	0.026 to 0.040	0.933	0.920	0.058	188.719	< 0.001
5b. Timing (2 factors)	**78632.511**	**78869.419**	**78710.635**	**194.053**	**102**	**0.033**	**0.026 to 0.040**	**0.934**	**0.923**	**0.058**	**188.407**	**< 0.001**

Table 8a: Regression Statistics for Single Word Reading (Model 2b)

Predictor	*b*	*SE(b)*	*β*	*t*	*p*
Complexity PS Model					
Simple	-0.539	0.397	-0.064	-1.356	0.175
Complex	-3.978	0.410	-0.471	-9.706	< .001
Total Model R^2 = 0.254, (p < .001)					
Complexity PS Full Model					
Simple	-0.735	0.350	-0.087	-2.099	0.036
Complex	-1.216	0.513	-0.144	-2.367	0.018
CTOPP RLN	-1.391	0.291	-0.165	-4.786	< .001
CTOPP Elision	3.178	0.281	0.376	11.308	< .001
Age	-2.788	0.479	-0.330	-5.818	< .001
Sex	0.400	0.240	0.047	1.668	0.095
Grade 3	-1.758	0.323	-0.208	-5.442	< .001
Grade 5	2.818	0.433	0.334	6.516	< .001
Total Model R^2= 0.471, (p < .001)					

Note: CTOPP Elision = CTOPP Phoneme Elision, CTOPP RLN = CTOPP Rapid Letter Naming

Table 8b: Regression Statistics for Single Word Reading (Model 5b)

Predictor	*b*	*SE(b)*	*β*	*t*	*P*
Timing PS Model					
Latency	-0.630	0.398	-0.075	-1.583	0.113
Efficiency	-3.885	0.411	-0.460	-9.444	< .001
Total Model R^2 = 0.248, (p < .001)					
Timing PS Full Model					
Latency	-0.779	0.345	-0.092	-2.258	0.024
Efficiency	-1.102	0.513	-0.130	-2.148	0.032
CTOPP RLN	-1.425	0.294	-0.169	-4.844	< .001
CTOPP Elision	3.193	0.282	0.378	11.338	< .001
Age	-2.798	0.479	-0.331	-5.846	< .001
Sex	0.421	0.238	0.500	1.769	0.077
Grade 3	-1.778	0.322	-0.210	-5.521	< .001
Grade 5	2.863	0.431	0.339	6.646	< .001
Total Model R^2= 0.470, (p < .001)					

Note: CTOPP Elision = CTOPP Phoneme Elision, CTOPP RLN = CTOPP Rapid Letter Naming

Table 9a: Regression Statistics for Reading Fluency (Model 2b)

Predictor	*B*	*SE(b)*	*β*	*t*	*p*
Complexity PS Model					
Simple	0.352	0.559	0.029	0.630	0.529
Complex	-7.117	0.603	-0.581	-11.812	< .001
Total Model R^2 = 0.323, (p < .001)					
Complexity PS Full Model					
Simple	0.143	0.474	0.012	0.301	0.764
Complex	-4.110	0.722	-0.335	-5.691	< .001
CTOPP RLN	-4.726	0.439	-0.386	-10.760	< .001
CTOPP Elision	1.631	0.366	0.133	4.461	< .001
Age	-5.308	0.685	-0.433	-7.754	< .001
Sex	0.544	0.335	0.044	1.623	0.105
Grade 3	-2.034	0.465	-0.166	-4.375	< .001
Grade 5	2.800	0.608	0.229	4.605	< .001
Total Model R^2= 0.504, (p < .001)					

Note: CTOPP Elision = CTOPP Phoneme Elision, CTOPP RLN = CTOPP Rapid Letter Naming

Table 9b: Regression Statistics for Reading Fluency (Model 5b)

Predictor	*b*	*SE(b)*	*β*	*t*	*p*
Timing PS Model					
Latency	0.174	0.555	0.014	0.314	0.753
Efficiency	-6.945	0.596	-0.567	-11.660	< .001
Total Model R^2 = 0.314, (p < .001)					
Timing Full Model					
Latency	0.025	0.466	0.002	0.055	0.957
Efficiency	-3.898	0.705	-0.318	-5.526	< .001
CTOPP RLN	-4.776	0.443	-0.390	-10.777	< .001
CTOPP Elision	1.638	0.364	0.134	4.504	< .001
Age	-5.388	0.685	-0.440	-7.870	< .001
Sex	0.604	0.333	0.049	1.814	0.070
Grade 3	-2.126	0.462	-0.173	-4.602	< .001
Grade 5	2.914	0.606	0.238	4.808	< .001
Total Model R^2= 0.500, (p < .001)					

Note: CTOPP Elision = CTOPP Phoneme Elision, CTOPP RLN = CTOPP Rapid Letter Naming

Table 10a: Regression Statistics for Reading Comprehension (Model 2b)

Predictor	*b*	*SE(b)*	*β*	*t*	*P*
Complexity PS Model					
Simple	0.326	0.473	0.033	0.689	0.491
Complex	-4.658	0.454	-0.468	-10.259	< .001
Total Model R^2 = 0.206, (p < .001)					
Complexity PS Full Model					
Simple	0.122	0.304	0.012	0.401	0.688
Complex	-2.255	0.508	-0.227	-4.440	< .001
WJ Oral Comp	1.981	0.277	0.199	7.156	< .001
WJ LWID	4.681	0.259	0.470	18.093	< .001
CTOPP RLN	-0.024	0.319	-0.002	-0.075	0.940
Sex	0.473	0.238	0.048	1.993	0.046
LEP	-1.595	0.210	-0.160	-7.612	< .001
Grade 3	3.451	0.299	0.347	11.545	< .001
Grade 5	-0.873	0.299	-0.088	-2.914	0.003
Total Model R^2= 0.651, (p < .001)					

Note: WJ Oral Comp = WJ-III Oral Comprehension, WJ LWID = WJ-III Letter-Word Identification, CTOPP RLN = CTOPP Rapid Letter Naming, LEP = Limited English Proficiency

Table 10b: Regression Statistics for Reading Comprehension (Model 5b)

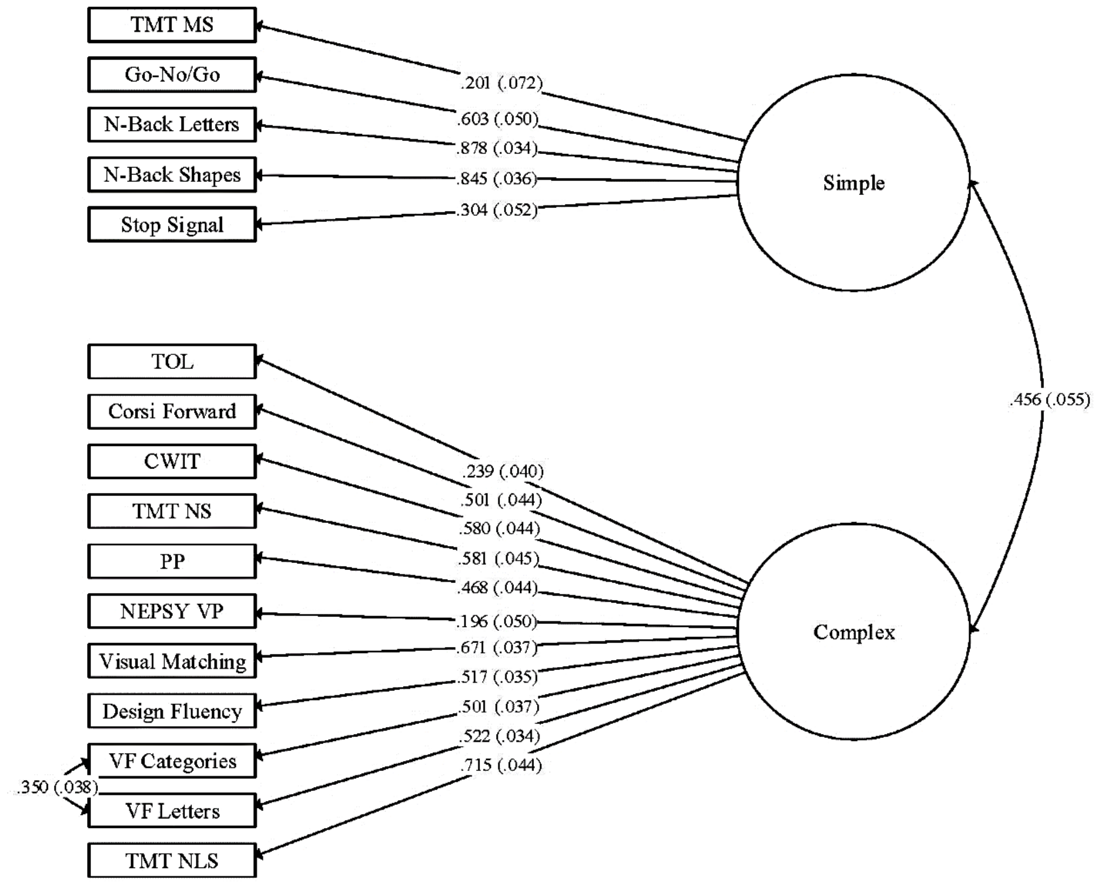
Predictor	*b*	*SE(b)*	*β*	*t*	*p*
Timing PS Model					
Latency	0.294	0.468	0.030	0.629	0.529
Efficiency	-4.658	0.446	-0.468	-10.435	< .001
Total Model R^2 = 0.207, (p < .001)					
Timing PS Full Model					
Latency	0.068	0.295	0.007	0.231	0.818
Efficiency	-2.170	0.492	-0.218	-4.412	< .001
WJ Oral Comp	1.959	0.280	0.197	6.998	< .001
WJ LWID	4.713	0.295	0.473	18.187	< .001
CTOPP RLN	-0.036	0.313	-0.004	-0.115	0.908
Sex	0.502	0.236	0.500	2.123	0.034
LEP	-1.595	0.209	-0.160	-7.630	< .001
Grade 3	3.427	0.297	0.344	11.549	< .001
Grade 5	-0.846	0.300	-0.085	-2.823	0.005
Total Model R^2= 0.650, (p < .001)					

Note: WJ Oral Comp = WJ-III Oral Comprehension, WJ LWID = WJ-III Letter-Word Identification, CTOPP RLN = CTOPP Rapid Letter Naming, LEP = Limited English Proficiency

Table 11: Predictive Aim Model Fit Statistics

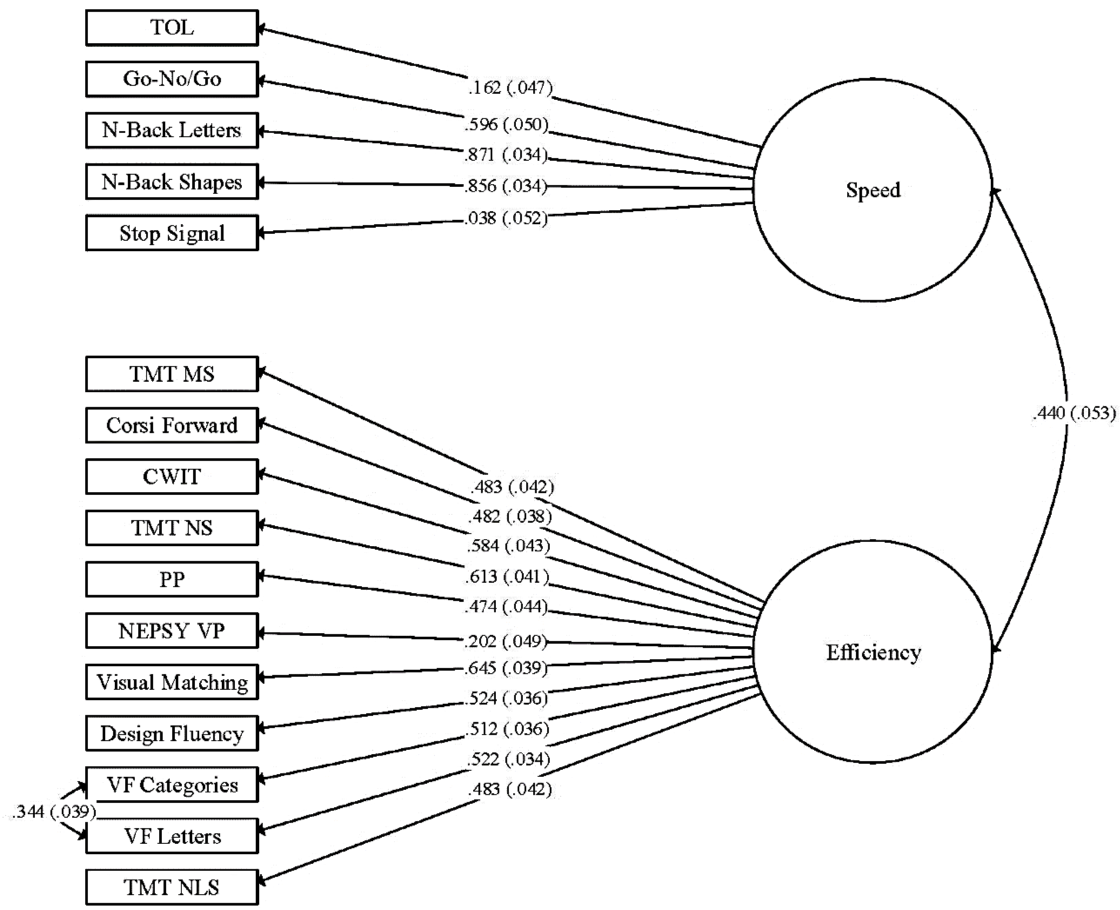
Model	**AIC**	**BIC**	**ABIC**	χ^2	*df*	**RMSEA**	**90% RMSEA C.I.**	**CFI**	**TLI**	**SRMR**
1a. Single Word Reading *(Complexity)*	92974.246	93438.585	93127.368	512.593	201	0.043	0.038 to 0.047	0.915	0.892	0.070
1b. Single Word Reading *(Timing)*	92929.699	93394.038	93082.821	475.825	201	0.040	0.036 to 0.045	0.925	0.905	0.060
2a. Fluency *(Complexity)*	93529.131	93993.470	93682.253	511.167	201	0.043	0.038 to 0.047	0.916	0.894	0.070
2b. Fluency *(Timing)*	93485.973	93950.312	93639.094	475.429	201	0.040	0.036 to 0.045	0.925	0.906	0.060
3a. Comprehension *(Complexity)*	97507.062	98028.259	97678.933	583.649	214	0.045	0.041 to 0.050	0.903	0.875	0.068
3b. Comprehension *(Timing)*	97460.355	97981.552	97632.226	543.997	214	0.043	0.038 to 0.047	0.913	0.888	0.057

Figure 1: Model 2b (Complexity)



Note: All loadings were significant at *p* < .001; TMT MS = DKEFS TMT: Motor Speed, TOL = Tower of London, CWIT = DKEFS CWIT: Color Naming, TMT NS = DKEFS TMT: Number Sequencing, PP = Purdue Pegboard, NEPSY VP = NEPSY Visuomotor Precision, Visual Matching = WJ-III Visual Matching, Design Fluency = DKFES Design Fluency: Empty Dots, VF Categories = DKEFS Verbal Fluency: Categories, VF Letters = DKEFS Verbal Fluency: Letters, TMT NLS = DKEFS TMT: Number-Letter Sequencing

Figure 2: Model 5b (Timing)



Note: All loadings were significant at $p < .001$; TOL = Tower of London, TMT MS = DKEFS TMT: Motor Speed, CWIT = DKEFS CWIT: Color Naming, TMT NS = DKEFS TMT: Number Sequencing, PP = Purdue Pegboard, NEPSY VP = NEPSY Visuomotor Precision, Visual Matching = WJ-III Visual Matching, Design Fluency = DKFES Design Fluency: Empty Dots, VF Categories = DKEFS Verbal Fluency: Categories, VF Letters = DKEFS Verbal Fluency: Letters, TMT NLS = DKEFS TMT: Number-Letter Sequencing