HHS Public Access
Author manuscript
J Cogn Dev. Author manuscript; available in PMC 2022 January 01.

Published in final edited form as:
J Cogn Dev. 2021 ; 22(1): 84–107. doi:10.1080/15248372.2020.1862121.

The Structure of Processing Speed in Children and its Impact on Reading

Elyssa H. Gerst,
Children's Healthcare of Atlanta

Paul T. Cirino,
University of Houston

Kelly T. Macdonald,
University of Houston

Jeremy Miciak,
University of Houston

Hanako Yoshida,
University of Houston

Steven P. Woods,
University of Houston

M. Cullen Gibbs
TIRR Memorial Hermann

Abstract

The present study had two aims. First, we set out to evaluate the structure of processing speed in children by comparing five alternative models: two conceptual models (a unitary model, a complexity model) and three methodological models (a stimulus material model, an output response model, and a timing modality model). Second, we then used the resulting models to predict multiple types of reading, a highly important developmental outcome, using other well-known predictors as covariates. Participants were 844 children enrolled in third through fifth grade in urban public elementary schools who received 16 measures of processing speed that varied in the above dimensions. A two-factor complexity model that differentiated between simple and complex processing speed was the preferred model and fit the data well. Both types of PS predicted reading fluency, and complex (but not simple) PS predicted single word reading and comprehension. Results offer insight to the structure of processing speed, its relation to closely related concepts (such as executive function), and provide nuance to the understanding of the way processing speed influences reading.

Keywords

Processing Speed; Literacy; Children

Corresponding Author: Paul T. Cirino, Ph.D., Department of Psychology, University of Houston, 4849 Calhoun Rd., Ste 480, Houston, TX 77204-6022. pcirino@uh.edu.

The *concept* of processing speed (PS) is intuitive, though its *operationalization* is widely variable. PS in this study can refer to any task where some cognitive processing is involved and time is a factor. The 'processing' of PS can range from perceptual to cognitive/strategic, and the 'speed' of PS can be assessed over different time scales (i.e., milliseconds or seconds). Studying the dimensionality of PS and how it relates to functional outcomes is highly relevant because PS can be affected by a variety of neurological and developmental disorders, and because impaired PS can adversely impact the rate of learning available and the acquisition of new skills in school-aged children (Marchman & Fernald, 2008). A key functional outcome for children is reading, and PS has been implicated for reading, both as a predictor (e.g., operationalized as rapid naming; Araújo, Reis, Petersson, & Faísca, 2015), and as a shared deficit in comorbid conditions of reading and attention (e.g., attention deficit hyperactivity disorder; McGrath et al., 2011). The present study evaluates the latent structure of PS and then uses these models to predict reading skills in a large group of struggling readers in late elementary school.

Processing Speed Models

The structure of PS is not ubiquitously accepted, and few models focus on children. Many studies that invoke PS do not attempt to delineate its dimensionality, instead utilizing a single PS measure or a PS composite score (e.g., Borella & Ribaupierre, 2014; Shaul & Nevo, 2015). Where studies do evaluate the dimensionality of PS, five potential models can be distinguished. Two of these (unitary versus complexity) are informed by theoretical and empirical work that differentiates the complexity of the processing involved, and thus are conceptual in nature. The remaining three (stimulus material versus output modality versus timing modality) are more methodological, focusing on varying surface features or task parameters, but also have some empirical support. Comparing within and between conceptual and methodological models has been done in the area of executive function (EF; Cirino et al., 2018a; Wiebe, Espy, & Charak, 2008), but we are unaware of a similar evaluation for PS in children.

Unitary.

A unitary model of PS suggests that a latent variable built from any kind of timed measurement would provide a strong fit 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). This unitary construct view of PS has gained support though factor analyses that identify a single latent variable of PS among other latent variables of cognitive function (Barth, Catts, & Anthony, 2008; Nigg, Jester, Stavro, Ip, Puttler, & Zucker, 2017; Pires, Moura, Geurrini, Buekenhout, Simoes, & Leitao, 2019). Interestingly, some of these studies also included a latent variable of EF, and found robust and similar latent correlations with PS ($r = .62$; Nigg et al., 2017, and $r = .64$; Pires et al., 2019).

Complexity.

In contrast to a unitary model, “complexity” models distinguish between the levels of ‘processing’ required. This has found some support in the literature. For example, Chiaravalloti, Christodoulou, Demaree, and DeLuca (2003) found support for a simple versus complex distinction (along with a working memory factor) with 11 measures, though this study was small and with a mixed medical sample of adults that relied on principal components analyses rather than confirmatory techniques. Demetriou, Christou, Spanoudis, Platsidou, Fischer, and Dawson (2002) in a longitudinal sample of 113 children ages 8 to 16 found a hierarchical structure; across three types of stimuli, their “incompatible/control” tasks (e.g., the word green written in red ink) were more complex than “compatible/speed” versions (e.g., the word green written in green ink), and each of these factors loaded to a second order factor. Also, a distinction along the lines of complexity is also apparent in Carroll’s (1993) taxonomy (e.g., broad speediness or Gs versus processing speed or Gt).

The present study examines three levels of complexity that differentiate between: (a) a simple level of PS operationalized as reaction time or latency to respond to a perceptual target, with no additional cognitive demands; (b) a middle level of complexity operationalized as speed of response on a measure with minimal goal-directed demands (i.e., the task is relatively easy but does require, for example, simple sequencing); and (c) a high level of complexity that requires goal-directed processing and efficiency (thus overlapping with EF).

The relationship of PS with EF is highly relevant given that EF factor analytic work often includes timed/speeded measures (e.g., Cirino et al., 2018a; Huizinga, Dolan, & van der Molen, 2006; Miyake, Friedman, Emerson, Witzki, & Howerter, 2000), and given the relation of these constructs (Nigg et al., 2017; Pires et al., 2019). Conceptually, such work suggests the necessity to demarcate where PS “ends” and EF “begins,” particularly in children where cognitive structures/relationships can vary across developmental stage. For example, a unitary factor of EF in preschool gives way to separate but related processes throughout development (Anderson, Anderson, Northam, Jacobs, & Catroppa, 2001; Cirino et al., 2018a; Miyake et al., 2000); it is unknown if a similar pattern may be evidenced for PS. The relation of PS to EF factors (particularly working memory; WM) may also vary depending on the child’s developmental stage (Demetriou et al., 2014; Kail, Lervag, & Hulme, 2016). The late elementary school age-range within this study is particularly relevant given important school transitions in reading. The complexity model of PS examined here can set the stage for future studies that might combine the resulting structure with a structural model of EF, particularly one that includes both timed/speeded and untimed EF tasks.

Stimulus Material (Input).

One surface task parameter that could influence performance is the nature of the stimuli. The distinction between alphanumeric (i.e., letters and words) and non-alphanumeric (i.e., shapes and colors) stimuli has overlap with, but is separable from, a verbal-auditory/visual distinction and has been previously examined for WM (Baddeley, 2003). Leonard et al. (2007) found that incorporating a general speed model with subfactors of linguistic and nonlinguistic speed fit best when differentiating among PS and WM in children with language impairment. Kail and Miller (2006) though not using latent variables, did distinguish between language and nonlanguage measures of PS, and showed different developmental trajectories for those measures (with language PS faster at age 9, but nonlanguage PS growing more rapidly through age 14). Therefore, a stimulus-based (input) methods model of PS is an important alternative model to consider.

Response Type (Output).

A second surface task parameter that may vary is the nature of the motor response required for a given PS stimulus (e.g., oral versus manual). Such a two-factor model has been found in children by others. For example, Shanahan et al. (2006), with 12 measures of processing speed, differentiated verbal versus motor output factors (although it should be noted that in general the verbal tasks were alphanumeric and the motor tasks were not). Babcock, Laguna, and Roesch (1997) used nine PS measures and were able to differentiate three factors that represented alphanumeric, geometric, and motor PS, though these factors correlated highly with one another ($r = .69$ to .92). In that study and others, there was not a comparison nor differentiation from an input/material model such as described above. Because response type may or may not track with stimulus material (e.g., an alphanumeric stimulus could require either an oral or manual response), such a comparative model is useful to include in order to differentiate these possibilities.

Timing.

A third surface task parameter that may vary involves the nature of timing involved. For example, timing can be operationalized as the latency between a presentation of a stimulus and a correct response on a single task item (Deary & Der, 2005; Salthouse, 2000), which can itself vary in its cognitive demands (i.e., Dennis et al., 2015). Alternatively, timing can be invoked on tasks assessing efficiency – either accuracy within a specified time limit (time-dependent; naming within a 60 second trial), or through tasks that are timed through completion (timed; how long it takes to complete a set of items). While no known studies have directly examined this proposed three-factor model, Denney, Gallagher, and Lynch (2011) did find differences between measures that “explicitly” measure speed (e.g., where it is made clear that time is an important component) and those that “covertly” measure speed (e.g., where the capture of speed appears secondary to accuracy) in a principal components analysis of adults.

Reading Skills and Processing Speed

Reading outcomes are a strong external validity target for the PS models described above. Single word reading, reading fluency, and reading comprehension will be examined in the present study given their separability, as well as importance as distinct intervention targets for this age-range (Cirino et al., 2013). These reading components develop simultaneously and interactively into and beyond late elementary school (Duke & Carlisle, 2010). Reading proficiency is dependent on the co-occurring development (or bi-directional influence) of other cognitive processes. These include phonological awareness (PA; the ability to break a word down to its component parts; Wagner, Torgesen, & Rashotte, 1994) and rapid automatized naming (RAN; the ability to quickly and efficiently name alphanumeric stimuli; Norton & Wolf, 2012). They also include word reading and listening comprehension (Gough & Tunmer, 1986); WM and other EF (Kibby, Lee, & Dyer, 2014); strategy use (Oakhill & Cain, 2012); and also background knowledge (Speece, Ritchey, Cooper, Roth, & Schatschneider, 2004).

The relation of PS with reading has most often been viewed through the lens of rapid automatized naming or RAN, which is consistent with the double-deficit hypothesis of Wolf and Bowers (1999) that attributes poor reading automaticity in reading disability (RD) to both a phonological deficit as well as an underlying processing speed deficit. PS has also been invoked with regard to how RD intersects with other neurodevelopmental disorders as a shared cognitive predictor (e.g., with math disability and ADHD), particularly with reference to the multiple deficit model of developmental disorders (Pennington, 2006).

Many studies focus on the robust RAN-reading relationship per se (e.g., see studies in the meta-analysis of Araújo et al., 2015; overall $r = 43$). However, a small group of studies simultaneously evaluate multiple PS with latent variables (in each case, a verbal PS latent variable with RAN indicators is differentiated from a more “nonverbal/perceptual” PS latent variable), with children and adolescents, often while also considering a number of other cognitive factors (Christopher et al., 2012; Georgiou, Parrila, & Papadopoulos, 2016; McGrath et al., 2011; Papadopoulos, Spanoudis, & Georgiou, 2016; Peterson et al., 2017; Shanahan et al., 2006). The Georgiou et al. (2016) and Papadopoulos et al., (2016) studies only examined reading fluency in elementary school, and did so in a transparent orthography (Greek); in both studies, there was mixed evidence of a direct effect of PS on reading fluency in the context of RAN, occurring moreso longitudinally than concurrently, and moreso for silent versus oral reading. The McGrath et al. (2011) and Peterson et al. (2017) studies, across a wider age range (8 to 16) both found that RAN and PS were both predictive of their reading outcome (single word reading). Shanahan et al. (2006) also found that both RAN and PS differentiated reading groups (who were defined on the basis of a reading composite which included single word reading and reading comprehension). Christopher et al. (2012) is the only one of these studies to explicitly evaluate differential contributions of RAN and PS to both single word reading and reading comprehension. In contrast to some other studies (Georgiou et al., 2016; Papadopoulos et al. 2016), Christopher et al. (2012) found unique effects for PS (moreso for single word reading than comprehension), but RAN did not have unique effects for either reading outcome.

The above studies are important and provide valuable information, but leave many questions unanswered. For example, none compared different models of the dimensionality of PS, and the measurement of PS outside of RAN was limited generally, and specifically for alphanumeric material and verbal output. Moreover, although as noted above there is empirical support to justify the relation of PS with different types of reading, none of those studies simultaneously evaluated single word reading, reading fluency, and reading comprehension. Doing so would clarify how different types of PS might differentially relate to each type of reading. The rationale for the role of PS for reading fluency is perhaps the most obvious, since at a manifest level, both involve explicit timing. However, accurate reading of single words is also likely facilitated by stronger underlying PS, as doing so requires rapid matching of graphemes and phonemes. In addition to efficient word reading skill, successful reading comprehension further requires readers to make rapid connections between words and their meaning, which then is linked to background knowledge in order to facilitate the understanding of a passage of text.

Summary and Hypotheses

This study has two aims. The first considers five plausible models of PS, including two conceptual models and three alternative methodological models (outlined in Table 1). Doing so will further understanding about the structure of PS in children, as well as its relationship with potentially closely related constructs (e.g., EF). Of the five models, we expect the Complexity model to demonstrate the strongest fit to the data when compared to the rest, given its conceptual nature, and given that many studies do not find a unitary PS; we are though unaware of prior work that has directly compared all of the present options. The second aim is to examine the external validity of PS (presumed to be represented by the Complexity model) by examining how different types of PS relate to different aspects of a highly important outcome for children, reading (single word reading, reading fluency and reading comprehension). Accounting for multiple relevant demographic and language-related covariates, we expect each of the three factors of the Complexity model (simple, middle, and high) to uniquely predict each reading outcome, for two reasons. First, most prior studies found contributions of both verbal (RAN-based) and nonverbal PS to reading when it has been examined, and those tasks have spanned the levels of complexity as we referred to them above. Second, given the age and reading level of our sample (see below), it is unlikely that most students in the present study are “automatic” readers, leaving more room for individual variability in PS to influence reading. Despite this, we do expect the PS model to be most related to reading fluency relative to other reading skills given the speeded nature of reading fluency.

Methods

Participants

Participants were 844 students (mean age 9.98, SD = 0.91) enrolled in public elementary schools from medium to large school districts in two cities in the southwestern US. Data was collected as part of a larger project that focused on reading, its cognitive and imaging correlates, and intervention. Students in third through fifth grade were enrolled because of the important developmental changes that occur during this time period (from learning-to-read to reading-to-learn). Students who were struggling readers were oversampled given the focus on intervention (Vaughn et al., 2016; though the data here were designed to be collected pre-intervention). Table 2 provides demographic data. Prior studies from this project have some overlap in terms of sample (Cirino et al., 2018a, 2019; Miciak et al., 2018b; Vaughn et al., 2016).) However, these prior works did not evaluate processing speed or its relations with reading.

Measures

Descriptive information for PS and reading measures appears in Table 3. Further details including reliability and validity, can be found on the Cirino et al., (2018a, 2019). Below, we present information about task requirements of the analyzed variables, along with a brief rationale of how they correspond to the hypothesized levels of complexity.

Simple Level PS.—The variables chosen for this cluster have in common that perceptual identification is the primary cognitive demand, where individual differences derive from speed rather than accuracy (as the latter is expected to be near-perfect). The dependent measure for *Go/No Go* (*Inquisit 3*, 2003) was the recorded latency (in milliseconds) between stimuli presentation and response for all valid Go trials. For the *Delis-Kaplan Executive Function System (D-KEFS); Trail Making Test* (TMT; Condition 5: Motor Speed; Delis, Kaplan, & Kramer, 2001), the dependent measure was the total completion time (in seconds). The dependent measure for the *N-Back Tasks (Shapes & Letters;* Inquisit 3, 2003) was the mean RT (in milliseconds) for all valid 0-back trials. For *Stop Signal* (*Inquisit 3*, 2003), the dependent measure was the mean RT (in milliseconds) for latency to respond to a simple (go) command.

Middle Level PS.—The variables in this cluster have in common that some modest level of cognitive processing is required, but switching, inhibition, and working memory are not. Although several "parent" tasks are common EF measures, the specific variables here are not those considered to be the "executive" variables. For *Corsi Block-Tapping Task* (*Forward Condition*; Inquisit 3, 2003), the dependent variable was the total completion time (in milliseconds) for all correct trials. The dependent measures for *Delis-Kaplan Executive Function System (D-KEFS) Color Word Interference Test* (*CWIT; Condition 1: Color Naming*; Delis et al., 2001), for *D-KEFS Trail Making Test* (*TMT; Condition 2: Number Sequencing*; Delis et al., 2001), and for *NEPSY-II; Visuomotor Precision* (Korkman, Kirk, & Kemp, 2007), were the total completion time (in seconds). For *Purdue Pegboard* (Lafayette Instruments, 1999), the dependent measure was the total number of pegs placed in the allotted time, using both hands simultaneously. For *Woodcock-Johnson III Tests of Academic Achievement; Visual Matching* (WJ-III; Woodcock, McGrew, & Mather, 2001), the dependent measure was the total number of correctly identified matches within the allotted time.

High Level PS.—The variables in this cluster are most aligned with what could be classified as a very specific class of EF – one that emphasizes speed/efficiency rather than problem solving or working memory or cognitive flexibility. The dependent measure for *D-KEFS Verbal Fluency (Letter and Category Fluency Conditions;* Delis et al., 2001) was the total number of accurate responses across all prompts (three letters or two categories) for each measure (60 seconds per prompt). For *D-KEFS Design Fluency* (*Condition 2: Empty Dots*; Delis et al., 2001), the dependent measure was the total correct number of correct designs within the allotted time (60 seconds). The dependent measure for *D-KEFS TMT* (*Condition 4: Number-Letter Sequencing*; Delis et al., 2001) was the total completion time (in seconds). For the *Tower of London Task* (TOL; Shallice, 1982; *Inquisit 3*, 2003), the dependent measure was the latency time (in milliseconds) for the first move for all correct problems (and thus invokes planning to some extent); the more traditionally used accuracy-based total score was not used, to better capture the speed-related processes of the task (Kaller, Unterrainer, Rahm, & Halsband, 2004).

Reading Outcome Measures.—Single word reading was operationalized by the *WJ-III Letter-Word Identification (LWID) subtest* (Woodcock, McGrew, & Mather, 2001). Reading fluency was assessed with the *Test of Word Reading Efficiency – Second Edition (TOWRE-2) Sight Word Efficiency subtest* (Torgesen, Wagner, & Rashotte, 1999), and comprehension was assessed with the *Gates MacGinitie Reading Tests – 4th Edition (GMRT) Passage Comprehension subtest* (MacGinitie, MacGinitie, Maria, Dreyer, & Hughes, 2000). The outcomes were the standard scores generated from these measures.

Language Covariates.—Total raw scores were used for the *WJ-III Oral Comprehension subtest* (Woodcock, McGrew, & Mather, 2001), and the *Comprehensive Test of Phonological Processing (CTOPP) Elision subtest* (Wagner, Torgesen, & Rashotte, 1999). For *CTOPP Rapid Letter Naming subtest* (Wagner, Torgesen, & Rashotte, 1999), we used time to complete forms A and B. Raw scores were used so that all predictors are expressed in the same fashion.

Procedures

Data were collected by trained examiners over a six-month period. The larger study included many more measures, so 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. The Gates MacGinitie Reading Test was collected in a group setting; all other measures were collected in individual testing settings over multiple sessions. Procedures were approved by the participating Institutional Review Board.

Analyses

Preliminary analyses included evaluation of sample-based and model-based residual outliers, and variable distributions (e.g., skewness and kurtosis). Most variables had satisfactory properties, though 20 extreme observations across three measures (Go/No Go, Purdue Pegboard and the Corsi tasks) were Winsorized (set to three SD, but maintaining original rank ordering). Tower of London and Rapid Naming variables displayed more pervasive skew, and were log transformed to normalize distributions.

Confirmatory factor analyses (CFA) were conducted in Mplus (Muthén & Muthén, 2012). A “weight” variable was included in the models to account for the large percentage of students in the 4th grade who were struggling readers (Cirino et al., 2018a). 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. Of note, the results below were not substantively affected by this weighting.

Model fit was examined at both global and local levels. Global fit indices included: the model chi-square (χ^2); 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); and the Akaike information criterion (AIC) and the Bayes information criterion (BIC), with smaller values across models indicative of better fit (Kline, 2004). Local fit of parameters focused on factor loadings and beta weights (for structural relations) (Kline, 2004). Chi-square (χ^2) comparisons were used to compare nested models and the Satorra-Bentler (2001) alternate χ^2 difference test was used to account for the weighted sample. Parsimony per se was not the only goal, as not all models were sequentially nested. Where this was the case (e.g., models with the same degrees of freedom), the preferred model was selected on the basis of (a) comparisons against the Unitary model; (b) values relative to established cutpoints; (c) model differences on other metrics, such as change in CFI (Cheung & Rensvold, 2002); and (d) theoretical and empirical support in the literature.

Structural regressions within Mplus directly evaluated the predictive role of latent PS factors for reading. Demographic covariates included age, gender, Limited English Proficiency (LEP) status, grade, and free/reduced lunch eligibility. Because grade had three levels (Grades 3, 4, and 5), it was dummy coded as two contrasts of grades 3 and 5 with the largest group (Grade 4). Relevant language covariates included CTOPP Elision and Rapid Naming given their well-known relation to reading (Schatschneider, Fletcher, Francis, Carlson, & Foorman, 2004); WJ-III Letter Word Identification was considered as a covariate for reading fluency and reading comprehension, and WJ-III Oral Comprehension was additionally considered for reading comprehension, per the Simple View of Reading (Gough & Tunmer, 1986). Specific details regarding which covariates were included in prediction models are described below. Models were run hierarchically, first with demographic and cognitive covariates, to which PS variables were added. Satorra-Bentler χ^2 difference tests were used to evaluate the unique role of PS.

Results

Individual processing speed variables had significant small to medium correlations with one another (range $r = |.03$ to $.52|$), and with reading outcomes (range $r = |.02$ to $.43|$), and with language covariates (range $r = |.01$ to $.48|$). Two exceptions were NEPSY Visuomotor Precision and TOL latency, which correlated rather weakly with most measures.

Processing Speed Structure Results (Aim 1)

All model fits can be found in Table 4. A single (conceptually appropriate) covariance (of two verbal fluency measures) was added to all models. Model 1 (Unitary) had a single latent variable for all 16 PS indicators and was a poor fit to the data. Chi-square differences between each subsequent model and Model 1 were examined using the Satorra-Bentler (2001) scaled (mean-adjusted) chi-square formula.

Model 2a (Complexity) had three latent variables: Simple, Middle, and High. This model showed an adequate fit to the data, and was a significant improvement in fit over Model 1, $p < .001$ (see Table 4). However, the Middle and High factors perfectly correlated ($r = 1.06$). Thus Model 2a was collapsed into a two-factor Complexity model (Model 2b) with the same

Simple factor and a new Complex factor consisting of all 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 better than Model 1 in χ^2 difference comparisons, $p = .002$. The correlation between the two factors (Simple and Complex) was moderate ($r = .46$, $p < .001$).

Model 3 (Stimulus Input), with two latent factors (Alphanumeric and Non-Alphanumeric), showed a poor fit to the data and did not differ from (Unitary) Model 1, χ^2 difference, $p = .108$ (see Table 4). Additionally, the Alphanumeric and Non-Alphanumeric factors were strongly intercorrelated, $r = .90$, $p < .001$. Similarly, Model 4 (Output Response), with two response-based latent factors (Verbal and Manual), also was a poor fit to the data, did not differ from Model 1, χ^2 difference $p = .460$; Verbal and Motor latent factors were strongly intercorrelated, $r = .94$, $p < .001$. Chi-square difference tests between these models and Model 2b could not be examined because all models had the same df, but other indices (χ^2 value, CFI, TLI, SRMR, RMSEA) suggested a much better fitting model for Model 2b, relative to Models 3 and 4 (and Model 1).

Model 5a had three Timing latent factors (Latency – time to begin activity; Time-Dependent – accuracy within a specified time; Timed – total time to complete activity), and provided a strong fit to the data, with global fit indices exceeding those of all other models (see Table 4), and significantly better than Model 1 in χ^2 difference comparisons, $p < .001$. However, the Time-Dependent and Timed latent factors were perfectly correlated ($r = 1.00$), and therefore were collapsed into a single Efficiency factor in Model 5b. Model 5b provided a similar fit to the data as Model 5a, and the resultant correlation between the two factors (Latency and Efficiency) was moderate, $r = .44$, $p < .001$. Model 5b met the aforementioned standard criteria for global fit indices and was significantly better from Model 1 in χ^2 difference comparisons, $p < .001$.

Models 5b (Timing) and 2b (Complexity) could not really be compared with statistics. Although Table 4 reveals that Model 5b could be considered a better fit to the data on the basis of alternative metrics, these models differ only on two indicators (TOL and TMT Motor Speed), and factor loadings for other measures were similar across models. Also, results of the prediction models below were run with both Models 2b and 5b, and results were substantively the same. Given this, and the fact that Model 2b (Complexity) was conceptually derived and has support in the literature, the prediction results below report only this more theoretically driven model.

Reading Prediction Results (Aim 2)

For parsimony, we considered which of the above-noted covariates were related to outcomes at the zero-order level, as well as when considered collectively. Economic disadvantage was missing systematically (~10% sample), although the sample overall was highly (90%) disadvantaged, and likely for this reason, it was not a significant covariate in final models and so was excluded. Demographics with the strongest zero-order relations were age, grade, and LEP status; all cognitive/academic covariates were also quite strong. When covariates were considered collectively, the relevant covariates for single word reading were age, grade, CTOPP Elision, and CTOPP Rapid Naming. For reading fluency, relevant covariates were age, grade, CTOPP Rapid Naming and WJ-III LWID. Finally, for reading comprehension, the relevant covariates were LEP status, grade, CTOPP Rapid Naming, and WJ-III LWID and Oral Comprehension. Results for final prediction models appear in Table 5. It should be noted that the PS factors were scaled so that a more negative score indicated better (faster) PS.

Single Word Reading.—The model with PS variables only was significant, $R^2 = .090$, $p < .001$, with significant effects for Complex PS, $p < .001$, but not Simple PS, $p = .819$. The model without PS variables (covariates alone) was significant, $R^2 = .450$, $p < .001$. Adding PS variables yielded $R^2 = .465$, $p < .001$, with significant effects for PA, RAN, age, grade (all $p < .05$), and for Complex PS, $p = .043$, but not Simple PS, $p = .054$. The ΔR^2 value derived from examination of the models with and without the PS latent factors was .015, and Satorra-Bentler χ^2 difference testing yielded a significant value, $t = 13.54$, $p = .005$. Better word reading performance was associated better PA, faster RAN, younger age, and stronger (faster) Complex PS. Considering all other variables in the model, Grade 3 students had lower reading standard scores than Grade 4 students, and Grade 5 students had higher reading standard scores than those in Grade 4.

Reading Fluency.—The model with PS variables only was significant, $R^2 = .158$, $p < .001$, with significant effects for both Simple PS, $p = .031$, as well as Complex PS, $p < .001$. The model without PS variables was significant, $R^2 = .618$, $p < .001$. Adding PS variables yielded $R^2 = .644$, $p < .001$, with significant effects for LWID, RAN, age, grade (all $p < .05$), and for both Simple PS, $p = .027$, and Complex PS, $p < .001$. Better word reading fluency was associated better LWID, faster RAN, younger age, and stronger (faster) Complex PS. Considering all other variables, both Grade 3 and Grade 5 students had higher reading standard scores than Grade 4. Also, and somewhat surprisingly, Simple PS was inversely related to reading performance. The ΔR^2 value comparing models with and without PS was .026, and the model comparison with and without PS was significant, $t = 25.21$, $p = .002$.

Reading Comprehension.—A model with PS variables alone was significant, $R^2 = .206$, $p < .001$, with effects for Complex PS, $p < .001$, but not Simple PS, $p = .717$. The model without PS variables was significant, $R^2 = .625$, $p < .001$. Adding PS variables yielded $R^2 = .642$, $p < .001$, with significant effects for LWID, Oral Comprehension, LEP, and grade (all $p < .05$), and for Complex PS, $p < .001$, but not for RAN or for Simple PS (all $p > .05$). Better reading comprehension was associated with better LWID and Oral Comprehension, faster RAN, not having LEP status, and stronger (faster) Complex PS. Considering all other variables in the model, Grade 3 students had better reading standard scores than Grade 4 students. The ΔR^2 value (.017) comparing models with and without PS was significant, $t = 20.24$, $p = .002$.

Discussion

The goals of the present study were to evaluate the structure of PS in children, and to relate this structure to reading. Key strengths of the study included its large sample size, the large number of PS measures (all separate from RAN), its latent-variable comparison of different models of PS dimensionality (unitary, complexity, timing, input, output), and the evaluation of the role of those resultant models for multiple types of reading outcomes (decoding, fluency, and comprehension). The nature of the sample, elementary students having generally low reading performances, is also advantageous in that it is for such children that identifying key predictors is especially useful. The preferred model was one that fit PS as a two-factor model, differentiating along the lines of Simple versus Complex processing. Complex PS was uniquely predictive of each reading skill examined, even accounting for strong language covariates; Simple PS was additionally predictive of reading fluency.

PS as a Two-Factor Model

The present study had as one goal to compare five models of PS to one another (see Table 1). However, neither of our hypothesized three-factor models (of complexity and timing) were viable – although data fit was excellent (see Table 4, Models 2a and 5a), each had factors that correlated at unity (Middle and High for Model 2a; Time-Dependent and Timed for Model 5a). In each case, those factors were collapsed (into Complex for Model 2b; into Efficiency for Model 5b), and these two resultant two-factor models continued to fit the data well. These models also both clearly better than a Unitary model, or methodological models that stressed either Input or Output (see Table 4).

The two factor Complexity and Timing models could not be differentiated on the basis of χ^2 difference tests (because they have the same degrees of freedom), and comparison on other statistical grounds was also difficult because the models differed on only two indicators. Thus, one could question whether 'processing' or 'speed' is the driving difference. However, Model 2b (Complexity) is preferred because it is conceptually rather than methodologically derived, and has more prior empirical support (e.g., Carroll, 1993; Chiaravalloti et al., 2003; Demetriou et al., 2002). Given their overlap, it also implies that the indicators of the Efficiency factor of Model 5b were more cognitively complex than those of the Model 5b Latency factor. Further, the Complexity model, unlike the Timing model, is more able to be meaningfully contrasted with models of EF. Based on all the above, we therefore interpret the findings of this study as support for PS in children as being separable along a complexity continuum (Simple versus Complex). Of course, future studies would be needed to replicate and extend the current findings, and to further dissociate models of this type from others.

Tasks of the Simple PS factor had in common that they were low-cognitive demand, relatively "pure speed" measures, whereas the tasks of the Complex PS factor involved some degree of cognitive load. Some of the tasks of Complex PS (e.g., verbal and design fluency) could directly be considered measures of EF, which is why they were a priori assigned to the highest level of complexity. Other indicators of Complex PS were derived from measures of inhibition (e.g., Stop Signal, Color-Word Inhibition) or flexibility (Trailmaking), each of which is closely linked with EF. However, the specific indicators chosen for that factor were *not* those that are typically indexed to measure 'EF' (and thus why they were hypothesized to represent a "middle" level of complexity). As noted above, however, these two factors were indistinguishable. We are unaware of studies that attempt to more systematically parse the "speeded executive" from "speeded non-executive" components of the same set of measures, particularly in latent fashion, though doing so would be important for demarcating the boundaries between (complex) processing speed and speeded executive function. The results of the present study provide some guidance as to how such a comparison might be made, thus highlighting its relevance. For example, an important model to test would be one that separates Simple PS, Complex PS (derived from tasks with no EF component), Speeded EF tasks, and untimed EF tasks. Doing so would require a large enough number of tasks to also control for input, output, and method of timing. Evaluating the role of those resulting factors for functional outcomes would also be of benefit.

Contribution of PS to Reading

The predictive role of PS in the evaluation of key reading skills for third through fifth grade children has variable support in the literature (Christopher et al., 2012; Cormier, McGrew, Bulut, & Funamoto, 2017; Shaul & Nevo, 2015). Results from this study provide support for the hypothesis that Complex PS is a significant predictor of single word reading, reading fluency, and reading comprehension. Simple PS factor was contributory only for word reading fluency. Given the structural models tested, and covariates utilized, these contributions of PS are not attributable to the use of alphanumeric material, or verbal output, or due to individual differences in general (e.g., oral comprehension) or specific (e.g., PA and RAN) language.

Somewhat unexpectedly, PS as a whole accounted for small, relatively similar amounts of unique variance in all three reading outcomes (~2%). Although this at first appears to be a small contribution, models without covariates demonstrated that PS variables predicted substantial portions of reading variance in single word reading, fluency, and comprehension (9%, 16%, and 21%, respectively). This pattern suggests that a substantial portion of the total variance for any given outcome was shared. For example, in the comprehension model, the latent Complex PS factor correlated $r = .58$ with rapid naming, in line with extant literature, given that the latent relation of PS and RAN varies from $r = .41$ (Pires et al., 2019) to $r = .74$ (McGrath et al., 2011). Complex PS also correlated $r = -.50$ with single word reading, and $r = -.52$ with oral comprehension, and the standardized beta weight for Complex PS was similar to that of oral comprehension. A second highly relevant consideration is that these percentage contributions are over and above prediction models where baseline variables (demographic and language covariates) are already extremely strong predictors. These “value added” contributions, much like the case of EF (Miciak et al., 2018b), are more impressive in such a context.

That PS is related to word decoding is well-supported, regardless of how PS is defined and captured, as evidenced in the large literature evoking PS as a shared cognitive factor for reading, particularly in its comorbid contexts (Catts et al., 2002; Christopher et al., 2012; Shaul & Nevo, 2015). However, as noted above, the overall effects of PS (both Simple and Complex) showed the weakest individual effects for decoding. Stronger effects were noted for reading fluency, where both Simple and Complex PS were significant predictors, though even here, its independent contribution (as denoted by standardized beta weight) was small (Table 4). PS has been less systematically related to reading comprehension, but it requires an array of cognitive processes (e.g., EF; Butterfuss & Kendeou, 2017; Cirino et al., 2018a), and therefore the contribution of (Complex) PS was to be expected. The large contribution of Complex PS to comprehension (in the absence of covariates) was somewhat surprising, although in struggling readers, time may be more of a factor given reduced automaticity (although the Gates MacGinitie has a time limit, it is not typically considered a speeded test).

Prior studies that have evaluated the simultaneous role of RAN and PS for reading have been mixed. Georgiou et al. (2016) and Papadopoulos et al. (2016) found that RAN had stronger direct effects, whereas Christopher et al. (2012) found that PS had stronger direct effects, and McGrath et al. (2011) and Peterson et al. (2017) found that both had direct effects. The present results are most similar to those of McGrath et al. (2011) and Peterson et al. (2017) for single word reading and fluency, but aligned with those of Christopher et al. (2012) with regard to reading comprehension. This pattern makes sense given that the RAN-reading relationship is weaker for comprehension than for word reading (Araujo et al., 2015), and the present results provide some clarity to this literature.

Implications

A definitive, multi-field agreed upon definition of PS remains elusive. In reviewing the labels commonly assigned to the construct of PS in the literature, the Simple PS factor may align best with terms such as “reaction time” or “perceptual speed” and may be best captured by computerized, millisecond-based tasks that require very few cognitive requirements. Complex PS, on the other hand, aligns better with terms such as “cognitive tempo”, “information processing”, or “cognitive processing speed” (Gs; Cormier et al., 2017) and can be captured at the second-to-second level to account for varying degrees of cognitive processing. However, as noted, the results of the present study highlight the need for a stronger test of the differentiation of complexity from method of timing, both in terms of structure, but also for how each relates to important functional outcomes.

The relatively weak predictive effects of the Simple PS factor for reading suggests that the role for PS in functional outcomes suffers as it gets closer to capturing the “speed” of PS relative to the “processing” of PS. On the other hand, the closer a PS measure gets to capturing a more cognitively complex process, the more important the consideration of overlap with other cognitive processes (such as EF) becomes. In fact, one intent of the present study was to examine where PS might “end” and EF might “begin”; commonality 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). However there was no clear differentiation between PS and EF in the present study, again noting that EF was very narrowly considered. As eluded to above, the present study is informative for future studies to more clearly evaluate any such potential distinctions in terms of structure and prediction.

Another implication of these results concerns the role of PS as a shared cognitive process for comorbid disorders, such as RD, math disability (MD), and ADHD. For example, Peterson et al. (2017) found PS to account for some of the overlap between attention with either reading or math. Within the adult literature, slowed PS has been theorized to be a broad trait of externalizing psychopathology, whereas EF was more closely tied to specific disorder (e.g., ADHD; Nigg et al., 2017). Our results suggest that Complex PS would be a stronger candidate for any such shared process, relative to Simple PS, given that reading, math, and attention are all complex multi-faceted outcomes.

Given the role of (especially Complex) PS for each reading outcome identified in this study, it would be tempting to suggest that intervening on PS would be a fruitful means of directly improving reading. However, given the difficulties associated with transfer when training other cognitive skills (e.g., WM; Jacob & Parkinson, 2015; Sala & Gobet, 2020), it may be more relevant to accommodate PS weakness in the context of content-focused interventions.

Limitations

One limitation of the present study is that the PS measures chosen did not capture all possibilities, and the measures used were selected in part for the purposes of a larger study. However, many of these measures have been used in prior studies examining PS (Demetriou et al., 2014). The present study also did not use standard-practice clinical measures of PS (i.e., Coding, Symbol Search, Cancellation; Wechsler, 2014), and it is known that these are related to reading skill (Mayes & Calhoun, 2007). However, few studies separate the contributions of such measures from those of rapid naming, and even these tasks vary in their "processing" requirements. We also did not derive our PS measures as separate "speed" factors from inductive or reasoning tasks that are not typically timed (e.g., Papadopoulos, Georgiou, Deng, & Das, 2018; Ren, Wang, Sun, Deng, & Schweizer, 2018; Zeller, Reiß, & Schweizer, K. (2020). Importantly, though, each of those studies is with adults, and do not allow for a comparison of unitary versus complexity versus methodological models. Nonetheless, the present study raises interesting questions regarding how such a speed factor(s) would relate to the Simple and Complex PS factors here, though we would expect moreso with the latter than the former given that the speed factors are produced from complex cognitive (i.e., reasoning) tasks.

The demographic make-up of the sample might also be a limitation. As noted earlier, there was an abundance of struggling readers in 4th grade (though the weighting variable was included to partially compensate for this). Ninety-percent of the sample was also eligible for free or reduced lunch, a proxy for socioeconomic status (Harwell & LeBeau, 2010; Ransdell, 2012). SES is an important factor in the development of reading skills and PS (Hackman & Farah, 2009), although limited variability here is a possibility for why it did not contribute uniquely in the present study. All measures in this study were presented in English, and poor English proficiency can impact academic performance (Abedi, 2002; Lesaux, Crosson, Kieffer, & Pierce, 2010). We included this designation in the present study, and this was found to be a factor for the reading comprehension model, but it did not eliminate effects of PS. The results of the present study should nonetheless be considered with regard to the constellation of this sample, and the robustness of the structure across samples with different characteristics would be a welcome future area of investigation.

Conclusion

PS can be operationalized as a two-level construct with separation apparent between a simple, speed-based level and more complex, efficiency-based level of cognitive processing. However, separation between the complex level of PS and EF is as yet undetermined.

Complex PS is predictive of single word reading, reading fluency and reading comprehension for late elementary-aged children, even in the context of highly relevant demographic and language covariates, highlighting its relevance. The present study can inform future examinations of how to more carefully differentiate the structure and predictive utility of each defined level of PS, particularly EF, and particularly those that control from timing, input, and output parameters.

Acknowledgement

This research was supported by Award Number P50 HD052117, Texas Center for Learning Disabilities, from the Eunice Kennedy Shriver National Institute of Child Health & Human Development to the University of Houston. The content is the sole responsibility of the authors and does not necessarily represent the official views of the Eunice Kennedy Shriver National Institute of Child Health & Human Development or the National Institutes of Health.

References

Abedi J (2002). Standardized Achievement Tests and English Language Learners: Psychometrics Issues. Educational Assessment, 8(3), 231–257. 10.1207/S15326977EA0803_02

Anderson VA, Anderson P, Northam E, Jacobs R, & Catroppa C (2001). Development of executive functions through late childhood and adolescence in an Australian sample. Developmental Neuropsychology, 20(1), 385–406. 10.1207/S15326942DN2001_5 [PubMed: 11827095]

Araújo S, Reis A, Petersson KM, & Faísca L (2015). Rapid automatized naming and reading performance: A meta-analysis. Journal of Educational Psychology, 107(3), 868–883. 10.1037/edu0000006

Babcock RL, Laguna KD, & Roesch SC (1997). A comparison of the factor structure of processing speed for younger and older adults: Testing the assumption of measurement equivalence across age groups. Psychology and Aging, 17(2), 268–286.

Baddeley A (2003). Working memory: looking back and looking forward. Nature Reviews Neuroscience, 4(10), 829–839. 10.1038/nrn1201 [PubMed: 14523382]

Barth AE, Catts HW, & Anthony JL (2008). The component skills underlying reading fluency in adolescent readers: a latent variable analysis. Reading and Writing, 22(5), 567–590. 10.1007/s11145-008-9125-y

Borella E, & De Ribaupierre A (2014). The role of working memory, inhibition, and processing speed in text comprehension in children. Learning and Individual Differences, 34, 86–92. 10.1016/j.lindif.2014.05.001

Butterfuss R, & Kendeou P (2017). The Role of Executive Functions in Reading Comprehension. Educational Psychology Review, 1–26. 10.1007/s10648-017-9422-6

Carroll JB (1993). Human cognitive abilities: A survey of factor-analytic studies. Cambridge, UK: Cambridge University Press

Catts HW, Gillispie M, Leonard LB, Kail RV, & Miller CA (2002). The Role of Speed of Processing, Rapid Naming, and Phonological Awareness in Reading Achievement. Journal of Learning Disabilities, 35(6), 510–525. 10.1177/00222194020350060301

Cheung GW, & Rensvold RB (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. Structural Equation Modeling: A Multidisciplinary Journal, 9, 233–255.

Chiaravalloti ND, Christodoulou C, Demaree HA, & DeLuca J (2003). Differentiating Simple Versus Complex Processing Speed: Influence on New Learning and Memory Performance. Journal of Clinical and Experimental Neuropsychology, 25(4), 489–501. 10.1076/jcen.25.4.489.13878 [PubMed: 12911103]

Christopher ME, Miyake A, Keenan JM, Pennington B, DeFries JC, Wadsworth SJ, … Olson RK (2012). Predicting word reading and comprehension with executive function and speed measures across development: A latent variable analysis. Journal of Experimental Psychology: General, 141(3), 470–488. 10.1037/a0027375 [PubMed: 22352396]

Cirino PT, Ahmed Y, Miciak J, Taylor WP, Gerst EH, & Barnes MA (2018a). A framework for executive function in the late elementary years. Neuropsychology,32(2), 176–189. doi:10.1037/neu0000427 [PubMed: 29528682]

Cirino PT, Miciak J, Ahmed Y, Barnes MA, Taylor WP, Gerst EH (2019). Executive function: Association with multiple reading skills. Reading and Writing, 32, 1819–1846. doi:10.1007/s11145-018-9923-9 [PubMed: 31680727]

Cirino PT, Romain MA, Barth AE, Tolar TD, Fletcher JM, & Vaughn S (2013). Reading skill components and impairments in middle school struggling readers. Reading and Writing, 26(7), 1059–1086. 10.1007/s11145-012-9406-3 [PubMed: 24000271]

Cormier DC, McGrew KS, Bulut O, & Funamoto A (2017). Revisiting the Relations Between the WJ-IV Measures of Cattell-Horn-Carroll (CHC) Cognitive Abilities and Reading Achievement During the School-Age Years. Journal of Psychoeducational Assessment, 35(8), 731–754. 10.1177/0734282916659208

Deary IJ, & Der G (2005). Reaction Time, Age, and Cognitive Ability: Longitudinal Findings from Age 16 to 63 Years in Representative Population Samples. Aging, Neuropsychology, and Cognition, 12(2), 187–215. 10.1080/13825580590969235

Delis D, Kaplan E, & Kramer J (2001). Delis-Kaplan Executive Function Scale. San Antonio, TX: The Psychological Corporation.

Demetriou A, Christou C, Spanoudis G, Platsidou M, Fischer KW, & Dawson TL (2002). The development of mental processing: Efficiency, working memory, and thinking. Monographs of the Society for Research in Child Development, 67(1), vii–154.

Demetriou A, Spanoudis G, Shayer M, Van der Ven S, Brydges CR, Kroesbergen E, … & Swanson HL (2014). Relations between speed, working memory, and intelligence from preschool to adulthood: Structural equation modeling of 14 studies. Intelligence, 46, 107–121. 10.1016/j.intell.2014.05.013

Denney DR, Gallagher KS, & Lynch SG (2011). Deficits in Processing Speed in Patients with Multiple Sclerosis: Evidence from Explicit and Covert Measures. Archives of Clinical Neuropsychology, 26(2), 110–119. 10.1093/arclin/acq104 [PubMed: 21216726]

Dennis M, Cirino PT, Simic N, Juranek J, Taylor WP, & Fletcher JM (2015). White and grey matter relations to simple, choice, and cognitive reaction time in spina bifida. Brain Imaging and Behavior, 1–14. 10.1007/s11682-015-9388-2 [PubMed: 25724689]

Duke N, & Carlisle J (2010). The Development of Comprehension. In Handbook of Reading Research (Vol. 4, pp. 199–228).

Fry AF, & Hale S (1996). Processing Speed, Working Memory, and Fluid Intelligence: Evidence for a Developmental Cascade. Psychological Science, 7(4), 237–241. 10.1111/j.1467-9280.1996.tb00366.x

Georgiou GK, Parrila R, & Papadopoulos TC (2016). The anatomy of the RAN-reading relationship. Reading and Writing, 29, 1793–1815.

Gough PB, & Tunmer WE (1986). Decoding, Reading, and Reading Disability. Remedial and Special Education, 7(1), 6–10. 10.1177/074193258600700104

Hackman DA, & Farah MJ (2009). Socioeconomic status and the developing brain. Trends in Cognitive Sciences, 13(2), 65–73. 10.1016/j.tics.2008.11.003 [PubMed: 19135405]

Harwell M, & LeBeau B (2010). Student eligibility for a free lunch as an SES measure in education research. Educational Researcher, 39(2), 120–131. 10.3102/0013189X10362578

Holland PW, & Thayer DT (1987). Notes on the Use of Log-Linear Models for Fitting Discrete Probability Distributions. ETS Research Report Series, 1987(2), i–40. 10.1002/j.2330-8516.1987.tb00235.x

Hu L, & Bentler PM (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Structural Equation Modeling: A Multidisciplinary Journal, 6(1), 1–55. 10.1080/10705519909540118

Huizinga M, Dolan CV, & van der Molen MW (2006). Age-related change in executive function: Developmental trends and a latent variable analysis. Neuropsychologia, 44(11), 2017–2036. 10.1016/j.neuropsychologia.2006.01.010 [PubMed: 16527316]

Inquisit 3. (2003). Seattle, WA: Millisecond Software.

Jacob R, & Parkinson J (2015). The potential for school-based interventions that target executive function to improve academic achievement a review. Review of Educational Research, 85, 512–552. 10.3102/0034654314561338

Kail R (2000). Speed of Information Processing: Developmental Change and Links to Intelligence. Journal of School Psychology, 38(1), 51–61. 10.1016/S0022-4405(99)00036-9

Kail RV, Lervag A, & Hulme C (2016). Longitudinal evidence linking processing speed to the development of reasoning. Developmental science, 19(6), 1067–1074. 10.1111/desc.12352 [PubMed: 26537631]

Kail RV, & Miller CA (2006). Developmental change in processing speed: Domain specificity and stability during childhood and adolescence. Journal of Cognition and Development, 7(1), 119–137.

Kaller CP, Unterrainer JM, Rahm B, & Halsband U (2004). The impact of problem structure on planning: insights from the Tower of London task. Cognitive Brain Research, 20(3), 462–472. 10.1016/j.cogbrainres.2004.04.002 [PubMed: 15268923]

Kibby MY, Lee SE, & Dyer SM (2014). Reading performance is predicted by more than phonological processing. Educational Psychology, 5, 960 10.3389/fpsyg.2014.00960

Kline RB (2004). Principles and Practice of Structural Equation Modeling, Second Edition (Second Edition edition). New York: The Guilford Press.

Korkman M, Kirk U, & Kemp S (2007). A Developmental NeuroPsychological Assesment (NEPSY) (II). Pearson Assesment.

Instruments Lafayette. (1999). Purdue pegboard model #32020 instructions and normative data. Lafayette, IN: Lafayette Instruments.

Leonard LB, Ellis Weismer S, Miller CA, Francis DJ, Tomblin JB, & Kail RV (2007). Speed of Processing, Working Memory, and Language Impairment in Children. Journal of Speech Language and Hearing Research, 50(2), 408 10.1044/1092-4388(2007/029)

Lesaux NK, Crosson AC, Kieffer MJ, & Pierce M (2010). Uneven profiles: Language minority learners' word reading, vocabulary, and reading comprehension skills. Journal of Applied Developmental Psychology, 31(6), 475–483. 10.1016/j.appdev.2010.09.004 [PubMed: 21243117]

MacGinitie W, MacGinitie R, Maria K, Dreyer LG, & Hughes KE (2000). Gates-MacGinitie Reading Tests (GMRT) Fourth Edition. Itasca, IL: Riverside Publishing.

Marchman VA, & Fernald A (2008). Speed of word recognition and vocabulary knowledge in infancy predict cognitive and language outcomes in later childhood. Developmental Science, 11(3), F9–16. 10.1111/j.1467-7687.2008.00671.x [PubMed: 18466367]

Mayes SD, & Calhoun SL (2007). Wechsler Intelligence Scale for Children - Third and -Fourth Edition predictors of academic achievement in children with attention deficit hyperactivity disorder. School Psychology Quarterly, 22(2), 234–249.

McGrath LM, Pennington BF, Shanahan MA, Santerre-Lemmon LE, Barnard HD, Willcutt EG, … Olson RK (2011). A multiple deficit model of reading disability and attention-deficit/hyperactivity disorder: searching for shared cognitive deficits. Journal of Child Psychology and Psychiatry, 52(5), 547–557. 10.1111/j.1469-7610.2010.02346.x [PubMed: 21126246]

Miyake A, Friedman NP, Emerson MJ, Witzki AH, & Howerter A (2000). The unity and diversity of executive functions and their contributions to complex "frontal lobe" tasks: A latent variable analysis. Cognitive Psychology, 41(1), 49–100. 10.1006/cogp.1999.0734 [PubMed: 10945922]

Moses TP, & von Davier AA (2006). A Sas Macro for Loglinear Smoothing: Applications and Implications. ETS Research Report Series, 2006(1), i–42. 10.1002/j.2333-8504.2006.tb02011.x

Muthén LK, & Muthén BO (2012). Mplus (Version 7.0). Los Angeles, CA.

Nigg JT, Jester JM, Stavro GM, Ip KI, Puttler LI, & Zucker RA (2017). Specificity of executive functioning and processing speed problems in common psychopathology. Neuropsychology, 31(4), 448 10.1037/neu0000343 [PubMed: 28094999]

Norton ES, & Wolf M (2012). Rapid Automatized Naming (RAN) and Reading Fluency: Implications for Understanding and Treatment of Reading Disabilities. Annual Review of Psychology, 63(1), 427–452. 10.1146/annurev-psych-120710-100431

Oakhill JV, & Cain K (2012). The Precursors of Reading Ability in Young Readers: Evidence From a Four-Year Longitudinal Study. Scientific Studies of Reading, 16(2), 91–121. 10.1080/10888438.2010.529219

Papadopoulos TC, Spanoudis GC, & Georgiou GK (2016). How is RAN related to reading fluency? A comprehensive examination of the prominent theoretical accounts. Frontiers in Psychology, 7, #1217. doi: 10.3389/fpsyg.2016.01217

Papadopoulos TC, Georgiou GK, Deng C, & Das JP (2018). The Structure of Speed of Processing Across Cultures. Advances in Cognitive Psychology, 14(3), 112–125. 10.5709/acp-0243-7 [PubMed: 32337001]

Pennington BF (2006). From single to multiple deficit models of developmental disorders. Cognition, 101(2), 385–413. 10.1016/j.cognition.2006.04.008 [PubMed: 16844106]

Peterson RL, Boada R, McGrath LM, Willcutt EG, Olson RK, & Pennington BF (2017). Cognitive prediction of reading, math, and attention: Shared and unique influences. Journal of Learning Disabilities, 50(4), 408–421. 10.1177/0022219415618500 [PubMed: 26825667]

Pires L, Moura O, Guerrini C, Buekenhout I, Simões MR, & Leitão J (2019). Confirmatory factor analysis of neurocognitive measures in healthy Young adults: The relation of executive functions with other neurocognitive functions. Archives of Clinical Neuropsychology, 34(3), 350–365. 10.1093/arclin/acy040 [PubMed: 29688248]

Ransdell S (2012). There's still no free lunch: Poverty as a composite of SES predicts school-level reading comprehension. American Behavioral Scientist, 56(7), 908–925. 10.1177/0002764211408878

Ren X, Wang T, Sun S, Deng M, & Schweizer K (2018). Speeded testing in the assessment of intelligence gives rise to a speed factor. Intelligence, 66, 64–71.

Sala G, & Gobet F (2020). Working memory training in typically developing children: A multilevel meta-analysis. Psychonomic Bulletin & Review, 27, 423–434. [PubMed: 31939109]

Salthouse TA (2000). Aging and measures of processing speed. Biological Psychology, 54(1–3), 35–54. 10.1016/S0301-0511(00)00052-1 [PubMed: 11035219]

SAS Institute Inc. (2012). SAS 9.4.

Satorra A, & Bentler PM (2001). A scaled difference chi-square test statistic for moment structure analysis. Psychometrika, 66(4), 507–514.

Schatschneider C, Fletcher JM, Francis DJ, Carlson CD, & Foorman BR (2004). Kindergarten Prediction of Reading Skills: A Longitudinal Comparative Analysis. Journal of Educational Psychology, 96(2), 265–282. 10.1037/0022-0663.96.2.265

Shallice T (1982). Specific Impairments of Planning. Philosophical Transactions of the Royal Society of London. B, Biological Sciences, 298(1089), 199–209. 10.1098/rstb.1982.0082 [PubMed: 6125971]

Shanahan MA, Pennington BF, Yerys BE, Scott A, Boada R, Willcutt EG, … DeFries JC (2006). Processing Speed Deficits in Attention Deficit/Hyperactivity Disorder and Reading Disability. Journal of Abnormal Child Psychology, 34(5), 584–601. 10.1007/s10802-006-9037-8

Shaul S, & Nevo E (2015). Different speed of processing levels in childhood and their contribution to early literacy and reading abilities. Early Childhood Research Quarterly, 32, 193–203. 10.1016/j.ecresq.2015.03.006

Speece DL, Ritchey KD, Cooper DH, Roth FP, & Schatschneider C (2004). Growth in early reading skills from kindergarten to third grade. Contemporary Educational Psychology, 29(3), 312–332. 10.1016/j.cedpsych.2003.07.001

Torgesen JK, Wagner R, & Rashotte CA (1999). TOWRE-2 Test of Word Reading Efficiency (2nd ed.). Austin, TX: Pro-ed.

Vaughn S, Solís M, Miciak J, Taylor WP, & Fletcher JM (2016). Effects from a randomized control trial comparing researcher and school implemented treatments with fourth graders with significant reading difficulties. Journal of Research on Educational Effectiveness, 9(sup1), 23–44. doi:10.1080/19345747.2015.1126386 [PubMed: 28491206]

Wagner RK, Torgesen JK, & Rashotte CA (1994). Development of reading-related phonological processing abilities: New evidence of bidirectional causality from a latent variable longitudinal study. Developmental Psychology, 30(1), 73–87. 10.1037/0012-1649.30.1.73

Wagner RK, Torgesen JK, & Rashotte CA (1999). Comprehensive test of phonological processing: CTOPP. Austin, TX: Pro-ed.

Wechsler David. (2014). Wechsler Intelligence Scale for Children-Fifth Edition. Bloomington, MN: NCS Pearson, Inc.

Wiebe SA, Espy KA, & Charak D (2008). Using confirmatory factor analysis to understand executive control in preschool children: I. Latent structure. Developmental Psychology, 44(2), 575–587. 10.1037/0012-1649.44.2.575 [PubMed: 18331145]

Wolf M, & Bowers PG (1999). The double-deficit hypothesis for the developmental dyslexias. Journal of Educational Psychology, 91(3), 415–438. 10.1037/0022-0663.91.3.415

Woodcock RW, McGrew KS, & Mather N (2001). The Woodcock-Johnson III Tests of Achievement. Illinois: Riverside Publishing.

Zeller F, Reiß S, & Schweizer K (2020). Does speededness in collecting reasoning data lead to a speed factor? European Journal of Psychological Assessment, Vol 36(1), 96–104.

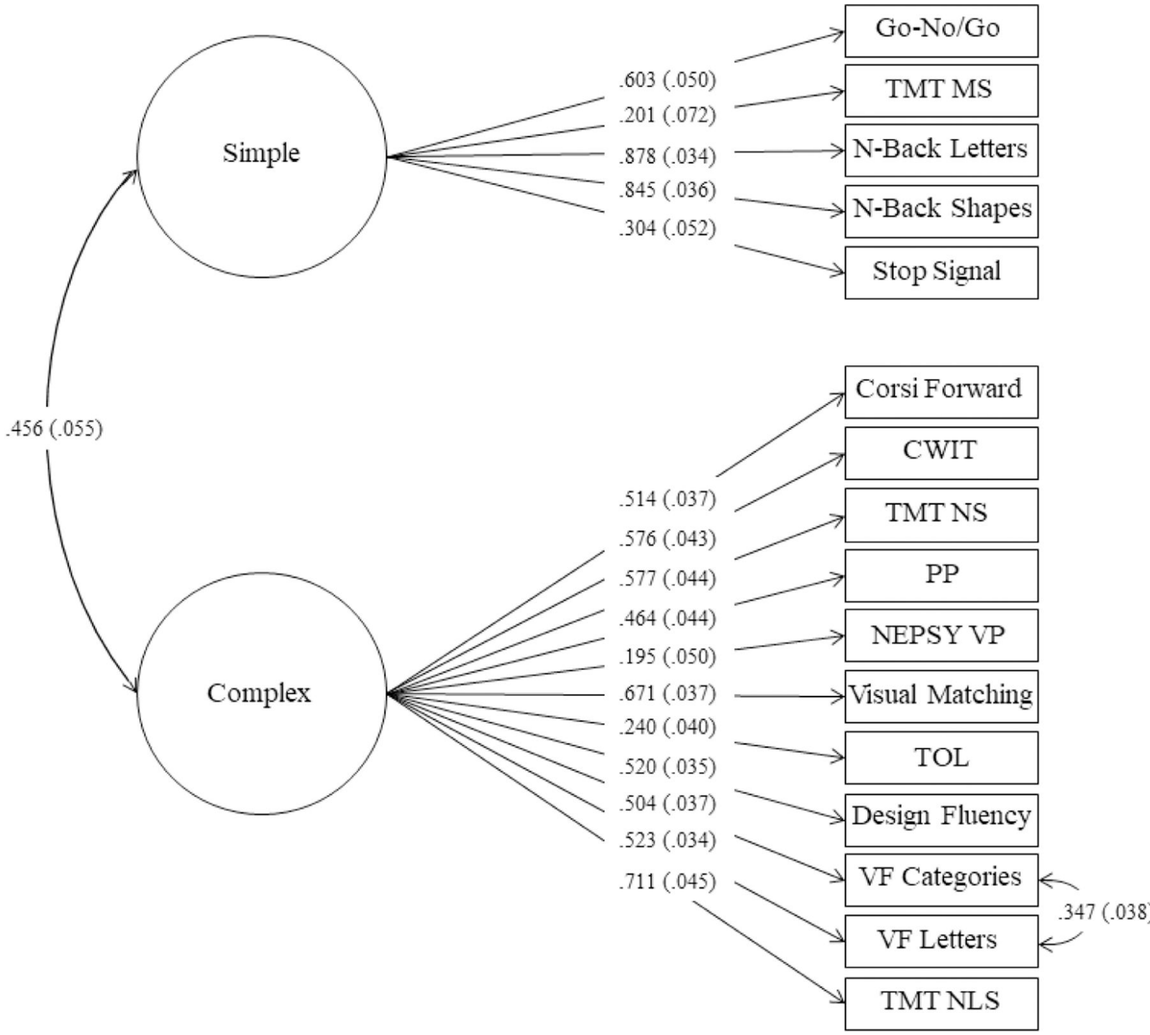

Figure 1:
Model 2b (Complexity)
Note: All loadings were significant at *p* < .001; TMT MS = DKEFS TMT: Motor Speed, TOL = Tower of London, CWIT = DKEFS CWIT: Color Naming, TMT NS = DKEFS TMT: Number Sequencing, PP = Purdue Pegboard, NEPSY VP = NEPSY Visuomotor Precision, Visual Matching = WJ-III Visual 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.

Table 1.

Indicator Variables by Predicted Model

		Complexity Model			Output Model		Input Model		Timing Model		
Task Name	**Unitary**	**Simple**	**Middle *(Complex)***	**High *(Complex)***	**Verbal**	**Manual**	**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 Indicators, Outcomes and Covariates

						Data Patterns					
Variable	**N**	**Mean**	**SD**	**Skewness**	**Kurtosis**	**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						

						Data Patterns					
Variable	**N**	**Mean**	**SD**	**Skewness**	**Kurtosis**	**1**	**2**	**3**	**4**	**5**	**6**
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 = DKEFS 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:

Structural Aim Model Fit Statistics

Model	AIC	BIC	ABIC	$\chi 2$	*df*	RMSEA (90% C. I.)	CFI	TLI	SRMR	SB $\chi 2$ diff	*p*
1.Unitary (1 factor)	64234.2	64466.4	64310.8	382.985	103	0.057 0.051 to 0.063	0.801	0.769	0.086	--	--
2a. Complexity (3 factors)	64045.5	64291.8	64126.7	226.770	100	0.039 0.032 to 0.045	0.910	0.892	0.075	198.932	<0.001
2b. Complexity (2 factors)	**64046.9**	**64283.8**	**64125.0**	**231.271**	**102**	**0.039 0.032 to 0.045**	**0.908**	**0.892**	**0.075**	**367.867**	**.002**
3. Input (2 factors)	64226.8	64463.7	64305.0	376.543	102	0.056 0.050 to 0.063	0.805	0.771	0.085	5.847	0.108
4. Output (2 factors)	64234.9	64471.8	64313.1	381.556	102	0.057 0.051 to 0.063	0.802	0.767	0.085	1.133	0.460
5a. Timing (3 factors)	64005.8	64252.2	64087.1	195.048	100	0.034 0.027 to 0.041	0.933	0.919	0.058	267.615	<0.001
5b. Timing (2 factors)	**64002.2**	**64239.1**	**64080.3**	**195.464**	**102**	**0.033 0.026 to 0.040**	**0.934**	**0.922**	**0.058**	**1122.037**	**<0.001**

Note: AIC = Akaike Information Criteria; BIC = Bayesian Information Criteria; ABIC = Sample-Size Adjusted Bayesian Information Criteria; df = degrees of freedom; RMSEA = Root Mean Squared Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Fit Index; SRMR = Squared Root Mean Residual; SB $\chi 2$ diff = t value for model comparison using the Satorra-Bentler scaled chi-square difference test, relative to unitary model.

Table 5:

Prediction Aim Regression Statistics for Complexity Full Model (Model 2b)

Predictor	*β*	*b*	*SE(b)*	*t*	*p*
Single Word Reading					
CTOPP Elision	0.383	1.026	0.089	11.511	< .001
CTOPP Rapid Letter Naming	−0.146	−7.224	1.743	−4.144	< .001
Age	−0.758	−10.29	0.771	−13.351	< .001
Grade 3	−0.109	−3.199	1.025	−3.122	.002
Grade 5	0.451	13.00	1.559	8.337	< .001
Simple PS	−0.079	−0.920	0.477	−1.927	.054
Complex PS	−0.127	−1.129	0.557	−2.027	.043
Total Model R^2= 0.465, $p < .001$					
Reading Fluency					
WJ-III Letter Word Identification	0.454	0.261	0.017	15.112	< .001
CTOPP Rapid Letter Naming	−0.275	−15.11	2.084	−7.253	< .001
Age	−0.549	−8.261	0.684	−12.079	< .001
Grade 3	0.094	3.076	0.988	3.113	.002
Grade 5	0.167	5.324	1.481	3.594	< .001
Simple PS	0.071	0.912	0.412	2.214	.027
Complex PS	−0.242	−2.372	0.532	−4.457	< .001
Total Model R^2= 0.644, $p < .001$					
Reading Comprehension					
WJ-III Letter Word Identification	0.454	0.247	0.014	17.146	< .001
WJ-III Oral Comprehension	0.186	0.147	0.022	6.648	< .001
CTOPP Rapid Letter Naming	−0.012	−0.621	1.607	−0.387	.699
Limited English Proficient	−0.165	−6.618	0.858	−7.713	< .001
Grade 3	0.358	10.960	0.866	12.648	< .001
Grade 5	−0.035	−1.070	0.892	−1.200	.230
Simple PS	0.010	0.123	0.345	0.357	.721
Complex PS	−0.207	−1.850	0.439	−4.211	< .001
Total Model R^2= 0.642, $p < .001$					

Note. PS = Processing Speed. Grade 3 and Grade 5 represent contrasts of students in these grades with the reference group (Grade 4). See Tables 1 and 3 for other acronyms.