The purpose of this research was to investigate the cognitive abilities that explain reading comprehension across childhood and early adulthood. Drawing from the standardization sample of the Woodcock–Johnson III, analyses were conducted with large samples at age levels spanning early childhood to early adulthood: 5 to 6 (n = 639), 7 to 8 (n = 720), 9 to 13 (n = 1,995), 14 to 19 (n = 1,615), and 20 to 39 (n = 1,409). Using a model including factors representing general intelligence, Cattell–Horn–Carroll broad abilities, and reading decoding skills, results revealed significant direct effects for reading decoding skills and Crystallized Intelligence on reading comprehension across all age levels. Memory-related abilities, processing speed, and auditory processing demonstrated indirect effects on reading comprehension through reading decoding skills. The magnitude of direct and indirect effects varied as a function of age. The results provide support for integrative models of reading that include both direct and indirect effects of cognitive abilities on reading comprehension and for consideration of developmental differences in the cognitive aptitudes predicting reading comprehension. © 2012 Wiley Periodicals, Inc.

Explanatory models guide professionals in better understanding the multiple processes contributing to success in reading comprehension, which is the extraction and construction of meaning from text (Ruddell & Unrau, 2004). Models of reading comprehension have been categorized as following along a continuum from top-down to bottom-up based on the extent to which they focus on higher-order skills and lower-order skills.

**Explanatory Models**

Top-down models highlight the importance of the knowledge the reader brings to the activity of reading, and such models suppose that the reader brings meaning to the print by sampling it and engaging in hypothesis development about the remainder of the stimuli (see Goodman, 1967; Smith, 1982). These concept- or knowledge-driven models focus on the reader’s active participation with the text (Duke, Pressley, & Hilden, 2004; Galda & Beach, 2001). In contrast, bottom-up models reflect the importance of information processing closely linked to the print itself (i.e., letters and words), and they suppose that the reader extracts meaning from the print only after the lower-order processes, such as basic cognitive and linguistic processes involved in word decoding, have been completed (see LaBerge & Samuels, 1974). A familiar model of reading comprehension that has strong bottom-up components is the *simple view of reading* (Gough, Hoover, & Peterson, 1996; Gough & Tunmer, 1986; Hoover & Gough, 1990). According to this model, when readers become fluent in word recognition and decoding and demonstrate at least adequate listening comprehension, they will be able to comprehend the text. Thus, meaning from the text is derived primarily from words that are read (Duke et al., 2004).
In contrast to top-down and bottom-up models, integrative models purport that information stores (i.e., semantic, syntactic, lexical, and orthographic knowledge) interact with one another throughout the reading process. Integrative models were developed to address the inadequacy of strictly top-down models and bottom-up models. Indeed, research has shown that lower-level and higher-level processes may work in combination or compensate for one another during reading (Adams, 1990; Rumelhart, 1994). For example, less-skilled readers who are provided with text at their relative reading level are able to use context to facilitate word recognition to perform as well as more-skilled readers (Stanovich, 1980, 1984). This finding dispels the notion that higher-level processes, such as context facilitation, must await the development of lower-level skills such as word recognition, and it highlights the interactive nature of the reading process. At present, general consensus exists in the literature that reading processes are interactive in nature. For example, recent versions of automaticity theory (LaBerge & Samuels, 1974), a classic bottom-up processing model, were revised to allow for more interaction with top-down processes (Samuels, 2004, 2006). Other recent models such as the convergent skills model (Vellutino, Tunmer, Jaccard, & Chen, 2007) depict the role of both bottom-up and top-down processes in the construction of meaning from text.

Explanatory Models and Developmental Trends

Despite debate across decades regarding the relative merits of top-down and bottom-up models, little attention has been paid to developmental trends in the contributions of the competencies described in each model. Furthermore, it appears that a plethora of related, but semi-independent, reading processes influencing reading comprehension have been proposed and that the processes that are highlighted by researchers have varied somewhat by developmental level of their participants. For example, researchers investigating the reading comprehension of elementary-school-age children have included in their models measures of reading decoding skills, phonological and orthographic awareness, rapid automatic naming, reading fluency, a variety of memory abilities (e.g., long-term memory, short-term memory, working memory, and semantic memory), comprehension monitoring, oral language processing (e.g., listening comprehension), executive functions, and prior knowledge (e.g., Adlof, Catts, & Lee, 2010; Duke et al., 2004; Goff, Pratt, & Ong, 2005; Ouellette & Beers, 2010; Vellutino, 2003). Researchers investigating the reading comprehension of adolescents and adults have included in their models a somewhat different and more restricted subset of measures: vocabulary knowledge, domain knowledge, reading decoding skills, long-term memory, working memory, inference generation, and strategic processing (e.g., Cromley & Azevedo, 2007; Kintsch, 1998; Landi, 2010; Murphy & Alexander, 2002; Perfetti, Marron, & Foltz, 1996). It is likely that the variation in the types of reading processes targeted in such research reflects, in part, actual developmental differences in the competencies that fuel reading comprehension. For example, it is logical—and consistent with many theoretical models—that, as more basic skills (e.g., reading decoding skills and their underlying reading processes) become more automatic, individual differences in other reading competencies will exercise more influence on reading for understanding. Too few studies, however, have considered a broad range of reading competencies in competing explanatory models targeting reading comprehension across a broad developmental period.

Latent-Variable Reading Comprehension Research

We believe that latent-variable research via structural equation modeling (SEM) provides researchers a sound method for investigating the influences of lower-order and higher-order abilities on reading comprehension across development. SEM offers a number of advantages over other statistical analyses examining the relations between observed variables, such as correlations and multiple regression. SEM allows for (a) consideration of error-free variables representing the
constructs of interest and their influences on other variables, (b) the simultaneous estimation of both direct and indirect effects, and (c) the inclusion of variables at multiple levels of generality in explanatory models (see Keith, 2006).

To illustrate both the potential utility of SEM research as well as apparent limitations of the extant research, we reviewed 29 studies published prior to 2008 that used latent-variables analyses in an attempt to explain reading comprehension. Several patterns are evident. First, the vast majority of the studies targeted the reading comprehension of children of elementary-school age. Of the 29 studies, 18 studies (62%) include only elementary-school-age children (i.e., those in Grades 1 to 5 or up to age 11). Only four studies (14%) included children from across elementary, middle, and high school years, and only one study (3%) included participants older than age 18. These findings represent the general trend of researchers failing to consider developmental differences in reading competencies across a wide age range. Second, despite the functional relation between reading decoding skills and reading comprehension, 10 of these studies (34%) either (a) did not include a variable measuring reading decoding skills, reading fluency, or reading prosody or (b) did not include paths from more basic cognitive abilities to reading decoding skills, reading fluency, or reading prosody as well as to reading comprehension. The examination of possible indirect effects on reading comprehension via more basic cognitive abilities should lead to a richer understanding of the reading process.

Third, despite targeting the explanation of reading comprehension using latent-variable models, which allow for representation of the constructs of interest using multiple indicators, the majority of these studies (n = 17, 59%) included only a single indicator of reading comprehension. Single indicators of the constructs may lead to methodological bias, which is particularly troublesome for understanding developmental differences because of the multidimensional nature of reading comprehension (see Francis et al., 2006; Shuy, McCardle, & Albro, 2006). Fourth, it is evident that a wide variety of constructs have been represented in these studies, but there appears to be little consistency in the use of labels for these constructs across studies. This finding suggests a lack of an established taxonomy for describing the reading competencies and cognitive abilities that enable reading comprehension. Finally, 17 studies (59%) did not appear to consider the general factor of intelligence when constructing models; there is substantial evidence demonstrating that measures of the general factor are strongly related to measures of listening comprehension and reading comprehension (e.g., Jensen, 1998; Nation, Clarke, & Snowling, 2002; Swanson & Alexander, 1997; Vellutino, 2003).

Purpose of the Study

To overcome some of the limitations of this prior research, a roadmap that describes the connections between the constructs of interest is needed lest important influences on reading comprehension be omitted from explanatory models. We have chosen to use the Cattell–Horn–Carroll (CHC) theory of cognitive abilities (Carroll, 1993; McGrew, 2009) because it is well suited to ensure sampling from a wide array of ability constructs to represent, in a general way, groups of more elemental processes involved in reading. The CHC theory describes a hierarchical framework of cognitive abilities that varies according to level of generality: narrow abilities (Stratum I), broad abilities (Stratum II), and general intelligence (Stratum III). At the apex of this hierarchical model is the general factor representing general intelligence.

To extend the research examining the effects of the general factor, more specific cognitive abilities, and reading decoding skills on reading comprehension performance, we sought to answer

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1 A table presenting these results is available in the Supporting Information.
five questions using models derived from CHC theory. First, which cognitive abilities best explain reading comprehension? Second, what is the size of the effects of these cognitive abilities on reading comprehension? To address these two questions, we used SEM to develop, test, and validate models specifying general factors, more specific factors, and a reading decoding skill factor as influencing reading comprehension. Across all models, each factor (including reading comprehension) was represented by at least two indicators to ensure broad construct representation and to acknowledge the multidimensional nature of the constructs they represent. A two-stratum model was developed from recent research using SEM to examine the general factor and CHC broad cognitive abilities influencing reading decoding skills (Floyd, Keith, Taub, & McGrew, 2007). This previous research provides a solid base on which to develop models examining the direct and indirect effects of a variety of types of abilities on reading comprehension. More specifically, this prior modeling allows for consideration of the indirect effects of broad cognitive abilities on reading comprehension through reading decoding skills.

Because of the relative paucity of research focusing on developmental differences in the explanation of reading comprehension, we were interested in illuminating these differences across an age range unseen in previous SEM research. Our third question focused on how the effects of cognitive abilities on reading comprehension changed across the period from the preschool years through early adulthood. We considered that these effects may change in type and in their strength across development. To investigate this question, we drew from the same five age-differentiated samples, ranging from age 5 to age 39 as did Floyd et al. (2007). Finally, we sought to examine two additional questions to test the assumptions made in our modeling as well as the validity of preliminary findings from our exploratory modeling. Based on assertions that the general factor should be considered a priori in explaining reading comprehension, we tested whether the general factor demonstrated direct or indirect effects on reading comprehension. To test a central premise differentiating top-down and bottom-up models, we tested whether reading decoding skills affect reading comprehension or whether reading comprehension affected reading decoding skills.

**METHOD**

**Participants**

Participants were drawn from the standardization sample of the Woodcock–Johnson III (WJ III; Woodcock, McGrew, & Mather, 2001). The WJ III standardization sample was formed using a stratified sampling plan that controlled for 10 individual (e.g., race, sex, educational level, occupational status) and community (e.g., community size, community socioeconomic status) variables as described by the United States Census projections for the year 2000. Five age-based samples were formed from the standardization sample (Floyd et al., 2007; McGrew & Woodcock, 2001). Age ranges and sample sizes were as follows: 5 to 6 (n = 639), 7 to 8 (n = 720), 9 to 13 (n = 1,995), 14 to 19 (n = 1,615), and 20 to 39 (n = 1,409). For cross-validation of the exploratory models, each age-based sample was randomly split into a calibration sample and a validation sample (cf. MacCallum, Roznowski, Mar, & Reith, 1994). Table 1 provides more information about sample sizes.

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2 Analyses were also completed using a three-stratum model (see Floyd et al., 2007), but they are not presented here due to (a) difficulties differentiating narrow abilities from broad abilities (e.g., as indicated by frequent Heywood cases in the paths from broad ability to narrow ability factors) and (b) space limitations. These results can be obtained from the first author.
Table 1
Means and Standard Deviations for Passage Comprehension and Reading Vocabulary, Sample Size Ranges, and Percentage of Missing Data for the Calibration Samples and the Validation Samples across Five Age Groups

<table>
<thead>
<tr>
<th>WJ III Test</th>
<th>Ages 5 to 6</th>
<th>Ages 7 to 8</th>
<th>Ages 9 to 13</th>
<th>Ages 14 to 19</th>
<th>Ages 20 to 39</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>C</td>
<td>V</td>
<td>C</td>
<td>V</td>
<td>C</td>
</tr>
<tr>
<td>Passage Comprehension</td>
<td>97.5</td>
<td>13.6</td>
<td>98.0</td>
<td>14.4</td>
<td>100.5</td>
</tr>
<tr>
<td>Reading Vocabulary</td>
<td>95.6</td>
<td>14.3</td>
<td>97.7</td>
<td>16.0</td>
<td>100.7</td>
</tr>
<tr>
<td>Minimum n</td>
<td>122</td>
<td>110</td>
<td>201</td>
<td>179</td>
<td>548</td>
</tr>
<tr>
<td>Maximum n</td>
<td>318</td>
<td>321</td>
<td>363</td>
<td>357</td>
<td>1007</td>
</tr>
<tr>
<td>% Missing</td>
<td>15.6</td>
<td>18.0</td>
<td>18.3</td>
<td>16.0</td>
<td>18.0</td>
</tr>
</tbody>
</table>

Notes. Scores were age-based standard scores ($M = 100, SD = 15$). C: calibration sample; V: validation sample.
Measures

All measures were age-based standard scores \((M = 100, SD = 15)\) stemming from the WJ III tests (Woodcock et al., 2001). McGrew and Woodcock (2001) and Woodcock, McGrew, Mather, and Schrank (2003) presented estimates of reliability and validity evidence for these tests. We reproduce their median split-half reliability estimates in sections that follow, and a body of validity evidence based on content, response processes, internal structure, and external relations is available for each test (McGrew & Woodcock, 2001; Woodcock et al., 2003). Furthermore, the development, standardization, and psychometric properties of these tests have been evaluated favorably by independent reviewers (e.g., Cizek, 2003; Sares, 2005). Means and standard deviations for the WJ III tests (except Passage Comprehension and Reading Vocabulary) across all samples were reported in Floyd et al. (2007); these values for Passage Comprehension and Reading Vocabulary are reported in Table 1.

**Reading comprehension.** Two tests from the WJ III Tests of Achievement were used as indicators of reading comprehension. Passage Comprehension requires examinees to match icons to color images, read pairs of words and identify corresponding images in an array, and provide missing words in the context of sentences and paragraphs. Reading Vocabulary is composed of three subtests requiring examinees to read words and provide synonyms, antonyms, and other words to complete verbal analogies. For ages 5 to 39, the median split-half reliability coefficients for Passage Comprehension and Reading Vocabulary were .85 and .87, respectively (McGrew & Woodcock, 2001).

**Reading decoding.** Two tests from the WJ III Tests of Achievement were used as indicators of reading decoding skills. Letter–Word Identification requires examinees at the earliest ages to identify letters by name and to identify spoken words; more advanced examinees were required to pronounce words. Word Attack requires examinees at the earliest ages to identify letters associated with sounds and to produce sounds made by letters; more advanced examinees were required to pronounce phonically regular nonwords. For ages 5 to 39, the median split-half reliability coefficient for Letter–Word Identification was .92, and for Word Attack, it was .87 (McGrew & Woodcock, 2001).

**Cognitive abilities.** A total of 18 tests from the WJ III Tests of Cognitive Abilities, 4 tests from the WJ III Tests of Achievement, and 7 tests from the Woodcock–Johnson III Diagnostic Supplement (Woodcock et al., 2003) were used as indicators of CHC cognitive abilities. (Refer to the boxes on the left side of Figure 1 for the list of these tests). All tests, except those that follow, demonstrated median split-half reliability coefficients of .80 or higher for ages 5 to 39 in the standardization sample (McGrew & Woodcock, 2001). Exceptions to this standard included Picture Recognition (median split-half reliability coefficient = .73), Cross Out (.75), Incomplete Words (.78), and Memory for Words (.78).

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3 Substantial validity evidence supports indicators of this factor. The Passage Comprehension and Reading Vocabulary tests form the WJ III Reading Comprehension cluster (Woodcock et al., 2001), and their prior versions formed the Reading Comprehension cluster from the Woodcock–Johnson Psycho-Educational Battery–Revised: Tests of Achievement (Woodcock & Johnson, 1989) and the Woodcock Reading Mastery Tests–Revised (WRMT-R; Woodcock, 1998).

4 Substantial validity evidence supports indicators of this factor. The Letter–Word Identification and Word Attack tests form the WJ III Basic Reading Skills cluster (Woodcock et al., 2001), and their prior versions formed the Basic Reading Skills cluster from the WJ-R (Woodcock & Johnson, 1989) and the WRMT-R (Woodcock, 1998).

5 The tests Picture Vocabulary, Academic Knowledge, Oral Comprehension, and Story Recall were used as indicators to ensure broad construct representation in the measurement of the broad ability Crystallized Intelligence.

6 When the data sets used in this study were constructed, two tests, Number Series and Number Matrices, produced a score labeled Numerical Reasoning (Woodcock et al., 2003).
FIGURE 1. The Two-Stratum Model used in explanation of Reading Comprehension at ages 7 to 8. Gf = Fluid Reasoning, Gv = Visual Processing, Gs = Processing Speed, Glr = Long-Term Retrieval, Ga = Auditory Processing, Gsm = Short-Term Memory, Gc = Crystallized Intelligence, g = General Intelligence, RD = Reading Decoding Skills, and RC = Reading Comprehension.

Analysis and Theoretical Models

Amos 5.0 (Arbuckle & Wothke, 2004) was used to develop and evaluate the latent-variable models. Maximum-likelihood estimation was used to estimate free parameters in the theoretical models that follow. Correlations and standard deviations for each calibration sample and validation sample were the input for Amos, and covariance matrices were analyzed. Calibration and validation matrices are available from the first author, by request. Correlations and standard deviations were
estimated using the missing values subprogram from SPSS; the EM algorithm was used to estimate the matrix in the presence of incomplete data (Schafer & Graham, 2002). In Table 1, the value listed for “Minimum n” is the minimum number of participants for any given variable, whereas “Maximum n” shows the maximum number of cases across variables. The row labeled “% Missing” lists the percentage of data missing for each sample. Values in the Maximum n row represent the size of each sample after data estimation.

The left side of Figure 1 presents the cognitive ability portion of the measurement model, which includes factors representing general intelligence and seven CHC broad abilities: Fluid Reasoning (Gf), Visual Processing (Gv), Processing Speed (Gs), Long-Term Retrieval (Glr), Auditory Processing (Ga), Short-Term Memory (Gsm), and Crystallized Intelligence (Gc). This measurement model was used for analysis of all five age groups. Consistent with standard SEM terminology, the measurement model includes (a) the scores from the cognitive ability tests, which are measured variables represented by rectangles on the left side of the figure; (b) the unique variances of the measured variables, which are represented by circles to the left of the rectangles; (c) the first-order broad ability factors, which are represented by ellipses to the right of the rectangles; and (d) the unique variances of the broad ability factors, which are represented by circles positioned above the broad ability factors. The second-order general factor is represented by a single ellipse at the top right of the figure. The bottom right of the figure shows the Reading Decoding Skills factor and the Reading Comprehension factor. For the Reading Decoding Skills factor, the figure includes (a) scores from the two reading decoding skills tests (using rectangles), (b) the Reading Decoding Skills factor (using an ellipse), and (c) the unique variances of the tests and the Reading Decoding Skills factor (using circles). Similarly, for the Reading Comprehension factor presented at the bottom right of the figure, there are scores from the two reading comprehension tests, the Reading Comprehension factor, and the unique variances of the tests and the Reading Comprehension factor.

Based on the results from Floyd et al. (2007), each model included significant structural paths from broad ability factors to Reading Decoding Skills. These paths varied somewhat across age groups (see Table 2 for these paths demonstrating indirect effects). For example, in Figure 1, Processing Speed, Short-Term Memory, and Crystallized Intelligence demonstrated significant direct effects on Reading Decoding Skills.

A two-stage process of model development was used to examine the structural models describing the effects of the CHC abilities and reading decoding skills on reading comprehension. The first stage involved an iterative process of testing structural models using the calibration sample for each age level. Using backward elimination methods, initial models included all structural paths from the seven broad ability factors, the general factor, and the Reading Decoding Skills factor to the Reading Comprehension factor. Backward elimination methods were chosen to reduce specification error (pervasive in specification searches) by including all relevant factors as predictors. After initial parameter estimates were obtained for a model, the structural path demonstrating the highest negative value was deleted, and the model was re-estimated. This process of model estimation, pruning, and re-estimation continued until all structural paths with negative parameter estimates were eliminated. Following the same process, structural paths that were not statistically significant at the .05 probability level were deleted. Finally, modification indices were examined to determine whether

7 There were five minor differences in the models across the five age groups stemming from slight differences in the match between the sample data and the model. The four sets of correlated unique variances for the tests shown in Figure 1 were included in all models except for those between the unique variances for Oral Comprehension and Academic Knowledge at ages 5 to 6, 14 to 19, and 20 to 39. Due to a path to Long-Term Retrieval factor from the general intelligence factor that was greater than unity at ages 20 to 39, these paths were set to a maximum of 1 by constraining the unexplained variance terms to 0.
Table 2
Fit Statistics for the Final Models Across Five Age Groups

<table>
<thead>
<tr>
<th>Model and Age Group</th>
<th>$\chi^2$</th>
<th>df</th>
<th>$p$</th>
<th>CFI</th>
<th>TLI</th>
<th>RMSEA</th>
<th>SRMR</th>
<th>AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ages 5 to 6</td>
<td>749.349</td>
<td>482</td>
<td>&lt;.001</td>
<td>.929</td>
<td>.923</td>
<td>.040</td>
<td>(.035–.046)</td>
<td>.0492</td>
</tr>
<tr>
<td>Ages 7 to 8</td>
<td>998.202</td>
<td>480</td>
<td>&lt;.001</td>
<td>.892</td>
<td>.882</td>
<td>.053</td>
<td>(.048–.057)</td>
<td>.0553</td>
</tr>
<tr>
<td>Ages 9 to 13</td>
<td>1396.671</td>
<td>480</td>
<td>&lt;.001</td>
<td>.906</td>
<td>.897</td>
<td>.049</td>
<td>(.046–.052)</td>
<td>.0454</td>
</tr>
<tr>
<td>Ages 14 to 19</td>
<td>1410.024</td>
<td>481</td>
<td>&lt;.001</td>
<td>.890</td>
<td>.879</td>
<td>.056</td>
<td>(.052–.059)</td>
<td>.0508</td>
</tr>
<tr>
<td>Ages 20 to 39</td>
<td>1468.186</td>
<td>483</td>
<td>&lt;.001</td>
<td>.866</td>
<td>.853</td>
<td>.062</td>
<td>(.059–.066)</td>
<td>.0556</td>
</tr>
</tbody>
</table>


any deleted structural paths should be respecified. To validate or modify the models developed using the calibration samples, the second stage involved estimating the final model stemming from the calibration samples using the validation samples (MacCallum et al., 1994). Structural paths that were not statistically significant at the .05 probability level were not included, although modification indices were examined to determine whether deleted structural paths should be added. Results from the final models stemming from the validation samples at each age level are reported.

RESULTS
Across models, all paths in the measurement model were statistically significant, $p < .05$. All paths in the structural model shown to be significant using the calibration samples were shown to be significant using the corresponding validation samples. At ages 7 to 8 and 20 to 39, the paths from the general factor to the Fluid Reasoning factor were greater than unity, so they were set to a maximum of 1. No structural paths were added based on modification indexes.

Table 2 presents relevant fit statistics for the final models across the five age groups. Although the Tucker–Lewis index (TLI) and comparative fit index (CFI) indicate the models fit the observed data fairly well across age groups (Hu & Bentler, 1999), these fit indexes tend to worsen when models with many different variables, such as ours, are estimated. The root mean square error of approximation (RMSEA) and the standardized root mean square residual (SRMR) provide more accurate estimates of model fit with complex models (Kenny & McCoach, 2003). Using these indexes, the model fit at each age level can be considered good (Hu & Bentler, 1998, 1999).

Core Questions and Models
For purposes of illustration, the final structural model for ages 7 to 8 is shown in Figure 1. This figure includes the standardized path coefficients from the CHC ability factors and the Reading Decoding Skills factor to the Reading Comprehension factor. Table 3 presents the standardized path coefficients for all age groups. These coefficients, like beta weights from multiple regression, indicate the proportion of standard deviation units that the Reading Comprehension factor changes as a function of 1 SD change in an ability factor or the Reading Decoding Skills factor. Standardized coefficient effect sizes of .05 or greater can be considered small effects, effect sizes around .15 can be considered moderate effects, and effect sizes greater than .25 can be considered large effects.

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8 Consistent with other research using the exact same method (e.g., Floyd et al., 2007), alpha inflation across a family of related analysis was not controlled for using alpha corrections. For example, a Bonferroni correction would have reduced the $a$ priori alpha level to .00625. Based on review of the results of each analysis, use of such an alpha correction would have not altered the results reported in this article.
Table 3
Standardized Direct Effects of Reading Decoding Skills and Crystallized Intelligence, Indirect Effects (through Reading Decoding) of CHC Broad Cognitive Abilities, and Squared Multiple Correlation Values for Predictors on Reading Comprehension Across Five Age Groups

<table>
<thead>
<tr>
<th>Age Group</th>
<th>Standardized Effects 5 to 6</th>
<th>Standardized Effects 7 to 8</th>
<th>Standardized Effects 9 to 13</th>
<th>Standardized Effects 14 to 19</th>
<th>Standardized Effects 20 to 39</th>
</tr>
</thead>
<tbody>
<tr>
<td>From RD: Direct</td>
<td>.75</td>
<td>.90</td>
<td>.63</td>
<td>.43</td>
<td>.38</td>
</tr>
<tr>
<td>From Ge: Direct</td>
<td>.16</td>
<td>.17</td>
<td>.44</td>
<td>.68</td>
<td>.70</td>
</tr>
<tr>
<td>From Gc: Indirect</td>
<td>.27</td>
<td>.22</td>
<td>.22</td>
<td>.21</td>
<td>.21</td>
</tr>
<tr>
<td>From Glr: Indirect</td>
<td>.36</td>
<td>.30</td>
<td>.26</td>
<td>.16</td>
<td>.13</td>
</tr>
<tr>
<td>From Gs: Indirect</td>
<td>.30</td>
<td>.20</td>
<td>.30</td>
<td>.26</td>
<td>.16</td>
</tr>
<tr>
<td>From Ga: Indirect</td>
<td>.13</td>
<td>.13</td>
<td>.13</td>
<td>.13</td>
<td>.13</td>
</tr>
<tr>
<td>R² on RC</td>
<td>.72</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Notes. RD: Reading Decoding Skills; Gsm: Short-Term Memory; Gc: Crystallized Intelligence; Glr: Long-Term Retrieval; Gs: Processing Speed; Ga: Auditory Processing; g: General Intelligence; RC: Reading Comprehension. Direct effects are shown in boldface. R² values in the models exceeded 1.00 at ages 7 to 8, 14 to 19, and 20 to 39 but were reduced to in-bound estimates.

(Keith, 2006; cf. Pedhazur, 1997). Furthermore, Table 3 presents the squared multiple correlations representing the portion of the variance in the Reading Comprehension factor accounted for by its predictors; their values were lowest for the youngest age group (yet still sizeable, \( R^2 = .72 \)) and perfect or near perfect across the remaining age groups.

The effects of the broad abilities and reading decoding skills on reading comprehension and the developmental changes in these effects are of greatest interest (see Table 3). Only the Reading Decoding Skills and Crystallized Intelligence factors demonstrated significant direct effects on Reading Comprehension. Across all age groups, Reading Decoding Skills demonstrated large direct effects, but these effects declined notably in magnitude with age. In fact, Reading Decoding Skills had almost double the standardized effect on Reading Comprehension for the youngest age group as it did for the oldest age group. The path from the Reading Decoding Skills factor to the Reading Comprehension factor was .75 for ages 5 to 6 and .38 for ages 20 to 39. It is most notable that Reading Decoding Skills had its largest effect on Reading Comprehension for the 7 to 8 age group (.90). Crystallized Intelligence also demonstrated direct effects on Reading Comprehension across age groups. In contrast to Reading Decoding Skills, the effects of Crystallized Intelligence increased in magnitude with age. For ages 5 to 6 and 7 to 8, these effects were moderate. Starting at age 9 to 13, these effects became large, and they continued to increase to a magnitude of .70 at ages 20 to 39.

A number of broad abilities demonstrated significant indirect effects on Reading Comprehension through the Reading Decoding Skills factor. These findings reflect those direct effects on Reading Decoding Skills demonstrated by Floyd et al. (2007). It is worth noting that were the Reading Decoding Skills factor not in the model, these indirect effects would show up as direct effects. In other words, these indirect effects explain to some degree how these broad abilities affect Reading Comprehension (by influencing Reading Decoding Skills). In addition to its direct effects on Reading Comprehension, Crystallized Intelligence also demonstrated indirect effects through the Reading Decoding Skills factor. Beginning at ages 7 to 8 and continuing through the three remaining age levels, the Crystallized Intelligence factor demonstrated large indirect effects that were similar.
in magnitude across age groups. Other factors that did not demonstrate direct effects on Reading Comprehension demonstrated significant indirect effects, and these effects varied across age groups. For ages 5 to 6, the Long-Term Retrieval and Processing Speed factors demonstrated large indirect effects. For ages 7 to 8, the effects from Processing Speed remained significant but declined notably in magnitude from the 5 to 6 age level. Beginning at ages 7 to 8, the Short-Term Memory factor demonstrated large effects, but its effects declined to moderate at ages 13 to 19 and were nonsignificant at ages 20 to 39. The Auditory Processing factor demonstrated moderate effects only at this oldest age level.

The direct effect of the general factor on Reading Comprehension was not statistically significant across models (see Table 3). Instead, the general factor had an indirect effect on the Reading Comprehension factor. For instance, the general factor had direct effects on the broad ability factors, and at least one of these factors (i.e., Crystallized Intelligence) had a direct effect on Reading Comprehension. Thus, the general factor demonstrated large but indirect effects on Reading Comprehension factor for all five age groups (.68 to .88). Given the adequacy of our model, this finding suggests that it is through the broad ability of Crystallized Intelligence that general intelligence effects reading comprehension.

Additional Questions and Models

Does the general factor have direct effects? Based on our initial results, we developed and tested a series of post-hoc models using the validation samples to examine two additional research questions. We sought a direct test of whether the general factor had direct, in addition to indirect, effects on Reading Comprehension. To do so, we respecified the final model for each age group to include a single additional direct path from the general factor to the Reading Comprehension factor. The resulting fit statistics are presented in Table 4 in the column with the “Final+g” label.

Table 4
Fit Statistics for the Final Models Compared to Models Specifying Paths from the General Factor to Reading Comprehension Across Five Age Groups

<table>
<thead>
<tr>
<th>Age Group and Model</th>
<th>$\chi^2$</th>
<th>$df$</th>
<th>$p$</th>
<th>$\Delta \chi^2$</th>
<th>$\Delta df$</th>
<th>CFI</th>
<th>TLI</th>
<th>RMSEA</th>
<th>AIC</th>
<th>$\Delta$AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ages 5 to 6: Final</td>
<td>749.349</td>
<td>482</td>
<td>&lt;.001</td>
<td>0.000</td>
<td>1.470</td>
<td>1.470</td>
<td>.929</td>
<td>.923</td>
<td>.040</td>
<td>(.35–.046)</td>
</tr>
<tr>
<td>Ages 5 to 6: Final + g</td>
<td>747.879</td>
<td>481</td>
<td>&lt;.001</td>
<td>1.470</td>
<td>1.470</td>
<td>.929</td>
<td>.923</td>
<td>.040</td>
<td>(.35–.046)</td>
<td>907.879</td>
</tr>
<tr>
<td>Ages 5 to 6: g only</td>
<td>795.243</td>
<td>483</td>
<td>&lt;.001</td>
<td>1.470</td>
<td>1.470</td>
<td>.918</td>
<td>.910</td>
<td>.043</td>
<td>(.038–.049)</td>
<td>951.243</td>
</tr>
<tr>
<td>Ages 7 to 8: Final</td>
<td>998.202</td>
<td>480</td>
<td>&lt;.001</td>
<td>0.077</td>
<td>1.000</td>
<td>.077</td>
<td>.892</td>
<td>.882</td>
<td>.053</td>
<td>(.048–.057)</td>
</tr>
<tr>
<td>Ages 7 to 8: Final + g</td>
<td>998.125</td>
<td>479</td>
<td>&lt;.001</td>
<td>0.077</td>
<td>1.000</td>
<td>.077</td>
<td>.892</td>
<td>.881</td>
<td>.053</td>
<td>(.048–.057)</td>
</tr>
<tr>
<td>Ages 7 to 8: g only</td>
<td>1156.650</td>
<td>481</td>
<td>&lt;.001</td>
<td>1.000</td>
<td>1.000</td>
<td>.86</td>
<td>.846</td>
<td>.060</td>
<td>(.056–.064)</td>
<td>1316.649</td>
</tr>
<tr>
<td>Ages 9 to 13: Final</td>
<td>1396.671</td>
<td>480</td>
<td>&lt;.001</td>
<td>2.481</td>
<td>1.470</td>
<td>.890</td>
<td>.879</td>
<td>.056</td>
<td>(.052–.059)</td>
<td>1558.671</td>
</tr>
<tr>
<td>Ages 9 to 13: Final + g</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Ages 9 to 13: g only</td>
<td>1603.890</td>
<td>481</td>
<td>&lt;.001</td>
<td>2.481</td>
<td>1.470</td>
<td>.885</td>
<td>.874</td>
<td>.055</td>
<td>(.052–.058)</td>
<td>1763.894</td>
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<tr>
<td>Ages 14 to 19: Final</td>
<td>1410.024</td>
<td>481</td>
<td>&lt;.001</td>
<td>2.481</td>
<td>1.470</td>
<td>.890</td>
<td>.879</td>
<td>.056</td>
<td>(.052–.059)</td>
<td>1570.024</td>
</tr>
<tr>
<td>Ages 14 to 19: Final + g</td>
<td>1407.543</td>
<td>480</td>
<td>&lt;.001</td>
<td>2.481</td>
<td>1.470</td>
<td>.890</td>
<td>.879</td>
<td>.056</td>
<td>(.052–.059)</td>
<td>1569.543</td>
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<tr>
<td>Ages 14 to 19: g only</td>
<td>1496.630</td>
<td>482</td>
<td>&lt;.001</td>
<td>2.481</td>
<td>1.470</td>
<td>.88</td>
<td>.868</td>
<td>.058</td>
<td>(.055–.061)</td>
<td>1654.626</td>
</tr>
<tr>
<td>Ages 20 to 39: Final</td>
<td>1468.186</td>
<td>483</td>
<td>&lt;.001</td>
<td>2.481</td>
<td>1.470</td>
<td>.866</td>
<td>.853</td>
<td>.062</td>
<td>(.059–.066)</td>
<td>1624.186</td>
</tr>
<tr>
<td>Ages 20 to 39: Final + g</td>
<td>1464.639</td>
<td>482</td>
<td>&lt;.001</td>
<td>2.481</td>
<td>1.470</td>
<td>.866</td>
<td>.853</td>
<td>.062</td>
<td>(.059–.066)</td>
<td>1622.639</td>
</tr>
<tr>
<td>Ages 20 to 39: g only</td>
<td>1606.290</td>
<td>484</td>
<td>&lt;.001</td>
<td>2.481</td>
<td>1.470</td>
<td>.847</td>
<td>.833</td>
<td>.066</td>
<td>(.063–.070)</td>
<td>1760.289</td>
</tr>
</tbody>
</table>

Notes. g: General Intelligence; CFI: comparative fit index; TLI: Tucker–Lewis index; RMSEA: root mean square error of approximation; standardized RMR: standardized root mean square residual; AIC: Akaike Information Criterion. Comparisons are to the final model for each age group. The model for ages 9 to 13: Final + g was inadmissible.
When compared to the final model, this post-hoc model did not improve model fit \((p > .05)\) for four of the five age groups, and it produced inadmissible path coefficients for the fifth age group. We also tested the possibility that all influences on Reading Comprehension could be explained more parsimoniously by a single path from the general factor. Because this “g-only” model (see Table 4) is not nested within our final model, which included only direct effects from Reading Decoding Skills and Crystallized Intelligence to Reading Comprehension, we compared the models using the Akaike Information Criterion (AIC). The final models consistently demonstrated better fit (lower AICs) across age levels than did the g-only models. Together, these findings further support the conclusion that the general factor has indirect rather than direct effects on Reading Comprehension.

**Does reading comprehension influence reading decoding skills?** We assumed in initial models that if Reading Decoding Skills and Reading Comprehension are causally related, the influence is from Reading Decoding Skills to Reading Comprehension, rather than the reverse. This assumption seems reasonable based on prior research and theory (e.g., Sweet & Snow, 2003). Given that Reading Comprehension and Reading Decoding Skills have different influences, however, it is possible to develop nonequivalent models to test this assumption (see Keith, 2006; Kline, 2010; or Lee & Hershberger, 1990). To do so, we compared the final model for each age group to a model with the path from Reading Decoding Skills to Reading Comprehension reversed (i.e., the direction of the path was from Reading Comprehension to Reading Decoding Skills). As is evident in Table 5, for all age groups, the final model specifying a path from Reading Decoding Skills to Reading Comprehension fit better (based on AIC values) than the model specifying a path from Reading Comprehension to Reading Decoding Skills. In addition, for several age levels, the alternate (Reading Comprehension to Reading Decoding Skills) models resulted in path coefficient values outside the normal range, further suggesting their implausibility. The results suggest that the assumption that Reading Decoding Skills influence Reading Comprehension (rather than the reverse) is indeed valid.

**DISCUSSION**

In an attempt to understand better the abilities that affect reading comprehension, we developed and tested models based on CHC theory to examine the effects of general intelligence, broad cognitive

<table>
<thead>
<tr>
<th>Age Group and Model</th>
<th>(x^2)</th>
<th>df</th>
<th>(p)</th>
<th>CFI</th>
<th>TLI</th>
<th>RMSEA</th>
<th>AIC</th>
<th>(\Delta\text{AIC})</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ages 5 to 6: Final</td>
<td>749.349</td>
<td>482</td>
<td>&lt;.001</td>
<td>.929</td>
<td>.923</td>
<td>.040 (0.35–0.46)</td>
<td>907.349</td>
<td></td>
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<tr>
<td>Ages 5 to 6: RC to RD</td>
<td>794.785</td>
<td>482</td>
<td>&lt;.001</td>
<td>.917</td>
<td>.910</td>
<td>.044 (0.038–0.049)</td>
<td>952.785</td>
<td>45.436</td>
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<tr>
<td>Ages 7 to 8: Final</td>
<td>998.202</td>
<td>480</td>
<td>&lt;.001</td>
<td>.892</td>
<td>.882</td>
<td>.053 (0.048–0.057)</td>
<td>1160.202</td>
<td></td>
</tr>
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<td>Ages 7 to 8: RC to RD</td>
<td>1027.571</td>
<td>408</td>
<td>&lt;.001</td>
<td>.886</td>
<td>.875</td>
<td>.054 (0.050–0.059)</td>
<td>1189.571</td>
<td>29.369</td>
</tr>
<tr>
<td>Ages 9 to 13: Final</td>
<td>1396.671</td>
<td>480</td>
<td>&lt;.001</td>
<td>.906</td>
<td>.897</td>
<td>.049 (0.046–0.052)</td>
<td>1581.671</td>
<td></td>
</tr>
<tr>
<td>Ages 9 to 13: RC to RD</td>
<td>1419.962</td>
<td>480</td>
<td>&lt;.001</td>
<td>.904</td>
<td>.894</td>
<td>.050 (0.047–0.053)</td>
<td>1581.962</td>
<td>423.291</td>
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<tr>
<td>Ages 14 to 19: Final</td>
<td>1410.024</td>
<td>481</td>
<td>&lt;.001</td>
<td>.890</td>
<td>.879</td>
<td>.056 (0.052–0.059)</td>
<td>1570.024</td>
<td></td>
</tr>
<tr>
<td>Ages 14 to 19: RC to RD</td>
<td>1419.718</td>
<td>482</td>
<td>&lt;.001</td>
<td>.889</td>
<td>.878</td>
<td>.056 (0.052–0.059)</td>
<td>1577.718</td>
<td>7.694</td>
</tr>
<tr>
<td>Ages 20 to 39: Final</td>
<td>1468.186</td>
<td>483</td>
<td>&lt;.001</td>
<td>.866</td>
<td>.853</td>
<td>.062 (0.059–0.066)</td>
<td>1624.186</td>
<td></td>
</tr>
<tr>
<td>Ages 20 to 39: RC to RD</td>
<td>1469.918</td>
<td>484</td>
<td>&lt;.001</td>
<td>.866</td>
<td>.853</td>
<td>.062 (0.059–0.066)</td>
<td>1623.918</td>
<td>−0.268</td>
</tr>
</tbody>
</table>

**Notes.** RC: Reading Comprehension; RD: Reading Decoding; CFI: comparative fit index; TLI: Tucker–Lewis index; RMSEA: root mean square error of approximation; standardized RMR: standardized root mean square residual; AIC: Akaike Information Criterion. Comparisons are to the final model for each age group.

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abilities, and reading decoding skills on reading comprehension from the preschool years to early adulthood. Results revealed consistent patterns of direct effects on reading comprehension—from reading decoding skills and Crystallized Intelligence—but the magnitude of these effects varied substantially across age levels. A number of indirect effects, ranging from consistent, indirect effects of the general factor across age levels to inconsistent, indirect effects of broad cognitive ability factors, were also demonstrated (cf. Benson, 2008). We can conclude that, although the results of this study support many components of bottom-up models of reading—especially the classic simple view of reading (Gough et al., 1996)—they also suggest that many such models are overly simplified. A “less simple view” of reading seems more accurate, and it would likely be more beneficial for teachers and other professionals engaged in reading assessment and intervention (Pressley et al., 2009).

Direct Effects on Reading Comprehension

Reading decoding skills. Reading decoding skills describe the ability to recognize and decode words and regularly spelled pseudowords presented in isolation (Compton, 2000; Gough & Tunmer, 1986; Perfetti, 1985; Shankweiler et al., 1999). These skills form the foundation for the ability to read for understanding (Sweet & Snow, 2003). Thus, it was not unexpected that (a) one component of reading itself, reading decoding skills, demonstrated large direct effects on another, perhaps more complex component, reading comprehension and (b) it is not the reverse case that reading comprehension influences reading decoding skills. The strong association of reading decoding skills and reading comprehension performance has consistently been identified by researchers (see Francis, Fletcher, Catts, & Tomblin, 2005; Gough et al., 1996; Vellutino et al., 2007), but we believe that this is the first study of its type to demonstrate direct effects of reading decoding skills on reading comprehension across such a wide age range.

Despite the consistent finding of significant direct effects of reading decoding skills on reading comprehension, the magnitude of these effects demonstrated notable variation across the ages from early childhood to early adulthood. During the period when reading for understanding emerges, reading decoding skills had a large direct effect in both sets of models we tested. However, after this period, its effects declined precipitously. This finding of significant yet decreasing effects of reading decoding skills on reading comprehension with age is consistent with that of previous research demonstrating declining relations across development (Francis et al., 2005; Gough et al., 1996; Schwanenflugel, Meisinger, Wisenbaker, & Kuhn, 2006; Vellutino et al., 2007). However, a few studies have found stable relations between reading decoding skills and reading comprehension (Carver, 1998; Hoover & Gough, 1990).

Crystallized intelligence and more specific abilities. Some of the most important findings of this research were (a) that a broad ability factor associated with the comprehension of spoken language and the breadth and depth of world knowledge (i.e., Crystallized Intelligence) demonstrated large direct effects on reading comprehension and (b) that these effects increased in magnitude with age. Beginning at ages 14 to 19, effects from Crystallized Intelligence were large and the largest of any broad ability. Thus, in contrast to reading decoding skills, which peaked in effects during the early elementary school years and declined afterward, Crystallized Intelligence increased precipitously in its effects beginning with the 9 to 13 age range. Gough and colleagues (1996) revealed similar increasing magnitudes of relations between listening comprehension and reading comprehension via review of correlational research.

These findings reinforce the importance of language-based declarative knowledge and higher-order language processes to reading comprehension. Prior knowledge likely triggers processes important for comprehension, such as inference making or comprehension monitoring (Kintsch,
1998; Perfetti et al., 1996). Use of these language processes is common across completion of listening comprehension and reading comprehension tasks (Perfetti, 2007). These findings are also consistent with prior research guided by CHC theory (Floyd, Bergeron, & Alfonso, 2006; see McGrew & Wendling, 2010).

Indirect Effects on Reading Comprehension

*General factor.* It is possible that the general factor represents well what many researchers see as a product of the working memory system, which contributes to all conscious thought (including meta-cognition) and the management of information in immediate awareness and in the memory stores (Carroll, 1993; Jensen, 1998; Swanson & Alexander, 1997). It is tempting to think that when the general factor accounts for a large percentage of variance in reading comprehension performance, more specific abilities would have little additional effect. When the general factor was allowed to “compete” equally with the broad abilities as predictors of reading comprehension during model calibration, the results indicate that that this supposition is not supported. In both sets of SEM models used in this research, the general factor had large but indirect effects on Reading Comprehension through Crystallized Intelligence. When we contrasted the models specifying these indirect effects with others specifying direct effects, the models specifying indirect effects were better fitting. The consistent findings of indirect effects of the general factor and direct effects of broad ability factors across all five age groups mean that it is not the case of either the general factor alone or the more specific abilities alone influencing reading. More specific cognitive abilities influence reading decoding directly, but the general factor influences reading comprehension indirectly through these specific abilities. As a result, the idea of the general factor representing a domain-general working memory system fueling reading comprehension and its enabling abilities should continue its appeal.

Specific Cognitive Abilities Influencing Reading Decoding Skills

A number of lower-level, specific abilities were demonstrated to have indirect effects on reading comprehension—through reading decoding skills (cf. Floyd et al., 2007 and McGrew & Wendling, 2010). Thus, our findings indicate that lower-level processes (and their resultant cognitive abilities), which are prominent in bottom-up models, demonstrate direct effects during the process of reading words and nonwords and not during the process of reading for understanding. These direct effects are most apparent for the youngest age groups.

*Processing speed.* Individual differences in Processing Speed that contribute to reading decoding skills appear to diminish substantially after age 8 and no longer produce direct effects on reading decoding skills or indirect effects on reading comprehension. The finding of large indirect effects of Processing Speed at the two youngest age levels, across both sets of models, is consistent with reading research using a CHC framework (e.g., Flanagan, 2000; McGrew, Flanagan, Keith, & Vanderwood, 1997; cf. McGrew & Wendling, 2010) and with a wide array of research that indicates that processing speed is an important ingredient in the early stages of acquiring academic skills (e.g., Kail, Hall, & Caskey, 1999). The indirect effects of Processing Speed on reading comprehension support postulations that the more rapidly and efficiently an individual can automatize basic operations, such as reading words, the more attention and cognitive resources can be allocated to higher-level aspects of task performance, such as integrating prior knowledge with text content and drawing inferences. A few studies have revealed direct effects of Processing Speed on reading comprehension (e.g., Flanagan, 2000; Keith, 1999, McGrew, Flanagan, Keith, & Vanderwood, 1997), and other studies have tested but failed to demonstrate its direct effects (e.g., Kail & Hall, 1994; Tui, Thompson, & Lewis, 2003). It appears common, however, for researchers...
to overlook Processing Speed’s direct effects on reading decoding skills and its indirect effects on reading comprehension.

**Memory abilities.** Long-Term Retrieval had large effects on reading decoding skills, which led to large indirect effects on reading comprehension, at the earliest age level. Long-Term Retrieval represents the ability to store and retrieve information from memory in an efficient and effective manner. Evidence of direct effects of this ability on reading decoding skills is consistent with some recent research (Evans, Floyd, McGrew, & Leforgee, 2002; Windfuhr & Snowling, 2001), and some other research has revealed their effects on reading comprehension (e.g., Cain, Oakhill, Barnes, & Bryant, 2001; Goff et al., 2005). Although numerous studies have reported significant relations between measures of reading comprehension and those measures representing the limited capacity and management of phonological information in immediate awareness (a.k.a., phonological memory), results from this study reveal only indirect effects from the corresponding broad ability Short-Term Memory to Reading Comprehension (through Reading Decoding Skills). These effects were moderate to large from ages 7 to 8 and ages 14 to 19.

**Auditory processing.** Auditory Processing demonstrated weak indirect effects on reading comprehension at only the oldest age level. Auditory Processing subsumes the much-touted reading aptitude often called phonological awareness or phonemic awareness. As noted in Floyd et al. (2007), it was a surprising finding that neither of these abilities contributed direct effects to reading decoding skills at the earliest age levels. It is possible that variance in reading decoding skills accounted for by tasks representing Auditory Processing may be better accounted for by more powerful predictors, such as abilities associated with Short-Term Memory and Processing Speed, in the age groups that we targeted.

**Considerations and Limitations**

The interpretation of these findings should be tempered by five limitations. First, all measures used in this research came from a large but single battery of tests. This approach had the advantage that the instruments were standardized and normed on the same large group. However, this approach may have capitalized on similarities in task design and response requirements. Second, these data were collected using a cross-sectional design and not a longitudinal design. Future research should determine whether similar effects are shown when cognitive abilities, reading decoding skills, and reading comprehension are assessed through other tests and across time. Third, we did not test the invariance of our measurement or structural models across the five age groups. Because of the broad age range considered in this study, it is possible that the effects we identified do not have the same meaning across age groups. Future researchers should use multigroup modeling to test of the equality of constructs and effects across age groups (see Keith & Reynolds, 2012). Such analyses would allow stronger comparisons of cross-age effects. Fourth, although this study included a wide range of CHC cognitive abilities as predictors of reading comprehension, it may have omitted other important constructs, such as meta-cognitive skill usage and knowledge of text structure (Williams, Hall, & Lauer, 2004). Finally, although we used two different indicators of reading comprehension, they tap only a narrow range of comprehension skills and emphasize rather shallow levels of reading comprehension (Graesser, Swamer, Baggett, & Sell, 1996). It is possible that other tests of reading comprehension would have yielded somewhat different results, but this limitation may be obviated to some extent by the use of a latent Reading Comprehension variable. Future research should measure deep levels of comprehension as well as attend to the effects of text genre on comprehension (see Cutting & Scarborough, 2006; Sweet & Snow, 2003).

It is also worthwhile to review the advantages of this research. The models were developed based on both intelligence and reading theory research, and constructs were operationalized via

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multiple, normed, well-researched measures. Models were estimated using data from a nationally representative sample, and participants from a wide range of developmental levels, from the preschool- and early-elementary-school years to early adulthood, were included. The research also used a calibration–validation approach in which models were developed on one sample and then tested on a second sample. Such an approach guards against the dangers of specification searches and should produce more stable, reproducible findings.

Theoretical, Research, and Practical Implications

The results of this study yield several important implications to consider. First, they support an emerging recognition that the process of reading is characterized by developmental asymmetry (Vellutino et al., 2007). It seems that although lower-level skills that are the focus of bottom-up models (e.g., decoding and processing speed) are essential in the early stages of reading, their contributions diminish as children grow older. Conversely, higher-level processes from top-down models, such as those required to use prior knowledge, draw inferences from the text, and to make abstractions, may become primary in importance after children have mastered the basic skills of quickly and accurately identifying the words in text and they begin to encounter more complex materials (Chall, 1996; Sweet & Snow, 2003). Thus, our findings suggest that researchers and those engaged in professional practice should consider both top-down and bottom-up models within a developmental framework.

Second, our results suggest that researchers should specify and test indirect effects of cognitive abilities—at varying levels of generality—on reading comprehension. These indirect effects cannot be identified via bivariate correlations, and they are usually neglected in analysis using multiple regression. We believe that the consideration of indirect effects leads to a much richer understanding of the reading process. Our results suggest that the relations between some lower-level, specific abilities, such as Processing Speed and memory-related abilities, and reading comprehension are mediated by reading decoding skills. Similarly, the relation between the general factor and reading comprehension may be strong in magnitude, but this relation is mediated by the broad ability Crystallized Intelligence.

Third, based on these results, we suggest that those engaged in professional practice first consider the primary abilities outlined in the simple view of reading (Gough et al., 1996)—reading decoding skills and the broad cognitive ability Crystallized Intelligence in our study—in their assessments and interventions targeting reading comprehension problems. For example, our models indicate that the WJ III tests Letter-Word Identification and Verbal Comprehension (Woodcock et al., 2001) are the strongest indicators of reading decoding skills and Crystallized Intelligence, respectively. Thus, these tests—or others similar to them—could be used in screening and diagnostic batteries for children suspected of having severe reading comprehension difficulties. In addition, those engaged in professional practice should consider a few other abilities that fuel reading decoding skills and Crystallized Intelligence, and they should do so within a developmental framework. For instance, they should consider, across development, more specific abilities underlying reading decoding skills (such as speed of cognitive processing and working memory) as well as general intelligence, which influences knowledge acquisition and language processing (Pressley et al., 2009).

Although our results show that both reading decoding skills and Crystallized Intelligence are the most important influences on reading comprehension at every stage of development we targeted, those engaged in professional practice should focus most of the energies on reading decoding skills (and its underlying processes) during the earliest stages of reading development. In contrast, they should concentrate more so on language-related declarative knowledge and related strategies beginning at approximately age 9 (or approximately second or third grade). Instructional approaches,
such as Concept-Oriented Reading Instruction (Guthrie, 2003), and the cognitive strategy training (Pressley, 2000) address the interplay between these bottom-up and top-down processes very well.

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