Understanding the Relative Contributions of Lower-Level Word Processes, Higher-Level Processes, and Working Memory to Reading Comprehension Performance in Proficient Adult Readers

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There is considerable evidence concerning the contributions of lower-level word processes, higher-level processes, and working memory to individual differences in reading comprehension performance. However, because the bulk of the research has focused on a single source of individual differences in isolation, little is known about the relationships among these sources (Cornoldi, De Beni, & Pazzaglia, 1996; McNamara & Magliano, 2009; Perfetti, Landi, & Oakhill, 2005) or whether one or all of them make separate and important contributions to reading comprehension (Cornoldi et al., 1996). Furthermore, although most theories of reading comprehension provide details about the nature of mental representations of text, they frequently fail to account for complex relationships among the sources of individual differences that both form these mental representations and predict reading comprehension performance (McNamara & Magliano, 2009). The present study addresses these shortcomings by using structural equation models (SEMs) to examine the relationships among sources of individual differences in reading comprehension for proficient adult readers. Specifically, the principal SEM tested in this study, which is called the cognitive components-resource model of reading comprehension (CC-R model), proposes a set of relationships among (a) lower-level processes that decode words, (b) higher-level processes that extract explicit and implicit information from text and integrate text-based information with prior knowledge, and (c) limited cognitive resources that are shared by many processes (i.e., working memory).

Background

Most studies of reading comprehension have investigated the contribution of a single source of individual differences to reading comprehension performance in isolation (Hannon & Daneman, 2001a). However, the actual source under investigation...
has often varied from study to study, and there is little agreement among theories as to which source contributes the most to reading comprehension (Hannon & Daneman, 2001a). According to the simple view of reading (e.g., Gough, Hoover, & Peterson, 1996; Hoover & Gough, 1990; Tunmer, 2008) and two popular developmental theories of reading comprehension acquisition, the verbal efficiency (e.g., Perfetti, 1985, 1997) and automaticity theories (e.g., LaBerge & Samuels, 1974), word fluency (i.e., speed at accessing the meanings of words) is an important contributor to reading comprehension performance. In support of this assumption are a number of studies, including those assessing normal adult readers that show accuracies/efficiencies of lower-level word processes vary as a function of reading comprehension skill. For instance, studies that have classified adult readers as skilled or less skilled by using a mean split of performance on a measure of reading comprehension have shown that skilled adult readers are more efficient than less skilled adult readers at recognizing printed words (e.g., Bell & Perfetti, 1994). Skilled adult readers are also faster and more accurate at deriving phonology from print (e.g., Cunningham, Stanovich, & Wilson, 1990) and faster at accessing word meanings (e.g., Chabot, Zehr, Prinzo, & Petros, 1984). Indeed, for adult readers, the correlations between lower-level word processes and reading comprehension can be as high as 0.55 (Cunningham et al., 1990; see also Holmes, 2009).

According to other theories, higher-level processes that extract explicit and implicit information from text and integrate this text-based information with prior knowledge are the major source of individual differences in reading comprehension for adult readers (Graesser, Singer, & Trabasso, 1994; Hannon & Daneman, 2001a, 2009; Kintsch, 1998). In fact, studies assessing proficient adult readers have shown that higher-level processes account for as much as 34–60% of the variance in performance on standardized measures of reading comprehension (e.g., Hannon & Daneman, 2001a). Compared with less skilled adult readers, skilled adult readers are better at using their prior knowledge to connect or bridge ideas in a text (Singer & Ritchot, 1996), are better at inferring themes spontaneously as they read (Hannon & Daneman, 1998; Long, Oppy, & Seely, 1994), and are more likely to compute the antecedent referent of a pronoun (Long & De Ley, 2000). Adult skilled readers are also better than less skilled adult readers at remembering new explicit information presented in a text (Masson & Miller, 1983), are more likely to make correct text-based inferences (Long, Oppy, & Seely, 1997), and are better than less skilled adult readers at accessing semantic information from long-term memory (Hannon & Daneman, 2001a). For example, skilled adult readers are better at accessing facts, such as an elephant is larger than a dog, or an ostrich is larger than a robin (e.g., Hannon & Daneman, 2001a, 2001b, 2006, 2009).

Still other theories promote working memory, a limited resource shared by many cognitive processes, as a major source of individual differences in adult reading comprehension. According to the working memory theories proposed by Daneman and Carpenter (1980) and Just and Carpenter (1992), less-skilled readers are at a disadvantage with all of the processes that require the successive integration of information in a text because they have less working memory capacity to
keep the earlier information active (see also Hannon & Daneman, 2001a). Indeed, a meta-analysis of the working memory literature shows that working memory measures that include both processing (e.g., sentence verification) and storage components (e.g., remembering last words of sentences), such as the reading span and operation span, account for 17% of the variance in performance on general or global measures of reading comprehension and 27% of the variance in performance on specific measures of reading comprehension (Daneman & Merikle, 1996).

In contrast to the single-source approach for identifying important sources of individual differences in reading comprehension is the multiple-source approach. Britton, Stimson, Stennett, and Gülgöz (1998), for instance, examined the relative contributions of inferential processing, domain knowledge, metacognition, and working memory to learning from text in adult readers. Similar multivariate studies have been conducted with prereaders (Hannon & Frias, 2012), children (Cain, Oakhill, & Bryant, 2004), adolescents (Cromley & Azevedo, 2007), and seniors (Hannon & Daneman, 2009). Yet, there still has been little to no research about the relationships among lower-level word processes, higher-level processes, and working memory because few studies have examined these three sources simultaneously. Furthermore, there has been little research examining their relative contributions to reading comprehension performance in proficient adult readers. For instance, although Baddeley, Logie, Nimmo-Smith, and Brereton (1985) showed that lower-level word processes and working memory each make separate and significant contributions to reading comprehension performance in adult readers, Daneman and Hannon (2007) showed that working memory contributed little to reading comprehension performance for adults once the variances for higher-level processes were partialled out. Findings such as these suggest that when the contributions of lower-level processes, higher-level processes, and working memory are compared simultaneously, only lower- and higher-level processes make significant contributions. This latter possibility remains untested.

Furthermore, although many theories of reading comprehension acknowledge that lower-level word processes provide some of the information used by higher-level processes during comprehension, there are few theoretical assumptions pertaining to how these two sources of individual differences might interact. Indeed, based on a comparison of seven theories of reading comprehension (i.e., the construction–integration, structure-building, resonance, event-indexing, causal network, constructionist theory, and landscape models), McNamara and Magliano (2009) concluded that although most models of reading comprehension provide details and assumptions about the nature of mental representations of the text, they fail to account for complex relationships among lower-level word processes, higher-level processes, and characteristics of the reader. This finding is surprising given that measures of lower-level word processes, higher-level processes, and working memory routinely account for large amounts of variance in performance on measures of adult reading comprehension. Thus, the present study informs a number of important theories of reading comprehension ability by examining relationships among these three sources of individual differences.
The CC-R Model

The CC-R model is a SEM that was developed to examine the relationships among three sources of individual differences that contribute to reading comprehension performance: lower-level word processes, higher-level processes, and working memory. Other popular models of comprehension, such as the construction–integration model (e.g., Kintsch, 1988, 1994, 1998), also include some or all of these sources as predictors, although as mentioned earlier, these models fail to provide assumptions about how these processes might interact. Furthermore, the simple view of reading (e.g., Gough et al., 1996; Tunmer, 2008) includes word decoding and comprehension (as measured by tests of listening comprehension), the learning from text model (e.g., Britton et al., 1998) includes inferential processes and working memory, and the direct and mediation model of reading comprehension for adolescents (e.g., Cromley & Azevedo, 2007) includes inferential processes and lower-level word processes. This section covers a description of the CC-R model, explanations of its assumptions in the context of some reading comprehension theories, and a review of the literature supporting the relationships among its components. Although most of the supporting literature involves normal adult readers, developmental literature is also described in instances where the literature is limited.

Description of the CC-R Model

In the CC-R model, adult reading comprehension performance is presumed to result from a set of relationships among lower-level word processes, higher-level processes (i.e., text memory, text inferencing, knowledge access, knowledge integration), and resources (e.g., working memory, speed). This model hypothesizes that knowledge integration directly influences reading comprehension. That is, being able to integrate prior knowledge with new text-based information facilitates text comprehension. As a person reads, inchoate ideas are embellished with prior knowledge, text coherence is maintained by bridging two text-based ideas with prior knowledge, story outcomes are predicted because of schemas, global themes are inferred, and comparisons are made between new information in the text and prior knowledge in long-term memory.

Additionally, the CC-R model hypothesizes that knowledge integration is directly influenced by processes that access prior knowledge from long-term memory (i.e., knowledge access) and encode new text-based information (i.e., text memory, text inferencing). For example, to make the knowledge-based inference that the cigarette started the fire, a reader must use (a) text memory processes to encode the text-based information (i.e., A cigarette was carelessly discarded. The fire destroyed many acres of forest.) and (b) knowledge access processes to access his or her long-term semantic memory for the fact that cigarettes start fires to (c) integrate the text-based information with the information from semantic memory. If either his or her text memory or the knowledge access processes fail, knowledge integration will also fail. However, knowledge access and text-based processes (i.e., text memory, text inferencing) only indirectly influence reading.
comprehension because their influences are mediated by knowledge integration (i.e., knowledge access, text-based processes → knowledge integration → reading comprehension).

For the purposes of the present study, text-based processes are operationalized as those processes that are used to learn new ideas explicitly or implicitly presented in a text; text-based processes do not include those processes that decode/identify individual words. For example, in the following paragraph:

The plane flew over the house. The house was in Saskatoon. The plane landed in a field.

text memory process(es) are used to learn the explicit facts (e.g., The plane flew over the house; the plane landed in a field.), whereas text inferencing process(es) are used to learn the implicit facts (e.g., The plane flew over Saskatoon.). In contrast, knowledge access processes that are used to recall semantic information from long-term memory (e.g., Planes can fly; planes can land in fields.) are not used to learn explicit and implicit text-based information.

Finally, working memory, a resource shared by many cognitive processes (Daneman & Hannon, 2007), is also hypothesized to directly influence knowledge integration. However, because the CC-R model defines working memory as a limited cognitive resource, its influence on reading comprehension is largely indirect, mediated by those processes that draw on working memory, such as knowledge integration, and directly influence reading comprehension performance (i.e., working memory → knowledge integration → reading comprehension).

Further, the CC-R model hypothesizes that speed at reading, deciding, and/or processing sentences directly influences reading comprehension. For the purposes of this article, this speed measure is called sentence processing speed or just speed. Comprehending text is information laden, and consequently, speed at sentence processing influences comprehension inasmuch as slow and inefficient sentence processing can delay overall information processing, which in turn might result in information loss. In addition, the CC-R model hypothesizes that lower-level word processes, specifically speed at processing words (i.e., word fluency), directly influence reading comprehension. Like sentence processing speed, word fluency influences reading comprehension inasmuch as quick, efficient, and more accurate word processing decreases passage reading time, which in turn increases question answering time (see Bell & Perfetti, 1994, for more on the importance of word fluency in adult reading). Word fluency also has an indirect influence on reading comprehension because word fluency directly influences sentence processing speed, and sentence processing speed directly influences reading comprehension (i.e., word fluency → speed → reading comprehension). This latter direct influence on sentence processing speed is expected because speed at accessing the meanings of words (i.e., word fluency) is a component of sentence processing speed.
Assumptions of the CC-R Model

Assumption 1: Word-Level and Higher-Level Cognitive Processes Are Separate Constructs in Adult Readers. The quality/efficiency of an adult reader’s lower-level word processes that are used for decoding and recognizing words are separate from his or her higher-level cognitive processes that are used for learning and integrating text with prior knowledge (and vice versa). Although little to no adult research has examined the relationship between lower- and higher-level processes, there are a number of developmental studies that have shown nonsignificant relationships between measures of these two sources of individual differences (e.g., Aaron, Frantz, & Manges, 1990; August, Francis, Hsu, & Snow, 2006; Cain et al., 2004; Crain, 1989; Frith & Snowling, 1983; Oakhill, Cain, & Bryant, 2003). For instance, August et al. (2006) showed that measures assessing lower-level letter-word identification/pronunciation processes and the higher-level processes of text memory, text inferencing, and knowledge integration were, at best, weakly related in 5–8-year-olds. Similarly, Oakhill et al. (2003) showed that measures assessing word reading and knowledge integration were dissociable in 7–9-year-olds.

Assumption 2: There Are Multiple Higher-Level Cognitive Processes. Unlike the simple view of reading (Gough et al., 1996), which assumes that comprehension is a unitary component that is assessed with measures of listening comprehension, the CC-R model assumes that comprehension is a collection of higher-level processes (i.e., text memory, text inferencing, knowledge access, knowledge integration) that form a specific pattern of relationships. That is, text-based processes that are used to encode/learn new facts presented in a text (i.e., text memory, text inferencing) are highly related to one another but are weakly related to processes that access prior knowledge. Conversely, knowledge integration processes, which rely on new text-based information and existing information from prior knowledge, are related to both the text-based and knowledge access processes. Because the CC-R model identifies the types of higher-level processes that are used when comprehending text, it can be said that the CC-R model informs the simple view of reading by revealing that the comprehension component consists of multiple identifiable higher-level processes.

Assumption 3: Readers Form a Single Mental Representation of a Text That Varies in Quality From Reader to Reader. As readers are reading text, they form a single mental representation. However, because the qualities of lower- and higher-level processes and the amount of working memory resources used to construct this representation vary from reader to reader, the quality of the mental representation also varies from reader to reader. For instance, a mental representation of a text may be fragmented because a reader failed to use text inferencing or bridging inference processes to connect ideas in the text.
Assumption 4: For Adults, Lower-Level Word Processes Neither Consume Working Memory Resources nor Influence Higher-Level Processes. In the CC-R model, lower-level word processes neither consume limited cognitive resources nor indirectly influence the performance of higher-level processes. That is, because the lower-level word processes of proficient adult readers are substantially quicker and more efficient than those of beginning or struggling readers, the word processes of even the slowest adult reader are fast enough that they do not consume working memory resources that are necessary for executing higher-level processes. In support of this assumption are correlational studies which have shown, at best, minimal relationships between measures assessing lower-level word processes and working memory in proficient adult readers (e.g., Baddeley et al., 1985; Dixon, LeFevre, & Twilley, 1988).³

Assumption 5: Working Memory Exerts Little to No Direct Influence on Reading Comprehension Performance. According to the CC-R model, working memory has little to no direct influence on reading comprehension for proficient adult readers. Rather, its influence is largely indirect—mediated via higher-level processes (i.e., working memory → higher-level processes → reading comprehension). In support of this assumption are Britton et al.’s (1998) SEM findings. In their study, a SEM that included a path from working memory to higher-level processes but excluded a direct path from working memory to reading comprehension explained the data better than did a SEM that included both of these paths. Additionally, Daneman and Hannon (2007) showed that working memory accounted for little of the variance in adult reading comprehension performance once the variance for higher-level processes was partialed out (see Hannon & Daneman, 2009, for similar findings with older adults).

Literature Supporting the Paths in the CC-R Model

Figure 1 depicts the path diagram for the CC-R model. Each unidirectional arrow represents a direct path and its direction of influence; for example, the path from working memory to knowledge integration in Figure 1 signifies working memory’s direct influence on knowledge integration. The absence of a path indicates no direct influence. The path numbers are for organizing the supporting literature, which includes brief theoretical explanations where appropriate and, where possible, a variety of different studies (e.g., correlational, regression, SEM).

Path 1: The Influence of Knowledge Integration on Reading Comprehension. Most reading comprehension models (e.g., construction–integration, learning from text, constructionist) include knowledge-based inferences that are used to integrate information from prior knowledge with information from the text. Readers can generate a wide variety of knowledge-based inferences, such as causal antecedent, thematic, and predictive (Graesser et al., 1994), but only a subset is routinely generated during reading comprehension (Graesser et al., 1994; Singer, Graesser, & Trabasso, 1994). Further, frequency of inference
generation is related to reading comprehension skill. Long et al. (1994), for instance, showed that skilled adult readers (as determined by performance on a comprehension measure) are more likely than less skilled adult readers to generate inferences about themes of short passages. Murray and Burke (2003) showed that skilled adult readers are more likely than moderately or less skilled adult readers to generate predictive inferences automatically as they read. Still other researchers have shown that skilled adult readers are more likely to use prior knowledge to bridge ideas in a text to make otherwise incoherent text coherent (Halldorson & Singer, 2002; Keenan & Kintsch, 1974; Singer, Halldorson, Lear, & Andrusiak, 1992). For more examples, see Schmalhofer, McDaniel, and Keeffe (2002) and Zhang and Hoosain (2001); for a minimalist view on inferences, see McKoon and Ratcliff (1992).

**Paths 2 and 3: The Influences of Text-Based Processing and Knowledge Access on Knowledge Integration.** To date, few studies have shown that both text-based (i.e., text memory, text inferencing) and knowledge access processes influence knowledge integration. Potts and Peterson (1985), for instance, showed that the ability to integrate prior knowledge with new text-based information (i.e., knowledge integration) correlated with both the ability to learn explicit and implicit text-based information (i.e., text memory, text inferencing) and the ability to access information from prior knowledge (i.e., knowledge access). Hannon and Daneman (2006) replicated Potts and Peterson's pattern of correlations using SEMs, and August et al. (2006) replicated their pattern using a variant of Hannon and Daneman's measure and beginning readers. In addition, using think-aloud
protocols, Magliano, Trabasso, and Graesser (1999) showed that their “readers relied more on world knowledge as a basis for explaining [the text] when the prior context did not provide the sufficient causal conditions for [comprehending] the current sentence” (p. 626). In other words, their readers used both information from the text (i.e., the current sentence) and knowledge from long-term memory (i.e., world knowledge) to generate knowledge-based inferences. This research also suggested that text-based processes (e.g., text inferencing) are different from knowledge-based processes (e.g., knowledge-based inferencing).

Path 4: The Influence of Working Memory on Knowledge Integration. According to working memory theories of reading comprehension ability (Daneman & Carpenter, 1980; Just & Carpenter, 1992), working memory capacity is a limited resource that readers draw on to execute higher-level processes such as knowledge integration. In support of this assumption are studies that have shown relationships between working memory and knowledge integration (e.g., Calvo, 2001, 2005; Daneman & Hannon, 2007; Estevez & Calvo, 2000; Singer, Andrusiak, Reisford, & Black, 1992). Singer, Andrusiak, et al. (1992), for example, showed that readers with larger working memories are better at executing bridging inferences than readers with smaller working memories are. Using SEMs, Britton et al. (1998) showed that knowledge integration draws on working memory. Similar results have been found in studies using eye-tracking technology (e.g., Calvo, 2001), older adults (e.g., Hannon & Daneman, 2009), children (e.g., Cain et al., 2004), and prereaders (e.g., Hannon & Frias, 2012).

Path 5: The Influence of Speed on Comprehension. According to Hannon and Daneman (2001a), an adult reader’s speed at reading, deciding, and responding to test statements predicts reading comprehension performance. Indeed, these authors showed that their speed measure correlated quite well with reading comprehension performance inasmuch as faster adult readers, who had lower reaction times, tended to have higher comprehension scores, ranging from $r = -0.46$ to $-0.28$. This speed–comprehension correlation persists even when the passages are taken from the Verbal Scholastic Aptitude Test (e.g., Hannon & Daneman, 2006) or the population of interest is older adults (e.g., Hannon & Daneman, 2009). Similarly, Bell and Perfetti (1994), Baddeley et al. (1985), and Dixon et al. (1988) showed that reading time for passages accounted for small but significant amounts of variance in reading comprehension performance in adult readers (see Klauda & Guthrie, 2008, for more about the relationships among syntactic sentence fluency, semantic sentence fluency, and reading comprehension in adolescents; see also Lomax & McGee, 1987, who showed that the reading speed–reading comprehension relationship is indirect for pre- and beginning readers because it is mediated via lower-level word processes).

Path 6: The Influence of Word Processing on Reading Comprehension. The relationships between lower-level word processes and reading comprehension are well documented even with proficient adult readers (e.g., Baddeley et al.,
1985; Bell & Perfetti, 1994; Cunningham et al., 1990; Dixon et al., 1988; Holmes, 2009; Landi, 2010). Bell and Perfetti, for instance, showed that speed at reading lists of high-frequency words, low-frequency words, and pseudowords accounted for as much as 21% of the variance in adult reading comprehension. Cunningham et al. observed that speed at pronouncing pseudowords (e.g., danter, comt) accounted for 30.2% of the variance in adult reading comprehension. Baddeley et al. showed that speed at classifying words, nonwords, and homophones accounted for as much as 25% of variance in adult reading comprehension. Similar findings have also been found in the developmental literature (e.g., August et al., 2006; Jenkins et al., 2003; Kendeou, van den Broek, White, & Lynch, 2009; Klauda & Guthrie, 2008). However, findings from a meta-analysis by Gough et al. (1996) suggest that the influences that lower-level word processes exert on reading comprehension decrease with increases in age.

Path 7: The Influence of Word Processing on Speed. There is limited information about the relationship between word processing and speed of sentence processing because studies have only recently begun to examine their simultaneous contributions to reading comprehension. Further, most of these studies assessed children rather than adults. Nevertheless, the findings suggest a positive relationship between these two constructs. Jenkins et al. (2003), for example, observed a positive correlation between measures of word processing speed (i.e., seconds per word read correctly from a list) and sentence fluency (i.e., seconds per word read correctly from a passage) in a group of fourth graders (cf. Lomax & McGee, 1987, who showed that reading speed has a reciprocal relationship with word processing in pre- and beginning readers.). Similarly, Klauda and Guthrie (2008) observed strong correlations between measures of word processing (i.e., how quickly each word in a list is identified) and syntactic processing (i.e., accuracy and speed in processing phrase/sentence units of a text) in a group of fifth graders. Finally, using a group of proficient adult readers, Jackson (2005) observed a small but significant positive correlation (average $r = 0.29$) between multiple measures of word decoding (e.g., letter-word identification, pseudoword reading) and speed of sentence processing (e.g., reading rate, reading sentences, judging truthfulness; see also Dixon et al., 1988, who observed a small but significant correlation of $r = 0.21$ between similar measures in proficient adult readers).

Summary and Present Study
This study uses SEMs to assess the relationships among three sources of individual differences in adult reading comprehension. More specifically, the CC-R model examines the relationships among (a) lower-level processes that decode words, (b) higher-level processes that extract explicit and implicit information from text and integrate text-based information with prior knowledge, and (c) limited cognitive resources that are shared by many processes (i.e., working memory). To accomplish this goal, proficient adult readers (i.e., university students)
completed a battery of tasks that assessed reading comprehension and theory-relevant sources of individual differences. Performance on these tasks served as the observed variables for SEMs that assessed the CC-R model and most of its assumptions.

All the measures in the present study are frequently used and/or have good psychometric properties. For example, the two measures of general or global reading comprehension were versions of the frequently used Nelson-Denny Reading Test. Each version was administered as a timed test. Timed tests are often used by educators to evaluate student performance (e.g., SAT-V, GRE) and by researchers to assess reading comprehension skill (e.g., Bell & Perfetti, 1994; Long et al., 1994). Indeed, studies have shown that standard administrations of the Nelson-Denny have very good correlations with other measures of global reading comprehension, such as the passages taken from the SAT-V (e.g., Daneman & Hannon, 2001; Hannon & Daneman, 2006).

The measures of lower-level word processes were Bell and Perfetti’s (1994) orthographic and phonemic lexical decision tasks. In the orthographic task, readers select which of two letter strings is a word (e.g., *date* *dait*), whereas in the phonemic task, they select which of two letter strings sounds like a word (e.g., *heer* *heem*). Bell and Perfetti described the latter task as phonemic because decisions are based on pronunciation of pseudowords, whereas they described the first task as orthographic because decisions are based on spelling. Because the orthographic and phonemic tasks are free of contextual words that aid word identification processes, both tasks are considered good and relatively pure measures of word decoding (e.g., Perfetti, Marron, & Foltz, 1996).

Higher-level processes were assessed using Hannon and Daneman’s (2001a) component processes task (CPT). The CPT estimates a reader’s ability to recall text, make text-based inferences, and access and integrate prior knowledge with text-based information. The CPT accounts for 34–60% of the variance in performance on measures of reading comprehension and is better at predicting reading comprehension than measures of working memory or vocabulary. Each component has a high degree of construct validity and reliability; Cronbach’s αs are typically 0.86–0.88 (Hannon & Daneman, 2001a). The internal structure of the CPT has also been validated using SEMs, factor analysis, and correlations (e.g., Hannon & Daneman, 2001a, 2006, 2009). Finally, the reading and operation spans (Daneman & Carpenter, 1980; Turner & Engle, 1989) assessed working memory. Both tasks are considered to be good measures of working memory that consistently account for variance in reading comprehension (Daneman & Merikle, 1996).

**Method**

**Participants**
The participants were 150 University of Texas at San Antonio students who were 18–25 years of age and received $35 for their participation. All students were
prescreened to ensure that they were free of any known learning disability and that they were monolingual, native English speakers who spoke few words in another language. Thirty-two participants were male, 116 were female, and there was no information about the remaining two participants.

**Measures of Reading Comprehension Ability**

Students completed two of the four forms (i.e., E, F, G, H) of a standardized measure of general or global reading comprehension called the Nelson-Denny. Each form of the Nelson-Denny consists of seven or eight short passages and 36–38 multiple-choice questions. Each passage is approximately 260 words in length and assesses comprehension of a wide range of topics. For example, biographical topics include artists and philosophers (e.g., Browning, Caravaggio, Shelly, Homer, Keats, Jung), inventors (e.g., Fuller, Washington Carver) and conquerors (e.g., Napoleon). Explanation-based topics include science (e.g., atomic energy, mold, bacteria, hydrochloric acid, insect communication, compounds), business (e.g., marketing, governments, economics, schools), and professions (e.g., soil conservationists, hydrographers). Scores on the Nelson-Denny correlate well with scores on the SAT-V reading passages: \( r = 0.55 \) to 0.74 (e.g., Daneman & Hannon, 2001; Hannon & Daneman, 2006).

Forms E, F, G, and H were divided into two sets; set 1 contained forms E and H, and set 2 contained forms F and G. These pairings occurred because pretesting revealed that form E was the most difficult and form H was the easiest. Seventy-four students completed set 1, and 76 students completed set 2. Because a student’s performance can vary from session to session, it was deemed prudent to assess reading comprehension in each session. More important, from a psychometric perspective, an aggregate of multiple measures for a single construct is always better than a single measure (e.g., Lubinski, 2004). Students assigned to set 1 completed form E in session 1 and form H in session 2, and students assigned to set 2 completed form F in session 1 and form G in session 2.

During all administrations, students could refer to the passages as they answered the questions. In session 1, they had 20 minutes to complete either form E or F, and in session 2, they had 15 minutes to complete either form G or H. The alternate-form reliabilities for forms E and F and forms G and H are 0.77 and 0.81, respectively. Forms G and H were administered as 15-minute tests because pilot testing revealed that these forms were prone to ceiling effects when they were administered as 20-minute tests. Because students completed either form E or F in session 1 and either form G or H in session 2, the scores of form F were transformed to fit the scale for form E, and the scores for form G were transformed to fit the scale for form H. The transformation procedure involved converting the raw scores for forms F and G into z-scores and then converting these z-scores into raw scores for the appropriate form. These transformations were necessary because subsequent analyses treated the two reading comprehension forms in session 1 as the same measure and the two reading comprehension forms in session 2 as the same measure. However, because neither of the two
forms within the same session had the same mean and distribution, one form needed to be transformed to the distribution of the other form.

Finally, to verify that the aggregate of the reading comprehension forms in set 1 (i.e., forms E and H) were psychometrically equivalent to the aggregate of the reading comprehension forms in set 2 (i.e., forms F and G), I completed an invariant factor analysis, which compared the measurement models for each set of reading comprehension measures. I also statistically compared the zero-order correlations for the data from set 1 with the zero-order correlations for the data from set 2. Because the invariant factor analysis tests the measurement model, it includes all the relevant measures for each construct (see the measurement model for the CC-R model in Figure 2). The idea behind this analysis is that if it indicates that the two measurement models are equivalent, then the psychometric measurement of the two sets of reading comprehension measures are also equivalent. The results of the invariant factor analysis revealed no difference between the measurement models for sets 1 and 2: \( \chi^2(6) = 10.10, p = .12 \). In other words, according to this multivariate analysis, the reading comprehension measures in sets 1 and 2 are psychometrically equivalent. Furthermore, as Appendix A shows, there were no significant differences between the zero-order correlations associated with set 1’s reading comprehension forms and the zero-order correlations associated with set 2’s reading comprehension forms. In other words, the univariate z-tests support the findings of the multivariate test, the invariant factor analysis.

Figure 2. Path Diagram of the Measurement Model for the Cognitive Components and Resource Model of Reading Comprehension

Note. HKA = high-knowledge access; HKI = high-knowledge integration; LKA = low-knowledge access; LKI = low-knowledge integration; OLD = orthographic lexical decision; OS = operation span; PLD = phonemic lexical decision; R1 = reading comprehension measure from session 1; R2 = reading comprehension measure from session 2; RS = reading span; S = speed; TI = text inferencing; TM = text memory.
Measures of Lower-Level Word Processing

The phonemic and orthographic lexical decision tasks were variants of tasks used by Bell and Perfetti (1994) and Olson, Kliegl, and Davidson (1983). In the phonemic task, students decide which of two pseudowords can be pronounced as a real word (e.g., bair boir), whereas in the orthographic task, they decide which of two letter strings is a real word (e.g., bear bair). In each task, students viewed two letter strings positioned in the middle of a computer screen (e.g., frute frait) and then pressed a key marked L (left) or R (right) to represent their decision. Students completed four practice trials and then two blocks of 48 trials each. Average reaction times for correct responses were the dependent measures. The total time needed to complete the phonemic task was about 10–15 minutes, whereas for the orthographic task, it was about 8–10 minutes. Appendix B includes additional examples of stimuli.

Measures of High-Level Component Processes: Text Memory, Text Inferencing, Low- and High-Knowledge Access, Low- and High-Knowledge Integration, and Speed

Text memory, text inferencing, knowledge access, knowledge integration, and speed were assessed using a variant of the CPT (Hannon & Daneman, 2001a). The CPT consists of seven short paragraphs that describe relations among two real and three artificial terms. For example,

A WEMP resembles a WHALE but is larger and weighs more.
A whiskered TILN resembles a PIRANHA but is smaller and weighs more.
A LORK resembles a TILN but is smaller, weighs more and is kept as a pet.

Linear orderings (i.e., size: wemp > whale > piranha > tiln > lork) can be constructed by combining the relations described in a paragraph with world knowledge accessed from prior knowledge (i.e., A whale is larger than a piranha.). For more about the paragraphs and their presentation, see Hannon and Daneman (2001a, 2001b, 2006, 2009).

Test statements followed each paragraph, half of which were true and half false. In total, there were 240 accompanying statements. Explicit paragraph information was assessed by 84 text memory statements (e.g., “A WEMP is larger than a WHALE.”), whereas implicit paragraph information was assessed by 36 text inferencing statements (e.g., “A PIRANHA is larger than a LORK.”); neither of these statement types required prior knowledge. In contrast, the knowledge access statements measured access to prior knowledge, and no text-based information was required. There were 36 low-knowledge access statements (e.g., “A WHALE is larger than a GOLDFISH.”) and 24 high-knowledge access statements (e.g., “SHARKS are typically vicious, whereas WHALES are not.”). Low-knowledge access statements included a feature (e.g., larger than) and a real term from the paragraph (e.g., WHALE), whereas high-knowledge access statements included just a real term from the paragraph (e.g., WHALES). By including a feature and a term
not presented in the paragraph, the high-knowledge access statements required more sophisticated access to and reasoning about the relations between the real terms than did the low-knowledge access statements.

The two types of knowledge-integration measures required accessing prior knowledge and integrating it with text-based information. There were 24 low-knowledge integration statements (e.g., “A WHALE is larger than a TILN.”) and 36 high-knowledge integration statements (e.g., “Like SHARKS, WEMPS do not typically fit in a fish tank.”). These two types of statements varied in complexity; low-knowledge integration statements required integrating a prior knowledge fact (e.g., whales are larger than piranha) with a text fact (e.g., “A TILN is smaller than a PIRANHA.”), whereas high-knowledge integration statements required integrating a prior knowledge fact (e.g., a shark does not fit in a fish tank) with a fact that was implied in the text (e.g., a WEMP resembles a WHALE, and because whales do not fit in a fish tank, a WEMP cannot fit in a fish tank; see Appendix C for another example). Accuracy (i.e., number correct) was the primary dependent measure for each statement type.

Finally, speed was assessed using Hannon and Daneman’s (2001a) procedure. That is, a speed measure for each higher-level process (e.g., text memory, low-knowledge access) was calculated by averaging the reaction time for statements answered correctly (see Jackson, 2005, who also used sentence judgments to assess speed). Next, the correlations among the speed measures were inspected to verify that they were all indeed highly correlated with one another. Finally, the correlations between the speed and accuracy measures were inspected to verify that each speed measure was, at best, weakly correlated with its respective accuracy measure. For example, the correlation between the speed and accuracy measures for text memory was inspected to verify that it was weakly correlated. The results revealed that all the speed measures were highly correlated with each other (r = 0.64 to 0.79) but were, at best, weakly correlated with their respective accuracy measures (r = −0.18 to 0.01). These two patterns of correlations suggest that the speed measures are likely tapping a common factor and that this factor is different from those constructs assessed with the accuracy measures. Because all the statements represent a common factor, speed was calculated by averaging the reaction times for correct responses on all types of statements.

The instructions directed students to use their world knowledge while performing the task. They pressed the + key for the first sentence of a paragraph and then, after reading this sentence, pressed the + key for the next sentence. At this point, the first sentence disappeared, and the second sentence appeared. After reading all three sentences in this manner, test statements appeared randomly, one at a time, in the middle of the computer screen. If a student failed to respond to a test statement within a 12-second window, that test statement disappeared, and the next one appeared. All response failures were classified as errors. The total administration time was approximately 20–30 minutes.
**Measures of Working Memory**

Students completed two measures of working memory, reading span (Daneman & Carpenter, 1980) and operation span (Turner & Engle, 1989). Because the reading and operation span tasks are described in full elsewhere (e.g., Daneman & Hannon, 2001, 2007; Turner & Engle, 1989), they are only briefly described here. In the reading span task, students read aloud a set of unrelated sentences, made a sensibility judgment about each sentence, and then at the end of a set, recalled the last word of each sentence. For example, in a two-sentence set, students may have read “An eerie breeze chilled the warm, humid air. The umbrella grabbed its bat and stepped up to the plate.” Students should have responded yes after reading aloud the first sentence and no after reading aloud the second sentence. At the end of the set, they would recall air and plate.

In the operation span task, students read aloud a set of math equations followed by words, made judgments about the truthfulness of each math equation, and then at the end of a set, recalled the words accompanying each equation. For example, students may have read “(1 × 2) – 1 = 5 judge; (8/4) + 6 = 8 husband.” They should have responded no after reading the first equation and word, responded yes after reading the second equation and word, and then at the end of the set, recalled judge and husband. Reading and operation span were the total number of words out of 100 that a student could recall. The total administration time for the reading span task was about 25 minutes, whereas the total administration time for the operation span task was about 15–20 minutes.

**Design and Procedure**

In session 1, small groups of students (i.e., one to three) were administered the following tasks in the following order: the CPT (Hannon & Daneman, 2001a), a form of the Nelson-Denny, and the phonemic and orthographic lexical decision tasks (Bell & Perfetti, 1994). In session 2, each student was administered the following tasks in the following order: Daneman and Carpenter’s (1980) reading span task, another form of the Nelson-Denny, and Turner and Engle’s (1989) operation span task. The tasks in session 2 were administered individually because the two span measures required a student to speak aloud.

**Data Analysis–SEM Fitting**

LISREL 8.52 (Jöreskog & Sörbom, 2002) and maximum likelihood estimation were used to estimate the fits of the SEMs to the raw data. Fits were assessed for both the measurement and structural models.

**Measurement Model.** Each latent variable included at least two observed variables except speed, which included a single observed variable (see Britton et al., 1998, for a similar situation). As per the recommendations of Schumacker and Lomax (1996) and Jöreskog and Sörbom (1993), the reliability of the sole observed variable for the latent variable speed was specified; specifically, for the
measurement model and all other subsequent models, it was set to 0.85. Figure 2 depicts the measurement model.

**Structural Model.** As Figure 3 shows, the CC-R model has seven direct paths: (1) knowledge integration to reading comprehension, (2) speed to reading comprehension, (3) word processing to reading comprehension, (4) text-based processing to knowledge integration, (5) knowledge access to knowledge integration, (6) working memory to knowledge integration, and (7) word processing to speed. For all models, paths leading from one latent variable to another exert direct influence when their coefficients are significantly different from 0. From word processing to reading comprehension and the path leading from speed to reading comprehension would be negative because faster readers, who have lower reaction times, would tend to have higher comprehension scores. It was also expected that these path coefficients would be negative in the alternative models that were used to assess assumptions 4 and 5 of the CC-R model.

**Comparisons With Other Models.** As recommended by Jöreskog and Sörbom (2002), the CC-R model was compared with baseline and alternative models. Comparisons to baseline models are important because they assess the CC-R model’s fit of the data relative to the best and poorest fitting models. Comparisons to alternative models are important because they assess the veracity of the assumptions of the CC-R model. Assumptions 1, 2, 4, and 5 of the CC-R model were tested; assumption 3 was not testable using the existing experimental design.

**Figure 3. Structural Equation Model of the Cognitive Components and Resource Model of Reading Comprehension With Significant Path Coefficients**
Two types of comparisons were made between the CC-R and baseline/alternative models. Comparison 1 assessed the fit indexes that are described later. Model(s) with fit indexes outside acceptable limits were deemed to be less successful. Comparison 2 statistically compared the CC-R model to the baseline/alternative models using a $\chi^2$-difference test. In a $\chi^2$-difference test, the $\chi^2$ value for the baseline/alternative model is subtracted from the $\chi^2$ value for the CC-R model. The remaining difference is then assessed using a $\chi^2$ table and the net number of degrees of freedom (i.e., df for CC-R model – df for baseline/alternative model). If the $\chi^2$ difference is significant, then one model is significantly better at explaining the data than the other. It is important to note that of these two comparisons, comparison 2 is the most important.

The CC-R model was first compared with the upper and lower boundary baseline models, which were models that represented the best (i.e., upper boundary) and poorest (i.e., lower boundary) fits for the existing data. At the upper boundary was the measurement model. This model provided the best fit to the data because no explicit relations were defined among the latent variables. At the lower boundary was the lower bound null model. This model was similar to the measurement model except that its latent variables were constrained to be uncorrelated. In other words, this model assumed no relations among the latent variables and, therefore, represented the poorest fit to the data. Ideally, the theoretical model of interest (i.e., the CC-R model) should be significantly better at explaining the data than the lower bound model.

Besides the baseline models, alternative models were included to test some of the assumptions of the CC-R model. For assumption 1, which states that word- and higher-level processes are separate constructs, comparisons were made between two SEMs: (1) an independent SEM that included separate latent variables for word- and higher-level processes and (2) a nonindependent SEM that did not include separate latent variables for word- and higher-level processes. Both of these SEMs were similar to the measurement model except that the independent SEM had four latent variables (i.e., word processing, text-based processing, knowledge access, knowledge integration), whereas the nonindependent SEM had three latent variables (i.e., text-based processing, knowledge access, knowledge integration). In both SEMs, the latent variables were measured with the same observed variables used in the measurement model except that in the nonindependent SEM, each latent variable also included the two observed variables that assessed word processing (i.e., the orthographic and phonemic lexical decision tasks). If lower-level word processes and higher-level processes are separate constructs, then the independent SEM would be significantly better at explaining the data than the nonindependent SEM would. Conversely, if lower-level word processes and higher-level processes are not separate constructs (i.e., a violation of assumption 1), then the nonindependent SEM would be significantly better at explaining the data.

For assumption 2, which states that there are multiple higher-level processes, comparisons were made between (a) a multifactor SEM that included separate
latent variables for each of the higher-level processes and (b) a single-factor SEM that included a single latent variable that represented all of the higher-level processes. The multifactor SEM included three latent variables: text-based processing, knowledge access, and knowledge integration; the latent variables were measured with the same observed variables that were used in the measurement model. The single-factor SEM included a single latent variable that was measured with the six observed variables that measured the higher-level processes (i.e., text memory, text inferencing, low-knowledge integration, high-knowledge integration, low-knowledge access, high-knowledge access). If there are multiple higher-level processes, then the multifactor SEM should be significantly better at explaining the data than the single-factor SEM is. Conversely, if there is only a single higher-level process (i.e., a violation of assumption 2), then the single-factor SEM should be significantly better at explaining the data.

For part 1 of assumption 4, which states that lower-level word processes do not directly consume working memory resources, comparisons were made between two nearly identical SEMs: (1) the CC-R model, which does not include a path leading from word processes to working memory; and (2) the CC-R1-WM model, a variant of the CC-R model that includes a path leading from word processing to working memory. As Figure 4 shows, the CC-R1-WM model is identical to the CC-R model except that the CC-R1-WM model includes a direct path leading from word processing to working memory. It was expected that the coefficient for the path leading from word processing to working memory (i.e., the new path) would be negative because faster readers, who have lower reaction times, would tend to have higher working memory scores. If word processing directly influences working memory (i.e., a violation of assumption 4), then the CC-R1-WM model should be better at explaining the data than the CC-R model is. Conversely, if word processing does not directly influence working memory, then the CC-R model should be better at explaining the data than the CC-R1-WM model is.

For part 2 of assumption 4, which states that lower-level word processes do not directly influence higher-level processes, comparisons were made between two nearly identical SEMs: (1) the CC-R model, which does not include a path leading from lower-level word processes to higher-level processes; and (2) the CC-R1-WP model, a variant of the CC-R model that includes paths leading from word processing to the higher-level processes of text-based processing, knowledge access, and knowledge integration. As Figure 5 shows, the CC-R1-WP model is identical to the CC-R model except that the CC-R1-WP model includes direct paths leading from word processing to text-based processing, from word processing to knowledge access, and from word processing to knowledge integration. It was expected that the coefficients for the paths leading from word processing to text-based processing, knowledge access, knowledge integration (i.e., the new paths) would be negative. These negative coefficients mean that faster readers, who have lower reaction times, would tend to have higher text processing, knowledge access, and knowledge integration scores. If word processing directly influences higher-level processes (i.e., a violation of assumption 4), then the CC-R1-WP
Figure 4. Structural Equation Model of the CC-R1-WM Model With Path Coefficients

![Diagram of the CC-R1-WM Model](image)

Note. Solid lines represent significant path coefficients, whereas the broken line represents nonsignificant structure coefficients. This structural equation model is identical to the cognitive components and resource model of reading comprehension (CC-R model) except for the addition of a path leading from word processing to working memory.

Figure 5. Structural Equation Model of the CC-R1-WP Model With Path Coefficients

![Diagram of the CC-R1-WP Model](image)

Note. Solid lines represent significant path coefficients, whereas broken lines represent nonsignificant structure coefficients. This structural equation model is identical to the cognitive components and resource model of reading comprehension (CC-R model) except for the addition of paths leading from word processing to the higher-level processes of text-based processing, knowledge access, and knowledge integration.
model should be better at explaining the data than the CC-R model is. Conversely, if word processing does not directly influence higher-level processes, then the CC-R model should be better at explaining the data than the CC-R1-WP model is.

Finally, for assumption 5, which states that working memory exerts little to no direct influence on reading comprehension, comparisons were made between two nearly identical SEMs: (1) the CC-R model, which does not include a path leading from working memory to reading comprehension; and (2) the CC-R2 model, a variant of the CC-R model that includes a path leading from working memory to reading comprehension. As Figure 6 shows, the CC-R2 model is identical to the CC-R model except for the addition of a path leading from working memory to reading comprehension.

**Figure 6. Structural Equation Model of the CC-R2 Model With Path Coefficients**

Note. Solid lines represent significant path coefficients, whereas broken lines represent nonsignificant structure coefficients. This structural equation model is identical to the cognitive components and resource model of reading comprehension (CC-R model) except for the addition of a path leading from working memory to reading comprehension.

**Fit Indexes**

Following Hoyle and Panter’s (1995) recommendations, model fit was evaluated using a collection of fit indexes. The absolute fit indexes were the traditional $\chi^2$ test of exact model fit, the $\chi^2$ test of close model fit (Browne & Cudeck, 1993), the
goodness-of-fit index (GFI), the adjusted GFI (AGFI; Jöreskog & Sörbom, 1981),
the root mean square error of approximation (RMSEA; Steiger & Lind, 1980), and
the 90% confidence intervals for the RMSEA. The incremental fit statistic was the
comparative fit index (CFI; Bentler, 1989). For the $\chi^2$ test of exact fit (i.e., $p$ exact),
the hypothesis being tested assumes an exact model fit that is acceptable. Thus,
a good-fitting model is indicated by nonsignificant $\chi^2$ results, and the greater the $p$
value, the better the fit. For the $\chi^2$ test of close fit (i.e., $p$ close), the hypothesis is
for the alternative model, which states that RMSEA is $>0.05$. If the value for $p$ close
is $>0.05$, then it is concluded that the model fit is close (Kline, 2011). For the AGFI
and GFI, the guideline is that good-fitting models have values of $\geq0.90$; for the CFI,
the value was set to $\geq0.95$ (Russell, 2002). Conversely, for the RMSEA statistic, the
guideline is that values of $\leq0.05$ indicate a good-fitting model (Steiger, 1989). For
other views on the criteria for good model fit indexes, see Fan, Thompson, and
Wang (1999), Fan and Sivo (2005), Hu and Bentler (1999), and Marsh, Hau, and

**Results**

The results include four sections. Section 1 reports the results of the data screen-
ing, section 2 reports the preliminary descriptive statistics including the correla-
tional analysis, and section 3 reports the measurement model. Finally, section 4
reports the results of the CC-R SEM, comparisons of the CC-R model with the
baseline models, and the statistical tests of four of the assumptions of the CC-R
model.

**Data Screening**

SAS and PRELIS were used to screen the data for the following: (i) outliers (uni-
variate statistics: studentized residual, DFITTS, DFBETAS, Cook’s D; multivariate
statistic: Mahalanobis distance values; Tabachnick & Fidell, 2007); (ii) values
that exerted excessive leverage (leverage statistic, $h$, also known as the hat value);
(iii) linearity (bivariate scatterplots); (iv) normality (univariate: normality prob-
ability plots; multivariate: Mardia’s statistic; West, Finch, & Curran, 1995); and
(v) multicollinearity (tolerance test via regression analysis).

Preliminary regression analyses, which included all of the measures as pre-
dictors, revealed that one outlier exerted considerable leverage (i.e., studentized
residual, DFITTS, DFBETAS, and the leverage statistic, $h$, all above acceptable
limits). The outlier was removed, and all data screening was repeated on the
data for the remaining 149 students. The results revealed that all univariate and
multivariate screening statistics were within acceptable limits. Most notably, all
Mahalanobis distance scores were well below the limit (indicating no multivariate
outliers); Mardia’s statistic was 1.014, which is well below the critical 1.96 limit
(i.e., there was multivariate normality); and tolerance values were all above the
0.20 limit (indicating very little multicollinearity).
**Preliminary Descriptive Statistics**

Descriptive statistics, correlations, and Cronbach’s $\alpha$s for the measures are reported in Table 1. As the table shows, all the measures had excellent reliability, with standardized Cronbach’s $\alpha$s ranging from 0.83 to 0.97. In addition, the correlations provide some preliminary support for some of the assumptions of the CC-R model. For example, the measures of word processing and working memory were uncorrelated ($r = -0.16$ to $0.01$)—a finding that is consistent with the assumption that word processing does not consume limited working memory resources. The two measures of word processing and six measures of higher-level processes were, at best, weakly correlated ($r = -0.30$ to $-0.04$)—a finding that is consistent with the assumption that lower-level word processes and higher-level processes are separate constructs. The measure of speed was, at best, weakly correlated with the accuracy measures for the higher-level processes ($r = -0.17$ to $-0.06$)—a finding that suggests that speed is indeed a separate construct from text memory, text inferencing, knowledge access, and knowledge integration. Finally, there was a great deal of similarity between the correlations for the reading comprehension measure in session 1 and the correlations for the reading comprehension measure in session 2—a finding that suggests that these two measures are equivalent.

Of course, it is important to remember that correlations are limited in the amount of information they can convey. Although they provide some insight into what happens with two variables, they do not provide any insight into what happens when three or more variables are considered simultaneously. For this reason, the correlations should be considered as preliminary information for the SEMs.

**Measurement Model**

As shown in the last row of Table 1, all the factor loadings for the measurement model were significant (ranging from 0.62 to 0.97). Further, all of the fit indexes reported in Table 2 suggest that the measurement model fits the data well. Thus, based on these two criteria, it appears that each observed variable is suitable for measuring its respective latent variable. That is, the observed variables text memory and text inferencing are suitable for measuring the latent variable text-based processing, the observed variables low- and high-knowledge integration are suitable for measuring the latent variable knowledge integration, and so forth.

**The CC-R Model**

**Fit of the CC-R Model.** Figure 3 depicts the path diagram for the CC-R model. To reiterate, for all SEMs, the numbers on the paths are path coefficients, which can be used to gauge the size of a relationship between the latent variables. Solid lines represent relationships with coefficients significantly different from 0, whereas dashed lines represent relationships with coefficients not significantly different from 0. As Figure 3 shows, all the path coefficients for the CC-R model were significant. Further, the pattern of relationships among the latent variables for text-based processing, knowledge access, and knowledge integration confirmed the pattern observed by Hannon and Daneman (2006). That is, knowledge
Table 1. Correlations, Descriptive Statistics, Cronbach’s αs, and Factor Loadings for Measures of Lower-Level Word Processes, Higher-Level Processes, Working Memory, and Reading Comprehension (n = 149)

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<td>—</td>
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<td>0.32</td>
<td>0.33</td>
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<td>−0.36</td>
<td>0.37</td>
<td>0.37</td>
<td>0.34</td>
<td>0.43</td>
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<td>0.25</td>
<td>−0.37</td>
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<td>3. Orthographic lexical decision</td>
<td>—</td>
<td>0.53</td>
<td>−0.30</td>
<td>−0.21</td>
<td>−0.18</td>
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<td>−0.11</td>
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<td>4. Phonemic lexical decision</td>
<td>—</td>
<td>−0.11</td>
<td>−0.06</td>
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<td>−0.15</td>
<td>−0.21</td>
<td>−0.04</td>
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<td>0.01</td>
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<td>5. Text memory</td>
<td>—</td>
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<td>6. Text inferencing</td>
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<td>7. Low-knowledge integration</td>
<td>—</td>
<td>0.62</td>
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<td>8. High-knowledge integration</td>
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<td>9. Low-knowledge access</td>
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<td>10. High-knowledge access</td>
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<td>11. Speed</td>
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Mean

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<td>Skewness</td>
<td>−0.37</td>
<td>−0.10</td>
<td>1.13</td>
<td>1.09</td>
<td>−0.82</td>
<td>−0.59</td>
<td>−0.71</td>
<td>−0.31</td>
<td>−1.27</td>
<td>−1.14</td>
<td>0.13</td>
<td>0.48</td>
<td>0.01</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>−0.53</td>
<td>−0.55</td>
<td>1.42</td>
<td>1.32</td>
<td>−0.90</td>
<td>−0.44</td>
<td>−0.29</td>
<td>−0.70</td>
<td>1.75</td>
<td>1.46</td>
<td>−0.77</td>
<td>−0.25</td>
<td>−0.06</td>
</tr>
<tr>
<td>Lowest score</td>
<td>11.00</td>
<td>15.00</td>
<td>721.84</td>
<td>1,882.80</td>
<td>38.00</td>
<td>13.00</td>
<td>12.00</td>
<td>15.00</td>
<td>22.00</td>
<td>15.00</td>
<td>2,469.33</td>
<td>37.00</td>
<td>35.00</td>
</tr>
<tr>
<td>Highest score</td>
<td>34.00</td>
<td>37.00</td>
<td>1,964.00</td>
<td>7,074.72</td>
<td>83.00</td>
<td>36.00</td>
<td>24.00</td>
<td>36.00</td>
<td>36.00</td>
<td>24.00</td>
<td>5,477.81</td>
<td>94.00</td>
<td>90.00</td>
</tr>
<tr>
<td>Maximum score</td>
<td>36.00</td>
<td>38.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>100.00</td>
<td>100.00</td>
</tr>
<tr>
<td>Cronbach’s α</td>
<td>0.84</td>
<td>0.89</td>
<td>0.90</td>
<td>0.86</td>
<td>0.95</td>
<td>0.91</td>
<td>0.90</td>
<td>0.94</td>
<td>0.91</td>
<td>0.83</td>
<td>0.95</td>
<td>0.92</td>
<td>0.85</td>
</tr>
<tr>
<td>Factor loading</td>
<td>0.85</td>
<td>0.80</td>
<td>0.78</td>
<td>0.68</td>
<td>0.96</td>
<td>0.89</td>
<td>0.74</td>
<td>0.83</td>
<td>0.62</td>
<td>0.64</td>
<td>0.97</td>
<td>0.87</td>
<td>0.66</td>
</tr>
</tbody>
</table>

Note. For r ≥ 0.161, p < .05. The measures of word processing are items 3 and 4. The measures of higher-level processes are items 5–11. The factor loadings reported are for the measurement model.
Table 2. Fit Statistics for Models of Reading Comprehension (n = 149)

<table>
<thead>
<tr>
<th>Competing Models</th>
<th>( \chi^2 )</th>
<th>df</th>
<th>( \Delta \chi^2 )</th>
<th>( \Delta df )</th>
<th>p Exact</th>
<th>p Close</th>
<th>GFI</th>
<th>AGFI</th>
<th>RMSEA</th>
<th>CI(_{90}) for RMSEA</th>
<th>CFI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measurement</td>
<td>48.24</td>
<td>45</td>
<td></td>
<td></td>
<td>.34</td>
<td>.86</td>
<td>0.95</td>
<td>0.90</td>
<td>0.022</td>
<td>0.000–0.061</td>
<td>1.00</td>
</tr>
<tr>
<td>CC-R</td>
<td>59.23</td>
<td>53</td>
<td>10.99</td>
<td>8</td>
<td>.26</td>
<td>.84</td>
<td>0.94</td>
<td>0.90</td>
<td>0.028</td>
<td>0.000–0.061</td>
<td>0.99</td>
</tr>
<tr>
<td>Lower bound null</td>
<td>465.84</td>
<td>66</td>
<td>406.61*</td>
<td>13</td>
<td>.00</td>
<td>.00</td>
<td>0.67</td>
<td>0.55</td>
<td>0.200</td>
<td>0.190–0.220</td>
<td>0.76</td>
</tr>
<tr>
<td>Independent</td>
<td>16.81</td>
<td>14</td>
<td></td>
<td></td>
<td>.27</td>
<td>.59</td>
<td>0.97</td>
<td>0.93</td>
<td>0.032</td>
<td>0.000–0.092</td>
<td>1.00</td>
</tr>
<tr>
<td>Nonindependentb</td>
<td>53.54</td>
<td>15</td>
<td>36.73*</td>
<td>1</td>
<td>.00</td>
<td>.00</td>
<td>0.92</td>
<td>0.80</td>
<td>0.132</td>
<td>0.095–0.170</td>
<td>0.93</td>
</tr>
<tr>
<td>Multifactor</td>
<td>4.36</td>
<td>6</td>
<td></td>
<td></td>
<td>.63</td>
<td>.80</td>
<td>0.92</td>
<td>0.97</td>
<td>0.000</td>
<td>0.000–0.089</td>
<td>1.00</td>
</tr>
<tr>
<td>Single-factorc</td>
<td>54.53</td>
<td>9</td>
<td>50.17*</td>
<td>3</td>
<td>.00</td>
<td>.00</td>
<td>0.89</td>
<td>0.74</td>
<td>0.185</td>
<td>0.140–0.230</td>
<td>0.94</td>
</tr>
<tr>
<td>CC-R1-WM(^a)</td>
<td>86.70</td>
<td>55</td>
<td>27.47*</td>
<td>2</td>
<td>.00</td>
<td>.20</td>
<td>0.92</td>
<td>0.86</td>
<td>0.062</td>
<td>0.036–0.087</td>
<td>0.97</td>
</tr>
<tr>
<td>CC-R1-WP(^a)</td>
<td>99.21</td>
<td>55</td>
<td>39.98*</td>
<td>2</td>
<td>.00</td>
<td>.05</td>
<td>0.91</td>
<td>0.85</td>
<td>0.074</td>
<td>0.050–0.097</td>
<td>0.96</td>
</tr>
<tr>
<td>CC-R2(^d)</td>
<td>54.27</td>
<td>52</td>
<td>4.96*</td>
<td>1</td>
<td>.39</td>
<td>.90</td>
<td>0.95</td>
<td>0.91</td>
<td>0.017</td>
<td>0.000–0.056</td>
<td>1.00</td>
</tr>
<tr>
<td>CC-R2+IWM(^d)</td>
<td>57.17</td>
<td>53</td>
<td>3.10</td>
<td>1</td>
<td>.32</td>
<td>.88</td>
<td>0.94</td>
<td>0.90</td>
<td>0.023</td>
<td>0.000–0.058</td>
<td>0.99</td>
</tr>
</tbody>
</table>

2.06 0

Note. CC-R model = cognitive components and resource model of reading comprehension. CC-R1-WM = the CC-R model plus a path leading from word processing to working memory. CC-R1-WP = the CC-R model plus paths leading from word processing to the higher-level processes of text-based processing, knowledge access, and knowledge integration. CC-R2 = the CC-R model plus a path leading from working memory to reading comprehension. CC-R2+IWM = the CC-R2 model minus the path leading from working memory to knowledge integration. CI\(_{90}\) = 90% confidence interval for RMSEA.

\(^a\)With the exception of the CC-R model, \( \Delta \chi^2 \) represents the difference in \( \chi^2 \) between the model of interest and the CC-R model. The \( \Delta \chi^2 \) and \( \Delta df \) for the CC-R model represent the difference between the CC-R model and the measurement model.\n
\(^b\)\( \Delta \chi^2 \) is between the independent and nonindependent models.\n
\(^c\)\( \Delta \chi^2 \) is between the multiple- and single-factor models.\n
\(^d\)The first \( \Delta \chi^2 \) is the difference between the CC-R2 and the CC-R2+IWM, and the second \( \Delta \chi^2 \) is the difference between the CC-R and the CC-R2+IWM; p exact tests for discrepancies between the data and the model (Kline, 2011), and p close tests the alternative model that the RMSEA is >0.05. If the value for p close is >0.05, then it is concluded that the fit of the model is close (Kline, 2011).\n
\(^*\)A significant difference from the model at p < .05.
integration was directly influenced by both text-based processing and knowledge access. In addition, as Table 2 shows, all the fit indexes for the CC-R model fell well within acceptable limits. Thus, based on these criteria, it appears that the CC-R model is a good model for explaining the existing data.

To determine the relative contribution of each source of individual differences to reading comprehension performance, the direct, indirect, and total effects were calculated for each latent variable. As Table 3 shows, higher-level processes and word processing exerted considerably more influence on reading comprehension performance than did working memory (−0.513 to 0.156 versus 0.078, respectively). Indeed, when combined, higher-level processes had the largest total effect (0.410 + 0.238 + 0.156 = 0.804) relative to speed of word processing (−0.513), speed (−0.170), and working memory (0.078).

### Comparisons With Baseline Models.

To reiterate, baseline models are used to gauge how well the theoretical model fits the data. The first comparison was between the CC-R model and the upper boundary model, the measurement model. As shown in Table 2, these two models were equivalent: \( \chi^2 \)-difference(8) = 10.99, \( p = .202 \). This finding suggests that the CC-R model is as good as the upper boundary model for explaining the existing data. The second comparison was between the CC-R and lower bound models. As Table 2 shows, none of the fit indexes for the lower bound model were within acceptable limits; as mentioned earlier, this was expected. Further, the \( \chi^2 \)-difference test between the two models was significant: \( \chi^2 \)-difference(13) = 406.61, \( p < .001 \). This latter finding suggests that the

<table>
<thead>
<tr>
<th>Variable</th>
<th>Direct</th>
<th>Indirect</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CC-R model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge integration</td>
<td>0.410</td>
<td>—</td>
<td>0.410</td>
</tr>
<tr>
<td>Speed</td>
<td>−0.170</td>
<td>—</td>
<td>−0.170</td>
</tr>
<tr>
<td>Word processing</td>
<td>−0.450</td>
<td>−0.063</td>
<td>−0.513</td>
</tr>
<tr>
<td>Working memory</td>
<td>—</td>
<td>0.078</td>
<td>0.078</td>
</tr>
<tr>
<td>Text-based processing</td>
<td>—</td>
<td>0.238</td>
<td>0.238</td>
</tr>
<tr>
<td>Knowledge access</td>
<td>—</td>
<td>0.156</td>
<td>0.156</td>
</tr>
<tr>
<td><strong>CC-R2 model</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Knowledge integration</td>
<td>0.240</td>
<td>—</td>
<td>0.240</td>
</tr>
<tr>
<td>Speed</td>
<td>−0.160</td>
<td>—</td>
<td>−0.160</td>
</tr>
<tr>
<td>Word processing</td>
<td>−0.450</td>
<td>−0.056</td>
<td>−0.506</td>
</tr>
<tr>
<td>Working memory</td>
<td>0.250</td>
<td>0.036</td>
<td>0.286</td>
</tr>
<tr>
<td>Text-based processing</td>
<td>—</td>
<td>0.144</td>
<td>0.144</td>
</tr>
<tr>
<td>Knowledge access</td>
<td>—</td>
<td>0.094</td>
<td>0.094</td>
</tr>
</tbody>
</table>

**Note.** \( p < .05 \) for all values. The CC-R2 model is identical to the cognitive components and resource model of reading comprehension (CC-R) model except for the addition of a direct path from working memory to reading comprehension (see Figure 6).
CC-R model is a significantly better model for explaining the existing data than is the lower bound null model.

**Testing Assumption 1.** To test the assumption that word- and higher-level processes are separate constructs, comparisons were made between (a) an independent SEM that included separate latent variables for word- and higher-level processes and (b) a nonindependent SEM that did not include separate latent variables for word- and higher-level processes. Table 2 shows the fit indexes for the independent and nonindependent SEMs. As the table shows, all of the fit indexes for the independent SEM were within acceptable limits. In contrast, some of the fit indexes for the nonindependent SEM, such as the $p$-exact, $p$-close, AGFI, and RMSEA indexes, were outside acceptable limits. Further, the $\chi^2$-difference test suggested that the independent SEM was significantly better at explaining the data than the nonindependent SEM was: $\chi^2$-difference(1) = 36.73, $p < .001$. In other words, these findings support the CC-R model’s assumption that lower-level word processes and higher-level processes are separate constructs.

**Testing Assumption 2.** To test the assumption that there are multiple higher-level processes, comparisons were made between (a) a multifactor SEM that included separate latent variables for each of the major higher-level processes and (b) a single-factor SEM that included a single latent variable that represented all of the higher-level processes. Table 2 shows the fit indexes for the multiple- and single-factor SEMs. As the table shows, all of the fit indexes for the multifactor SEM were within acceptable limits. In contrast, some of the fit indexes for the single-factor SEM, such as the $p$-exact, $p$-close, AGFI, and RMSEA indexes, were outside acceptable limits. Further, the $\chi^2$-difference test between the multiple- and single-factor SEMs suggested that the multifactor SEM was significantly better at explaining the data than a single-factor SEM was: $\chi^2$-difference(3) = 50.17, $p < .001$. In other words, these findings support the CC-R model’s assumption that there are multiple higher-level processes.

**Testing Assumption 4.** To test the assumption that lower-level word processes have no influence on working memory, comparisons were made between (a) the CC-R model, which does not include a direct path leading from lower-level word processes to working memory, and (b) the CC-R1-WM model, which is identical to the CC-R model except that the CC-R1-WM model includes a direct path leading from lower-level word processes to working memory. As shown in Table 2, some of the fit indexes for the CC-R1-WM model (e.g., $p$-exact, RMSEA) were poor, especially when they were compared with those of the CC-R model. Also, the $\chi^2$-difference test suggested that the CC-R1-WM model had a poorer fit to the data than the CC-R model did: $\chi^2$-difference(2) = 27.47, $p < .001$. Thus, taken as a whole, these findings suggest that a model that excludes a path from word processing to working memory (i.e., the CC-R model) explains the data better than does a model that includes this path (i.e., the CC-R1-WM model). In other words,
these findings support the CC-R model’s assumption that lower-level word processes do not consume limited working memory resources.

To test the assumption that lower-level word processes do not influence higher-level processes, comparisons were made between (a) the CC-R model, which does not include a direct path leading from lower-level word processes to higher-level processes, and (b) the CC-R1-WP model, which is identical to the CC-R model except that the CC-R1-WP model includes direct paths leading from lower-level word processes to text-based processing, from lower-level word processes to knowledge access, and from lower-level word processes to knowledge integration. As shown in Table 2, some of the fit indexes for the CC-R1-WP model (e.g., $p$-exact, RMSEA) were poor, especially when they were compared with those of the CC-R model. Also, the $\chi^2$-difference test suggested that the CC-R1-WP model had a poorer fit to the data than the CC-R model did: $\chi^2$-difference(2) = 39.98, $p < .001$. Thus, taken as a whole, these findings suggest that a model that excludes paths leading from word processing to the higher-level processes (i.e., the CC-R model) explains the data better than does a model that includes these paths (i.e., the CC-R1-WP model). In other words, these findings support the CC-R model’s assumption that lower-level word processes do not influence higher-level processes.

**Testing Assumption 5.** To test whether working memory has little to no direct influence on reading comprehension, comparisons were made between two nearly identical models: (1) the CC-R model, which does not include a direct path leading from working memory to reading comprehension, and (2) the CC-R2 model, which is identical to the CC-R model except that the CC-R2 model includes a direct path leading from working memory to reading comprehension. As shown in Table 2, all of the fit indexes for the CC-R2 model were significant. Moreover, the values for the fit indexes were as good as, and in some instances better than, those for the CC-R model. In addition, the $\chi^2$-difference test suggested that the CC-R2 model fit the data better than the CC-R model did: $\chi^2$-difference(1) = 4.96, $p = .026$. Taken as a whole, these findings suggest that a model that includes both direct and indirect paths from working memory to reading comprehension (i.e., the CC-R2 model) explains the data better than does a model that excludes the direct path (i.e., the CC-R model). In other words, these findings do not support the assumption that working memory exerts only an indirect influence on reading comprehension. Table 3 shows the specific values for these influences.

To reconcile the difference between this finding and previous research that has shown that working memory contributes little to reading comprehension performance once the variance attributed to higher-level processes is accounted for (Daneman & Hannon, 2007; Hannon & Daneman, 2001a), the amount of variance in reading comprehension that was accounted for by the CC-R versus CC-R2 models was examined. The LISREL output revealed that the CC-R and CC-R2 models accounted for 60% and 62% of the variance, respectively. This small 2.0% difference is consistent with earlier research that has shown that working memory accounts for little additional variance in reading
comprehension performance once higher-level processes are accounted for (e.g., Daneman & Hannon, 2007). In addition, in conjunction with the earlier finding of the present study, although the CC-R2 model provides a better fit to the data, this better fit accounts for only 2.0% additional variance in reading comprehension performance.

Given that the results suggest that the CC-R2 model is better than the CC-R model at explaining the data, the CC-R2 model was compared with a new SEM that includes just a direct influence between working memory and reading comprehension. This new SEM is called the CC-R2+IWM (CC-R2 plus independent working memory model). As shown in Figure 7, the CC-R2+IWM model is identical to the CC-R2 model except that the CC-R2+IWM model excludes the non-significant path leading from working memory to knowledge integration. The exclusion of this path makes working memory’s influence on reading comprehension performance completely direct and independent of higher-level processes. If so, then the CC-R2+IWM model should be better at explaining the data than does the CC-R model, which includes an indirect path. The CC-R2+IWM model should also be as good as, or perhaps even better than, the CC-R2 model, which includes both direct and indirect paths.

As shown in Table 2, all of the fit indexes for the CC-R2+IWM model were within acceptable limits. However, a subsequent $\chi^2$-difference test revealed no significant difference between the CC-R2+IWM and CC-R models, even though the $\chi^2$-difference test approached significance in favor of the CC-R2 model:

Figure 7. SEM of CC-R2+IWM Model With Path Coefficients

Note. Solid lines represent significant path coefficients, whereas the broken line represents nonsignificant structure coefficients. This SEM is identical to the cognitive components and resource model of reading comprehension (CC-R model) except for the addition of a path leading from working memory to reading comprehension (CC-R2 model) and the exclusion of the path leading from working memory to knowledge integration.
Understanding the Relative Contributions of Lower-Level Word Processes...  

\[ \chi^2\text{-difference}(1) = 3.10, \ p = .078. \] Based on this latter finding and the earlier finding that the CC-R2 model is better at explaining the existing data than the CC-R model is, it appears that the CC-R2 model is the best model for explaining the relationship between working memory and reading comprehension performance. That is, rather than have an indirect (i.e., CC-R model) or direct (i.e., CC-R2+IWM model) influence on reading comprehension performance, the present findings suggest that working memory has both direct and indirect influences (i.e., CC-R2 model).

Discussion

Although it is generally accepted that comprehension is not simply the sum of its processes (Kintsch & Rawson, 2005), little is known about how many of its processes interact (Cornoldi et al., 1996; Perfetti et al., 2005) or whether one or all of them make separate and important contributions to reading comprehension performance (Perfetti et al., 1996). This lack of knowledge is quite surprising given that it has strong implications for major theories of comprehension that include lower-level word processes, higher-level cognitive processes, and working memory capacity. The present study addresses these limitations by developing and testing a SEM called the CC-R model—a model of reading comprehension that proposes a set of relationships among lower-level processes, higher-level processes, and working memory.

The results show that a variant of the CC-R model, namely the CC-R2 model, explains the present data well. That is, the CC-R2 model is suitable for both understanding the relationships among lower-level word processes, higher-level processes, and working memory and for predicting performance on standardized measures of adult reading comprehension. Next is a detailed discussion of the results, their theoretical and practical implications, and their limitations.

Relationships Among Lower-Level Processes, Higher-Level Processes, and Working Memory

With respect to lower-level word processing (i.e., word fluency), higher-level processes, and working memory, the present study reveals a number of findings that fill gaps in the literature. First, the zero-order correlations suggest little to no relationship between lower-level word processes and working memory, a finding that suggests that lower-level processes and working memory are separate constructs. Further, a comparison between two SEMs showed that the CC-R model, which excludes a path from word processing to working memory, is superior to the CC-R1-WM model, which includes that path. Thus, taken as a whole, these findings support previous research that has shown that lower-level word processes exert little influence on working memory in adults (e.g., Baddeley et al., 1985; Dixon et al., 1988). The new contribution of this specific finding is the use of a SEM as well as the use of multiple measures of word processes and working memory simultaneously.

Of course, one could argue that the reason why the word processing–working memory relationship is absent is because not all of the tasks were
measuring nonverbal information. That is, perhaps differences in the types of information being processed in the measures of word processes (i.e., verbal) versus the operation span task (i.e., math + verbal) eliminated the possibility of a strong relationship between word processing and working memory. Although this possibility has merit, it seems unlikely because scores on the same verbal word processing measures failed to correlate with scores on the reading span task (a verbal measure of working memory) and the CPT (a verbal measure of multiple higher-level processes). Thus, when one considers this pattern of results, it seems that differences in the types of information being processed fails to explain the lack of a word processing–working memory relationship.

A second finding is there are, at best, weak relationships between measures of lower-level word processing and higher-level processes. Indeed, both the zero-order correlations and the comparisons between the SEMs testing assumptions 1 and 4 support this finding. The present results are some of the first to provide evidence of the idea that lower- and higher-level processes might be separate constructs in an adult population. The results are also consistent with the modest pattern of relationships that Cain et al. (2004) and August et al. (2006) observed with children and that Hannon and Frias (2012) observed with prereaders who were 4 and 5 years old.

A third finding is the weak relationship between word processing and speed. Although the tasks for both constructs measured reaction time (i.e., the word fluency task measured speed at deciding which string of letters is a word; the speed task measured speed at processing CPT test statements), and word processing directly influenced speed (i.e., word processing speed), both constructs separately predicted reading comprehension performance. This latter finding parallels findings from recent developmental research (e.g., Jenkins et al., 2003; Klauda & Guthrie, 2008) inasmuch as it suggests that word decoding and speed are not a unitary construct. From a theoretical perspective, this finding adds an interesting twist to the cognitive slowing hypothesis prominent in the aging literature because according to this hypothesis, speed is a unidimensional construct rather than a multidimensional one.

A fourth finding is that the higher-level processes form a very specific pattern of relationships. For example, the zero-order correlations suggest that text-based processes that are used to encode/learn new facts presented in a text (e.g., text memory, text inferencing) are highly related to one another but are, at best, weakly related to processes that access prior knowledge from long-term memory. Conversely, knowledge integration processes, which rely on new text-based information and existing information from prior knowledge, are related to both the text-based and knowledge access processes. Further, a comparison between two SEMs showed that a multifactor model, which depicted higher-level processes forming a specific pattern of separate factors, was superior to a single-factor model, which specified that higher-level processes form a single factor. Thus, taken as a whole, these findings support the idea that there are multiple higher-level processes (i.e., assumption 2). The findings also provide a framework for
future research that might assess how other processes or resources, not assessed in the present study, might interact with the higher-level processes that were assessed in the present study.

In addition, these findings inform the simple view of reading (e.g., Gough et al., 1996), a very popular conceptualization of reading comprehension that defines reading comprehension as a multiplicative function of two separate clusters of abilities: word decoding x language comprehension (i.e., \( R = D \times C \)). Consistent with the simple view of reading, the present study supports the notion that lower-level word processes are separate or independent of higher-level processes that are used for comprehension. Conversely, the simple view of reading defines comprehension as a single unitary factor/process, whereas the present study suggests that there are multiple higher-level processes used for comprehension that form a very specific pattern of relationships. Furthermore, the results suggest that whereas some of these higher-level processes are related to one another (e.g., text processing with knowledge integration, knowledge access with knowledge integration), others are, at best, weakly related (e.g., text processing and knowledge access).

Finally, the present findings inform a number of theories of reading comprehension. As mentioned earlier, theories of reading comprehension have primarily focused on understanding and explaining the nature of mental representations of text rather than complex relationships among lower-level word processes, higher-level processes, and characteristics of the reader (McNamara & Magliano, 2009). The present study informs these theories by (a) proposing a set of relationships between lower- and higher-level processes, (b) showing that an individual-differences approach is suitable for assessing the relationships between lower- and higher-level processes, and (c) showing that SEMs are a viable statistical tool for assessing models of reading comprehension. In other words, the present study provides a foundation for future research to test and compare theories of reading comprehension, to assess the relationships among lower- and higher-level processes and other sources of individual differences, and to assess the relative predictive powers of sources of individual differences with various genres of text.

**Predicting Performance on Measures of Adult Reading Comprehension**

With regards to predicting performance on standardized measures of reading comprehension in adults, the present study shows that lower-level word processes, higher-level processes, and working memory each account for significant amounts of variance in reading comprehension performance. Indeed, as Table 3 shows, the effects for these three sources of individual differences are all significant. Also, the CC-R and CC-R2 models account for 60% and 62% of the variance in reading comprehension performance, respectively.

Notwithstanding, the results assessing the veracity of the assumptions of the CC-R model fail to support the assumption that working memory only indirectly influences reading comprehension. Rather, they reveal a more complicated
relationship. Consistent with assumption 5, a SEM that includes both direct and indirect working memory–reading comprehension relationships (i.e., CC-R2 model) accounts for only 2% more variance in reading comprehension performance than does the CC-R model, a SEM that includes only an indirect working memory–reading comprehension relationship. In other words, the addition of the direct relationship accounted for little additional variance in reading comprehension performance, a finding that also replicates previous regression analysis research (e.g., Daneman & Hannon, 2007; Hannon & Daneman, 2001a). Conversely, inconsistent with assumption 5, a SEM that includes both direct and indirect working memory–reading comprehension relationships (i.e., CC-R2 model) is a better fit for the existing data than the CC-R model is. In other words, a variant of the CC-R model—the CC-R2 model—is significantly better than the CC-R model at explaining the existing data.

It should be noted, however, that this latter finding fails to replicate previous SEM research that has shown that working memory exerts only an indirect influence on reading comprehension (e.g., Britton et al., 1998). In other words, previous research supported assumption 5 of the CC-R model. Of course, there are numerous differences between the measures used by Britton et al. and those of the present study. Nevertheless, given that the CC-R2 model accounts for only 2% additional variance in reading comprehension performance over and above the original CC-R model, it is recommended that future research examine the working memory–reading comprehension relationship(s) using different measures of working memory and higher-level processes.

Additional Findings and Other Contributions

There are also other findings that are not the primary focus of the present study but still warrant discussion. For example, methodologically speaking, the present study goes well beyond previous research in at least three important ways. First, for most of the sources of individual differences, multiple measures were included as opposed to a single measure. This approach increases the probability that the present results will generalize to other studies. Also, by examining multiple sources of individual differences simultaneously, the present study reveals the relationships among the sources. Specifically, word processing appears to be a separate construct from higher-level processes and working memory, whereas the higher-level process of knowledge integration draws on working memory resources.

Further, the tasks measuring the sources of individual differences differed from the reading comprehension measures in a number of ways. For instance, whereas the reading comprehension measures assessed reading comprehension via multiple-choice questions, the measures for the sources assessed their respective constructs via lexical decisions (i.e., word processing), true/false statements (i.e., higher-level processes), and free recall (i.e., working memory). Whereas the reading comprehension measures assessed reading comprehension via number of correct answers, the measures for word processing assessed word processes...
via reaction time. Finally, whereas the reading comprehension measures allowed readers to refer back to the passages, the measures for the higher-level processes and working memory had greater memory demands inasmuch as both tasks required readers to retain information in memory and then recall it.

Also, it is important to acknowledge the utility of the CPT. Measures with strong psychometric properties are invaluable for assessing cognitive constructs delineated by theories of comprehension processing in cognitive science (e.g., Pellegrino, Baxter, & Glaser, 1999; Pellegrino & Glaser, 1979). Unfortunately, prior to the CPT, there were few measures assessing higher-level processes with good psychometric properties. Consequently, research was hampered because researchers were unable to assess the relative contributions of lower-level word processes, higher-level processes, and working memory to performances on measures of reading or listening comprehension. Researchers were also unable to assess or compare theoretical models of comprehension. The findings of the present study suggest that with measures like the CPT, researchers can advance knowledge about higher-level processes, their relationships with one another, their relationships with other important constructs such as lower-level word processes and working memory, and their predictive powers with respect to important constructs such as reading comprehension, listening comprehension, and fluid intelligence.

Also of practical interest is the finding that performance on a standardized measure of adult general or global reading comprehension consists of many separate sources of individual differences. This finding is of interest to educators because it implies that no single source is likely to be the cause of poor comprehension. Indeed, the results of the present study add to a growing developmental literature that suggests that poor comprehension might be attributed to one or many sources of individual differences—poor word decoding, weak knowledge integration, and/or small working memory capacities (e.g., Cain et al., 2004; Oakhill et al., 2003)—and each of these sources of individual differences might require a different intervention.

Finally, of theoretical interest is the finding that high-knowledge integration is an important source of individual differences in adult reading comprehension. This finding is consistent with recent research that has advocated integration of text-based information with prior knowledge as an important process in reading comprehension (Britton et al., 1998; Hannon & Daneman, 2001a, 2006, 2009). This finding also supports theories of reading comprehension that advocate building text structures (Gernsbacher, 1990), extending working memory by integrating prior knowledge with text-based information (Ericsson & Kintsch, 1995), and models of learning from instructional text (Britton et al., 1998).

**Limitations**

Although the present study has a number of theoretical and practical implications, the present study is only a beginning, as other factors, such as test administration, might influence the relative predictive powers of lower-level word processes.
processes, higher-level processes, and working memory for reading comprehension performance? Consider, for example, preestablished time restrictions frequently imposed during administrations of reading comprehension measures. In the present study, standardized reading comprehension measures with time restrictions were selected because timed tests are often used by educators to evaluate students (e.g., SAT-V, GRE) and by researchers to assess adult reading comprehension skill (e.g., Bell & Perfetti, 1994; Cunningham et al., 1990; Daneman & Hannon, 2001; Dixon et al., 1988; Hannon & Daneman, 1998, 2006; Holmes, 2009; Landi, 2010; Long et al., 1994; Masson & Miller, 1983). By selecting this type of test, however, it is possible that the predictive powers of the speed measures (i.e., word processing, speed) were simply an artifact of the imposed time limits of the reading comprehension measures.

Although this might be a factor, other studies have suggested that the speed–reading comprehension correlation is not simply an artifact of speed = a speeded or timed measure. For example, Hannon and Daneman (2001a) found that speed correlated with scores on untimed measures of vocabulary knowledge (i.e., Mill Hill Vocabulary Scale) and vocabulary acquisition yet failed to correlate with scores on timed measures of verbal analogies and bridging inferences. Similarly, Klauda and Guthrie (2008) observed that scores on a measure of passage processing speed correlated with scores on an untimed measure of inference generation. Although this is a question for future research, perhaps speed of processing sentences/responding to test statements is more a general or global factor that influences many types of cognitive constructs (see Verhaeghen et al., 1993, for a similar argument in the aging literature). Finally, regardless of the explanation, the present findings show that speed is highly predictive of scores on a frequently administered, standardized test of reading comprehension.

A second factor that might affect the relative predictive powers of the sources of individual differences for reading comprehension is whether the test of reading comprehension permits referrals back to the passages. Frequently used measures of reading comprehension ability, such as the Nelson-Denny and SAT-V, allow referrals to passages as students answer the questions; in fact, the SAT-V includes passage line numbers to assist with referrals. By allowing referrals, however, it is possible that students rely more heavily on test-taking strategies rather than cognitive processes and resources that are used for learning and integrating text. Indeed, studies have shown that some students will simply scan passages for answers to questions rather than monitor their performance or integrate a passage into a coherent text representation (e.g., Farr, Pritchard, & Smitten, 1990). Studies have also shown that passage availability during question answering can greatly influence the predictive powers of domain knowledge about the passages (e.g., Ozuru, Best, Bell, Witherspoon, & McNamara, 2007). Again, these findings do not diminish the findings of the present study but do suggest the interesting possibility that perhaps some cognitive processes and resources, such as high-knowledge integration and working memory, might be more predictive of reading comprehension when passages are absent during test taking. Conversely, other
processes, such as lower-level word processes, might become less predictive (see Andreassen & Braten, 2010, for evidence of these latter two possibilities with fifth-grade students).

A third factor that might influence the relative predictive powers of the sources of individual differences for reading comprehension is the type of text, narrative versus expository. The reading comprehension measures administered in the present study consisted of short, expository texts. Although this type of text is representative of the texts that students frequently encounter, expository texts differ substantially from narrative texts, particularly in their potential for using existing knowledge, schemas, and scripts. Whereas narrative texts share conversational characteristics that occur frequently in everyday conversations (e.g., contextual situations, temporal/causal sequences), expository texts share characteristics with lectures and factual oral documentaries that occur less frequently (Graesser et al., 1994). Narrative texts often include familiar content (e.g., eating a meal), which makes it easier to draw on existing knowledge and schemas. In contrast, expository texts often include unfamiliar content (Graesser et al., 1994; Singer, Harkness, & Stewart, 1997), which reduces the potential for drawing on existing knowledge and schemas.

Because the present study used standardized reading comprehension measures composed of expository texts and because expository and narrative texts differ in their potential for using prior knowledge and schemas, it is possible that the predictive powers of the sources of individual differences differ for these two types of texts. For example, perhaps lower-level word processes will be less predictive of comprehension of narrative texts than expository texts would be because the common conversational characteristics inherent in narrative texts might place fewer demands on accessing word meanings. In contrast, knowledge access might be more predictive of comprehension of narratives because it measures access to prior knowledge, a resource that is more important for reading narrative texts rather than expository ones.

A fourth factor that might influence the relative predictive powers of the sources of individual differences is the use of the Nelson-Denny as the only measure of reading comprehension. At present, there are conflicting views about the extent to which the Nelson-Denny might be assessing elemental processes (e.g., text memory) versus more sophisticated processes (e.g., knowledge integration). On the one hand, researchers have pointed out that a large percentage of the multiple-choice questions in form F of the Nelson-Denny assess elemental facts rather than knowledge acquired from more sophisticated inferences and concepts typically found in the global context or situation model (Magliano, Millis, Ozuru, & McNamara, 2007). On the other hand, researchers have shown that even if multiple-choice questions are assessing knowledge for basic elemental facts, the cognitive processes that these questions assess are not necessarily basic elemental processes. Rather, the questions may be assessing more sophisticated processes. For example, Hannon and Daneman (2001a) showed that multiple-choice...
questions assessing elemental detail facts explicitly mentioned in historical and biographical passages were better at assessing sophisticated processes (e.g., knowledge integration) than elementary text-based processes (e.g., text memory). In other words, questions assessing basic elemental facts did not assess only elemental processes.

Finally, critics have argued that measures like the Nelson-Denny are more off-line measures of comprehension rather than online ones (e.g., Magliano et al., 2007; Magliano, Millis, the RSAT Development Team, Levinstein, & Boonthum, 2011). For this reason, researchers are currently developing new reading comprehension tools, such as the Reading Strategy Assessment Tool (RSAT; Magliano et al., 2011), that are designed to assess comprehension processes as they unfold online.

Besides considering factors that might influence the relative predictive powers of the sources of individual differences used in the present study, there are other cognitive resources, processes, and strategies that are predictive of reading comprehension that were not studied. For instance, absent were measures of prior knowledge and the metacognitive skill of sensing breaks in a passage—two other known predictors of reading comprehension and learning performance (Britton et al., 1998). Although these omissions do not invalidate the present results, questions remain as to how these other factors might predict reading comprehension performance relative to the three sources of individual differences found in the CC-R and CC-R2 models.

Another limitation is that the present study’s experimental design does not permit assessment of the veracity of assumption 3, which states that readers form a single representation that varies in quality from reader to reader. Although not assessing assumption 3 does not diminish the present results, it would be interesting to test this assumption. On the one hand, it seems to make sense because one would expect the better cognitive processes of the skilled readers to form a more complete representation. On the other hand, recent neural research suggested that the picture might not be so simple because skilled and less skilled adult readers represent discourse differently across the two hemispheres (e.g., Prat, Long, & Baynes, 2007). Unlike their less skilled counterparts, skilled readers show a more left-lateralized pattern of discourse representation, including exclusive sensitivity to propositional and topic relations in the left hemisphere (Prat et al., 2007). In contrast, less-skilled readers show a more mixed-hemispheric pattern of discourse representation, whereas their sensitivity to topic relations is exclusive to the right hemisphere (Prat et al., 2007).

Another potential limitation is that perhaps the strong correlations between measures of lower-level word processes and reading comprehension and the strong correlations between measures of higher-level processes and reading comprehension were because all of these measures assessed verbal information. Although this limitation exists and its extent should be explored in future
research, it is important to remember that it does not reduce the differences in the relative influences that lower-level word processes versus higher-level processes make on reading comprehension performance. Nor does this limitation explain the minimal relationship between lower- and higher-level processes.

Yet another limitation is that the latent variable speed had only one observed variable. As mentioned earlier, this is an acceptable practice, although it is not recommended (Jöreskog & Sörbom, 1993). By using a single observed measure of a latent variable, it is assumed that the observed variable is a perfect measure of the latent variable. It is for this reason that Schumacker and Lomax (1996) and Jöreskog and Sörbom (1993) recommended that the reliability of the observed variable be set, which was the procedure used in the present study. Further, it should be noted that using only one or two observed variables for each latent variable is also a limitation; using three observed variables is preferable. For this reason, future research should explore the CC-R and CC-R2 models with more than two observed variables representing the latent variables.

Finally, it should be noted that unlike the construction–integration model (Kintsch, 1998), which explains different types of comprehension for a number of different populations, the present findings provide evidence only that the CC-R model and its variant, the CC-R2 model, are good SEMs for explaining reading comprehension in a rather circumscribed population of adult readers, namely university students. Future research should test whether these models are suitable for predicting other types of comprehension (e.g., listening) and whether they generalize to other populations, such as a community sample of adult readers, adolescents, or beginning readers.

**Conclusion**

The present study used SEMs to examine the relationships among three sources of individual differences in adult reading comprehension: lower-level word processes, higher-level processes, and working memory. Using a population of proficient adult readers, the results show that a variant of the CC-R model, the CC-R2 model, is suitable for both understanding the relations among the sources of individual differences and predicting performance on standardized measures of reading comprehension. Indeed, the CC-R2 model accounted for 62% of the variance in reading comprehension performance. Of course, the present findings are limited to the measures used in the present study, and future research should examine whether they generalize to other measures. In addition, future research should explore the relationships among lower-level word processes, higher-level processes, and working memory using other types of methodology. For example, the assumptions of the CC-R and CC-R2 models could be tested experimentally or in real time using computer models. Finally, future research should assess whether the CC-R and CC-R2 models prevail across the life span.
When this chapter was written, Hannon was at the University of Saskatchewan.

I would like to thank Joe Magliano for his very helpful comments. I also thank Jill Argus for helping with data collection and Corey Vogel for helping with data scoring.

1 There are many ways to classify cognitive processes and resources. For the purposes of the present study, I classify cognitive processes and resources in terms of a hierarchy. More specifically, those processes that are used to pronounce sounds and decode/identify words are classified as lower-level word processes. Those processes that are used to process larger units of information, such as ideas or propositions, are classified as higher-level processes.

2 In many respects, this process account of the text representation is analogous to the process account of memory. That is, rather than propose a host of different types of memory that are presumably stored in different locations in our brains, memory researchers are starting to explain different types of memory in terms of different cognitive processes acting on the same memories (see Haberlandt, 1999, for more on this point).

3 The major assumption of the automaticity and verbal efficiency theories is the opposite of assumption 4 of the CC-R model (LaBerge & Samuels, 1974; Perfetti, 1985). According to these developmental theories, word processes directly influence working memory because their efficiency influences the amount of working memory available for executing higher-level processes (Jenkins, Fuchs, van den Broek, Espin, & Deno, 2003). Slower word processes consume many working memory resources that are needed for executing higher-level processes, whereas faster word processes consume few working memory resources. Of course, the former two theories describe the acquisition of reading in beginning readers, whereas the CC-R model describes the processes of reading in proficient adult readers. For this reason, the automaticity and verbal efficiency theories might be a more appropriate model for beginning readers, whereas the CC-R model might be more appropriate for adults.

4 In retrospect, it was unwise to counterbalance the forms of the Nelson-Denny because it potentially increases error and reduces power. However, the alternate form reliabilities for the Nelson-Denny are high (0.77 or higher), which suggests that the forms are interchangeable. Further, the subsequent analysis shows that the counterbalancing had a minimal

QUESTIONS FOR REFLECTION

1. How do the assumptions of the cognitive components-resource model of reading comprehension (CC-R2) compare with Kintsch’s construction–integration model?

2. What implications for instruction might surface as a result of Hannon’s theory that word-level and higher-level cognitive processes are different in adult readers and young children?

3. How does the CC-R2 model as described by the author provide direction for your teaching of young readers?

4. How do the findings of this study counter the “simple view of reading” that views comprehension as a multiplicative function of word decoding and language comprehension (R = D × C)?

NOTES

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influence (see Engle, Tuholski, Laughlin, & Conway, 1999, who also made a similar error with counterbalancing).

Although speed is a composite score of the reaction time for the test statements for the higher-level processes, speed is not really a higher-level process, nor can it be considered a lower-level word process. Rather, consistent with Verhaeghen, Marcoen, and Goossens (1993), speed should perhaps be classified as a general or more global factor/resource that may or may not influence other resources (e.g., working memory) or specific processes (e.g., lower-level word processes, text memory, text inferencing, knowledge access, knowledge integration).

As noted by one of the reviewers, maximum likelihood estimation is very sensitive to non-normal data (see also Fan et al., 1999). For this reason, the reviewer suggested examining the statistics for univariate skew and kurtosis. The results of this analysis revealed that the skew and kurtosis for the low-knowledge access measure exceeded the maximum allowable limits for normality for skew and kurtosis (i.e., ±1.5 for skew, ±3.0 for kurtosis). A closer inspection of the data for this measure revealed that three data points were below the −3.0 standard deviation limit for univariate outliers. Based on the recommendations of Kline (2011), these three data points were replaced with values that were equivalent to the mean minus three standard deviations. Table 1 shows the new, recalculated descriptive statistics for the low-knowledge access measure. As this table shows, all the descriptive statistics for this measure are within normal limits. All subsequent data analysis (i.e., correlations, factor analysis, SEMs) are based on this transformed data.

Factors affecting the relative influences of lower-level word processes, higher-level processes, and working memory apply to all theories of reading comprehension, not just the CC-R model.

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APPENDIX A

Z-Tests Assessing the Relative Contributions of Each Predictor to Performance on the Nelson-Denny Forms Used in Set 1 Versus Performance on the Nelson-Denny Forms Used in Set 2

As noted in the Methods section, students completed two forms of the Nelson-Denny, either set 1 (forms E and H) or set 2 (forms F and G). To test whether the zero-order correlations between scores on the predictors and the reading comprehension forms are equivalent, I completed a number of z-tests. These z-tests were computed between forms that were matched in the same session. That is, comparisons were made between form E and form F and between form H and form G for each of the predictors. For instance, a z-test assessed whether the correlation between scores on text memory and form E (i.e., set 1, session 1) was equivalent to the correlation between scores on text memory and form F (i.e., set 2, session 1); a z-test assessed whether the correlation between scores on text memory and form H (i.e., set 1, session 2) was equivalent to the correlation between scores on text memory and form G (i.e., set 2, session 2); and so forth. None of the z-tests was significant. For example, for the largest \( z = -1.28, p > .10 \).

<table>
<thead>
<tr>
<th>Predictor</th>
<th>( z )-Score Between Forms E and F</th>
<th>( z )-Score Between Forms H and G</th>
</tr>
</thead>
<tbody>
<tr>
<td>Text memory</td>
<td>(-0.40)</td>
<td>(-0.10)</td>
</tr>
<tr>
<td>Text inferencing</td>
<td>(0.07)</td>
<td>(-0.38)</td>
</tr>
<tr>
<td>Low-knowledge integration</td>
<td>(-1.19)</td>
<td>(0.88)</td>
</tr>
<tr>
<td>High-knowledge integration</td>
<td>(-0.29)</td>
<td>(-0.33)</td>
</tr>
<tr>
<td>Low-knowledge access</td>
<td>(-0.03)</td>
<td>(-0.07)</td>
</tr>
<tr>
<td>High-knowledge access</td>
<td>(0.29)</td>
<td>(-0.35)</td>
</tr>
<tr>
<td>Speed</td>
<td>(0.10)</td>
<td>(-0.10)</td>
</tr>
<tr>
<td>Reading span</td>
<td>(1.16)</td>
<td>(1.17)</td>
</tr>
<tr>
<td>Operation span</td>
<td>(0.3)</td>
<td>(1.03)</td>
</tr>
<tr>
<td>Orthographic task</td>
<td>(-1.10)</td>
<td>(0.91)</td>
</tr>
<tr>
<td>Phonemic task</td>
<td>(-1.28)</td>
<td>(0.93)</td>
</tr>
</tbody>
</table>
APPENDIX B

Examples of Stimuli Used in the Phonemic and Orthographic Lexical Decision Tasks

<table>
<thead>
<tr>
<th>Phonemic</th>
<th>Orthographic</th>
</tr>
</thead>
<tbody>
<tr>
<td>daiw dair</td>
<td>date dait</td>
</tr>
<tr>
<td>heer heem</td>
<td>cheer cheer</td>
</tr>
<tr>
<td>paz pai</td>
<td>rare rair</td>
</tr>
<tr>
<td>yeat yeer</td>
<td>fite fight</td>
</tr>
<tr>
<td>voat voam</td>
<td>meek meak</td>
</tr>
<tr>
<td>faid foid</td>
<td>prair prayer</td>
</tr>
<tr>
<td>stawe stane</td>
<td>yearn yurn</td>
</tr>
<tr>
<td>myde syde</td>
<td>kurl curl</td>
</tr>
<tr>
<td>spair spaor</td>
<td>mate mait</td>
</tr>
<tr>
<td>hoap hoate</td>
<td>furst first</td>
</tr>
</tbody>
</table>

APPENDIX C

Sample Paragraphs and Questions From the Component Processes Task*

Vehicle Item

Paragraph

A NORT resembles a JET but is faster and weighs more.

A BERL resembles a CAR but is slower and weighs more.

A SAMP resembles a BERL but is slower and weighs more.

Features/Relations

speed NORT > JET > CAR > BERL > SAMP

weight NORT > JET > CAR > SAMP > BERL > CAR

Test Statements

Text Memory

A NORT is faster than a JET. (true)

A JET is faster than a NORT. (false)
Text Inferencing
A SAMP is slower than a CAR. (true)
A CAR is slower than a SAMP. (false)

Low-Knowledge Access
A JET is faster than a CAR. (true)
A CAR is faster than a JET. (false)

High-Knowledge Access
A JET has a pilot, whereas a MOTORCYCLE doesn’t. (true)
A JET has a driver, whereas a MOTORCYCLE doesn’t. (false)

Low-Knowledge Integration
A NORT is faster than a CAR. (true)
A CAR is faster than a NORT. (false)

High-Knowledge Integration
Like ROCKETS, NORTS travel in the air. (true)
Like MOTORCYCLES, NORTS travel across the land. (false)
Like MOTORCYCLES, BERLS travel across the land. (true)
Like ROCKETS, BERLS travel in the air. (false)

Speed
Average reaction time for all correctly answered test statements.