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Predictors of Reading Comprehension Among Struggling Readers Who Exhibit Differing Levels of Inattention and Hyperactivity

Elizabeth Swanson, Marcia Barnes, Anna-Mari Fall, and Greg Roberts

The University of Texas at Austin, Austin, TX, USA

ABSTRACT

The purpose of this study was to investigate the impact of inference making, decoding, memory, and vocabulary on reading comprehension among 7th-through 12th-grade struggling readers with varying levels of inattention and hyperactivity. We categorized a group of 414 struggling readers into 3 groups based on results from factor mixture modeling: (a) low inattention + low hyperactivity, (b) high inattention + high hyperactivity, and (c) high inattention + low hyperactivity. Results indicated that vocabulary and inference making, but not decoding, predicted reading comprehension outcomes among all 3 groups of struggling readers. Working memory predicted reading comprehension among struggling readers in the low inattention + low hyperactivity and high inattention + high hyperactivity groups.

Reading comprehension is key to school and postsecondary success (ACT, 2006). For students with inattention and hyperactivity, reading can be difficult (DuPaul, Gormley, & Laracy, 2013), as evidenced by lower scores on standardized reading tests (e.g., Frazier, Youngstrom, Glutting, & Watkins, 2007; Loe & Feldman, 2007) and lower classroom grades in reading (Loe & Feldman, 2007). Recently, researchers have made significant contributions by investigating the skills and knowledge related to reading comprehension. Although there is not complete agreement, most acknowledge inference making, vocabulary knowledge, word reading, and background knowledge as essential components that contribute to reading comprehension (e.g., Cromley & Azevedo, 2007; Kendeou, Van den Broek, White, & Lynch, 2009; Kintsch, 1998; Perfetti & Stafura, 2014; Van den Broek & Kendeou, 2008). Cromley and Azevedo (2007) synthesized this important body of literature and proposed the direct and inferential mediation (DIME) model, which hypothesizes relations between background knowledge, inference making, reading comprehension strategies, vocabulary, and word reading. Among ninth graders (Cromley & Azevedo, 2007) and college students (Cromley, Snyder-Hogan, & Luciw-Dubas, 2010), vocabulary and background knowledge made the largest contributions to comprehension, followed by inference making and then comprehension strategies. Word reading was also related to reading comprehension, but only in the ninth-grade sample. The DIME model was recently examined as a structural model among a large, diverse sample of middle and high school students (Ahmed et al., 2016). The authors reported that when method variance was controlled, inference making had the largest effect on reading comprehension. This was followed by knowledge, a latent construct that included word knowledge and background knowledge. Findings across examinations of the DIME model suggest that readers with better inference-making skills, background knowledge, and vocabulary knowledge are better able to comprehend connected text (Ahmed et al., 2016; Cromley & Azevedo, 2007; Cromley et al., 2010).

CONTACT Elizabeth Swanson a easwanson@austin.utexas.edu The Meadows Center for Preventing Educational Risk, The College of Education, The University of Texas at Austin, 1912 Speedway D4900, Austin, TX 78712, USA. Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/urwl. 2017 Taylor & Francis Executive functions appear to have some bearing on reading comprehension as well. For example, working memory is well recognized as a predictor of reading comprehension (e.g., Arrington, Kulesz, Francis, Fletcher, & Barnes, 2014; Borella, Carretti, & Pelegrina, 2010; Daneman & Merikle, 1996; Palladino & Ferrari, 2013). However, it has been argued that the relation between working memory and reading comprehension is at least partly mediated by attention control (Friedman, Rapport, Raiker, Orban, & Eckrich, 2017); that is, working memory is affected by the ability to resist attentional capture from distracting stimuli in order to accurately attend to the task at hand and prevent mind wandering (McVay & Kane, 2012). Within the context of text reading, attention control, measured by the ability to suppress irrelevant information, is related to reading comprehension (Borella et al., 2010; Pimperton & Nation, 2010; Roberts et al., 2014), albeit to a small extent in some investigations (e.g., Barnes, Stuebing, Fletcher, Barth, & Francis, 2016; Henderson, Snowling, & Clarke, 2013).

Attention control is a domain-general capacity that determines the contents of working memory by (a) actively maintaining information in working memory that is relevant to the task at hand and also (b) inhibiting information that is irrelevant (Engle & Kane, 2004; McVay & Kane, 2012). In one example, self-reported instances of inattention during reading interfere with undergraduate students' ability to retrieve factual information (Smallwood, McSpadden, & Schooler, 2008). Perhaps more compelling is a report that among undergraduate students, inattention (i.e., mind wandering) is a significant mediator in the relationship between working memory capacity and reading comprehension (McVay & Kane, 2012), which suggests that the relationship between working memory and reading comprehension is explained, at least in part, by an ability to attend to the task at hand and resist interference from non-task-related factors. Specific to text reading among undergraduate students, mind wandering occurs more frequently when one is reading difficult versus easy texts and has a relatively greater effect on comprehension for these more difficult texts (Feng, D'Mello, & Graesser, 2013). This phenomenon may be particularly problematic for struggling readers. For this group of students, almost all text reading is difficult and is probably exceedingly difficult for struggling readers with high levels of inattention. Therefore, it is important to understand the relation between working memory and reading comprehension among struggling readers with and without inattention. One way to address this question concerning the roles of working memory and attention in struggling readers is to investigate whether working memory and other comprehension-related factors differentially predict reading comprehension in individuals with and without difficulties in attention.

The purpose of this study was to determine to what extent inference making, decoding, vocabulary, and working memory predict reading comprehension among seventh- through 12th-grade struggling readers who score (a) high on inattention and low on hyperactivity, (b) high on both, or (c) low on both. The following research question guided our work: What student-level variables (inference making, decoding, vocabulary, and working memory) predict reading comprehension among struggling readers with and without inattention and/or hyperactivity? We hypothesized that (a) vocabulary and inference making would most strongly predict reading comprehension across all student groups and (b) working memory would more strongly predict reading comprehension among students who score low on measures of inattention.

Method

Participants

A total of 1,765 students in Grades 7–12 in four school districts within the greater Houston area were initially invited to join the study. Researchers secured institutional review board approval for the study and collected consent and assent prior to student participation in the study. Students were screened on decoding and general intelligence. Students who scored at or above the 20th percentile on the Woodcock–Johnson III Tests of Achievement (WJ–III) Letter Word Identification subtest (Woodcock, McGrew, & Mather, 2001) and had a verbal and/or fluid intelligence score at or above 70 as indicated by the Kaufman Brief Intelligence Test–2 (Kaufman & Kaufman, 2004) were eligible to

	Full sample ($N = 414$)		Class 1 (<i>n</i> = 203)		Class 2 (n = 69)		Class 3 (n = 142)	
Variable	n	%	n	%	n	%	n	%
Gender								
Male	248	59.9	98	48.3	52	75.4	98	69
Female	166	40.1	105	51.7	17	24.6	44	31
Ethnicity								
Hispanic	232	56	124	61.1	38	55.1	70	49.3
White	84	20.3	34	16.7	15	21.7	35	24.6
African American	86	20.8	38	18.7	16	23.2	32	22.5
Asian/Pacific Islander	4	1	4	2	0	0	0	0
Multiple	4	1	2	1	0	0	2	1.4
American Indian/Alaska Native	4	1	1	.5	0	0	3	2.1
Economic disadvantage								
No economic disadvantage	108	26.1	50	24.6	16	23.2	42	29.6
Free lunch	257	62.1	130	64	47	68.1	80	56.3
Reduced lunch	46	11.1	22	10.8	6	8.7	18	12.7

Table 1. Descriptive statistics by class membership.

Note. Class 1 = 1 low inattention + low hyperactivity; Class 2 = high inattention + high hyperactivity; Class 3 = high inattention + low hyperactivity.

continue in the study. These 1,196 students (n = 520 struggling and n = 676 adequate comprehenders) were tested on the larger assessment battery. From this larger sample, the subset of 414 struggling readers (59.9% male) who completed all of the required assessments was included in the present study. Students were identified as struggling readers if they failed the Texas Assessment of Knowledge and Skills (TAKS) reading test or scored within 1 standard error of measurement above the minimum passing score. Table 1 contains the demographic characteristics of the study participants.

Procedures

Each student was tested over two or three sessions within 1 week. Members of the research team trained to adhere to standardized administration procedures administered all measures. The Gates-MacGinitie Reading Tests were administered in a group setting (MacGinitie, MacGinitie, Maria, & Dreyer, 2000). All other measures were administered individually.

Measures

Screening

Two measures were used to screen students for inclusion in the sample. First, we administered the Kaufman Brief Intelligence Test–2 Verbal Knowledge subtest, an individually administered test of receptive vocabulary and general word knowledge (Kaufman & Kaufman, 2004). The examiner asks a question and the participant is asked to choose one of six illustrations that best corresponds to the question. Internal consistency coefficients (split-half) for the Verbal Knowledge subtest for Grades 6–12 range from. 89 to. 94. Second, the TAKS reading test (Texas Education Agency, 2003) was used to identify the struggling reader sample. The TAKS is a criterion-referenced test of reading comprehension aligned with grade-based reading standards. Students read expository and narrative texts and answer a series of multiple-choice, short-answer, and essay questions. The internal consistency (coefficient alpha) of the 2010 TAKS (Grades 7–12) ranged from. 73 to. 89, and 2011 TAKS alphas (Grades 7–12) ranged from. 87 to. 89.

Decoding

The Phonemic Decoding Efficiency and Sight Word Reading Efficiency subtests of the Test of Word Reading Efficiency (Torgesen et al., 1999) were used in combination with the WJ–III Letter Word Identification subtest to create a latent variable representing decoding. Both Test of Word Reading Efficiency subtests are individually administered tests. The Sight Word Reading Efficiency subtest is designed to measure the accuracy and speed of read-word reading. Students are given a list of

104 words that are increasingly challenging and asked to read the words as accurately and quickly as possible. The number of words read correctly within 45 s is recorded. The Phonemic Decoding Efficiency subtest is a measure of students' ability to pronounce phonemically regular nonwords accurately and fluently. There are 63 items on this subtest. The two subtests demonstrate good alternate-forms coefficients of. 91 to. 97, respectively. The WJ–III Letter Word Identification subtest assesses students' ability to read real words. Students name letters and then read words aloud from a list that gets progressively more difficult. The subtest has excellent psychometric properties, all exceeding. 90.

Working memory

The Recognition Memory test of the Goldman-Fristoe-Woodcock (GFW) Auditory Memory Tests (Goldman, Fustoe, & Woodcock, 1974) was used to assess working memory. This task measures the ability to hold previously heard words in memory and judge whether the next word is one that was heard prior in the list; therefore, the task requires concurrent storage and processing of a continuous list of stimuli. The task was administered individually with a computer. A student heard a list of words through the headphones connected to the computer. After hearing each word, the student was asked to say "yes" if he or she had heard that word before and "no" if he or she had not. The examiner wrote down the student responses. Every word was repeated twice in the list of words. Some of the repeated words had no intervening words, such as "sugar," "sugar," (0-back item), and others had between one and eight intervening words. An example with two intervening words would be "rolling," "wretched," "magic," "rolling" (2-back item). The task was composed of five practice items and 110 test items administered in three blocks. The test was composed of 55 words, with each word repeated twice, making a total accuracy raw score of 110. The order of the *n*-back items was randomized. Reliability coefficients (Kuder-Richardson formula 20) for the entire tested sample for Grades 6-12 ranged from. 71 to. 93 (M = .88) for raw scores and from. 88 to. 94 (M = .90) for standardized scores. The total accuracy score was used in analyses collapsing across *n*-back conditions.

Vocabulary

Vocabulary was measured using the Gates–MacGinitie Vocabulary subtest (MacGinitie et al., 2000). Each test word is presented in a brief context. The student is expected to select the word or phrase that means the same as the test word. Alternate-forms reliability coefficients are. 83 to. 89 for Grades 7–9 and. 75 to. 88 for Grades 10–12.

Inference making

Inference making was measured using the Bridge-IT task (Barth, Barnes, Francis, Vaughn, & York, 2015), an individually administered computer task designed to measure the effect of two text-based features on students' ability to bridge inferences: (a) textual distance (near vs. far) and (b) concept consistency (consistent vs. inconsistent continuation). The Bridge-IT comprises 32 five-sentence narrative passages. Students were randomly presented with 32 passages that began with four sentences of text followed by the statement sentence. After reading each passage, students pressed the space bar and were presented with a 3- to 12-word continuation sentence. Students were asked to indicate whether the test sentence represented a consistent continuation of the passage by pressing a green button or an inconsistent continuation by pressing a red button. Each student received eight near-consistent items, eight far-consistent items, eight near-inconsistent items, and eight far-inconsistent items in random order. See Table 2 for examples of these item types. For each item, reaction time was obtained for passage reading time and continuation sentence reading time. Accuracy data were obtained for each continuation sentence judgment. Average reliability coefficients (Kuder–Richardson formula 20) are. 85 for near-consistent, 83 for far-consistent, and. 87 for far-inconsistent continuations.

Reading comprehension

The Gates-MacGinitie Reading Comprehension subtest (MacGinitie et al., 2000) was used to measure reading comprehension. In this test, students read passages followed by a small number of associated

Near	Far	Consistent	Inconsistent	Example
X		Х		Tim went to Mike's birthday party in the afternoon. The birthday party had an ancient Egypt theme. At the party they played some video games and then opened presents. Mike's mom served a delicious birthday cake. Tim was very full because his mother had made him a very big lunch. (test sentence): Tim asked if he could take his cake home to eat later.
	х	X		Tim was very full because his mother had made him a very big lunch. Tim went to Mike's birthday party in the afternoon. The birthday party had an ancient Egypt theme. At the party they played some video games and then opened presents. Mike's mom served a delicious birthday cake. (test sentence): Tim asked if he could take his cake home to eat later.
х			X	Tim went to Mike's birthday party in the afternoon. The birthday party had an ancient Egypt theme. At the party they played some video games and then opened presents. Mike's mom served a delicious birthday cake. Tim was very full because his mother had made him a very big lunch. (test sentence): Tim ate a large slice of cake and asked for seconds.
	х		X	Tim was very full because his mother had made him a very big lunch. Tim went to Mike's birthday party in the afternoon. The birthday party had an ancient Egypt theme. At the party they played some video games and then opened presents. Mike's mom served a delicious birthday cake. (test sentence): Tim ate a large slice of cake and asked for seconds.

Table 2. Examples of items from the Bridge-IT task.

multiple-choice questions. Alternate-forms reliability coefficients are adequate for the assessment and are. 83 for Grade 7, 83 for Grade 8, 80 for Grade 9, 83 for Grade 10, 74 for Grade 11, and. 89 for Grade 12.

Attention and hyperactivity

Strengths and Weaknesses of ADHD and Normal Behavior Rating Scales was used to rate students' attention and hyperactivity (Swanson, 1995). The SWAN is an individually scored 18-question teacher rating scale based on the *Diagnostic and Statistical Manual of Mental Disorders* (American Psychiatric Association, 2013) and is used to assess for the indication of attention-deficit/hyperactivity disorder (ADHD) in children. Each question on the SWAN is scored on a 7-point scale ranging from *far below average* (-3) to *far above average* (3). The first nine questions correspond to the attention scale and the last nine questions correspond to the hyperactivity scale. The maximum score on the SWAN is 63. The more attention problems a student has, the lower his or her score on the rating scale will be. Internal consistency is. 95, and test–retest coefficients range from. 71 to. 76 (Lakes, Swanson, & Riggs, 2012).

Data analysis

To answer our research questions, we analyzed the data in three steps. In the first step, we used factor mixture modeling (FMM) to group participants into discrete classes based on their scores on the SWAN. In the second step, after fitting the most appropriate number of classes through an iterative process, we tested the across-class equivalence of the measurement models for the latent variables (inference making, vocabulary, and decoding). In the third step, we used multigroup structural equation modeling (MG-SEM) to test the association between cognitive predictors and reading comprehension across the classes identified in the FMM. Models were fitted using Mplus Version 7.31 (L. K. Muthén & Muthén, 1998–2015).

FMM

To capture the unobserved heterogeneity within a population and classify students into groups based on SWAN data we used FMM (Lubke, 2007; Lubke & Muthén, 2005). FMM is a useful technique because both diagnostic class membership and the range of severity within and across diagnostic classes can be modeled concurrently (Clark et al., 2013). The latent class variable allows for the classification of individuals into groups while the two factors model the heterogeneity of the ADHD behavior within the latent class.

We separately examined the fit of several models, each consisting of two latent factors (inattention and hyperactivity) and one to five latent classes. To evaluate model fit and determine the optimal number of classes, we used (a) Akaike's information criterion (AIC; Akaike, 1987), (b) the Bayesian information criterion (BIC; Schwarz, 1978), (c) the adjusted Bayesian information criterion (ABIC; B. Muthén, Asparouhov, & Nylund, 2007), (d) the index for entropy (Celeux & Soromenho, 1996), and (e) the Vuong–Lo–Mendell–Rubin likelihood ratio test (Lo, Mendell, & Rubin, 2001). Lower AIC, BIC, and ABIC values indicate better fit to the data and increased probability of replication. Entropy values range from 0 to 1, with a value of 1 indicating perfect class membership. The Vuong–Lo–Mendell–Rubin likelihood ratio test compares a model with *c* classes to a model with c - 1 classes. A nonsignificant likelihood ratio test indicates that the additional classes are not needed to adequately describe the data and that the model should be rejected in favor of the more parsimonious c - 1 class model. Because there are no definitive tests of the true number of classes (B. Muthén et al., 2007), model selection was also based on substantive theory as well as statistical support.

Testing the measurement model

As a preliminary step, we assessed the measurement invariance of the measurement models to confirm that the relationship between the observed variables and their underlying latent variables was the same across the classes identified in the FMM (Meredith & Horn, 2001). Three models were tested for invariance analyses. Configural invariance was initially specified as a baseline model to determine whether the pattern of factor structures was the same across time. If configural invariance was supported, further parameter constraints were imposed on the model. First factor loadings were constrained to be equal across groups to test the invariance of the factor loadings. A difference test was then conducted to determine whether the baseline model was significantly different from the loading-constrained model. A nonsignificant difference test indicated that the strength of the relationship between each item and its factor was the same across groups, satisfying metric invariance. Furthermore, based on the metric invariance model, intercepts were constrained to be equal across groups. Difference tests between the metric invariance model and scalar invariance model were also conducted. A nonsignificant difference test meant that intercepts were invariant across groups, satisfying scalar invariance. To determine whether constraints in each model yielded a significant decrease in fit, we conducted chi-square difference testing and calculated comparative fit index (CFI) decrements (Cheung & Rensvold, 2002). Measurement model results are summarized in Table 3.

Factor and model	χ^2	df	Model comparison	$\Delta \chi^2$	∆df	р	CFI	ΔCFI
Inference making								
1a. Configural invariance	18.597	15					.99	
2a. Metric invariance	25.562	25	2a vs. 1a	7.341	10	.69	.99	.00
3a. Scalar invariance	44.556	35	3a vs. 2a	19.298	10	.04	.99	.00
Vocabulary								
1b. Configural invariance	0	0					1.00	
2b. Metric invariance	7.509	4	2b vs. 1b	7.509	4	.11	.99	.01
3b. Scalar invariance	9.969	8	3b vs. 2b	2.482	8	.65	.99	.00
Decoding								
1c. Configural invariance	0	0					1.00	
2c. Metric invariance	4.293	4	2c vs. 1c	4.293	4	.37	.99	.01
3c. Scalar invariance	12.323	8	3c vs. 2c	7.877	4	.09	.99	.00

Table 3. Fit indices for testing measurement invariance.

Note. CFI = comparative fit index.

Testing the structural model

To examine the effects of cognitive predictors on reading comprehension, we used MG-SEM in Mplus (L. K. Muthén & Muthén, 1998–2015), with classes as the grouping variable. Multigroup analysis allowed us to test whether the pattern of relationship between cognitive predictors and reading comprehension differed across classes. In addition, to compare the strength of the association between the predictors and reading comprehension, we used the MODEL CONSTRAINT command using the NEW option in Mplus. We also used bootstrapping and requested that Mplus produce bias-corrected bootstrap confidence intervals (CIs) for the difference between two paths (Lau & Cheung, 2012). We requested 1,000 bootstrap samples drawn with replacement from the full data set of 414 cases.

Results

FMM

Fit indices are presented in Table 4. Values for the AIC, BIC, and ABIC were the lowest for the fourgroup solution; however, there was a sharp decrease in values up to three classes and only minor improvements in model fit after three classes. Values for the Vuong–Lo–Mendell–Rubin test suggested no significant improvement in model fit when we added the fifth class, which suggests that the four-class solution was preferable to the five-class solution. Because there are no definitive tests of the true number of classes (B. Muthén et al., 2007), model selection was based on substantive theory as well as interpretability of classes (see Figures 1–3). Based on this, we selected the three-class solution as the final model. Figures 1–3 show the odds of scoring in the highest response category of the 18 recoded SWAN questionnaire items across the two-, three-, and four-class solutions.

Representing the largest of the three groups, Class 1 had 203 students who scored low on both the inattention and hyperactivity/impulsivity items of the SWAN questionnaire. Class 1 was labeled *low inattention* + *low hyperactivity*. Class 2 had 69 students. As Figure 2 shows, the odds pertaining to the inattentiveness items and the odds pertaining to the hyperactivity items were both elevated in Class 2. This group was thus defined as *high inattention* + *high hyperactivity*. Class 3 had 142 students who had high scores on the inattention items of the SWAN questionnaire while scoring relatively lower on the hyperactivity/impulsivity items. We refer to this group as students with *high inattention* + *low hyperactivity*. Table 5 presents descriptive data on these students.

Measurement model equivalence

As shown in Table 3, full measurement invariance was evident for inference making ($\Delta CFI = .00$ for metric/configural and scalar/metric comparisons and $\Delta CFI = .00$ for scalar/metric comparisons), decoding ($\Delta CFI = .01$ for metric/configural and scalar/metric comparisons and $\Delta CFI = .00$ for scalar/metric comparisons), and vocabulary ($\Delta CFI = .01$ for metric/configural and scalar/metric comparisons and $\Delta CFI = .00$ for scalar/metric comparisons). Therefore, we can conclude that the measurement properties of the three latent variables were identical across the three classes.

Table 4. Fit indices from model testing.

			5			
Classes	AIC	BIC	ABIC	Entropy	TECH11	Class composition
2	11,034.83	11,336.77	11,098.77	.96	.00	$n_1 = 179, n_2 = 235$
3	10,235.91	10,549.93	10,302.42	.95	.03	$n_1 = 203, n_2 = 69, n_3 = 142$
4	9,882.96	10,209.05	9,952.02	.96	.04	$n_1 = 207, n_2 = 132, n_3 = 62, n_4 = 13$
5	9,561.04	9,899.21	9,632.66	.95	.07	$n_1 = 15, n_2 = 130, n_3 = 55, n_4 = 167, n_5 = 47$

Note. The numbers reported in the far right column represent the distribution of the participants across the classes for that particular model. AIC = Akaike's information criterion; BIC = Bayesian information criterion; ABIC = sample size-adjusted Bayesian information criterion; TECH11 = Vuong-Lo-Mendell-Rubin adjusted likelihood ratio test.

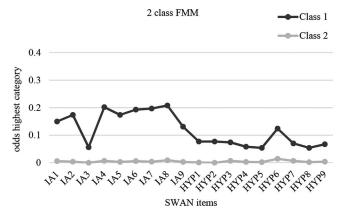


Figure 1. The probability of scoring in the highest response category of the 18 SWAN items compared to scoring in any of the other categories in the two-class mixture model. FMM = factor mixture modeling; SWAN = Strengths and Weaknesses of ADHD and Normal Behavior Rating Scale; IA = inattention; HYP = hyperactivity/impulsivity; ADHD = attention-deficit/hyperactivity disorder.



Figure 2. The probability of scoring in the highest response category of the 18 SWAN items compared to scoring in any of the other categories in the three-class mixture model. FMM = factor mixture modeling; SWAN = Strengths and Weaknesses of ADHD and Normal Behavior Rating Scale; IA = inattention; HYP = hyperactivity/impulsivity; ADHD = attention-deficit/hyperactivity disorder.

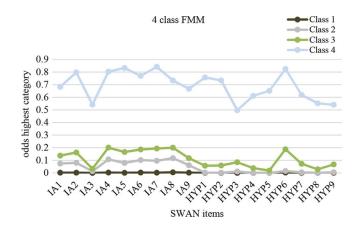


Figure 3. The probability of scoring in the highest response category of the 18 SWAN items compared to scoring in any of the other categories in the four-class mixture model. FMM = factor mixture modeling; SWAN = Strengths and Weaknesses of ADHD and Normal Behavior Rating Scale; IA = inattention; HYP = hyperactivity/impulsivity; ADHD = attention-deficit/hyperactivity disorder.

	Table 5.	Descriptive	statistics	for the	e three-class	solution.
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Variable	Class	п	М	SD
Attention				
SWAN: Inattention	1	203	-6.13	7.57
	2	69	15.72	6.96
	3	142	9.33	5.48
SWAN: Hyperactivity	1	203	-9.49	8.60
	2	69	13.46	6.13
	3	142	-1.99	7.61
SWAN: Total raw score	1	203	-15.62	15.04
	2	69	29.19	10.46
	3	142	7.34	7.94
Reading comprehension				
Gates-MacGinitie	1	198	517.82	30.21
	2	65	512.2	28.06
	3	138	516.76	26.74
Inference making				
Causal inference	1	201	2.63	0.73
	2	68	2.64	0.78
	3	140	2.60	0.80
Temporal inference	1	201	2.48	0.71
	2	68	2.46	0.75
	3	140	2.41	0.74
Bridging inferences near correct	1	194	0.74	0.16
	2	61	0.68	0.16
	3	134	0.74	0.16
Bridging inferences far correct	1	191	0.54	0.16
5 5	2	63	0.53	0.15
	3	129	0.56	0.16
Bridging inferences near reaction time	1	194	2.13	0.61
5.5	2	61	2.03	0.50
	3	134	2.1	0.67
Bridging inferences far reaction time	1	191	2.08	0.62
	2	63	1.90	0.45
	3	129	1.94	0.55
Decoding				
WJ–III Letter Word Identification	1	203	95.46	6.26
	2	69	93.64	6.15
	3	142	96.20	7.01
TOWRE PD	1	201	93.09	10.35
TOTALE TO	2	69	91.20	10.75
	3	138	91.74	10.29
TOWRE SW	1	201	89.94	9.25
	2	69	88.48	7.75
	3	139	88.88	9.58
Memory	5	155	00.00	2.50
Goldman-Fristoe-Woodcock (GFW)	1	170	41.67	8.91
Recognition Memory	1	170	41.07	0.91
Recognition Memory	2	52	38.90	8.37
	3			
Vocabulary	3	114	41.25	9.44
Gates–MacGinitie Vocabulary	1	100	515.02	07 FC
Gales-MacGinille VocaDulary	1 2	199	515.93	27.79 27.01
		65	512.42	
Packground Knowledge 10, 12	3	138	518.5	26.82
Background Knowledge 10–12	1	202	18.91	5.12
	2	68	17.49	4.93
	3	140	19.11	4.55
Background Knowledge 7–9	1	201	20.82	3.49
	2	69	19.93	3.25
	3	140	21.09	3.45

Note. SWAN = Strengths and Weaknesses of ADHD Symptoms and Normal Behavior Rating Scale; WJ-III = Woodcock-Johnson III Tests of Achievement; TOWRE PD = Test of Word Reading Efficiency Phonemic Decoding Efficiency; TOWRE SW = Test of Word Reading Efficiency Sight Word Reading Efficiency; ADHD = attention-deficit/hyperactivity disorder.

		Class 1			Class 2			Class 3		
		BC 95% CI			BC 95% CI			BC 9		
Predictor	β	Cl _{lower}	Cl _{upper}	β	Cl _{lower}	Cl _{upper}	β	Cl _{lower}	Cl _{upper}	
Inference making	28.17***	18.32	36.11	26.66***	12.20	40.73	20.99***	8.46	45.99	
Decoding	-0.79	-2.65	0.92	0.76	-1.12	2.49	0.29	-1.10	1.86	
Memory	0.61*	0.09	1.21	0.78	0.04	1.717	0.08	-0.46	0.64	
Vocabulary	0.97***	0.86	1.09	1.07***	0.85	1.35	0.81***	0.56	1.02	

Table 6.	Results	of the	structural	equation	modeling	analysis.
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Note. BC 95% CI = bias-corrected 95% confidence interval (if it does not contain 0, the effect is significant). *p < .05. ***p < .001.

MG-SEM

MG-SEM was performed on reading comprehension predicted by comprehension-related reading and cognitive variables. Those variables included inference making, decoding, working memory, and vocabulary. The results from the MG-SEM analysis with the constrained measurement parts and free estimates of the regression coefficients for the structural part of the model for each group are shown in Table 6.

The model fit for estimating the effect of inference making on reading comprehension was good $(\chi^2 = 90.234, df = 50, \text{ root mean square error of approximation [RMSEA]} = .08, 95\% \text{ CI } [0.05, 0.10],$ CFI = .97, Tucker-Lewis index [TLI] = .96). The parameter estimates in the respective groups indicated that inference making had a statistically significant effect on reading comprehension in all three groups ($\beta = 28.17$, SE = 4.61, p = .00, for Class 1; $\beta = 26.66$, SE = 7.41, p = .00, for Class 2; and $\beta = 20.99$, SE = 8.66, p = .02, for Class 3). That is, an increase in inference making was associated with increased scores on reading comprehension in all three groups. The model testing the effect of decoding on reading comprehension fit the data well ($\chi^2 = 25.022$, df = 13, RMSEA = .08, 95% CI [0.03, 0.13], CFI = .97, TLI = .95). Results indicated no significant association between decoding and reading comprehension among students in any of the classes ($\beta = -0.79$, SE = 0.89, p = .38, for Class 1; $\beta = 0.76$, SE = 0.91, p = .40, for Class 2; and $\beta = 0.29$, SE = 0.77, p = .71, for Class 3). Next we tested the association between vocabulary and reading comprehension. The fit of this model was excellent ($\chi^2 = 20.304$, df = 14, RMSEA = .06, 95% CI [0.00, 0.11], CFI = .99, TLI = .98). Similar to inference making, vocabulary had a statistically significant effect on reading comprehension in all three groups ($\beta = 0.97$, SE = 0.06, p = .00, for Class 1; $\beta = 1.07$, SE = 0.13, p = .00, for Class 2; and $\beta = 0.81$, SE = 0.11, p = .00, for Class 3). Finally, working memory was predictive of reading comprehension among students in the low inattention + low hyperactivity group ($\beta = 0.61$, SE = 0.31, p = .05) and in the high inattention + low hyperactivity group ($\beta = 0.78$, SE = 0.43, p = .07). It is important to note that in the high inattention + high hyperactivity group, the p value approached statistical significance, but the bias-corrected bootstrap CI did not include 0.

In addition, when we compared the strength of association between the predictors and reading comprehension we found that none of the paths differed significantly across classes (see Table 7).

					Differences					
	C	lass 1 – Class	2	C	lass 1 – Class	3	Class 2 – Class 3			
		BC 95% CI			BC 95% CI			BC 95	95% Cl	
Predictor	β	Cl _{lower}	Cl _{upper}	β	Cl _{lower}	Cl _{upper}	β	Cl _{lower}	Cl _{upper}	
Inference making	1.51	-13.35	20.44	7.18	-13.35	22.53	5.67	-19.76	24.91	
Decoding	-1.55	-4.29	0.97	-1.08	-3.49	1.07	0.47	-1.83	2.73	
Memory	-0.17	-1.35	0.78	0.53	-0.33	1.34	0.70	-0.30	1.74	
Vocabulary	-0.10	-0.38	0.12	0.16	-0.07	0.41	0.27	-0.03	0.65	

Note. BC 95% CI = bias-corrected 95% confidence interval (if it does not contain 0, the effect is significant).

Discussion

The purpose of this study was to determine whether component skills (inference making, decoding, and vocabulary) and a cognitive correlate of reading comprehension—working memory—are related to reading comprehension among adolescent struggling readers with differing levels of inattentiveness. The results of our study indicate that vocabulary and inference making, but not decoding, predict reading comprehension outcomes among struggling readers in three groups: students with (a) low inattention and low hyperactivity, (b) high inattention and high hyperactivity, and (c) high inattention and low hyperactivity. In addition, working memory predicts reading comprehension among struggling readers with high inattention and low hyperactivity. Authors of prior research have investigated the role of cognitive and behavioral factors in reading comprehension, most frequently with adequate readers but recently with struggling readers as well. Rarely, however, have these factors been investigated among struggling readers with accompanying inattention and/or hyperactivity.

Vocabulary and inference making

We hypothesized that vocabulary and inference making would most strongly predict reading comprehension across all student groups. Our report that vocabulary and inference making are predictive of reading comprehension aligns with results from prior studies (Ahmed et al., 2016; Cromley & Azevedo, 2007; Cromley et al., 2010) and extends findings on the relation between vocabulary, inference making, and reading comprehension to being applicable among seventh- through 12th-grade struggling readers no matter their inattention or hyperactivity profile. This invariance is interesting to note when considering the nature of inattention and hyperactivity among adolescents. For diagnostic purposes, ADHD is divided into three subtypes: (a) hyperactive, (b) inattentive, and (c) hyperactive and inattentive (American Psychiatric Association, 2013). However, these subtypes are not stable over time, and inattention and hyperactivity follow different developmental trajectories (Willcutt et al., 2012). For example, preschool children who are diagnosed with hyperactivity display a decline in hyperactive behavior through age 9 although symptoms of inattention do not change significantly (Willcutt et al., 2012). The results presented here may reflect this developmental shift in the nature and effect of hyperactivity in that by adolescence, students are less likely to display high levels of hyperactivity. This developmental trend is supported by the few number of students we identified in Class 2 with high inattention and hyperactivity (n = 69) compared to Class 3 with high inattention and low hyperactivity (n = 142). In sum, among adolescent struggling readers, the relation between vocabulary or inference making and reading comprehension does not seem to be dependent on an inattention or hyperactivity profile. A different pattern of findings might be obtained for younger children with symptoms of inattention and/or hyperactivity.

Working memory

We thought that working memory might more strongly predict reading comprehension among students with low levels of inattention in line with theories of working memory that strongly link working memory and inattention (e.g., Alloway, Gathercole, Kirkwood, & Elliott, 2009; Engle & Kane, 2004; Lui & Tannock, 2007). Our findings confirm this hypothesis. However, the findings also indicate that the relation between working memory and reading comprehension is significant for students who are not rated as being either inattentive or hyperactive, and the relation between working memory and reading comprehension approaches significance in the high inattention + high hyperactivity group. In other words, regardless of the presence of inattention and/or hyperactivity, working memory is related to reading comprehension.

We can make some observations based on the descriptive working memory and inattention data. First, consider the working memory scores presented in Table 5. We see that on this measure of working memory, scores for students in the low inattention + low hyperactivity and high

inattention + low hyperactivity groups were exceedingly similar. However, students in the high inattention + high hyperactivity group performed more poorly on working memory than students in either of the two other classes. This difference in performance on the working memory measure may be due to this added hyperactivity factor; however, we think it is more likely to be related to the severity of inattention symptoms. Considering the inattentiveness scores for the three groups in Table 5, it becomes apparent that students in Class 2 (high inattention + high hyperactivity) exhibit the highest score on inattentiveness, one that is much higher than that of students in Class 3 (high inattention + low hyperactivity). According to this observation, the difference in the working memory scores may be due to a threshold effect of inattention. In other words, as inattention rises, it affects working memory but only when it is sufficiently high enough. This evidence may support the supposition that students with a greater ability to attend to relevant information and suppress distractors may perform better on measures of working memory until an inattention threshold is reached, at which point inattention then impairs working memory. This diverges slightly from McVay and Kane's (2012) executive attention theory of working memory, which reports that working memory's role is mediating in nature between working memory and reading comprehension. However, our hypothesis is plausible, and it would be interesting to determine the impact of inattention on working memory itself. It could be that inattention is related to working memory and is also a mediator in the relationship between working memory and reading comprehension. Confirming this hypothesis will require additional experimental investigation.

Implications for practice

Findings from this study indicate that vocabulary, inference making, and working memory, but not decoding, predict reading comprehension regardless of inattention or hyperactivity level. The Institute of Education Sciences published a report detailing best practice for improving adolescent literacy (National Center for Education Evaluation and Regional Assistance, 2008). In the report, the authors recommended providing explicit vocabulary instruction and opportunities for extended discussion of text meaning and interpretation, including inference making. Findings from this study provide support for those recommendations in that these skills are predictive of reading comprehension among struggling readers, no matter their level of inattention or hyperactivity. The idea of providing working memory interventions is an interesting one. Although it may seem intuitive that one can improve working memory through intervention, a recent meta-analysis of working memory interventions (Melby-Lervag & Hulme, 2013) provided evidence that this might not be the case. It seems that although memory training interventions produce short-term effects, they do not generalize to other skills (e.g., verbal ability, word decoding, attention inhibition). Effects are also not maintained over time, which casts doubt on the clinical relevance of working memory interventions, particularly when used as methods for enhancing cognitive functioning.

Limitations

Several limitations of this study may be addressed in future work. There were some measurement issues regarding the interrelated nature of working memory and inattention. Using more than one measure of working memory may shed some light on which assessments are truly targeting working memory alone. Furthermore, there has been some criticism of whether continuous performance memory tasks such as the one we used measure recognition-based processes to a greater extent than they measure central executive aspects of working memory (e.g., Kane, Conway, Miura, & Colflesh, 2007). Finally, the lowest of decoders were not included in this study. This is reflected in the truncated scores for letter word identification. Indeed, we only accepted students into the study if they had a Letter Word Identification score above the 20th percentile for grade. Future research is necessary to see whether these patterns of reading comprehension prediction might be replicated among adolescents who also have significant deficits in word decoding.

Conclusions

According to prior investigations investigating component skills that are related to reading comprehension (Cromley & Azevedo, 2007) among middle and high school students (Ahmed et al., 2016), inference making and knowledge (measured by a latent construct including word knowledge and background knowledge) contributed significantly to reading comprehension. Our results confirm this finding among struggling readers with differing levels of inattention and hyperactivity. In fact, these same constructs predict reading comprehension among adolescents who struggle with reading regardless of their inattention and hyperactivity levels.

This study extends the investigation of the role of cognitive and behavioral factors in reading comprehension among struggling readers with accompanying inattention and/or hyperactivity. First, we demonstrated that vocabulary and inference making, but not decoding, predict reading comprehension among struggling readers with and without inattention and/or hyperactivity. Second, we reported that working memory predicts reading comprehension among struggling readers regardless of their inattention and/or hyperactivity levels. The DIME model is a component model of reading comprehension previously studied among middle school students (Ahmed et al., 2016) and high school students (Ahmed et al., 2016; Cromley & Azevedo, 2007) as well as college students (Cromley et al., 2010). Findings from this study extend understanding of the DIME model to struggling readers with varying levels of inattention and/or hyperactivity.

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