CHILD DEVELOPMENT

Child Development, xxxx 2016, Volume 00, Number 0, Pages 1–12

Exploring the Co-Development of Reading Fluency and Reading Comprehension: A Twin Study

Callie W. Little and Sara A. Hart
Florida State University

Jamie M. Quinn and Elliot M. Tucker-Drob
University of Texas at Austin

Jeanette Taylor and Christopher Schatschneider
Florida State University

This study explores the co-development of two related but separate reading skills, reading fluency and reading comprehension, across Grades 1–4. A bivariate biometric dual change score model was applied to longitudinal data collected from 1,784 twin pairs between the ages of 6 and 10 years. Grade 1 skills were influenced by highly overlapping genetic and environmental factors. Growth in both skills was influenced by highly overlapping shared environmental factors. Cross-lagged parameters indicated bidirectional effects, with stronger effects from fluency to comprehension change than from comprehension to fluency change.

Reading comprehension (RC) is a dynamic process facilitated by fast and accurate word reading (Cain & Oakhill, 2009). The ability to successfully comprehend text is associated with greater overall academic competence and proficiency continuing beyond formal education (Berkman, Sheridan, Donahue, Halpern, & Crotty, 2011; Hernandez, 2011). Developmental models suggest that children progress through several stages on the road to adept reading ability (Chall, 1983). Under Chall's widely accepted theory of the stages of reading development, children pass through two major developmental phases: "learning to read" followed by "reading to learn." Stages 0–2 constitute the "learning to read" or prereading phase of development. During these stages, children develop knowledge of print structure, basic understanding of the rules of language, word decoding skills, and practice fluent reading skills. Stage 3 represents the transition from the "learning to read" phase to the "reading to learn" phase and comprises the mastery of fluent reading skills along with the integration of new knowledge and information from what is being read. The fourth and fifth stages expand on Stage 3 with RC strategies increasingly contributing to the successful integration of new ideas, understanding complex concepts, and making judgments about content that is read (Chall, 1983). Failure to reach proficiency by fourth grade suggests a failure to transition from Stage 2 to 3 of Chall's developmental model of reading. This failure puts students' "reading to learn" comprehension skills at risk and indicates severe challenges to future academic success (Chall & Jacobs, 2003). Increased identification and understanding of broad factors that influence the development of RC skills is crucial to assisting students through the "learning to read" stage.

Reading fluency (RF) or the ability to read connected text with speed and accuracy has been identified as a component skill that is principal in the development of RC (Adams, 1990; Fuchs, Fuchs, Hosp, & Jenkins, 2001). Oral RF (ORF) has been used as a predictor of current and future RC ability with correlations ranging from .48 to .76 (Good, Simmons, & Kame'enui, 2001; Kim, Petscher, Schatschneider, & Foorman, 2010; Petscher & Kim, 2011; Roberts, Good,

Callie W. Little was supported by the Predoctoral Interdisciplinary Fellowship, funded by the Institute of Education Sciences, U.S. Department of Education (R305B090021). The research project was supported, in part, by a grant from the *Eunice Kennedy Shriver* National Institute of Child Health and Human Development (P50 HD052120). Views expressed herein are those of the authors and have neither been reviewed nor approved by the granting agencies. The authors thank the twins and their families for their participation in making this research possible.

Correspondence concerning this article should be addressed to Sara A. Hart, 1107 W. Call Street, Tallahassee, FL 32306. Electronic mail may be sent to shart@fcrr.org.

 0009-3920/2016/xxxx-xxxx
DOI: 10.1111/cdev.12670

& Corcoran, 2005; Roehrig, Petscher, Nettles, Hudson, & Torgesen, 2008). Moreover, both initial skill level and growth rate in RF can be used to predict RC. Kim et al. (2010) demonstrated this using multilevel growth modeling, which indicated that both initial RF status and growth in RF were significant predictors of RC, longitudinally.

The relation between RF and RC is not always conceptualized as unidirectional; however, and there is some evidence that better comprehension leads to faster and more efficient word-level reading (Jenkins, Fuchs, Van Den Broek, Espin, & Deno, 2003; Smith, 2012). Some previous investigations using reaction times have found that readers use context to assist with word recognition and better understanding of context leads to improved word-reading speed and accuracy (Perfetti, Goldman, & Hogaboam, 1979; Perfetti & Roth, 1981), but investigations using more naturalistic settings (i.e., classrooms instead of lab settings) have provided mixed conclusions (Bowey, 1984; Jenkins et al., 2003).

These conflicting findings of whether RF leads to RC or vice versa allow for the additional possibility of bidirectional, dynamic, co-development between the two. The "interactive model" of reading development posits that the subcomponent skills of reading work in synthesis with each other and that the initiation of higher-order skills is not dependent on the successful execution of lower-level skills (Stanovich, 1980). Namely, higher-order processes at any level are able to compensate for shortages in lower-level processes. Since its proposal; however, the interactive theory of reading has undergone limited empirical testing (Stanovich, 2000).

Although all of these models of reading development are theoretically plausible, to test them properly requires specialized data and methods. To fully test the interactive model of reading requires both RC and fluency to be measured simultaneously and longitudinally. Testing this theory using the proper data and methods can elucidate whether there is a unidirectional influence of fluency on RC or RC on fluency versus a bidirectional influence. Using longitudinal data allows for more accurate measurement of developmental processes over cross-sectional or other data collection methods, and can be used in conjunction with advanced statistical modeling techniques such as latent change score models. In addition to identifying whether there are unidirectional or bidirectional influences between constructs, it is important to account for whether change occurs within RF or RC over time. Otherwise, it could not be determined whether any resulting unidirectional or bidirectional influences were leading to increasing or decreasing rates of change.

Latent change score models provide the opportunity to examine the functional form of change over time and can model dynamic change within and across multiple variables concurrently (Ferrer & McArdle, 2010; McArdle, 2009). Multivariate dual change score models (DCSMs) are able to explore the dynamic relations between multiple constructs by estimating several types of change: constant change for each construct, proportional or time-point-to-time-point change for each construct, and cross-lagged change between constructs. Constant change captures the average growth rate over multiple time points, and proportional change captures variance in the rate of change from time point to time point. Finally, cross-lagged estimates capture how time-specific levels in one trait relate to subsequent change in another. Commonly, these influences are referred to in terms of leading and lagging indicators. When skill-level changes in one trait primarily influence ensuing changes in another trait, that trait is considered a leading indicator of the other. The second trait is considered a lagging indicator as changes in this trait lag behind changes in the other. These models of inter individual differences in intra individual change have been applied to research on the relations between general verbal knowledge (e.g., Ferrer, Shaywitz, Holahan, Marchione, & Shaywitz, 2010; Ferrer et al., 2007; Reynolds & Turek, 2012) or more specific vocabulary knowledge (e.g., Quinn, Wagner, Petscher, & Lopez, 2015) and RC. Understanding levels of change in and between RF and RC through DCSM can help to elucidate the processes by which these constructs co develop, allowing for a test of the interactive model of reading development.

Beyond the phenotypic literature, the behavioral genetic literature has explored the extent to which genetic and/or environmental influences play a role in the relation between, and development of, RC and fluency. In particular, twin studies are unique in that they allow for the variance among traits to be decomposed into genetic and environmental influences by comparing the known similarities between monozygotic and dizygotic twin pairs. Sources of variance can be categorized as additive genetic influences (or heritability; A), shared environmental influences (i.e., nongenetic influences that make siblings more similar; C), and nonshared environmental influences (i.e., nongenetic effects that make siblings different, plus error; E). Both RF and RC have been found to be moderately to highly heritable (h^2 = .29–.84 and .32–.82, respectively) with low and mostly nonsignificant shared environmental influences and low to moderate and significant nonshared environmental influences (e^2 = .29–.39 and .30–.54, respectively; Hart, Petrill, & Thompson, 2010; Keenan, Betjemann, Wadsworth, DeFries, & Olson, 2006; Logan et al., 2013; Petrill et al., 2012). Recent applications of genetically sensitive latent growth models have found inconsistent etiological influences on reading growth (Christopher et al., 2013a; Hart et al., 2013; Logan et al., 2013; Petrill et al., 2010), with some findings indicating both significant genetic and shared environmental influences on growth in reading (Hart et al., 2013; Logan et al., 2013; Petrill et al., 2010) and another concluding that primarily genetic influences were present within the U.S. and Australian samples, but some significant shared environmental influences were present within a Scandinavian sample (Christopher et al., 2013b). Beyond the growth factor, overlapping genetic influences between initial reading levels and growth in reading have been found (Hart et al., 2013; Petrill et al., 2010), but unique genetic influences on reading growth beyond those for initial skill level have been identified as well (Logan et al., 2013). In addition, shared environmental influences have been found both to overlap between initial reading levels and rate of change (Hart et al., 2013), and to contribute uniquely to growth in reading (Petrill et al., 2010).

A recent article has also used simplex modeling to examine the time-point-to-time-point development of RF (Hart et al., 2013). Simplex modeling is able to reflect change incrementally, where status at one time point takes into account the most recent time point rather than all previous time points included together. This work indicated stable as well as novel genetic influences on reading development from first to fifth grades but only stable shared environmental influences during this period (Hart et al., 2013). The results of these previous genetically sensitive studies of reading development have provided initial evidence of the genetic and environmental influences on reading development using latent growth curve and simplex modeling techniques as separate models. Biometric DCSMs are newer and valuable developmental tools because they are able to simultaneously combine the representation of how initial status influences constant cumulative development captured by latent change score models with the incremental or time-point-to-time-point changes represented with simplex modeling while also modeling cross-lagged influences between multiple constructs. Importantly, these models also account for genetic and environmental influences on growth.

This study extends previous phenotypic and behavioral genetic research on reading development by exploring the co-development of RF and RC using biometric latent change score modeling. Initially, a bivariate phenotypic DCSM was fit to the data. Following phenotypic analyses, the bivariate DCSM was modified to include estimates of biometric influences on the mean growth across the time points. The addition of the biometric component to the DCSM allows for the decomposition of influences on growth in reading skills into genetic and environmental sources (McArdle & Hamagami, 2003). This allows for a full test of the interactive theory of reading development, as well as information on the unique and overlapping influences of genes and environment on this developmental process.

Method

Participants

Participants were obtained from the Florida Twin Project on Reading, a cohort-sequential twin project in Florida (Taylor, Hart, Mikolajewski, & Schatschneider, 2013; Taylor & Schatschneider, 2010). Achievement data from Florida's Progress Monitoring and Reporting Network (PMRN), a statewide educational database, were used for all analyses. Zygosity was determined by a five-item questionnaire (Lykken, Bouchard, McGue, & Tellegen, 1990) sent to families of twins identified through the PMRN based on a match of children in the database on last name, birth date, and school. For this study, scores from the Dynamic Indicators of Basic Early Literacy Skills (DIBELS) and the Stanford Achievement Test, 10th ed. (SAT–10) on Grades 1–4 were obtained from the PMRN database. These assessments were administered by trained school staff during the 2003–2004 to 2007–2008 school years and uploaded into the PMRN database. DIBELS scores were obtained during the spring (February through May) of each school year, and SAT–10 scores were also collected during the spring (April). Recruitment into the Florida Twin Project on Reading was conducted in stages. Therefore, twins were able to enter the project at any grade, and not all twins who entered in the 2003–2004 school year were followed to 2007–2008. Reading scores from DIBELS and SAT–10 were obtained for 1,784 twin pairs (615 monozygotic or MZ, 1,169 same sex and opposite sex dyzygotic or DZ) in first to fourth grades. Table 1 displays the number of participants with DIBELS and SAT–10 data by grade and zygosity along with mean ages at each grade level. Participants ranged in

Table 1
Mean (M), *Standard Deviation* (SD), *Minimum* (Min) *and Maximum* (Max) *Values for RF and RC in Grades 1–4*

	MZ					DZ				
Variable	*M*	*SD*	Min	Max	*n*	*M*	*SD*	Min	Max	*n*
RF Grade 1	61.45	36.19	0	215	983	69.66	37.93	0	207	1,832
RF Grade 2	100.61	38.50	0	208	912	108.07	38.66	0	220	1,666
RF Grade 3	114.89	38.08	0	236	613	121.55	36.50	12	236	1,194
RF Grade 4	116.89	38.64	3	233	215	121.02	37.08	15	216	368
RC Grade 1	557.34	51.11	437	667	302	565.54	46.70	454	667	479
RC Grade 2	604.53	42.01	494	729	200	600.78	36.68	507	729	347
RC Grade 3	636.18	41.61	503	740	380	643.90	39.06	523	763	695
RC Grade 4	652.48	36.69	581	753	94	656.65	37.16	564	753	165

Age	*M*	*SD*	*n*
Grade 1	6.76	.43	889
Grade 2	7.77	.51	852
Grade 3	8.71	.63	700
Grade 4	9.83	.47	264

Note. RF = reading fluency; RC = reading comprehension; *n* = number of individuals.

age from 6 years in Grade 1 to 10 years in Grade 4 with girls representing 49.6% of the sample. The racial and ethnic makeup of this sample included 51% White, 16.7% Black, 4.6% Multiracial, 1.7% Asian, and 2% other, with 23.9% of the full sample identifying as Hispanic. The percentage of twins who qualified for free or reduced lunch status was 56%.

Measures

Dynamic Indicators of Basic Early Literacy Skills: Oral Reading Fluency

The DIBELS ORF is a measure of fluency (reading-rate) and accuracy while reading grade-level connected text (Good & Kaminski, 2002; Good et al., 2001). This assessment is administered by allowing participants 1 min to read a passage with words omitted, substituted, and hesitations of more than 3-s scored as errors. ORF is scored as the number of correct words read within the passage. Test–retest reliabilities ranged from .92 to .97 and criterion-related validity ranged from .52 to .91 (Good & Kaminski, 2002).

Stanford Achievement Test, 10th ed.

The SAT–10 (Brace, 2003) is a widely used standardized measure of RC. Teachers administer this untimed assessment to groups of students in participating schools. Students read narrative and expository passages and then respond to a total of 54 multiple choice items. The reliability coefficient for SAT–10 on a representative, nation wide sample of students was .88. Content, criterion-related, and construct validity were established with other standardized assessments of RC (Brace, 2003). The SAT–10 subtests are vertically equated so that each has its own scale score, which provides the opportunity for comparisons across levels and the ability to measure performance over time. This feature serves to make the SAT–10 measure one that facilitates developmental modeling of RC ability.

Analyses

A bivariate DCSM allows for the estimation of several types of change. Constant change parameters (represented by the RF and RC slopes in Figure 1) capture the overall growth rate over multiple time points, and time-point-to-time-point change (represented by the latent difference scores labeled with Δ in Figure 1) captures change within construct between time points. The means of the constant change factors are represented by μ_x and μ_y. Proportional effects of the levels of construct a particular time point on its subsequent time-point-to-time-point change are represented by β_x and β_y. Finally, dynamic relations between constructs indicate the extent to which change in level of

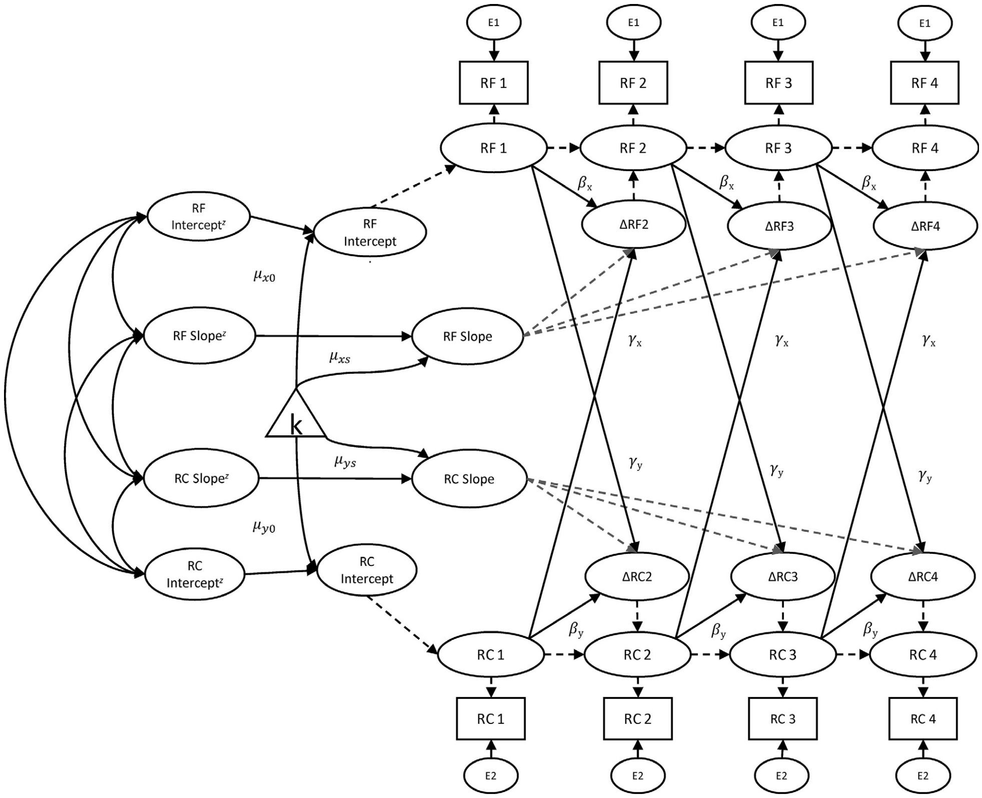

Figure 1. Bivariate dual change score model of RF and RC for four time points.
Note. RF = reading fluency; RC = reading comprehension. 1 = first grade; 2 = second grade; 3 = third grade; 4 = fourth grade. Solid lines represent freely estimated parameters. Dotted lines represent parameters set to be equal to 1. Intercepts and slopes labeled *z* have been scaled to the *z*-metric by fixing their variances to 1.0 and freely estimating their loadings such that they represent the standard deviation of the corresponding random effect.

performance for one construct could account for subsequent change in the other construct and are represented as γ_x and γ_y.

Initially, a phenotypic model based on the bivariate dynamic model proposed by McArdle and Nesselroade (2003) was fit to the data (Figure 1). Next, the phenotypic model was modified to allow for biometric modeling on the constant change factors, using a correlated factors approach. The correlated factors approach decomposes the variance of the intercept and slope factors from the constant change portion of the model into additive genetic influences (h^2), shared environmental influences (c^2) and nonshared environmental influences (e^2), represented by A, C, and E (respectively) latent factors. Simultaneously, correlations between the latent genetic (*r*A), shared environmental (*r*C), and nonshared environmental (*r*E) factors were estimated. This biometric extension of the DCSM allowed for an estimation of the univariate genetic and environmental influences of each of the constant change factors, as well as the genetic and environmental correlations between the constant change factors.

Phenotypic and biometric model fitting was conducted in Mplus 7.31 (Muthén & Muthén, 2012), with missing data handled using full-information maximum likelihood estimation. Observed raw scores for DIBELS and standard scores for SAT–10 were developmentally *z*-scored based on the means and standard deviations from the first time point (first grade) in line with recent studies using dual change score approaches to modeling RC and component skills developmentally (Quinn et al., 2015). Data for the two measures were scaled differently, and by developmentally *z*-scoring each measure, the unit of change could be conceptualized as standardized relative to the variability observed at the first time point. Each model's fit was evaluated using multiple criteria: the chi-square statistic, the root mean square of approximation (RMSEA), Bentler's comparative fit index (CFI; Hu & Bentler, 1999), and the Tucker–Lewis index (TLI). Better fitting models are indicated by chi-square values lowest and closest to the degrees of freedom. Chi-square values that are nonsignificant are preferred; however, this statistic is highly sensitive to large sample sizes and should be evaluated with caution (Kline, 2011). Values of the CFI and TLI above .95 indicate close model fit, whereas for the RMSEA, values < .08 indicate adequate model fit (Browne, Cudeck, & Bollen, 1993).

Results

Table 1 presents the descriptive information (mean, standard deviations, and minimum and maximum values) calculated on raw scores from Grades 1–4. Mean scores for both RF and RC show a developmental pattern of increasing performance with the rate of increase slowing over time. Variability for RF remains relatively fixed while variability in RC shows a gradual decrease over time. Table 2 presents correlations between all time points of RF and RC, which were high and significant. Correlations within each construct were also high and significant, with some indication of them decreasing in magnitude across time points.

Bivariate Latent Change Score Model

A full, bidirectional bivariate DCSM with proportional and cross-lagged change constrained to be equal across time points was evaluated (McArdle & Nesselroade, 2003). Resulting model fit statistics indicated the model fit was good, $\chi^2(24) = 75.424$, $p < .001$, CFI = .984, TLI = .981, RMSEA = .035 (95% CI: [.026, .044]). Figure 2 displays the structure and estimates for the phenotypic model. Constant change parameters, reflected by the mean slope, for RF were statistically significant, large in magnitude and positive (.65; 95% CI: [.59, .70]), and for RC were statistically significant, moderate in magnitude and positive (.38; 95% CI: [.28, .48]). Proportional change for both measures was statistically significant, negative, and moderate with a smaller magnitude for RF (−.80; 95% CI: [−.96, −.64]) than RC (−.91; 95% CI: [−1.15, −.65]). Cross-lagged estimates indicated a positive and large (.52; 95% CI: [.25, .79]) influence of initial RF on subsequent change in RC and a small and significant influence from initial RC to change in RF (.20; 95% CI: [.03, .36]). Statistically significant and moderate to large correlations were estimated between the constant change intercept factors ($r = .90$; 95% CI: [.83, .96]), the RC intercept factor to RF slope factor ($r = .69$; 95% CI: [.60, .78]), RF intercept factor to slope factor ($r = .91$; 95% CI: [.87, .94]), and RC intercept factor to slope factor ($r = .31$; 95% CI: [.08, .55]).

Table 2
Phenotypic Correlations for RF and RC in Grades 1–4

Variable	1	2	3	4	5	6	7
1. RF Grade 1							
2. RF Grade 2	.86*						
3. RF Grade 3	.79*	.86*					
4. RF Grade 4	.76*	.85*	.88*				
5. RC Grade 1	.73*	.66*	.62*	.64*			
6. RC Grade 2	.53*	.65*	.61*	.59*	.58*		
7. RC Grade 3	.54*	.66*	.69*	.58*	.55*	.74*	
8. RC Grade 4	.58*	.62*	.66*	.60*	.58*	.60*	.72*

Note. RF = reading fluency; RC = reading comprehension. *$p < .05$.

Next, the bivariate DCSM described earlier was modified into a biometric DCSM, where the correlations among the constant change factors were decomposed into additive genetic (A), shared environmental (C), and nonshared environmental (E) correlated factors. The model fit indicated a less than ideal, although acceptable, model fit: $\chi^2(256) = 2{,}307.75$, $p < .001$, CFI = .788, TLI = .801, RMSEA = .095 (95% CI: [.091, .098]). Parameter estimates for proportional and dynamic change in the phenotypic and biometric models were very similar; therefore, the results from the rest of the model are not re-reported.

Results of biometric portion of the model are represented in Figures 3–5. Univariate heritability, shared environmental, and nonshared environmental estimates are next to each constant change factor. In general, the heritability was high for intercept factors ($h^2 = .73$ and .62) and moderate for the slope factors ($h^2 = .42$ and .29), and subsequently, the shared environmental estimates were low for the intercept factors ($c^2 = .16$ and .25) and high for the slope factors ($c^2 = .52$ and .68). All nonshared environmental estimates were low ($e^2 = .03$–.12).

The genetic correlation (Figure 3) between the intercept factors was large and statistically significant (rA = .91), and between slope factors, the genetic correlation was almost zero (rA = −.06). The genetic correlations between the intercept and slope factors across constructs were both moderate and statistically significant (rA = −.37 and .49). The genetic correlation between the intercept and slope factors of RF was high and statistically significant (rA = .74), and the genetic correlation between the intercept and slope factors of RC was small and negative and statistically nonsignificant (rA = −.16).

All shared environmental correlations (Figure 4) were statistically significant, with the shared

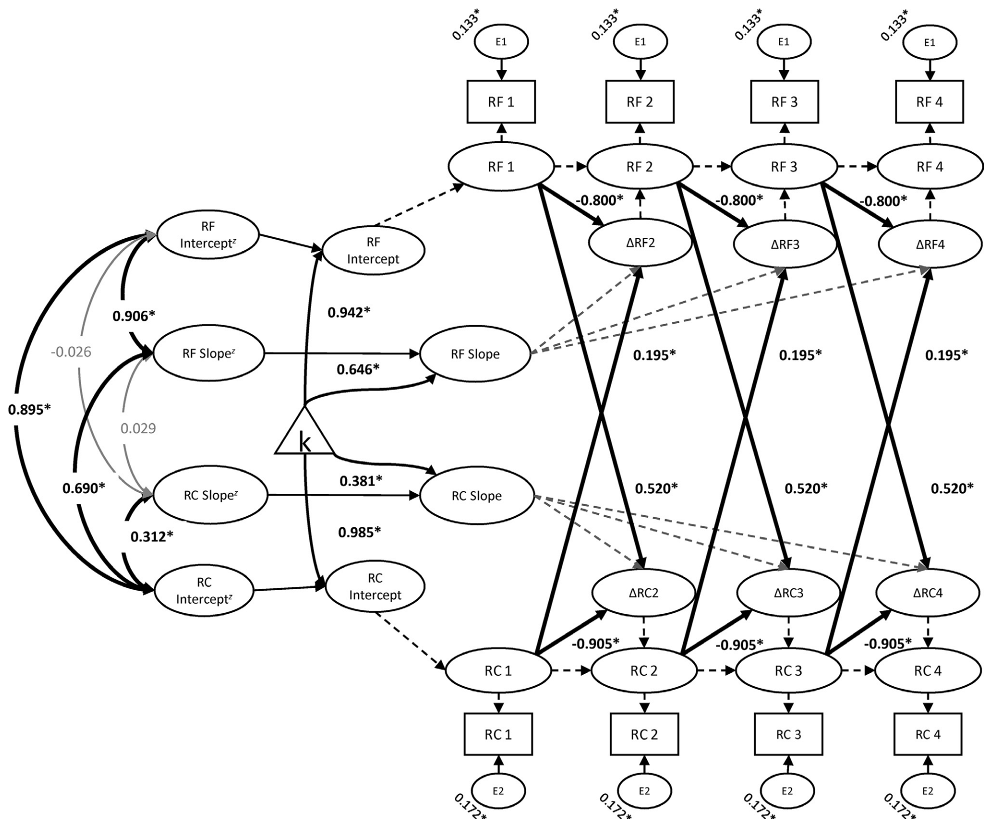

Figure 2. Unstandardized results for bivariate dual change score model of RF and RC for four time points.
Note. RF = reading fluency; RC = reading comprehension. 1 = first grade; 2 = second grade; 3 = third grade; 4 = fourth grade. Asterisks (*) and bolded lines indicate significance at $p < .05$. Solid lines represent freely estimated parameters. Dotted lines represent parameters set to be equal to 1. Intercepts and slopes labeled *z* have been scaled to the *z*-metric by fixing their variances to 1.0 and freely estimating their loadings such that they represent the standard deviation of the corresponding random effect.

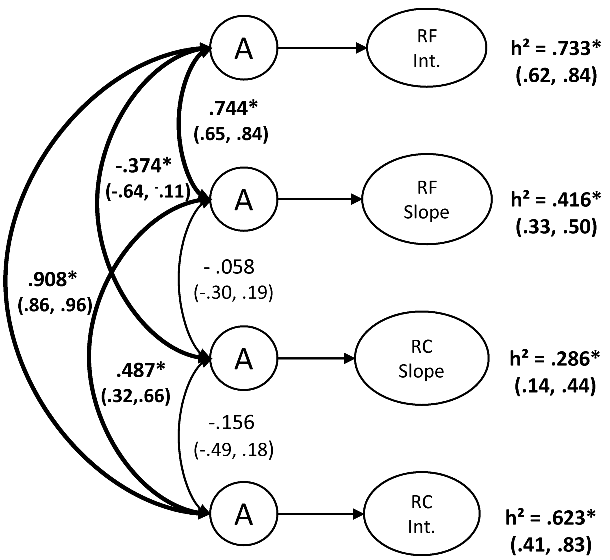

Figure 3. Univariate heritability (h^2) and genetic correlations for reading comprehension and reading fluency intercepts and slopes. 95% CI in brackets. Asterisks (*) and bolded pathways indicate significance at $p < .05$.

environmental correlation between the intercept factors (rC = .99), and between the slope factors (rC = .98), almost at unity. The remaining shared environmental correlations were moderate in magnitude. Finally, the nonshared environmental correlations (Figure 5) were large and statistically significant between the intercept factors (rE = .76) and between the intercept and slope factors for RF (rE = .88). The nonshared environmental correlation between the slope factor for RF and the intercept factor for RC was moderate and statistically significant (rE = .59). The remaining nonshared environmental correlations were low to moderate but nonsignificant.

Discussion

The dynamic codevelopment between RF and RC was examined using a biometric DCSM. The results of the bivariate DCSM elucidated several key patterns in the development and codevelopment of RF

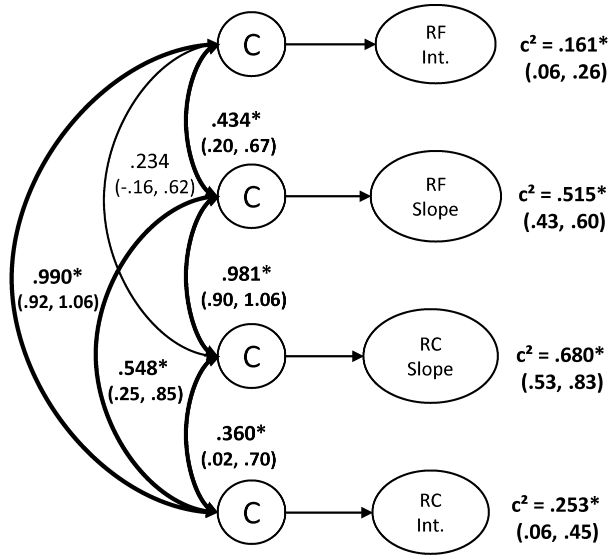

Figure 4. Univariate shared environmental estimates (c^2) and shared environmental correlations for reading comprehension and reading fluency intercepts and slopes. 95% CI in brackets. Asterisks (*) and bolded pathways indicate significance at $p < .05$.

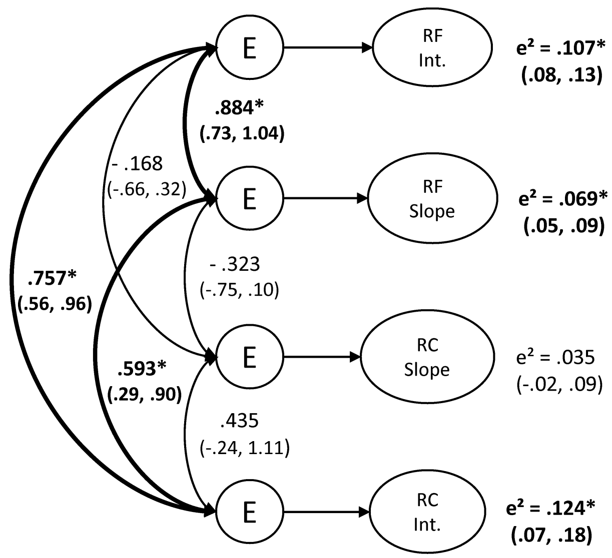

Figure 5. Univariate nonshared environmental estimates (e^2) and nonshared environmental correlations for reading comprehension and reading fluency intercepts and slopes. 95% CI in brackets. Asterisks (*) and bolded pathways indicate significance at $p < .05$.

and RC. When examining development within each reading skill from first to fourth grades, there was positive constant growth but negative proportional change (i.e., positive growth occurred across the school years but slowed over time). In total, students grew across the elementary school years, with the better initial performers growing faster across the years, and the lower performers showing greater time-point-to-time-point change. This same pattern replicates recent work using this same model with different reading skills and different samples (e.g., Hart & Quinn, 2015; Quinn et al., 2015).

The cross-lagged portion of the model examined the dynamic co-development between RF and RC, testing the dynamic "interactive theory" of reading development. Results revealed a positive and large influence of initial RF on subsequent change in RC. This result suggested RF was a leading indicator of change in RC. The directionality of this relation corroborates much of the evidence suggesting RF as a precursor skill to RC (Petscher & Kim, 2011; Roehrig et al., 2008). Although smaller, there was also a reverse relation, in that RC was also an indicator of change in RF. The finding of a bidirectional effect supports the interactive model of reading development (Stanovich, 1980), which allows for the co development of lower-level and higher-level reading skills.

Importantly, RC, as measured in the early school years as in this study, may be a somewhat different construct than RC as measured during later developmental phases (Keenan, Betjemann, & Olson, 2008). Keenan et al. (2008) provided evidence that measures of RC were more likely to encapsulate precursor skills such as decoding when administered to children who were still in the "learning to read" phase of development (i.e., when reading component skills are being actively instructed). Although these findings held across multiple test formats (e.g., cloze, short answer, multiple choice), the current measure (SAT–10) was not included in their analyses. Thus, the weak bidirectional relation found in the present analyses may not hold when examining change across later periods of development during which RC could depend more on underlying skills such as executive functioning or general intelligence and less on decoding (Carretti, Borella, Cornoldi, & De Beni, 2009; Sesma, Mahone, Levine, Eason, & Cutting, 2009; Swanson & Ashbaker, 2000). Indeed, the bidirectional relation found may be due to RC, as measured here, relying heavily on decoding.

Interventions targeting RF have a history of effective improvement of RC skills in elementary school children and children with learning disabilities (Chard, Vaughn, & Tyler, 2002; Rasinski, Samuels, Hiebert, Petscher, & Feller, 2011). However, a review examining how fluency-based interventions effect RC outcomes in older children

(Grades 6–12) revealed only a small number of interventions led to minimal gains in RC, suggesting other factors such as background knowledge or working memory may influence comprehension more as children get older (Wexler, Vaughn, Edmonds, & Reutebuch, 2008). The bidirectional nature of the co development found within this study further suggests that changes in RC may also contribute to the rate of change in RF and that building the two skills simultaneously may result in the greatest gains for general reading development. Interventions in which repeated text readings have been used to improve RF skills have long been utilized by educational researchers and practitioners, with mixed results (Levy, Abello, & Lysynchuk, 1997; O'Connor, White, & Swanson, 2007; Therrien, Kirk, & Woods-Groves, 2012). The majority of these previously used fluency training models have neglected to include comprehension-building methods, however, and the current results suggest perhaps adding specific comprehension strategies to RF training during development may serve to augment these practices and to capitalize on the nature of the codevelopment of RF and RC.

Results of the biometric portion of the model suggest that genetic and environmental influences that underlie first-grade RF are almost completely the same as the genetic and environmental influences that underlie first-grade RC. To our knowledge, this is the first bivariate genetically sensitive model of reading development over time, although work using bivariate genetically sensitive modeling of time-point-specific reading skills measured in the early school grades has also showed high genetic correlations (e.g., Petrill, Deater-Deckard, Thompson, DeThorne, & Schatschneider, 2006; Plomin & Kovas, 2005). Although not always supported (e.g., Gayán & Olson, 2003), shared environmental overlap has also been seen in other samples (Petrill et al., 2006) and using different variables in this same sample (Little & Hart, 2016). It is not surprising to find this, as RF and RC are closely related reading skills, and the high genetic correlation could represent shared genes for reading-related skills or those for more general traits such as executive function or working memory that underlie reading skill (Miller et al., 2013; Plomin & Kovas, 2005). The high shared environmental correlation could represent the extensive shared reading environment the twins share (e.g., home, kindergarten) and the high nonshared environmental correlation could represent peer influences (e.g., affiliation with academically oriented peers), and could also indicate time-specific variations that are shared with both measures given near the same time, such as illness, and test environment differences between twins.

Interestingly, there were no shared genes, yet almost completely overlapping shared environmental influences, between the growth factors of RF and RC. This suggests that how children grew in reading skills across the school years was almost entirely shared through the shared environment, such as the school (e.g., Greenwald, Hedges, & Laine, 1996) and family (e.g., Xu & Corno, 2003) environment, and not through shared genes, such as those related to learning processes (e.g., *g*). This finding mirrors and extends previous genetically sensitive univariate growth curve work, which has indicated high shared environmental estimates on the growth factor of various reading skills (e.g., Hart et al., 2013; Logan et al., 2013), though other research has shown significant genetic influence on univariate growth (Christopher et al., 2013a and b). This finding shows that whatever these shared environmental influences are on the growth of reading skills, they are shared across reading skills.

Finally, the results from the biometric modeling between intercept and growth factors indicate that in general there are some shared genetic and environmental influences but also independent genetic and environmental influences on each, as indicated by genetic and environmental correlations much less than unity. This mirrors previous work (e.g., Logan et al., 2013) and indicates that there may be different underlying skills involved at the start and then in building RF and RC, and perhaps represents different instructional practices used for RF compared with RC.

Limitations of this study include the use of single-indicator latent factors of RF and RC. The measures chosen to represent RF and RC, though widely used and reliable, do not capture the full breadth and depth of these constructs. Multiple indicators were not available at all time points for the present analyses; therefore, single-indicator latent factors were created using model constraints similar to those imposed with previous single-indicator latent change score models (Ferrer et al., 2007, 2010; Reynolds & Turek, 2012). Furthermore, the time points used in the present analyses were limited to the "learning to read" phase of reading development. Future investigations may find a different pattern of results between RF and RC using a series of developmental time points occurring later than those in the present analyses.

Finally, it is important to note that this study was conducted using measures of English orthography and other studies examining orthographies that are either more or less transparent may not follow the same pattern of results that were found within the present sample. Following this initial examination of the early stages of reading development, the codevelopment of RF and RC can be further explored across multiple orthographies, by extending the number of measures for each construct as well as extending the developmental period and increasing the sample to include other languages.

This study builds on previous literature by using a biometric bivariate DCSM to investigate the genetic and environmental influences responsible for initial skill levels and growth in reading, while accounting for proportional and coupled change. In general, where students started was genetically and environmentally mediated (by the same genes and environments), students grew across the elementary school years, mostly due to the same shared environments, with better initial performers exhibiting faster constant change across the years due to a mix of the same and different genes and environments, and lower performers showing greater time-point-to-time-point change. Future behavioral genetic studies of reading can build on these results by including additional component skills of reading in order to look for patterns of genetic and environmental influences overlapping between initial status and change over time with multiple reading-related skills. Furthermore, future studies may explore the etiologies of reading component skills at different developmental trajectories to further examine the nature of the unique genetic and environmental influences that were present for RF and RC.

The current investigation provided the unique opportunity to present novel evidence for the leading role that RF has on ensuing change in RC and, to a lesser extent, vice versa, under an interactive model of development, which has important practical and theoretical implications. Theoretically, support of the interactive model of reading allows for future conceptualization of RF and RC as acting bidirectionally on each other's development rather than acting strictly from RF to RC or from RC to RF. Practically, these findings suggest future directions for facilitating the development of RF and RC by implementing instructional techniques that support the dynamic nature of their codevelopment. The inclusion of the biometric portion of the model also allowed for both theoretical and practical conclusions to be drawn when considering the genetic and environmental influences on the development of RF and RC. Given the consistency of these results to the literature related to the genetics of the growth of reading, there is building support that a developmentally sensitive theory concerning the role of the genetic and environmental influences on reading should be put forth. Practically, these results also support a building literature indicating that the growth of reading is greatly influenced by the environment, supporting the importance of instructional approaches when teaching reading.

References

Adams, J. J. (1990). *Beginning to read: Thinking and learning about print*. Cambridge, MA: MIT Press.

Berkman, N. D., Sheridan, S. L., Donahue, K. E., Halpern, D. J., & Crotty, K. (2011). Low health literacy and health outcomes: An updated systematic review. *Annals of Internal Medicine*, *155*, 97–107. doi:10.7326/0003-4819-155-2-201107190-00005

Bowey, J. A. (1984). The interaction of strategy and context in children's oral reading performance. *Journal of Psycholinguistic Research*, *13*, 99–117. doi:10.1007/BF01067695

Brace, H. (2003). *Stanford achievement test—tenth edition: Technical data report*. San Antonio, TX: Author.

Browne, M. W., Cudeck, R., & Bollen, K. A. (1993). Alternative ways of assessing model fit. *Sage Focus Editions*, *154*, 136.

Cain, K., & Oakhill, J. (2009). Reading comprehension development from 8 to 14 years: The contribution of component skills and processes. In R. K. Wagner, C. Schatschneider, & C. Phytian-Sence (Eds.), *Beyond decoding: The behavioral and biological foundations of reading comprehension* (pp. 143–175). New York, NY: Guilford.

Carretti, B., Borella, E., Cornoldi, C., & De Beni, R. (2009). Role of working memory in explaining the performance of individuals with specific reading comprehension difficulties: A meta-analysis. *Learning and Individual Differences*, *19*, 245–251. doi:10.1016/j.lindif.2008.10.002

Chall, J. S. (1983). *Stages of reading development*. New York, NY: McGraw-Hill.

Chall, J. S., & Jacobs, V. A. (2003). Poor children's fourth-grade slump. *American Educator*, *27*(1), 14–17.

Chard, D. J., Vaughn, S., & Tyler, B. J. (2002). A synthesis of research on effective interventions for building reading fluency with elementary students with learning disabilities. *Journal of Learning Disabilities*, *35*, 386–406. doi:10.1177/00222194020350050101

Christopher, M. E., Hulslander, J., Byrne, B., Samuelsson, S., Keenan, J. M., Pennington, B., . . . Olson, R. K. (2013a). The genetic and environmental etiologies of individual differences in early reading growth in Australia, the United States, and Scandinavia. *Journal of Experimental Child Psychology*, *115*, 453–467. doi:10:1016/j.jecp.2013.03.008

Christopher, M. E., Hulslander, J., Byrne, B., Samuelsson, S., Keenan, J. M., Pennington, B., . . . Olson, R. K. (2013b). Modeling the etiology of individual differences in early reading development: Evidence for strong genetic influences. *Scientific Studies of Reading*, *17*, 350–368. doi:10.1080/10888438.2012.729119

Ferrer, E., & McArdle, J. J. (2010). Longitudinal modeling of developmental changes in psychological research. *Current Directions in Psychological Science*, *19*, 149–154. doi:10.1177/0963721410370300

Ferrer, E., McArdle, J. J., Shaywitz, B. A., Holahan, J. M., Marchione, K., & Shaywitz, S. E. (2007). Longitudinal models of developmental dynamics between reading and cognition from childhood to adolescence. *Developmental Psychology*, *43*, 1460–1473. doi:10.1037/0012-1649.43.6.1460

Ferrer, E., Shaywitz, B. A., Holahan, J. M., Marchione, K., & Shaywitz, S. E. (2010). Uncoupling of reading and IQ over time: Empirical evidence for a definition of dyslexia. *Psychological Science*, *21*, 93–101. doi:10.1177/0956797609354084

Fuchs, L. S., Fuchs, D., Hosp, M. K., & Jenkins, J. R. (2001). Oral reading fluency as an indicator of reading competence: A theoretical, empirical, and historical analysis. *Scientific Studies of Reading*, *5*, 239–256. doi:10.1207/S1532799XSSR0503_3

Gayán, J., & Olson, R. K. (2003). Genetic and environmental influences on individual differences in printed word recognition. *Journal of Experimental Child Psychology*, *84*, 97–123. doi:10.1016/S0022-0965(02)00181-9

Good, R., & Kaminski, R. (2002). *Dynamic indicators of basic early literacy skills (DIBELS)* (6th ed.). Eugene, OR: Institute for the Development of Educational Achievement. Retrieved from http://dibels.uoregon.edu

Good, R. H., Simmons, D. C., & Kame'enui, E. J. (2001). The importance and decision-making utility of a continuum of fluency-based indicators of foundational reading skills for third-grade high-stakes outcomes. *Scientific Studies of Reading*, *5*, 257–288. doi:10.1207/S1532799XSSR0503_4

Greenwald, R., Hedges, L. V., & Laine, R. D. (1996). The effect of school resources on student achievement. *Review of Educational Research*, *66*, 361. doi:10.3102/00346543066003361

Hart, S. A., Logan, J. A., Soden-Hensler, B., Kershaw, S., Taylor, J., & Schatschneider, C. (2013). Exploring how nature and nurture affect the development of reading: An analysis of the Florida twin project on reading. *Developmental Psychology*, *49*, 1971–1981. doi:10.1037/a0031348

Hart, S. A., Petrill, S. A., & Thompson, L. A. (2010). A factorial analysis of timed and untimed measures of mathematics and reading abilities in school aged twins. *Learning and Individual Differences*, *20*, 63–69. doi:10.1016/j.lindif.2009.10.004

Hart, S. A., & Quinn, J. M. (2015). *The development of the simple view of reading*. Manuscript submitted for publication.

Hernandez, D. J. (2011). *Double Jeopardy: How third-grade reading skills and poverty influence high school graduation*. Baltimore, MD: Annie E. Casey Foundation.

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

Jenkins, J. R., Fuchs, L. S., Van Den Broek, P., Espin, C., & Deno, S. L. (2003). Sources of individual differences in reading comprehension and reading fluency. *Journal of Educational Psychology*, *95*, 719–729. doi:10.1037/0022-0663.95.4.719

Keenan, J. M., Betjemann, R. S., & Olson, R. K. (2008). Reading comprehension tests vary in the skills they assess: Differential dependence on decoding and oral comprehension. *Scientific Studies of Reading*, *12*, 281–300. doi:10.1080/10888430802132279

Keenan, J. M., Betjemann, R. S., Wadsworth, S. J., DeFries, J. C., & Olson, R. K. (2006). Genetic and environmental influences on reading and listening comprehension. *Journal of Research in Reading*, *29*(1), 75–91. doi:10.1111/j.1467-9817.2006.00293.x

Kim, Y. S., Petscher, Y., Schatschneider, C., & Foorman, B. (2010). Does growth rate in oral reading fluency matter in predicting reading comprehension achievement? *Journal of Educational Psychology*, *102*, 652–667. doi:10.1037/a0019643

Kline, R. B. (2011). *Principles and practice of structural equation modeling*. New York, NY: Guilford.

Levy, B. A., Abello, B., & Lysynchuk, L. (1997). Transfer from word training to reading in context: Gains in reading fluency and comprehension. *Learning Disability Quarterly*, *20*, 173–188. doi:10.2307/1511307

Little, C. W., & Hart, S. A. (2016). Examining the genetic and environmental associations among spelling, reading fluency, reading comprehension and a high stakes reading test in a combined sample of third and fourth grade students. *Learning and Individual Differences*, *45*, 25–32. doi:10.1016/j.lindif.2015.11.008

Logan, J. A., Hart, S. A., Cutting, L., Deater-Deckard, K., Schatschneider, C., & Petrill, S. (2013). Reading development in young children: Genetic and environmental influences. *Child Development*, *84*, 2131–2144. doi:10.1111/cdev.12104

Lykken, D. T., Bouchard, T. J., McGue, M., & Tellegen, A. (1990). The Minnesota twin family registry: Some initial findings. *Acta Geneticae Medicae et Gemellologiae*, *39*(1), 35–70.

McArdle, J. J. (2009). Latent variable modeling of differences and changes with longitudinal data. *Annual Review of Psychology*, *60*, 577–605. doi:10.1146/annurev.psych.60.110707.163612

McArdle, J. J., & Hamagami, F. (2003). Structural equation models for evaluating dynamic concepts within longitudinal twin analyses. *Behavior Genetics*, *33*, 137–159. doi:10.1023/A:1022553901851

McArdle, J. J., & Nesselroade, J. R. (2003). Growth curve analysis in contemporary psychological research. In J.

Schinka, & W. Velicer (Eds.), *Comprehensive handbook of psychology*, Vol. *two* (pp. 447–480)., Research methods in psychology New York, NY: Wiley.

Miller, A. C., Keenan, J. M., Betjemann, R. S., Willcutt, E. G., Pennington, B. F., & Olson, R. K. (2013). Reading comprehension in children with ADHD: Cognitive underpinnings of the centrality deficit. *Journal of Abnormal Child Psychology*, *41*, 473–483. doi:10.1007/s10802-012-9686-8

Mplus User's Guide. Seventh Edition. Los Angeles, CA: Muthén & Muthén.

O'Connor, R. E., White, A., & Swanson, H. L. (2007). Repeated reading versus continuous reading: Influences on reading fluency and comprehension. *Exceptional Children*, *74*(1), 31–46. doi:10.1177/001440290707400102

Perfetti, C. A., Goldman, S. R., & Hogaboam, T. W. (1979). Reading skill and the identification of words in discourse context. *Memory & Cognition*, *7*, 273–282. doi:10.3758/BF03197600

Perfetti, C. A., & Roth, S. F. (1981). Some of the interactive processes in reading and their role in reading skill. In A. M. Lesgold & C. A. Perfetti (Eds.), *Interactive processes in reading* (pp. 269–298). Hillsdale, NJ: Erlbaum.

Petrill, S. A., Deater-Deckard, K., Thompson, L. A., DeThorne, L. S., & Schatschneider, C. (2006). Genetic and environmental effects of serial naming and phonological awareness on early reading outcomes. *Journal of Educational Psychology*, *98*, 112–121. doi:10.1037/0022-0663.98.1.112

Petrill, S. A., Hart, S. A., Harlaar, N., Logan, J., Justice, L. M., Schatschneider, C., . . . Cutting, L. (2010). Genetic and environmental influences on the growth of early reading skills. *Journal of Child Psychology and Psychiatry*, *51*, 660–667. doi:10.1111/j.1469-7610.2009.02204.x

Petrill, S., Logan, J., Hart, S., Vincent, P., Thompson, L., Kovas, Y., & Plomin, R. (2012). Math fluency is etiologically distinct from untimed math performance, decoding fluency, and untimed reading performance evidence from a twin study. *Journal of Learning Disabilities*, *45*, 371–381. doi:10.1177/0022219411407926

Petscher, Y., & Kim, Y. S. (2011). The utility and accuracy of oral reading fluency score types in predicting reading comprehension. *Journal of School Psychology*, *49*, 107–129. doi:10.1016/j.jsp.2010.09.004

Plomin, R., & Kovas, Y. (2005). Generalist genes and learning disabilities. *Psychological Bulletin*, *131*, 592–617. doi:10.1037/0033-2909.131.4.592

Quinn, J. M., Wagner, R. K., Petscher, Y., & Lopez, D. (2015). Developmental relations between vocabulary knowledge and reading comprehension: A latent change score modeling study. *Child Development*, *86*, 159–175. doi:10.1111/cdev.12292

Rasinski, T., Samuels, S. J., Hiebert, E., Petscher, Y., & Feller, K. (2011). The relationship between a silent reading fluency instructional protocol on students' reading comprehension and achievement in an urban school setting. *Reading Psychology*, *32*, 75–97. doi:10.1080/02702710903346873

Reynolds, M. R., & Turek, J. J. (2012). A dynamic developmental link between verbal comprehension-knowledge (Gc) and reading comprehension: Verbal comprehension knowledge drives positive change in reading comprehension. *Journal of School Psychology*, *50*, 841–863. doi:10.1016/j.jsp.2012.07.002

Roberts, G., Good, R., & Corcoran, S. (2005). Story retell: A fluency-based indicator of reading comprehension. *School Psychology Quarterly*, *20*, 304–317. doi:10.1521/scpq.2005.20.3.304

Roehrig, A. D., Petscher, Y., Nettles, S. M., Hudson, R. F., & Torgesen, J. K. (2008). Accuracy of the DIBELS oral reading fluency measure for predicting third grade reading comprehension outcomes. *Journal of School Psychology*, *46*, 343–366. doi:10.1016/j.jsp.2007.06.006

Sesma, H. W., Mahone, E. M., Levine, T., Eason, S. H., & Cutting, L. E. (2009). The contribution of executive skills to reading comprehension. *Child Neuropsychology*, *15*, 232–246. doi:10.1080/09297040802220029

Smith, F. (2004). *Understanding reading: A psycholinguistic analysis of reading and learning to read*. New York, NY: Routledge.

Smith, F. (2012). *Understanding reading: A psycholinguistic analysis of reading and learning to read*. New York, NY: Routledge.

Stanovich, K. E. (1980). Toward an interactive-compensatory model of individual differences in the development of reading fluency. *Reading Research Quarterly*, *16*(1), 32–71. doi:10.2307/747348

Stanovich, K. E. (2000). *Progress in understanding reading: Scientific foundations and new frontiers*. New York, NY: Guilford.

Swanson, H. L., & Ashbaker, M. H. (2000). Working memory, short-term memory, speech rate, word recognition and reading comprehension in learning disabled readers: Does the executive system have a role? *Intelligence*, *28*(1), 1–30. doi:10.1016/S0160-2896(99)00025-2

Taylor, J. E., Hart, S. A., Mikolajewski, A. J., & Schatschneider, C. (2013). An update on the Florida state twin registry. *Twin Research and Human Genetics*, *16*, 471–475. doi:10.1017/thg.2012.74

Taylor, J., & Schatschneider, C. (2010). Genetic influence on literacy constructs in kindergarten and first grade: Evidence from a diverse twin sample. *Behavior Genetics*, *40*, 591–602. doi:10.1007/s10519-010-9368-7

Therrien, W. J., Kirk, J. F., & Woods-Groves, S. (2012). Comparison of a reading fluency intervention with and without passage repetition on reading achievement. *Remedial and Special Education*, *33*, 309–319. doi:10.1177/0741932511410360

Wexler, J., Vaughn, S., Edmonds, M., & Reutebuch, C. K. (2008). A synthesis of fluency interventions for secondary struggling readers. *Reading and Writing*, *21*, 317–347. doi:10.1007/s11145-007-9085-7

Xu, J., & Corno, L. (2003). Family help and homework management reported by middle school students. *The Elementary School Journal*, *103*, 503–517. doi:10.1086/499737