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An Evaluation of the Utility of Reading Curriculum-Based Measurement as Progress Monitoring Tools and Predictors of Comprehension

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AN EVALUATION OF THE UTILITY OF READING CURRICULUM-BASED MEASUREMENT AS PROGRESS MONITORING TOOLS AND PREDICTORS OF COMPREHENSION

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ABSTRACT

Many American students struggle with reading, particularly in the area of comprehension. As such, early identification of reading difficulties, use of evidenced-based interventions, and monitoring of student reading progress over time is essential. Curriculum-based measurement (CBM) is a technically adequate, efficient tool whose features and design make it a good candidate for early identification and progress monitoring purposes, especially within a response to intervention framework. However, there is still some uncertainty regarding the utility of reading CBM as progress monitoring tools. Specifically, the literature has suggested that variability in the difficulty of CBM materials may influence how well these tools measure student growth over time. The present study aimed to reduce CBM variability by using field-testing and rank-ordering of performance means to create two equivalent second-grade reading CBM passage sets. These sets were derived from larger pools of extant, commercially-available passage sets. One passage set included oral reading fluency and story recall tasks. The second passage set was comprised of Maze tasks. These passage sets were then used to monitor progress in second-grade students who were at-risk for reading problems. Scores from each type of task were also used to determine which was the best predictor of student performance in reading comprehension. Hierarchical linear modeling was used to analyze student growth on CBM measures, as well as predict reading comprehension. Results indicated that only Maze tasks were sensitive to individual student growth over the study, and were the strongest predictors of reading comprehension in this sample compared to oral reading fluency and recall. Implications, limitations, and future directions are also discussed.

INTRODUCTION

The National Reading Panel (NRP; National Institute of Child Health and Human Development, 2000) reviewed the extant reading research with the goal of identifying the most effective ways of teaching children to read. After analyzing more than 100,000 studies, the panel identified five major areas of instruction that appear to be essential for reading: phonemic awareness, phonics, fluency, vocabulary, and comprehension. The NRP's findings regarding these "Big 5" areas of reading have made significant contributions to the formulation of educational curricula (i.e., Common Core State Standards, National Governors Associate Center for Best Practices, 2010) and the design of interventions aimed at improving reading performance. Despite these efforts and education laws designed to promote student achievement (i.e., Every Student Succeeds Act of 2015), American youth continue to struggle with reading. According to the 2015 Nation's Report Card, only 36% of fourth-graders and 34% of eighth-graders in the United States scored at or above a proficient level, indicating they are able to draw conclusions and make evaluations about what they read based on their understanding of the text (National Center for Education Statistics, 2015).

While these statistics are daunting at a surface level, their deeper implications are a cause for even greater concern. In upper elementary, middle school, and high school grades, student success becomes increasingly dependent on general reading ability. For instance, poor readers are not only likely to have worse outcomes in English and literature courses, but also in other subjects that rely on content-specific vocabulary and comprehension, such as geography, history, and science (Espin & Deno, 1993). As students progress through school and have more of their success dependent on reading and understanding various texts, Matthew Effects, or "the rich-get-richer while the poor-get-poorer," begin to emerge (Stanovich, 1986). Poor reading ability has also been associated with other adverse outcomes, including placing students at a higher risk for school dropout and increased rates of emotional and behavioral problems compared to typical readers (Arnold et al., 2005; Daniel et al., 2006).

Reading Comprehension

Given its essentiality in the reading process and its extension into nearly every other subject during later grades, reading comprehension has long been a major focus of educational research, assessment, and intervention. Meneghetti, Caretti, and De Beni (2006) define reading comprehension as "a complex cognitive ability requiring the capacity to integrate text information with the knowledge of the listener/reader and resulting in the elaboration of a mental representation (p. 291)." The operative term in this definition of comprehension seems to be *complex*, as

evidenced by research efforts aimed at identifying and measuring individual components that contribute to comprehension. In an effort to simplify the complexity of comprehension, Gough and Tunmer (1986) proposed a framework for better understanding reading, which they term the "simple view" of reading. In their model, reading comprehension is the product of decoding skills and listening comprehension. Numerous researchers have used this framework to design studies to better understand the construct of reading comprehension, and while the simple view of reading has been shown to be a useful framework that is still in frequent use, it may be too simple to capture the complexities of comprehension (Johnston, Barnes, & Desrochers, 2008).

Numerous other studies (e.g., Berninger, Abbott, Vermeulen, & Fulton, 2006; Catts, Herrera, Nielsen, & Bridges, 2015; Kendeou, Van den Broek, White, & Lynch, 2009; Meneghetti et al., 2006; Nation, Cocksey, Taylor, & Bishop, 2010; Tilstra, McMaster, Van den Broek, Kendeou, & Rapp, 2009;) have been conducted with the goal of identifying specific components of reading comprehension and understanding how these components relate to future comprehension. Overall, such studies have found that early skills in oral language (e.g., listening comprehension; Catts et al., 2015; Kendeou et al., 2009), vocabulary (Berninger et al., 2006; Catts et al., 2015), and decoding (Kendeou et al., 2009) show strong relationships to future comprehension abilities.

Furthermore, both Tilstra et al. (2009) and Berninger et al. (2006) found that reading fluency contributed significant variance in measures of reading comprehension. Tilstra et al. (2009) found this for students in fourth, seventh, and ninth grades, while Berninger and colleagues (2006) found similar effects for at-risk second graders. Despite the importance of reading fluency, these authors cautioned that reading fluency is necessary, but may not be sufficient, for the successful development reading comprehension in these students.

Indeed, a longitudinal study conducted by Nation et al. (2010) also suggests that indicators of reading fluency and accuracy may not necessarily detect future reading comprehension difficulties. Results of their study showed that students who were poor comprehenders at age 5 years were also poor comprehenders at age 8 years, despite showing age-appropriate levels of accuracy and fluency in word reading. Given these findings, the authors recommend early assessment for weaknesses in oral language skills in an effort to better identify students at risk for reading comprehension difficulties.

Another study (Catts et al., 2015) echoes the recommendations provided by Nation et al. (2010) in suggesting that early screening and assessment for oral language skills occur in addition to screening and assessment of early literacy skills such as alphabetic principle and phonological awareness. Catts and colleagues indicate that

while early literacy screening is helpful in predicting future comprehension difficulties, the addition of oral language skills screenings may add to this prediction.

Not only does reading comprehension seem to depend on a variety of skills, but it appears that the contribution of these skills depends on other factors, including a reader's age and skill level. Tilstra et al. (2009) found that relationships between various reading skills and reading comprehension vary by student grade level, in that more basic reading skills (e.g., decoding) are better predictors of comprehension in fourth graders, but that higher-level skills (e.g., listening comprehension) becomes a stronger predictor in later grades. In addition, a study by Kim, Wagner, and Foster (2011) investigated predictors of reading comprehension in first grade students. Overall, they found that word-list reading fluency predicted reading comprehension better for average readers than skilled readers, while listening comprehension predicted overall comprehension better for skilled readers compared to average readers.

Given the complex nature of comprehension, it can be difficult to assess and intervene. As such, substantial research efforts have been dedicated toward the identification of evidence-based assessments and interventions for reading comprehension.

Reading comprehension assessment and intervention. While comprehension is broadly interpreted as an understanding of what one reads, there is still debate regarding the best way to measure this construct (Keenan, Betjemann, & Olson, 2008). Indeed, there are several different "comprehension" tests and subtests which purportedly measure student understanding; however, these tests go about measuring comprehension in very different ways. Common strategies for measuring comprehension include passage/story retell, sentence completion, vocabulary skills, decoding, cloze tasks, true/false sentence recognition, sentence verification tasks, multiple-choice questions, and open-ended questions. There is an ongoing debate regarding which method is best, and each has its own advantages and disadvantages (see Cain & Oakhill, 2006 for a summary).

With each method, there are subtle differences in the components of comprehension measured and in the types of language and cognitive skills required to perform the task. In fact, Keenan and colleagues (2008) compared several common, standardized comprehension measures and found that these tests not only differ in the skills that they measure, but in some cases the same tests assessed different skills depending on the reader's developmental level. As such, the authors recommend that consumers should consider what they are seeking to measure and how when deciding on a measure of reading comprehension.

The majority of reading remediation in early elementary grades focuses on phonemic awareness, phonics, decoding, and fluency. For students in upper elementary (i.e., grades 4-5), however, interventions targeting reading comprehension become more prominent (Wanzek, Wexler, Vaughn, & Ciullo, 2010). This finding is not surprising given that a shift from "learning to read" to "reading to learn" typically happens between third and fourth grades (Chall & Jacobs, 2003). It is unclear whether this shift that is due to changes in student ability or changes in educational expectations, as evidenced by the emphasis on fourth-grade standardized tests. Regardless, it is clear that not all students are able to effectively shift into the "reading to learn" dynamic. Wanzek et al. (2010) recommend that, for these readers, it is important to identify specific skill deficits that are resulting in poor reading and provide evidence-based, multi-component interventions as appropriate.

Identifying Students in Need of Special Education Services in Reading

For students who exhibit substantial difficulties with reading, more intensive educational supports in the area of reading may be warranted. If so, these students may qualify for special education services under a verification of Specific Learning Disability (SLD) in reading. A recent report of students with disabilities indicates that more than 5.8 million U.S. students aged 6-21 are classified as having a disability. Approximately 40% of these students are receiving services under a verification of SLD, with the majority having an SLD in reading (U.S. Department of Education, 2014).

Changes in special education legislation have had a major impact on the identification of students with SLD, particularly following the reauthorization of the Individuals with Disabilities Education Act in 2004. This legislation, known as the Individuals with Disabilities Education Improvement Act of 2004 (IDEIA; P.L. 108-446), gave local education agencies a choice regarding the process by which they identify students with a specific learning disability. The reauthorization removed the previous requirement of identifying the student based on a significant intellectual/achievement discrepancy and added the option of using a process of identification based on the child's response to scientific, research-based intervention (U.S. Department of Education, 2004).

Response to Intervention

For local education agencies opting to use this updated process, Response to Intervention (RTI) is a useful framework for identification of SLD. RTI is an educational problem-solving process that involves multiple tiers of increasingly intense educational and behavioral supports (Germann, 2010). While RTI gained research and professional attention following its inclusion in IDEIA, it is also a useful tool for large-scale school improvement, in

both general and special education (Gresham, Reschly, & Shinn, 2010). In fact, Fletcher and Vaughn (2009) indicate that the primary goal of RTI in schools is to effectively prevent and remediate academic and behavioral concerns. They indicated a secondary goal of RTI as a way of gathering data that assists in decision-making and the identification of students with SLD. In order to accomplish these goals, RTI employs a standard set of strategies, including: tiered systems of support matched to student need, provision of evidence-based interventions with treatment integrity, problem solving, and data based decision-making. (Fletcher & Vaughn, 2009; Gresham et al., 2010; Shinn, 2010).

In general, RTI frameworks identify three tiers of support. Tier 1 includes core instructional interventions that are available to all students (i.e., universal), and are intended to be preventative and proactive. This tier also involves universal screening, in which all students are administered an assessment tool designed to identify students at risk for academic or behavioral problems (Fletcher & Vaughn, 2009). It is estimated that approximately 80-85% of students will respond adequately to Tier 1 interventions and not require additional supports. Based on data collected during Tier 1, students who are not showing adequate progress and are identified as requiring a greater level of support advance to Tier 2 and receive more targeted academic or behavioral interventions. These interventions are more intensive than Tier 1 interventions and are commonly administered in a small-group setting. It is estimated that 10-15% of students will require Tier 2 supports. In accordance with policies of data based decision-making, students in this tier are assessed regularly on some academic or behavioral outcome. This process is known as progress monitoring and helps schools objectively determine whether the student is responding to intervention efforts. Finally, students who do not respond to Tier 2 advance to Tier 3, where they receive intensive, individualized intervention. An estimated 5% of students require this level of support (Sugai, Horner, & Gresham, 2002).

Specific to the use of RTI in the identification of SLD, schools typically use a dual-discrepancy approach. In this approach, students must exhibit (a) severe low achievement compared to their peers, and (b) show evidence of nonresponse to evidence-based intervention efforts implemented with integrity (Ardoin, Christ, Morena, Cormier, & Klingbeil, 2013). The first discrepancy can be identified through universal screening in Tier 1, while progress monitoring in subsequent tiers provides evidence of the second discrepancy (Shinn, 2010). Opponents of the use of RTI in the identification of SLD maintain that comprehensive psychometric assessment is essential in identifying SLD, and suggest that RTI should not be used as a diagnostic model. Further, these opponents indicate that RTI

should be used only as a remediation model during the pre-referral stage, which includes the time prior to students being referred for a special education evaluation (Kavale, Kauffman, Bachmeir, & LeFever, 2008).

Despite ongoing controversy about the appropriateness of RTI in the identification of SLD (Fletcher & Vaughn, 2009; Kavale et al., 2008), RTI and its characteristic components (e.g., treatment integrity and data based decision-making) are becoming widespread in both research and practice. The current study focuses on data based decision-making, and, more specifically, monitoring student progress in reading.

Best practices in data based decision-making. The two major components of data based decision-making in RTI are universal screening and progress monitoring. The purpose of universal screening is to identify children who are functioning significantly below the academic or behavioral standards expected for their grade or age. Universal screening typically involves all students in a particular school building or district being administered an academic or behavioral indicator three times per year: once in the fall, winter, and spring. Results of these screenings help identify students who may be in need of more intensive services. Best practices for universal screening include consideration of three key features when selecting a screening tool: the appropriateness of the tool for the intended use, technical adequacy of the tool, and usability (Glover & Albers, 2007). Shinn (2010) indicates that once schools identify a technically adequate tool, only then should they consider time- and cost-efficiency as a factor.

Progress monitoring is the repeated, systematic assessment of behavior (National Center on Intensive Intervention, 2012). It is an evidence-based practice that allows educators to set goals, assess growth, evaluate effectiveness of intervention, and inform instructional changes (Deno 2003; Shapiro, Hilt-Panahon, & Gischlar, 2010). Within the context of RTI, it is recommended that schools explicitly use scientifically based assessment tools to monitor progress at each tier, and that these same tools be used across tiers (Shinn, 2010). One of the most common assessment tools used for both universal screening and progress monitoring purposes is curriculum-based measurement.

Curriculum-based Measurement

Curriculum-based measurement (CBM) is a general outcome measure used to assess student performance in basic academic skill areas (i.e., reading, math, spelling, writing) using a set of standardized measurement probes (Deno, 1985; Hintze, Christ, & Methe, 2006). It is important to note the distinction between general outcome measures such as CBM and specific subskill mastery approaches. General outcome measures represent a broad

construct, such as reading ability, and provide indications of overall functioning in a particular skill area (Fuchs, 2004). Specific subskill mastery measures often include small domains of test items of equal difficulty that are matched to a particular learning task and used to indicate mastery of an individual subskill (Hintze et al., 2006). As such, while certain CBM types may be used as indicators for specific outcomes (i.e., fluency, comprehension), they are actually conceptualized as multidimensional, integrated measures of a particular construct. Despite this distinction by experts in the development of CBM, these measures are often categorized by their intervention target (January & Ardoin, 2012).

Shinn (2002) uses the metaphor of CBM as a thermometer in that it is helpful at identifying the presence and severity of a problem, can be used to set goals and monitor changes in functioning, and is indicative of return to normal functioning. Like a thermometer, CBM is not a diagnostic tool, but rather an assessment of overall functioning and an indicator of a need for further assessment or treatment.

The history of CBM dates back to the early 1980s, when Stanley Deno and a group of graduate students at the University of Minnesota began to develop tools that could help educators assess special education students' progress toward goals on their individualized education plan (IEP) and evaluate the effectiveness of special education programming (Fuchs, 2004; Marston, Mirkin, & Deno, 1984; Parker, Hasbrouk, & Tindal, 1992). In other words, CBM was originally designed as a progress monitoring tool. CBM is a useful tool for progress monitoring because it was designed as a dynamic indicator of student performance; therefore, it is sensitive to short-term effects of instruction (Deno, 2003; Hintze et al., 2006). In addition, CBM meets the National Center for Student Progress Monitoring's standards for scientifically based progress monitoring. These standards require that a measure must be: reliable, valid, contain at least nine alternate but equivalent forms, be sensitive to student improvement over short periods of time, be linked to benchmarks, specify rates of improvement for various student groups, and show evidence that their use results in instructional planning and improves student achievement (Shinn, 2010).

In the thirty-plus years since its inception, CBM use has expanded considerably. While progress monitoring is still a common use of CBM, Deno (2003) identified additional uses, including universal screening, development of norms, and program evaluation. Stecker, Fuchs, and Fuchs (2005) found that teachers who use CBM data to inform instructional change effected greater growth in student outcomes than teachers who used their own methods of progress monitoring and recommendations for instructional change. CBM is used for students from preschool through high school and for students from diverse backgrounds, including those learning the English

language (McMaster, Wayman, & Cao, 2006; Wiley & Deno, 2005). Over time, the content of CBM materials has expanded to include early literacy, early numeracy, reading, math, and writing skills. Regardless of their use or content, CBM maintains certain characteristics. According to Deno (2003), CBM is defined by the use of technically adequate materials, standardized measurement tasks, standardized multiple equivalent samples, and time-efficient administration and scoring methods.

Curriculum-based measurement in reading. As mentioned above, a variety of CBM measures within the area of reading are currently available, including those that serve as indicators of early literacy skills (i.e., letter naming, letter sounds, phonemic awareness, phonics, and decoding), as well as more advanced skills such as fluency and comprehension. Of all subject areas for which CBM is available, reading has received the most research attention (Shinn, 2010). The two most common types of reading CBM measures are the read aloud measure and the Maze task. Another CBM reading measure, retell fluency, is also described.

Read aloud measures. The most commonly used CBM measure for reading is the read aloud measure (Reschly, Busch, Betts, Deno, & Long, 2009). This measure is also referred to as oral reading fluency (ORF), R-CBM, or CBM-R. For purposes of this study, this method of measurement will simply be referred to as "read aloud" unless the read aloud measure comes from a particular publisher.

Standard administration of a read aloud measure involves a student reading out loud from a typed, 150-400-word passage for one minute. As the student reads, the administrator marks any mispronunciations, word omissions, word substitutions, and hesitation greater than 3 seconds on any single word (Wayman, Wallace, Wiley, Tichá, & Espin, 2007). At the end of one minute, the student stops reading and the administrator calculates the number of words the student read correctly, resulting in a score of words read correctly per minute, or WRCM. Historically, read aloud passages were taken from curriculum materials such as basal readers (Hintze, Shapiro, Conte, & Basile, 1997). Now, multiple options exist for read aloud passages, including the commercially available AIMSweb (Howe & Shinn, 2002) and the Dynamic Indicators of Basic Early Literacy Skills (DIBELS; Good & Kaminski, 2002; 2011) series. Appendix A depicts a standard DIBELS read aloud measure.

Read aloud passages are typically administered based on the student's grade level or instructional level; however, Wayman et al. (2007) found that it is not necessary for CBM materials to be directly matched to a student's instructional level in order to maintain technical adequacy of the measure. In general, their review

indicates that reliability and validity remains intact if the CBM passages remain within one grade level above or below the student's instructional level.

Wayman, and colleagues (2007) conducted a literature synthesis of CBM in reading and found that, to date, research efforts have focused overwhelmingly on read aloud techniques compared to other reading measures. Evidence from the studies included in this synthesis suggests that read aloud is a reliable, valid predictor of student performance for elementary students in grades 2-5. While the literature supports the use of read aloud measures as a screening tool, results are mixed regarding its utility as a reliable, valid indicator of student progress. In fact, Ardoin et al. (2013) indicate that evidence reported in the literature supporting the use of read aloud as a progress monitoring tool may have been overgeneralized. These concerns will be addressed further in subsequent sections.

Maze measures. A second CBM reading measure is the Maze task. Although Maze has received less research attention and practical use than read aloud, it has been shown to be a reliable and valid measure of general reading ability (Fuchs & Fuchs, 1992). The Maze task evolved from cloze tasks (Parker et al., 1992), which consist of a typed passage that has every *n*th word deleted throughout the passage. In a cloze task, respondents are required to write in each missing word such that the sentence is complete and both the sentence and passage make sense. This task was modified and standardized for use in schools as a general outcome measure of reading, and in doing so became known as the "Maze" task.

Maze has undergone significant adjustments since its conception in the 1970s. For instance, early Maze tasks were commonly derived from basal readers and had varied deletion ratios ranging from 1/5 to 1/46. Parker and colleagues (1992) reviewed the history and use of Maze and made recommendations for development of future measures. Specifically, they recommended that Maze probes be between 250-400 words in length, only contain deleted content-related words (i.e., nouns, main verbs, adjectives, and adverbs), include four distractors for each deleted word, and not place a time limit on Maze passage completion. Individuals familiar with the composition and administration procedures of most commercially available Maze passages today know that some of these recommendations have been upheld, while others have not.

The most common Maze tasks currently in use involve a 150-400-word passage that has the first sentence intact. Starting with the first word of the second sentence, every 7th word is deleted and replaced with three words: one correct word and two distracter words. Maze administration typically involves a student reading the passage silently for a specified time limit, usually 1-3 minutes. As the student reads, he or she must choose (i.e., circle) the

correct word from the three choices at every 7th word. Like read aloud, standardized Maze passages are available to consumers through companies like AIMSweb (Howe & Shinn, 2002) and Dynamic Indicators of Basic Early Literacy Skills (DIBELS; Good & Kaminski, 2002; 2011). Appendix B demonstrates a sample Maze passage.

While Maze has been less frequently researched than read aloud, it does have some perceived benefits compared to read aloud measures. First, because Maze is a silent reading, time-limited assessment, it can be group-administered, whereas read aloud must be administered individually (Wayman et al., 2007). In addition, computer-based administration of Maze is currently available, making it even more efficient to administer and score. According to Parker and colleagues (1992), teachers may also perceive Maze as having greater face validity as a measure of reading comprehension compared to read aloud measures, which are commonly perceived as indicators of reading fluency. This perception is likely due to the test's construction and outcomes rather than test content; however, it has resulted in more frequent use of Maze in the upper elementary grades where comprehension becomes an outcome of interest. In fact, the DIBELS version of Maze, "Daze," is currently only available for third grade and beyond.

Just as the use of read aloud measures for progress monitoring is still unresolved by the literature, blanket recommendations about the use of Maze are hindered by mixed results regarding its utility. These mixed results have resulted in ongoing controversy regarding the best CBM measure to use for screening and progress monitoring, particularly when the target outcome is reading comprehension (Ardoin et al., 2004; January & Ardoin, 2012; Jenkins & Jewell, 1993; Marcotte & Hintze, 2009).

Retell measures. An additional method of assessing reading is retell fluency. This method is usually administered in conjunction with a read aloud measure (Bellinger & DiPerna, 2011). Standard administration involves a student reading a passage aloud for one minute, as in read aloud. Then, at the end of the minute, students are asked to recall as much of the story as they can remember, either orally or by writing it down. The purpose of retell is to gauge a reader's understanding of the passage they have just read (i.e., comprehension) and to identify students who may be reading fluently but are not understanding. In fact, some describe retell methods not as a general outcome measure but as a skill-specific assessment of reading comprehension (Roberts, Good, & Corcoran, 2005). The oral retell fluency (RTF) procedure is commonly used and recommended in the DIBELS system (Good & Kaminski, 2002; 2011); however, research regarding the utility of retell is limited and mixed.

Reed (2011) reviewed the research on the psychometric properties of retell measures and found high levels of variability in administration and scoring procedures. Overall, the results of the review indicated that retell measures on the whole require further validation. Roberts et al. (2005) found modest support for the use of retell measures in predicting broad reading achievement in a sample of first graders. Bellinger and DiPerna (2011) assessed whether RTF could reliably predict reading comprehension in fourth grade students. Their results found a low correlation between RTF measures and reading comprehension criterion measures (r = .33) Further, they found significant differences between RTF scores based on live versus recorded administrations, indicating reduced levels of examiner accuracy during live administrations. As such, the authors caution that poor reliability between raters and scores on RTF could affect its utility as a reliable and valid reading CBM measure. A sample RTF scoring procedure is depicted in Appendix C.

Evidence for Reading CBM Measures within an RTI Framework

Fuchs (2004) identified three stages of research for substantiating the use of any measure for the purposes of progress monitoring. The first stage investigates the technical features of a static score (i.e., universal screening). Stage 2 assesses the technical features of slope, in which changes in student scores over time are associated with improvement in the domain of interest. Finally, Stage 3 involves the assessment of instructional utility, or whether practitioners can use the progress monitoring tool in questions to improve instruction and intervention, and thereby impact student achievement. Subsequent sections present the existing evidence of reading CBM at each stage.

Stage 1 evidence of reading CBM measures as static predictors of achievement. As indicated earlier, the majority of research on read aloud supports it as a predictor of reading achievement based on a static measurement. Reschly, et al. (2009) conducted a meta-analytic review of the use of read aloud measures in predicting student reading achievement and found similar evidence to Wayman et al. (2007). Reschly et al. (2009) reviewed 41 studies and found that read aloud consistently showed a moderately high correlation with standardized tests of reading achievement (r = .67). In addition, they investigated a number of variables that could potentially moderate the relationship between read aloud and reading achievement tests. They found that read aloud shows a higher correlation with national tests of achievement compared to state tests. Another notable finding from the Reschly et al. (2009) review was that there were no significant differences between read aloud performance and student scores on various reading subtests (i.e., comprehension, decoding, and vocabulary). The authors posit that

these results speak to the conceptualization of read aloud as a general outcome measure of reading ability rather than a measure of specific skills such as decoding or comprehension.

Jenkins and Jewell (1993) examined the relationship between reading CBM measures (i.e., read aloud and Maze) and reading achievement in 335 students in grades 2-6. They administered three R-CBM passages and three Maze passages to each student. Their results indicated that oral reading was more strongly correlated with reading achievement for students in grades 2-4 than grades 5 and 6. The authors observed that, as grade level increased, correlations between oral reading fluency and reading achievement decreased. They found that correlations between Maze scores and reading achievement remained relatively consistent across grades.

Hosp and Fuchs (2005) conducted a study similar to that of Jenkins and Jewell (1993) in order to evaluate whether read aloud was differentially predictive across and within grades. They administered reading measures to 310 students in grades 1-4 and found that, across grades, there was no significant change in the relationship between read aloud measures and comprehension outcome measures. Overall and across grades, CBM had the strongest relationship with total reading scores, not with any individual skill. Like the findings from Reschly et al. (2009), these results support reading CBM as a general outcome measure.

Graney, Missall, Martinez, and Bergstrom (2009) evaluated within-year growth for students in grades 3-5 using both read aloud and Maze measures. They collected benchmark CBM data three times per year (i.e., fall, winter, and spring) over the course of two years. At the end of their study, they found no significant differences in read aloud growth rates across grade levels. In contrast, they found that growth rates for Maze increased with each successive grade level. They concluded that Maze may be a more sensitive measure than read aloud for older elementary students.

Wiley and Deno (2005) used read aloud and Maze measures to predict third-and fifth-graders' performance on state standards tests. Their sample included both English learners and non-English learners. Results showed that both Maze and read aloud showed moderate to moderately strong correlations with a state test in reading. In addition, the authors found that read aloud was a stronger predictor for both 3rd and 5th grade English learners, and that Maze added to the predictive abilities of read aloud for both grades of non-English learners, but not for English learners.

Christ, Silberglitt, Yeo, and Cormier (2010) found even more factors that influence universal screening scores. They used read aloud benchmark data to investigate growth patterns for students in grades 2-6. In general,

they found that students not receiving special education services showed a higher growth rate than students receiving these services. They also found that students in earlier grades show a higher rate of growth on read aloud measures compared to older elementary students. Finally, they observed a seasonal effect, in that more growth was observed from fall-to-winter than winter-to-spring. This seasonal effect was more prominent in younger students compared to older students.

Together, these findings indicate that the predictive utility of reading CBM measures is dependent on several factors, including student grade level, the skills being assessed by the criterion measure, season, and student abilities.

Universal screening with reading CBM. In addition to predicting future achievement, static CBM measurements can be used to identify students at risk for reading problems. Jenkins, Hudson, and Johnson (2007) reviewed studies on the classification accuracy of reading screeners for students in grades K-6 and found that; overall, the CBM reading measures commonly used for universal screening are "good but not great" (p. 598). Specifically, the review indicated that administering only read aloud screening measures resulted in inadequate classification accuracy. As such, the authors suggest that a screening battery consisting of more than one type of reading CBM type may be better at identifying readers who are at risk.

Decker, Hixson, Shaw, and Johnson (2014) investigated the use of a multiple-measure screening battery with seventh- and eighth-graders and found that administering both Maze and a read aloud resulted in classification accuracy rates that were either similar to or greater than the rates identified by individual predictors.

In another study of reading CBM as universal screening tools, Graney, Martinez, Missall, and Aricak (2010) compared the technical adequacy of read aloud and Maze as universal reading screeners in fourth- and fifth-graders. Results indicated that both read aloud and Maze demonstrated adequate test-retest and alternate-forms reliability in this sample. In particular, the authors found that read aloud demonstrated a mean short-term (i.e., 2-week) test-retest reliability of .96, while alternate-forms reliability was .91. For Maze, mean short-term test-retest reliability was .89. Based on recommendations from Salvia, Ysseldyke, and Bolt (2007), both read aloud and Maze demonstrate appropriate reliability for use as universal screening procedures in fourth- and fifth-grade students. Furthermore, Graney et al. (2010) found moderate to strong correlations between reading CBM measures and reading criterion measures in their study. The authors note that correlations varied significantly depending on the

criterion measure, indicating that predictive utility of reading CBM tools depends on the content and construction of various outcome measures.

Ardoin and colleagues (2004) investigated the incremental benefits of administering additional CBM measures beyond a single read aloud probe. In particular, they evaluated whether a) administering three versus one read aloud probes and b) administering a single Maze probe in addition to read aloud contributed to the prediction of student performance on a standardized achievement test. The authors found that, in their sample of 77 third grade students, a single read aloud probe was a better predictor of both total reading achievement (r = .70) and reading comprehension skills (r = .42) compared to Maze (r = .50 for reading achievement and r = .31 for reading comprehension). Further, adding Maze to a read aloud measure during universal screening did not explain significant unique variance in broad reading scores. These results contradict those found Decker et al. (2014) and suggested by Jenkins et al. (2007).

The existing literature on the use of reading CBM measures as universal screeners is promising, but unclear as to which specific measure to use and for whom. Collective results from the studies above would suggest that multiple-measure universal screening batteries that include both read aloud and Maze are more appropriate for use in upper elementary and middle school grades; however, this may be due to fewer studies using Maze for screening purposes in lower elementary grades, as read aloud is a more common screening tool for these grades.

Specific strategies to use reading CBM to predict comprehension. Munger and Blachman (2013) examined how well a battery of DIBELS Next (Good & Kaminski, 2011) measures and a vocabulary measure administered in first grade predicted reading comprehension scores in third grade. Specifically, they used DIBELS Next early literacy measures (phoneme segmentation fluency, nonsense word fluency, letter naming fluency, word use fluency, and oral reading fluency) and a standardized measure of receptive vocabulary. They found that first grade performance on oral reading fluency and the vocabulary measure shared the strongest relationships with third grade comprehension scores on a standardized test (r = .66 and r = .72, respectively) and explained the most variance in scores. The authors concluded that DORF is a strong predictor of reading comprehension and should continue to be used in screening efforts; however, it does not reliably measure oral language skills such as listening comprehension. As such, supplemental measures are needed in order to effectively predict comprehension outcomes.

In an effort to address concerns about the lack of face validity of read aloud as a measure of reading comprehension, one study attempted to identify new measures for assessing comprehension efficiently and effectively.

Marcotte and Hintze (2009) compared four methods for assessing and predicting reading comprehension in fourth grade students: Maze, retell fluency (RTF), written retell, and sentence verification technique. Maze and retell fluency methods are described above. The written retell method consisted of students being administered a 750-word passage, which they read silently for 5 minutes. After 5 minutes of reading, the students were given 5 minutes to write as much as they could remember from the story. A written retell score was calculated by counting the number of unique content words (i.e., distinct nouns, verbs, adjectives, and adverbs). Words synonymous with those contained in the passage were counted as correct. In the sentence verification technique, students were given a testing packet that contained four passages, each followed by 16 test sentences. During administration, students were instructed to read each passage and then answer the 16 test items by indicating whether a test sentence had the same meaning as a sentence in the story ("yes") or meant something different ("no"). Students were given 30 minutes to complete their packet.

According to the authors, the purpose of this comparison was to assess the incremental and predictive utility of each method in combination with read aloud. Results indicated that Maze, written retell, and sentence verification techniques were all significant predictors of reading achievement in combination with read aloud. The addition of these measures helped explain an additional 3-8% of observed variance in achievement scores. Overall, the combination of read aloud and Maze explained 70% of observed variability in the criterion measure of reading proficiency. Only retell fluency failed to contribute in explaining achievement above and beyond other measures. Based on these results, the use of multiple types of CBM measures may be warranted for screening and progress monitoring. Overall, this study suggests that while alternative methods show promise in predicting comprehension, they do not have standardized methods of administration and typically require more effort by developers and administrators (Bellinger & DiPerna, 2011).

Another study by Wise et al. (2010) investigated the relationships between different types of oral reading fluency measures and reading comprehension in at-risk second graders. They compared student performance on three different methods: a narrative passage similar to a read aloud measure, nonsense word fluency, and "real-world" oral reading fluency, which included students reading from a word list. Surprisingly, they found that the real-

word oral reading fluency measure was the most strongly related to a comprehension outcome measure. The authors suggest that the real-word method is an efficient way to screen for future comprehension difficulties. Indeed, these findings agree with those from the Kim et al. (2011) study described above, in which list-reading fluency was a better predictor of comprehension for average versus skilled readers. In sum, it would seem that early identification efforts should involve screening for multiple skills related to comprehension in an efficient, reliable way.

Stage 2 evidence of reading CBM measures as progress monitoring tools. While the evidence base for read aloud and Maze CBM measures supports their use as screening tools, less is known about the utility of these measures as progress monitoring tools (Wayman et al., 2007). In their review, Busch and Reschly (2007) reported that CBM measures of reading, including Maze and read aloud, are appropriate for use as progress monitoring tools in an RTI framework. At Tier 1, CBM measures allow schools to monitor students identified as "at-risk" for reading problems as identified by universal screening (Deno et al., 2009). At Tier 2, progress monitoring of students receiving evidence-based intervention provides objective data that can be used to inform whether instructional changes are necessary and to help determine an individual student's response to an intervention. Despite the logical fit between CBM and RTI, empirical evidence regarding the use of read aloud and Maze specifically as progress monitoring tools is lacking and results are mixed (Shapiro, 2013; Wayman et al., 2007). Emerging research on CBM reading measures as progress monitoring tools has begun to question previous recommendations about the process and content of progress monitoring (Shapiro, 2013).

Indeed, Ball and Christ (2012) caution that general outcome measures such as CBM are necessary, but not sufficient, for evaluating progress within an RTI model. They suggest that CBM be used in combination with specific subskill mastery measurement (discussed previously), which includes more targeted assessment of particular skills. Further, they recommend that CBM measures have more utility in evaluating generalized, long-term effects of an intervention whereas specific subskill mastery measurement is better suited for evaluating the short-term effects of an intervention.

Olinghouse, Lambert, and Compton (2006) demonstrated use of a specific subskill mastery measurement tool to monitor progress. In their study, they created an intervention-aligned word list and compared it to a read aloud measure in its utility in measuring student progress during a reading intervention. They found that the intervention-aligned word list accounted for unique variance on measures of timed and untimed word reading, decoding, and timed passage accuracy. The read aloud measure accounted for unique variance on a measure of

reading fluency. The authors suggest that, when choosing a progress monitoring tool, it is important that the tool be highly aligned to student skill level, the skill targeted for remediation, and the goals of the intervention.

Read aloud as a progress monitoring tool. Ardoin and colleagues (2013) conducted a review of the research on the use of read aloud measures for progress monitoring. Their review included a summary of factors that influence decision-making, including how many data points are obtained and methods for determining student progress. The authors reviewed 171 journal articles, book chapters, and instructional manuals related to progress monitoring with read aloud. Results indicate an overwhelming amount of variability in the literature. Studies recommend anywhere between 3-20 data points prior to making a decision based on progress monitoring data, with the modal recommendation being 7 data points. Regarding methods for determining student progress, the review found that an ordinary least squares (OLS) regression approach was the most commonly recommended procedure for determining progress. Overall, though, the results of this review indicate significant inconsistencies regarding the use of read aloud to monitor student progress, both in research and in practice. In fact, the authors go so far as to state that, "CBM-R progress monitoring is not an evidence-based practice for modeling growth of individual students' gains in reading" (p. 12).

Goffreda and DiPerna (2010) came to a similar conclusion when they reviewed 26 studies to arrive at a synthesis on the psychometric evidence for DIBELS measures. They found that DIBELS read aloud measures generally exhibit good technical adequacy; however, relative to evidence for these measures as a screening tool, research is less abundant on their use as a progress monitoring tool.

In sum, these findings calling the use of read aloud as a progress monitoring tool into question are somewhat paradoxical, given that evaluation of student progress was a primary impetus behind the development of CBM (Ardoin et al. 2013; Deno, 1985). Additional research regarding the measures and methods by which we measure reading progress are warranted.

Maze as a progress monitoring tool. Unlike read aloud, no research synthesis on Maze for progress monitoring is currently available. However, several studies exist that offer similar conclusions about its utility for this purpose. Fuchs and Fuchs (1992) conducted one of the first studies comparing alternative methods of reading CBM for measuring elementary students' growth in reading comprehension. The purpose of this study was to examine the validity, utility, and acceptability of four measures: question answering tests, recall procedures, cloze techniques, and maze procedures. These measures were proposed as alternatives to read aloud that could possibly

address some of the disadvantages of using a read aloud measure; namely, the time-consuming necessity of individual administration and the perception of read aloud as simply a measure of fluency and lacking face validity as a measure of reading comprehension. This multi-year study on progress monitoring revealed Maze as the most promising reading CBM measure of the four types examined. Namely, Maze was the best at detecting student growth over time and resulted in the smallest measurement error. It should be noted that Fuchs and Fuchs (1992) did not find recall measures, similar to RTF, to be reliable detectors of growth.

In recent years, much of the research regarding the use of Maze as a progress monitoring tool has been conducted with middle school students (Espin, Wallace, Lembke, Campbell, & Long, 2010; Ticha, Espin, & Wayman, 2009; Tolar, Barth, Fletcher, Francis, & Vaughn, 2014). Espin et al. (2010) analyzed growth curves for 31 eighth-grade students whose progress was monitored using read aloud and Maze. Their results found that Maze reflected growth over time, with students increasing their scores by an average of 2.88 selections per week. In contrast, read aloud measures did not indicate significant growth over time. Ticha et al. (2009) replicated the Espin et al. (2010) study. They administered read aloud and maze passages to a sample of 35 eighth-graders weekly for 10 weeks, then examined how well student growth on each measure predicted performance on reading criterion measures. Similar to Espin et al.'s (2010) findings, results from Ticha et al (2009) showed that Maze reflected significant growth over time and was also significantly related to reading criterion measures. Read aloud measures predicted performance on criterion measures but did not reflect significant growth.

Tolar et al. (2014) compared the utility of static measurement versus slope in predicting student outcomes on a reading criterion measure. Similar to other studies, the sample in this study included middle school students. Results indicate low slope reliability across reading CBM measures. Further, the only situation in which slope added to the prediction of reading outcomes was when the reading CBM measure was highly aligned to the outcome. These findings concur with those of Olinghouse et al. (2006), who found that measures that are highly aligned to intervention could account for unique variance in specific skill outcomes.

A study by Shin, Deno, and Espin (2000) examined the technical adequacy (i.e., reliability, sensitivity, and validity) of the Maze task for measuring reading growth in second graders. They administered computer-based Maze tasks once per month over the course of a school year to a sample of 43 students. Alternate-forms reliability results found a mean correlation of $r = .81$, with a range of reliability from .69 to .91. Sensitivity was assessed using hierarchical linear modeling (HLM, discussed later in detail). Results showed a significant mean growth rate,

indicating a reliable increase in Maze scores. Validity analyses showed a significant positive relationship between Maze growth and reading scores on a state standards assessment. Further, the authors did not find statistically significant differences in mean growth rates between general education students and those receiving remedial education.

Taken together, these findings suggest that Maze is a sensitive predictor of growth in middle school students and second grade students. Given the diversity of samples in these studies, it is reasonable to expect that Maze would be sensitive to monitoring progress in other grade levels, as well.

Form Effects and Passage Equivalence in Reading CBM

Passage equivalence is an ongoing concern regarding the use of CBM for progress monitoring purposes (Deno, Fuchs, Marston, & Shin, 2001). Hintze and Christ (2004) found that CBM passages controlled for difficulty (i.e., equivalent passages or forms) significantly reduced measurement error compared to uncontrolled passages, resulting in increased sensitivity and reliability.

The most common method for establishing passage equivalence in CBM measures is through the use of a readability formula. Readability formulas were designed to give a basic indication of reading difficulty. These formulas take into account different aspects of written text that theoretically make it more or less difficulty to read, such as vocabulary and sentence complexity (Begeny & Greene, 2014). As discussed above, reading is a complex construct which involves the confluence of many different skills. Given that readability formulas seem to take many of these skills into account, it has been suggested that they may be a better indicator of comprehension difficulty rather than fluency difficulty (Christ & Ardoin, 2009). If this holds, then the readability formulas used to develop read aloud passage sets may not be the most appropriate form of establishing passage equivalence. Some researchers have empirically investigated this question with interesting results.

Ardoin, Suldo, Witt, Aldrich, and McDonald (2005) compared the validity of eight different readability formulas in predicting student performance on read aloud. The authors found a modest relationship between reading fluency and read aloud passage difficulty as determined by reading formulas. Interestingly, the readability formulas most commonly used to categorize read aloud probes were the poorest predictors of reading fluency. Based on these results, the authors conclude that readability formulas are inadequate for establishing passage equivalence and may reflect inaccurate estimates of student progress.

Betts, Pickart, and Heistad (2009) investigated the equivalence of first-grade read aloud passages and found that, while readability formulas may be helpful for differentiating reading passages between grade levels, they are not sensitive enough to establish passage equivalence within a grade level. These results indicate that read aloud passages within grade levels have different levels of difficulty, which could be problematic when they are used as progress monitoring tools.

Poncy, Skinner, and Axtell (2005) administered third-grade level DIBELS (Good & Kaminski, 2002) read aloud probes to a sample of 37 students. Each student was administered 20 passages in a random order over the course of one school week. While passages had been equated on readability formulas during their development, Poncy and colleagues investigated whether there was still significant variability among passages. They found that, in these passages, 81% of variation in scores was attributed to person, while 10% of variation in scores was due to differences in passage. Through use of generalizability and decision studies, the authors found that if they altered passages to within 10 WCPM of the mean fluency score across passages, they could attribute 89% of variation in scores to person and reduce variation in scores due to passage to 2%. These results support the field-testing of reading CBM passages before use in progress monitoring, and the authors suggest that when identifying passage sets for this purpose, all measures should fall within 5 WCPM of the mean score for the set in order to reduce measurement error. This study marked an important effort in identifying ways to establish passage equivalence. They showed that field-testing passages and comparing mean performance rates was helpful for reducing measurement error. Others have attempted to identify additional strategies to achieve passage equivalence in read aloud measures.

Christ and Ardoin (2009) compared four methods of passage equivalence: random sampling, a readability formula, performance means, and Euclidean Distance. Like Poncy et al.'s (2005) method, the performance means and Euclidean Distance strategies relied on field-testing a set of existing read aloud passages. Euclidian Distance is a method of calculating the square root of the sum of squared differences between repeated measurements. By using this method, the authors were able to form distinct clusters of similar and dissimilar passages in order to reduce passage variability. Their results indicated that equivalence efforts that used field-testing (i.e., performance means and Euclidean Distance) resulted in the least measurement error compared to random selection and a readability formula. During read aloud field-testing with second- and third-graders, Christ and Ardoin (2009) found an average

difference of 46 WCPM between the easiest most difficult passages. As such, they concluded that student performance is dependent on the individual characteristics of passages.

Ardoin and Christ (2009) compared the standard errors associated with various read aloud passage sets, including DIBELS 6th Edition (Good & Kaminski, 2002), AIMSweb (Howe & Shinn, 2002), and an experimental passage set designed by the authors (i.e., Formative Assessment Instrumentation and Procedures for Reading; FAIP-R). DIBELS and AIMSweb passages were taken from the third-grade progress monitoring passages available from the publishers. The FAIP-R passage set was taken from a collection of passages the authors devised as part of previous study on passage equivalence (Christ & Ardoin, 2009, described above). Ardoin and Christ (2009) found that FAIP-R passages had the smallest magnitude of measurement error, including standard error of the slope and standard error of the estimate. AIMSweb passages had higher error rates than FAIP-R, but lower error rates than DIBELS passages. Again, the authors of this study concluded that equating read aloud passages through field-testing methods can help reduce measurement error. Further, they recommend that when schools use read aloud passages for progress monitoring, it is important to consider the amount of error inherent in growth measurement due to variability in passage difficulty.

While studies like those described above have shown that field-testing helps reduce measurement in read aloud scores, it may not always be sufficient to establish passage equivalence. During the development of their latest reading passage set (i.e., DIBELS Next; Good & Kaminski, 2011), the authors conducted field-testing in an effort to reduce passage variability. Cummings, Park, and Bauer-Schaper (2013) found significant form effects among DIBELS Next oral reading fluency probes, indicating that even after field-testing, passage equivalence had not been reliably established in these measures.

Given the concerns with form effects and passage equivalency stated above, it is evident that efforts to improve reading CBM are necessary if they continue to be used as progress monitoring tools within an RTI context.

Assessing Growth and Predicting Outcomes with CBM

Some (Deno et al., 2001; Fuchs & Fuchs, 1993) have attempted to identify average growth rates on CBM measures. While growth rates may be helpful as general indicators of expected progress, Deno et al. (2001) note that calculation of growth rates is highly dependent on several factors such as sample characteristics and CBM passage difficulty. They indicate that until passage equivalency can be established for CBM passages, growth rates should be used with caution.

The evaluation of progress monitoring necessitates the use of statistical techniques that are sensitive to growth, such as multilevel models or latent growth curve modeling (Hoffman, 2015). For purposes of this study, only multilevel models are described further. Multilevel models are also known as general linear mixed models or hierarchical linear models (HLM, Bryk & Raudenbush, 2003; Raudenbush & Bryk, 2002). Given that HLM was used in the current study, this descriptor will be used from here on to describe both the framework and statistical package used to carry out analyses.

As suggested in its name, hierarchical linear models are those that take the hierarchical structure of data into consideration (Field, 2009; Woltman, Feldstain, MacKay, & Rocchi, 2012). Hierarchical structures involve different levels of grouped or "nested" data. These structures are a common occurrence, particularly in education (i.e., students nested within classrooms nested within schools nested within districts, etc., Woltman et al., 2012). In longitudinal studies, repeated observations across time are viewed as being nested within individual participants (Raudenbush & Bryk, 2002). These models are also useful for assessing student growth because they can account for autocorrelation, or the co-variation of data that results from assessing the same participant over time. In other words, HLM techniques are not restricted by the assumption of independent data (Field, 2009). Another advantage of HLM is its ability to handle missing data.

Previous research has demonstrated that HLM is an appropriate method for analyzing students' academic growth within an RTI framework (Hampton, Lembke, Lee, Pappas, Chiong, & Ginsburg, 2012; Shin, Espin, Deno, & McConnell, 2004; Silberglitt & Hintze; 2007; Tichá et al., 2009). Unlike the use of average growth rates, HLM allows the user to model individual growth rates for students, which helps give a more accurate picture of individual progress.

Current Study

Given the advantages of field-testing and using mean performance rates for establishing passage equivalence and reducing measurement error in CBM, these strategies were used to create two equivalent passage sets: one AIMSweb Maze (R-Maze; Howe & Shinn, 2002) and one DIBELS Next oral reading fluency/retell (DORF/RTF; Good & Kaminski, 2011). Moreover, these new passage sets were used to monitor reading progress in a sample of second-grade students over the course of approximately 8 weeks. Finally, students were administered a standardized reading comprehension measure at the end of the study. These strategies were used to answer two main research questions:

1. After equating passages, which CBM probe type (i.e., R-Maze, DORF, or RTF) is the most sensitive to reading growth in second graders over eight weeks? Additionally, does growth differ depending on certain student characteristics (i.e., free/reduced lunch status or special education services)?
2. Which CBM probe type (i.e., R-Maze, DORF, or RTF) is the best predictor of reading comprehension?

Despite limited and mixed evidence regarding the use of RTF measures for progress monitoring and predictive purposes, they were included in the study based on their purported use as an indicator of reading comprehension, as well as their having a similar construction one particular subset of the reading comprehension outcome measure used in the current study (i.e, Reading Recall subtest of the Woodcock-Johnson IV (McGrew, LaForte, & Schrank, 2014)).

In order to answer research question one, HLM will be used to evaluate student growth on each different CBM probe type. While studies show that read aloud measures are sensitive to growth between benchmarks, less evidence is available regarding their sensitivity to short-term growth. Also, given that Shin et al. (2000) demonstrated that Maze measures are sensitive to reading growth in second graders, it was hypothesized that AIMSweb R-Maze would be most sensitive to changes in participants' reading scores over the course of the 8-week study. Based on mixed results regarding the utility of RTF as a progress monitoring tool, these measures were not expected to show sensitivity to growth. Further, it was hypothesized that students receiving special education services would show slower growth than peers who do not receive special education services. This hypothesis is based on findings from Christ et al. (2010) and Shin et al. (2000) who found differences in growth based on SPED status. Finally, it was hypothesized that growth rates for students who were eligible for free/reduced lunch would show different growth rates than students who were not, as previous research has shown that student socioeconomic status is related to student achievement (Raudenbush & Bryk, 2002).

Regarding the second research question, it was hypothesized that DORF measures would be the strongest predictor of reading comprehension. This hypothesis is the result of a review of a literature base which shows that, for students in lower elementary grades, read aloud measures have been the strongest predictors of overall reading achievement.

METHOD

Institutional Review Board approval was obtained prior to participant recruitment and data collection. After gaining school administrator and teacher permission, consent forms were sent home to parents of eligible participants. In Phase One, all second grade students were eligible to participate. In Phase Two, teachers sent parent consent forms home to all students whose mid-year reading scores were at or below benchmark for second grade. Because the schools in the study screened students using DIBELS (Good & Kaminski, 2002; 2011), "benchmark" refers to a WCPM score of 71 or below. Scores in this range place a student at higher risk for reading difficulties and indicate a need for supports.

For each phase, students whose parents consented to their participation were given a brief written and verbal explanation of the study and given the choice to participate. There were no students who declined to participate in Phase One, and there were four students in Phase Two who declined to participate following explanation of the study.

Participants

Participants for Phase One included 75 second-grade students recruited from four public elementary schools in a central Nebraska school district. The sample was comprised of 36 males (48%) and 39 females (52%). There were 62 Caucasian students (82.7%), nine Hispanic students (12%), three African-American students (4%) and one Asian student (1.3%) in this phase.

In Phase Two, a total of 32 second-grade students participated. These students were recruited from the same four schools in the same district in central Nebraska. In this phase, there were 19 males (59.4%) and 13 females (40.6%). Furthermore, there were 26 Caucasian students (81.3%), five Hispanic students (15.6%) and one Asian student (3.1%). A total of 15 students (46.9%) in this phase of the study were eligible for free or reduced lunch, while a total of 12 students (37.5%) received some type of special education services.

Measures

Maze. The AIMSweb Reading Maze (R-Maze) passage set for second grade includes a total of 30 passages: three benchmark passages and 27 passages for progress monitoring. The 27 R-Maze progress monitoring passages are the same stories as those used in administration of the AIMSweb read aloud measure (R-CBM). During AIMSweb passage development, an original pool of 50 probes was field-tested with elementary students and passages were evaluated based on difficulty, alternate-form reliability, and readability. Passages more than one

standard error of measurement above or below the overall mean difficulty (based on number of words read correctly), passages whose readability was outside of the intended grade range, and passages whose alternate-form reliability was less than .70 were eliminated from the pool. Passage length ranges from 150-400 words.

Developers modified each R-CBM passage for use as a Maze task using a procedure described by Fuchs and Fuchs (1992). The first sentence of each passage remains intact. Starting with the second sentence, every seventh word has been replaced by a bracketed set of three words. One of these three words is the word from the original passage (i.e., the correct choice), and the other two are distracter words. One distracter word is a word from the passage that is of the same part of speech but does not make sense or preserve meaning, while the second distracter is a word from the passage that is of a different part of speech and does not make sense in context (Howe & Shinn, 2002). Based on data from a standardization sample, the alternate-form reliability of R-Maze passages ranges from .68 - .78. Alternate-form reliability for the R-Maze passage set is .74.

Standard administration of the R-Maze involves students being given a standard set of instructions regarding the task, and, if appropriate, a practice task. Following these instructions, students are asked to read a passage silently and circle the correct word each time they come to a bracketed set of three words. Students have three minutes to complete the task. Because students read silently and indicate their answers by circling words, the R-Maze task can be administered in a large group, small group, or individual format. R-Maze scores are calculated by counting the total number of correct responses on each passage. Students who happen to complete the R-Maze task in less than three minutes have their score prorated based on a formula developed by test developers (Howe & Shinn, 2002).

Read aloud and retell. The Dynamic Indicators of Basic Early Literacy Skills Next (DIBELS Next; Good & Kaminski, 2011) Oral Reading Fluency (DORF) task is a standard read aloud measure, while DIBELS Retell Fluency (RTF) is a word recall task. DIBELS Next passages differ from earlier editions of DIBELS passage sets in that they have been field-tested with elementary students and have been equated empirically. Another new feature of DIBELS Next involves the combination DORF and retell tasks into a single administration with the goal of obtaining a more comprehensive measure of reading ability. The technical manual of the DIBELS Next indicates that DORF has multiple-probe alternate-form reliability of .96 and test-retest reliability of .91 in second-grade students. For RTF, multiple-probe alternate-form reliability was .68 and test-retest reliability was .27 and non-

significant. Measures of criterion validity for DORF and RTF with a standardized reading outcome measure were .69 and .53, respectively.

Standard administration of DORF/RTF takes place in an individual format. Students are given a standard set of instructions and then asked to read a written passage aloud to the examiner. Once the student begins reading aloud, the examiner begins timing for one minute. As the student reads, the examiner marks mispronunciations, omissions, and any other errors on their copy of the story. At the end of one minute, the examiner tells the student to stop reading. Immediately after the student stops reading for DORF, the examiner prompts the student to recall as much as they can from the story he/she just read (i.e., retell). Once the student begins retelling the story, the administrator starts timing for one minute and begins marking the number of words a student recalls that are relevant to the story. Scoring for the DORF task involves calculating the total number of words a student read, then subtracting the number of errors to arrive at the number of words the student read correctly in one minute (WRCM). Scoring for the RTF task involves counting the total number of words the student recalled that were relevant to the story.

Reading comprehension. The Woodcock-Johnson IV Tests of Achievement (WJ-IV; McGrew, LaForte, & Schrank, 2014) Reading Comprehension - Extended cluster consists of three subtests: Passage Comprehension, Reading Recall, and Reading Vocabulary. The Passage Comprehension subtest involves students reading a sentence or short passage and identifying a missing word that make sense in context. This subtest has a median reliability of r = .89. The Reading Recall subtest requires students to read a story silently and then recall as much of the story as possible. Median reliability of the Reading Recall subtest is r = .92. For the Reading Vocabulary subtest, students read target words aloud and provide a synonym or antonym as appropriate. This subtest has a median reliability of r = .88. (McGrew et al., 2014). The Reading Comprehension cluster has a median reliability of r = .96. Unlike CBM measures, subtests from the WJ-IV are untimed, although students may be prompted for a response following a period of silence. An online scoring package is available from the publishers, and provides a report that includes scaled scores, age equivalents, and grade equivalents.

Procedural Integrity and Interobserver Agreement

Because CBM is a standardized procedure, it is important that passages are administered with integrity. During Phase One, 27.4% of Maze administrations and 27.1% of DORF/RTF administrations were monitored for procedural integrity. During Phase Two, 26.2% of Maze administrations and 30.4% of DORF/RTF administrations

were monitored for procedural integrity. Procedural integrity by phase and probe type is found in Table 1. For all probe types, integrity was assessed using the administration checklist provided by test developers (See Appendices D, E, and F).

Table 1. Procedural Integrity by Phase and Probe Type

	Phase One			Phase Two		
Probe Type	Average	Minimum	Maximum	Average	Minimum	Maximum
R-Maze	98.2%	83.3%	100%	96.5%	83.3%	100%
DORF	98.8%	83.3%	100%	98.7%	83.3%	100%
RTF	95.4%	66.7%	100%	96.1%	83.3%	100%

To ensure scoring accuracy, a random sample of 25.9% of Maze administrations and 27.1% of DORF/RTF were re-scored by a separate rater during Phase One. In Phase Two, 36.7% of Maze probes and 30.4% of DORF/RTF probes were re-scored for accuracy. For R-Maze, the second rater re-scored paper copies of individual passages. For DORF/RTF, the second rater listened to recorded administrations of the passage once and re-score the paper copy. Given concerns in the literature regarding low reliability on scoring of retell measures (Bellinger & DiPerna, 2011), audio recordings helped enable a method of correcting for examiner errors in administration. If interobserver agreement (IOA) scores were below 80%, the score recorded by the primary rater (i.e., the author or a graduate assistant) was used for data analysis purposes. For WJ-IV subtests, 25% of administrations were recorded and re-scored for accuracy. Average IOA for subtests was 97.8% and ranged from 91.2% to 100%. For all measures, IOA was calculated using the following formula: Agreement = (Number of agreements/Number of agreements + Disagreements) *100. Additional results of IOA for each phase may be found in Table 2.

Table 2. Interobserver Agreement by Phase and Probe Type

	Phase One			Phase Two		
Probe Type	Average	Minimum	Maximum	Average	Minimum	Maximum
R-Maze	98.4%	94.1%	100%	99.2%	98.2%	100%
DORF	99.2%	92.4%	100%	98.8%	89.1%	100%
RTF	91.3%	52.6%	100%	89.1%	33.3%	100%

Procedure

Training. Graduate and undergraduate psychology majors assisted with data collection. All research assistants participated in a 3-hour training session prior to collecting data for the study. The training session was conducted by the author, and included an overview of reading CBM, including a brief history and its uses. Next, DIBELS DORF/RTF and AIMSweb R-Maze tasks were introduced, including specific administration and scoring rules for each. Research assistants then practiced scoring CBM probes using DIBELS training videos and

AIMSweb sample probes. During training, research assistants also practiced administering DORF/RTF and R-Maze tasks to the author using the scripts provided by the publishers. The author scored procedural integrity using checklists provided by the publishers (See Appendices D-F). After research assistants demonstrated at least 90% scoring and administration accuracy on training materials, they observed in vivo administrations of the measures and scored during live administrations. Once they demonstrated 90% scoring accuracy on three consecutive live administrations for each probe type, they were allowed to aid in data collection. Each research assistant received a training packet that included copies of administration scripts for each task, as well as an overview of scoring procedures. Research assistants were asked to use this packet a reference during data collection to increase procedural integrity, although extra copies were always available from the researcher.

Phase one: Identification of equivalent passage sets. R-Maze probes were selected from the pool of 27 AIMSweb (Howe & Shinn, 2002) progress monitoring passages described above, which were available for download from the AIMSweb website. Similarly, DORF/RTF passages were selected from a pool of 20 DIBELS Next (Good & Kaminski, 2011) progress monitoring passages available for download from the DIBELS website. Administration and scoring procedures were conducted according to the standardized instructions suggested by each respective publisher as described above. Students across the four participating schools were administered R-Maze and DORF/RTF passages in a random order until at least 25 passages from each pool were administered, or until the duration allowed for Phase One expired. At the end of Phase One, each student had completed an average of 9.0 R-Maze probes and an average of 7.4 DORF/RTF probes. R-Maze administration typically occurred in small-group formats (i.e., 3-5 students). DORF/RTF administration always occurred in an individual format, and administrations were voice-recorded for IOA scoring and treatment integrity purposes. The setting for passage administration varied across schools. Probes were administered at small tables and desks in the hallway in two schools, in the library at one school, and in an empty classroom at the fourth school.

A total of 14 probes administered during this phase (9 R-Maze; 5 DORF/RTF) were excluded from data analysis due to spoiled administrations. Spoiled administrations were defined as any occurrence that affected administration or scoring such that a) a valid score could not be obtained or b) the score obtained was likely to be inaccurate. Situations in which student effort or motivation resulted in a low score were not judged as spoiled administrations unless the student refused to participate or purposefully made errors. Spoiled administrations during this phase were typically the result of examiner error, such as failing to start timing appropriately. Spoiled

administrations were also the result of major interruptions or distractions (e.g., fire or tornado drills; announcements over the loudspeaker). In the event of a spoiled administration, the student was administered an alternate probe.

Phase two: Progress monitoring. Second-grade students who scored below the reading benchmark during winter universal screenings (i.e., 71 WCPM or lower) but were still capable of reading a second grade-level passage were recruited for phase two of the study. Teachers at participating schools were asked to identify these students and distribute parental consent forms to potential participants' parents. Following recruitment and parental consent, 33 students agreed to participate in this phase of the study. One student moved out-of-state during the study, bringing the final sample size for this phase to 32 students.

Each student in this phase was administered one R-Maze passage and one DORF/RTF passage per week for 8 weeks or until 8 occasions of data were collected. Data collection typically occurred once per week; however, due to various schedule conflicts (i.e, student absences, school holidays, field trips, assemblies, etc.) data collection occurred twice per week (Tuesday and Friday) for three students. R-Maze administration typically occurred in small-group formats (i.e., 3-5 students). DORF/RTF administration always occurred in an individual format, and administrations were voice-recorded for IOA scoring and treatment integrity purposes. Administration order of passages was randomized and balanced across students and schools to help account for order effects and additional form effects not accounted for by passage equivalency efforts. A random number generator function was used to devise the administration order of probes, which was balanced across schools. Following completion of progress monitoring data collection, each participant was administered the Reading Comprehension – Extended cluster of the WJ-IV. Individual administrations of WJ-IV subtests were also voice-recorded and reviewed by a second rater for IOA purposes. Settings of probe and outcome measure administration were identical to those in Phase One.

There were a total of four spoiled administrations during this phase of the study: one for R-Maze (which resulted in three spoiled participant probes, as there were three students in the group) and three for DORF/RTF. The spoiled Maze administration occurred when the administrator failed to start her timer at the beginning of probe administration. The spoiled DORF/RTF administrations were also the result of examiner error, including failing to administer the RTF task following DORF administration and inaccurate timing procedures. In all four cases, students were administered alternate probes following the spoiled administration.

Data Analyses

Phase one: Identification of equivalent passage sets. Data gathered during Phase One were entered into a data file in SPSS (IBM Corp., 2015) in order to facilitate calculation of descriptive statistics which resulted in rank-ordering and identification of new passage sets. A mean score (i.e., number of correct selections for R-Maze, words read correctly per minute for DORF, and number of content words recalled for RTF) was calculated for each passage in the pool, followed by calculation of a grand mean for each probe type. Mean scores for each passage were rank-ordered around the grand mean for R-Maze and DORF. Although mean scores were calculated for RTF, these passages were ranked around the average WCPM scores rather than the number of relevant words recalled during the RTF task. Given that DORF has been shown to be a more reliable measure and stronger predictor of reading performance, it was decided that a passage set formed around WCPM rather than RTF would be appropriate. The five passages whose means were immediately above and below the grand mean of each probe type were considered for inclusion in the next phase. For DORF, the WCPM ranges of these 10 passages were calculated and adjustments were made as needed such that the mean WCPM for all passages in the new set were within 5 WCPM of the grand mean for DORF.

Although Phase Two only included eight occasions of data collection, 10 passages for both DORF/RTF and R-Maze were selected for use in Phase Two. The two extra passages identified served as alternate passages to be used in the event of a spoiled administration, as described above.

Phase two: Progress monitoring. Probes administered during Phase Two were scored in the same way as those in Phase One with one exception: pro-rating formulas were not employed in situations where students finished the task in less than three minutes. Based on observations of student performance during live administrations during the R-Maze task, participants in this phase who finished in less than three minutes had a high likelihood of rushing through the task, which typically resulted in a high error rate (i.e., greater than 67%). As such, R-Maze probe scores in this phase consisted of a count of the total number of correct selections. This strategy was adopted given that pro-rating would result in inflated and inaccurate scores for these participants. Although such administrations may have been considered a spoiled administration, it was decided that applying a post-hoc scoring correction would be more time-efficient than re-administering these probes, particularly since some students persisted in rushing through the task even after being reminded of the task instructions and emphasizing that students should work as quickly as the can *without making mistakes*. Potential implications of scoring corrections are addressed in the Discussion section.

Data file structuring. Data gathered during Phase Two were entered into data files in SPSS (IBM Corp., 2015). In the file for growth models, data were structured hierarchically, such that each row of data included a single student's CBM scores on a single occasion of data collection. In other words, the original level-1 data file included 256 rows before removing outliers. Furthermore, data were sorted by their student identification number then by the occasion of data collection. The data file used for predicting comprehension included 32 rows of data, each of which included a single student's comprehension score and their CBM scores for the three different probe types on the first occasion (i.e., their initial status score for each CBM measure). In this file, data were sorted first by their school identification number then by their student identification number.

Assumptions. HLM holds the assumptions of normality and homogeneity of variance. After evaluating normality plots for CBM probe types, one clear outlier was observed in both R-Maze and DORF, while several outliers were identified for RTF. The outlier for R-Maze was a score in which the student completed the task in just over one minute and had an error rate of 50%. As such, it was determined that the score may not be a valid indicator of that student's performance and was thus deleted. For DORF, the outlier score was also determined to be possibly invalid and was thus deleted. After removing these occasions of data, both normality and homogeneity assumptions were met for these variables. For RTF, tests for normality indicated kurtosis (>1). This violation also has the potential to result in significant tests for heterogeneity of variance (Raudenbush & Bryk, 2002). As such, three extreme scores were removed for RTF (the highest and two lowest). These deleted cases resulted in a total of 255 occasions of R-Maze and DORF data and 253 occasions of RTF data for the final level-1 data set.

Variable coding. Time (occasion, or OCC) was centered on the first measurement occasion by subtracting each measurement occasion by 1. This aided in model interpretation such that the intercept indicated a particular student's score at the beginning of the study. Student eligibility for free or reduced lunch (FRL) and student special education status (SPED) were dummy coded such that "0" indicated a student who was not eligible for free or reduced lunch or did not receive special education services, while "1" indicated a student who was eligible for free or reduced lunch or did receive special education services.

HLM model building. The statistical modeling software HLM 7 (Scientific Software International; Raudenbush et al., 2011) was used to evaluate all models. For all models used in analysis, parameters were estimated through restricted maximum likelihood (RML). This is the default likelihood setting for HLM, and

maximizes sample residuals. This method is appropriate for small sample sizes, as it reduces estimate bias compared to full maximum likelihood (Singer & Willett, 2003).

Growth models. Given that the study involved eight occasions of data, it is possible that growth patterns would be better explained by a high-order polynomial (e.g., quadratic, cubic) rather than a linear model. To investigate this possibility, individual students' progress data were graphed and assessed through visual inspection and likelihood-ratio tests on deviance statistics. Samples graphs depicting individual students' progress by probe type, as well as aggregated mean CBM scores across occasions for each probe types may be found in Figures 1-6. While visual inspection initially suggested that a linear model would be most appropriate for each of the three probe types, a quadratic model was constructed for each probe type to test this empirically given that previous studies evaluating student progress with CBM measures have found evidence of a curvilinear relationship (i.e., a growth curve) and that quadratic models are more appropriate (e.g. Shin et al., 2004).

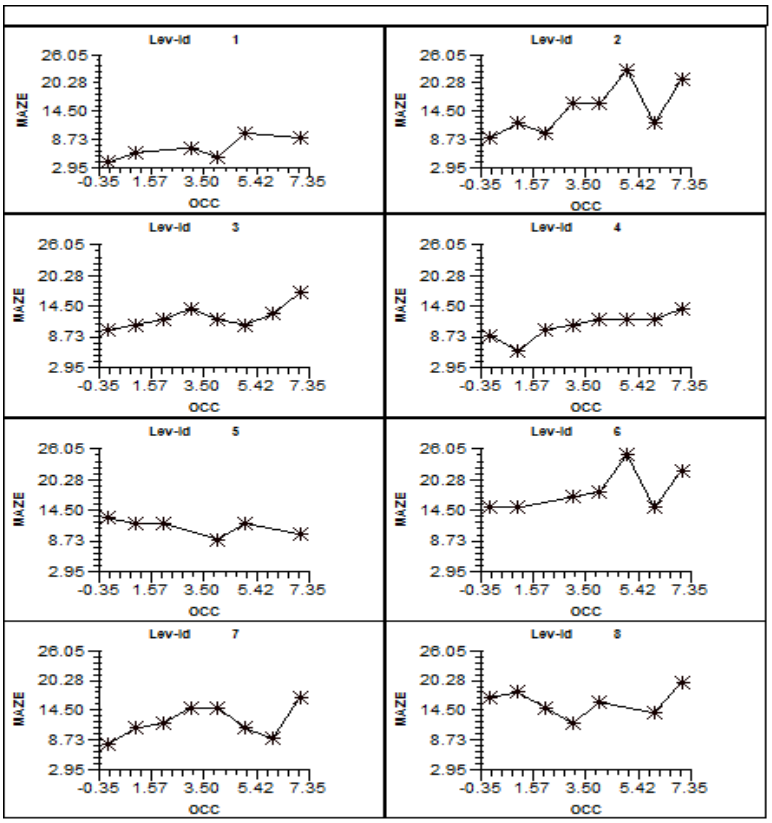


Figure 1. Sample student graphs of R-Maze scores (MAZE) as a function of measurement occasion (OCC).

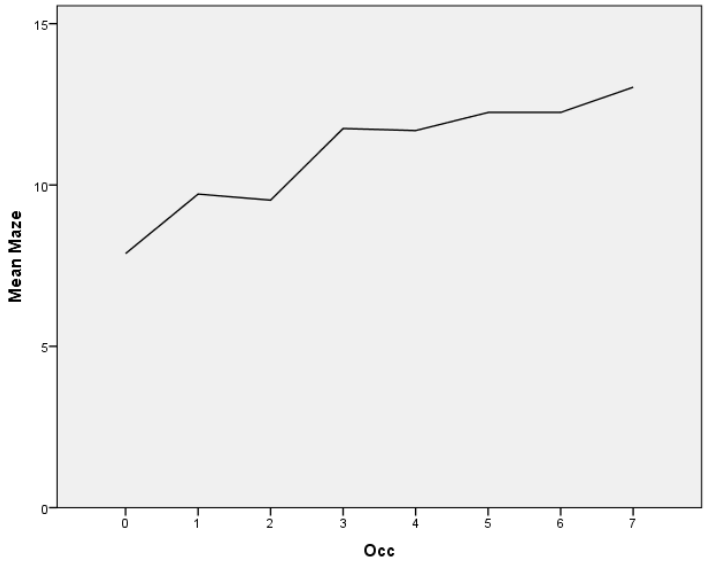


Figure 2. Aggregated average student R-Maze (Mean Maze) scores as a function of measurement occasion (Occ).

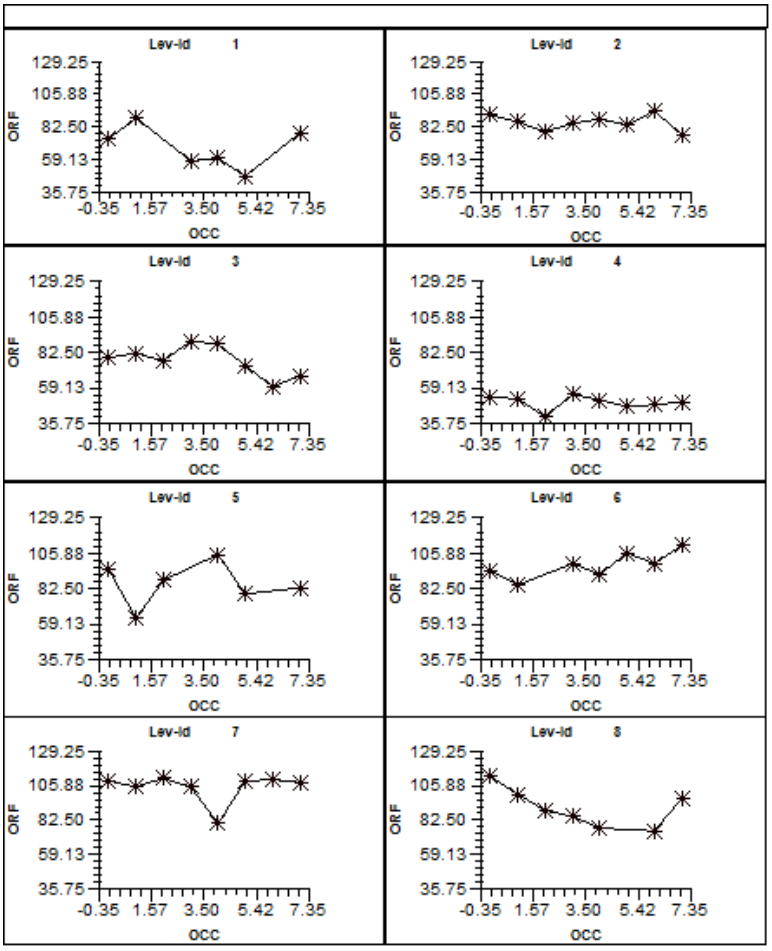


Figure 3. Sample student graphs of DIBELS oral reading fluency scores (ORF) as a function of measurement occasion (OCC).

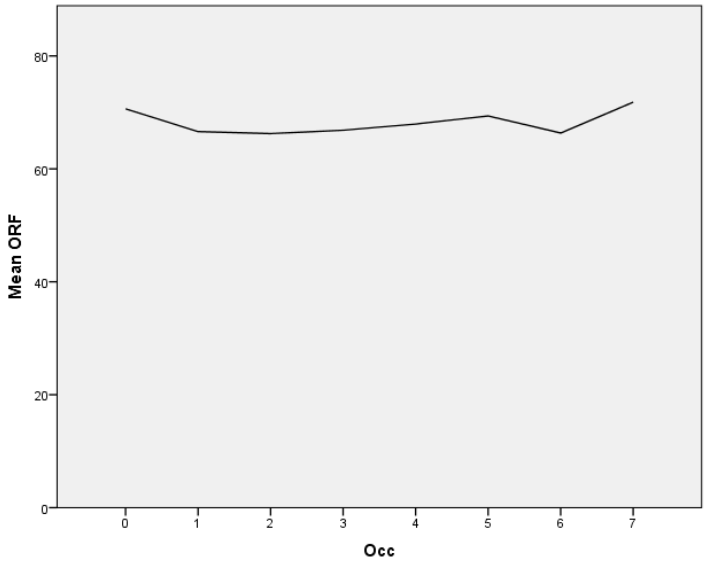


Figure 4. Aggregated average student DIBELS oral reading fluency (Mean ORF) scores as a function of measurement occasion (Occ).

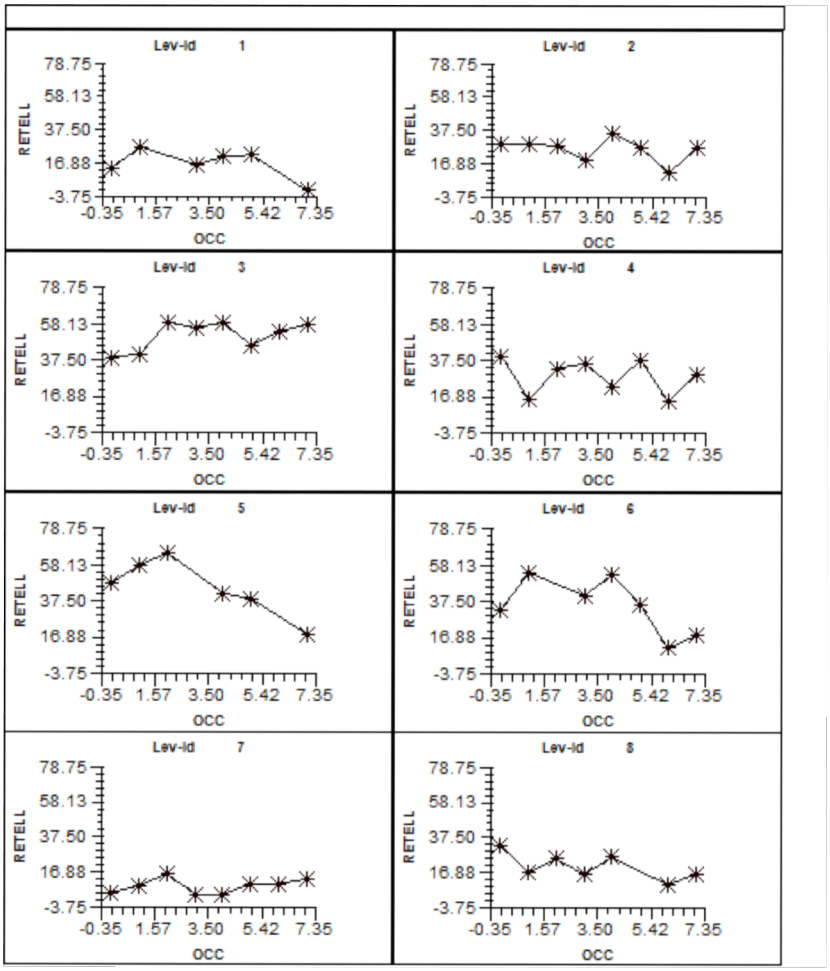


Figure 5. Sample student graphs of DIBELS retell fluency scores (RETELL) as a function of measurement occasion (OCC).

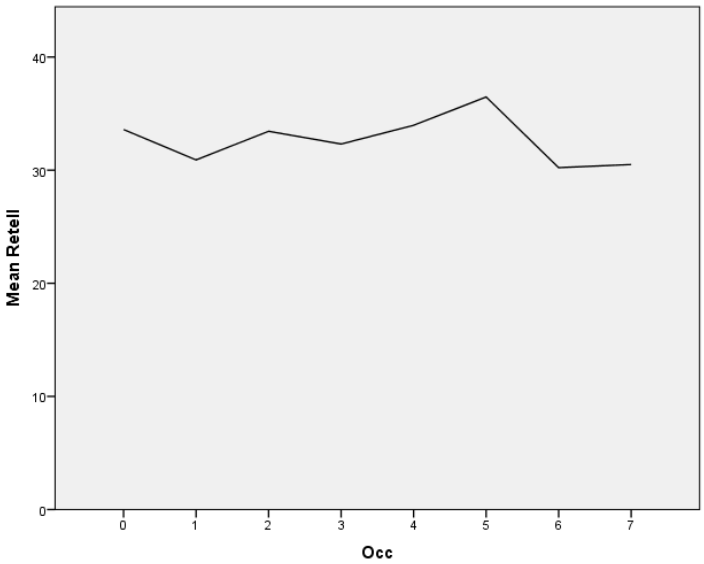


Figure 6. Aggregated average student DIBELS retell fluency (Mean Retell) scores as a function of measurement occasion (Occ).

Three separate growth models were built in an effort to answer research question one, one for each CBM probe type. Each model included two levels, in which measurement occasions (i.e., time) at level-1 were nested within individual students at level-2. The contributions of student socioeconomic status, as indicated by eligibility for free or reduced lunch (FRL), and student special education status (SPED) were also evaluated by including these variables as predictors at level-2. While a 3-level model could also be used given that students in the study were nested within schools, the variables of interest (i.e., time, student FRL status and student SPED status) were at level-1 and level-2. Furthermore, the small number of level-3 units (i.e., schools) limits interpretability of effects that would be found at this level. As such, 2-level models were used for evaluating student growth.

A taxonomical approach was used in building all growth models, such that simpler models were constructed first and that subsequent, more complicated models were fit as indicated by empirical evidence and theory (Singer & Willett, 2003). This approach provides a baseline to which future models may be compared (Raudenbush & Bryk, 2002). Given these recommendations, the first built was an unconditional means model (Singer & Willett, 2003). The unconditional means model, also known as the null or empty model, does not include any predictors, only the outcome variable. This model is essentially a one-way analysis of variance, and it allows the user to test the null hypothesis that the mean initial status is not statistically different from zero. (Raudenbush & Bryk, 2002). The unconditional means model equations for each probe type may be found in Table 3.

Table 3. Taxonomy of multilevel models for change fitted to CBM data

	Level-1/Level-2 specification		
Model	Level-1 Model	Level-2 Model	Composite Model
A	$Y_{ti} = \pi_{0i} + e_{ti}$	$\pi_{0i} = \beta_{00} + r_{0i}$	$Y_{ti} = \beta_{00} + r_{0i} + e_{ti}$
B	$Y_{ti} = \pi_{0i} + \pi_{1i}(OCC)_{ti} + e_{ti}$	$\pi_{0i} = \beta_{00} + r_{0i}$, $\pi_{1i} = \beta_{10} + r_{1i}$	$Y_{ti} = \beta_{00} + \beta_{10}(OCC)_{ti} + r_{0i} +$ $r_{1i}(OCC)_i + e_{ti}$
C	$Y_{ti} = \pi_{0i} + \pi_{1i}(OCC)_{ti} + e_{ti}$	$\pi_{0i} = \beta_{00} + \beta_{01}(FRL)_i + \beta_{02}(SPED)_i + r_{0i}$, $\pi_{1i} = \beta_{10} + \beta_{11}(FRL)_i + \beta_{12}(SPED)_i + r_{1i}$	$Y_{ti} = \beta_{00} + \beta_{01}(\text{FRL})_i +$ $\beta_{02}(\text{SPED})_i + \beta_{10}(OCC)_{ti} +$ $\beta_{11}(\text{FRL})_i(OCC)_{ti} +$ $\beta_{12}(\text{SPED})_i(OCC)_{ti+} r_{0i}$ $r_{1i}(OCC)_{ti+} e_{ti}$

Note: These models predict CBM scores as a function of time (OCC) at level 1 and free/reduced lunch status (FRL) and special education status (SPED) at level 2. Model A represents the unconditional means or "empty" model. Model B represents the unconditional growth model, and Model C represents the conditional model. Three separate model taxonomies were constructed – one for each CBM type.

Next, an unconditional growth model was estimated for each probe type. In this model, time was added to the unconditional means model as a level-1 predictor. The unconditional growth model allows one to partition and quantify variation across both people and time (Singer & Willett, 2003). Time was entered as a random effect, which allowed each student to have his or her own growth rate over the course of the study. Equations for unconditional growth models may be found in Table 21. For all probe types, measurement occasions were balanced across students with no missing data. Measurement occasions were adjusted such that 0 represented the first occasion of data collection.

Finally, student-level predictors (i.e., special education status and free/reduced lunch status) were added to each model at level 2. Model fit was evaluated at each progression using deviance statistics and a measure of Pseudo R^2. This statistic allows one to calculate how well subsequent models reduce the proportion of residual variance compared to the previous model (Singer & Willett, 2003). It is important to note that deviance statistics are only useful in comparing models that are nested within each other (Raudenbush & Bryk, 2002), and, in the use of RML, only differ in their variance components. As such, these statistics were only used to compare model fit between the unconditional means and unconditional growth models.

Prediction model. The model used to evaluate which CBM probe type best predicted reading comprehension included two levels, which included student scores on predictor variables at level-1 nested within schools at level-2. Again, the small number of schools limits interpretability; however, it was determined that it was important to account for the nested nature of scores. Like the growth models, a taxonomical approach was used to evaluate research question two. A taxonomy of model fitting may be found in Table 4.

Table 4. Taxonomy of multilevel models for change fitted to CBM data

	Level-1/Level-2 specification		
Model	Level-1 Model	Level-2 Model	Composite Model
A	$RCOMP_{ij} = \beta_{0j} + r_{ij}$	$\beta_{0j} = \gamma_{00} + u_{0j}$	$RCOMP_{ij} = \gamma_{00} + u_{0j} + r_{ij}$
B	$RCOMP_{ij} = \beta_{0j} + \beta_{1j}(MAZE_{ij})$	$\beta_{0j} = \gamma_{00} + u_{0j},$	$RCOMP_{ij} = \gamma_{00} + \gamma_{10}(MAZE_{ij}) +$
	$+ \beta_{2j}(DORF_{ij}) + \beta_{3j}(RTF_{ij}) +$	$\beta_{1j} = \gamma_{10}$	$\gamma_{20}(DORF_{ij}) + \gamma_{30}(RTF_{ij}) + u_{0j},$
	r_{0J}	$\beta_{2j} = \gamma_{20}$	$+ r_{0J}$
		$\beta_{3j} = \gamma_{30}$	

Note: These models use CBM scores (i.e., MAZE, DORF, RTF) to predict reading comprehension (RCOMP) scores at level 1. Model A represents the unconditional means or "empty" model. Model B represents the 2-level model with predictors included.

RESULTS

Phase One: Identification of Equivalent Passage Sets

Table 5 indicates the means, standard deviations, and final results of rank-ordering R-Maze passages by their respective grand means. Prior to rank-ordering, the range in mean correct selections between the 27 available R-Maze progress monitoring probes was 9.74 (13.58 – 23.32). After rank-ordering passages for R-Maze around the grand mean and selecting the five passages immediately above and below the mean, this range was reduced to 3.55 (16.60 – 20.15). The 10 R-Maze passages identified through rank-ordering around the grand mean were then retained for use in the next phase of the study.

Table 5. Numerical and Rank Ordering of R-Maze Probes following Passage Equating

Numerical Order			Rank Order		
R-Maze Probe Number	N	Number Correct Mean (SD)	R-Maze Probe Number	N	Number Correct Mean (SD)
4P04 *At my house*	25	20.08 (6.34)	2P14 *It all began*	22	23.32 (7.02)
2P05 *Aunt Pam worked*	28	19.25 (5.51)	2P18 *Kim was happy*	25	22.13 (6.25)
2P06 *Cam was a clam*	25	15.92 (7.88)	2P32 *Tom and his family*	22	20.91 (7.98)
2P07 *Cole and Meg*	26	16.00 (7.78)	2P16 *It was the first*	23	20.87 (6.27)
2P08 *Dad was upset*	24	20.42 (5.72)	2P29 *A mother held*	23	20.48 (5.46)
2P09 *Last week Grandpa*	25	16.56 (5.50)	2P08 *Dad was upset*	24	20.42 (5.72)
2P10 *I can say many*	28	16.25 (5.87)	2P28 *The lion was*	25	20.28 (6.01)
2P11 *I wish I*	25	17.64 (5.74)	2P19 *Maddie wanted to***	26	20.15 (7.90)
2P12 *Not very long ago*	24	20.00 (5.40)	4P04 *At my house***	25	20.08 (6.34)
2P14 *It all began*	22	23.32 (7.02)	2P12 *Not very long ago***	24	20.00 (5.40)
2P16 *It was the first*	23	20.87 (6.27)	2P05 *Aunt Pam worked***	28	19.25 (5.51)
2P17 *Joey liked to*	26	13.58 (7.67)	2P31 *Today is the animal***	25	19.16 (5.47)
2P18 *Kim was happy*	25	22.13 (6.25)	2P11 *I wish I***	25	17.64 (5.74)
2P19 *Maddie wanted to*	26	20.15 (7.90)	2P30 *This is a tale***	25	17.40 (6.02)
2P20 *My dad can fix*	25	16.60 (5.87)	2P27 *The kids in***	26	17.35 (5.77)
2P21 *My little sister Emma*	25	13.96 (7.97)	2P25 *Pat loved to make***	25	16.68 (5.66)
2P22 *My teacher says*	25	15.88 (5.88)	2P20 *My dad can fix***	25	16.60 (5.87)
2P23 *One spring day, Mark*	25	16.28 (7.06)	2P09 *Last week Grandpa*	25	16.56 (5.50)
2P25 *Pat loved to make*	25	16.68 (5.66)	2P23 *One spring day, Mark*	25	16.28 (7.06)
2P26 *Can animals really*	28	14.79 (5.10)	2P10 *I can say many*	28	16.25 (5.87)
2P27 *The kids in*	26	17.35 (5.77)	2P33 *Where is your fort*	25	16.12 (5.85)
2P28 *The lion was*	25	20.28 (6.01)	2P07 *Cole and Meg*	26	16.00 (7.78)
2P29 *A mother held*	23	20.48 (5.46)	2P06 *Cam was a clam*	25	15.92 (7.88)
2P30 *This is a tale*	25	17.40 (6.02)	2P22 *My teacher says*	25	15.88 (5.88)
2P31 *Today is the animal*	25	19.16 (5.47)	2P26 *Can animals really*	28	14.79 (5.10)
2P32 *Tom and his family*	22	20.91 (7.98)	2P21 *My little sister Emma*	25	13.96 (7.97)
2P33 *Where is your fort*	25	16.12 (5.85)	2P17 *Joey liked to*	26	13.58 (7.67)
Grand Mean (SD)	676	18.08 (6.74)	Grand Mean (SD)	676	18.08 (6.74)

Note: ** indicates passages retained for Phase Two.

The means, standard deviations, and final results of rank-ordering DORF passages by their respective WCPM grand means are found in Table 6.

Table 6. Numerical and Rank Ordering of DIBELS Oral Reading Fluency Probes following Passage Equating

Numerical Order			Rank Order		
DIBELS Probe Number	N	Mean WRCM (SD)	DIBELS Probe Number	N	Mean WRCM (SD)
L2PM1			L2PM10		
Building Happy Places	27	96.00 (28.82)	*Bats Are Not Birds*	32	116.16 (26.85)
L2PM2			L2PM15		
Luke Makes His Move	27	106.04 (26.97)	*Going to School*	25	115.48 (24.28)
L2PM3			L2PM12		
My Pen Pal	28	107.00 (35.38)	*Writing Your Own Book*	27	112.67 (25.91)
L2PM4			L2PM8		
Life on the River	27	102.78 (25.52)	*Dear Diary*	26	112.65 (40.96)
L2PM5			L2PM11		
A Day for Trees	32	90.44 (30.04)	*Cooking School*	32	108.75 (28.12)
L2PM6			L2PM16		
Making Orange Juice	28	103.89 (37.08)	*A Happy House Plant***	26	107.73 (41.05)
L2PM7			L2PM18		
Kim Gets Ready	32	106.53 (31.67)	*Canoe Fun***	26	107.62 (35.10)
L2PM8			L2PM3		
Dear Diary	26	112.65 (40.96)	*My Pen Pal***	28	107.00 (35.38)
L2PM9			L2PM7		
Circus Tickets	25	100.88 (36.03)	*Kim Gets Ready***	32	106.53 (31.67)
L2PM10			L2PM19		
Bats Are Not Birds	32	116.16 (26.85)	*African Drums***	27	106.38 (36.77)
L2PM11			L2PM2		
Cooking School	32	108.75 (28.12)	*Luke Makes His Move***	27	106.04 (26.97)
L2PM12			L2PM6		
Writing Your Own Book	27	112.67 (25.91)	*Making Orange Juice***	28	103.89 (37.08)
L2PM13			L2PM13		
In Space for an Hour	26	103.69 (34.72)	*In Space for an Hour***	26	103.69 (34.72)
L2PM14			L2PM4		
Wind Power	26	98.65 (33.50)	*Life on the River***	27	102.78 (25.52)
L2PM15			L2PM9		
Going to School	25	115.48 (24.28)	*Circus Tickets***	25	100.88 (36.03)
L2PM16			L2PM14		
A Happy House Plant	26	107.73 (41.05)	*Wind Power*[a]	26	98.65 (33.50)
L2PM17			L2PM1		
A Gift of Chores	27	94.33 (37.16)	*Building Happy Places*	27	96.00 (28.82)
L2PM18			L2PM17		
Canoe Fun	26	107.62 (35.10)	*A Gift of Chores*	27	94.33 (37.16)
L2PM19			L2PM20		
African Drums	27	106.38 (36.77)	*Flower Parts*	28	93.33 (30.37)
L2PM20			L2PM5		
Flower Parts	28	93.33 (30.37)	*A Day for Trees*	32	90.44 (30.04)
Grand Mean (SD)	554	104.55 (32.78)	Grand Mean (SD)	554	104.55 (32.78)

Note: ** indicates passages retained for Phase Two; [a]indicates a passage that was identified through rank-ordering but was then eliminated from the passage set due to having a WCPM score outside of the recommended range of the mean.

Prior to rank-ordering DORF passages, the range in mean WCPM for the 20 available DIBELS progress monitoring passages was 25.72 (90.44 – 116.16). After initial rank-ordering and identifying the five passages immediately above and below the grand mean, the difference in WCPM between passages in the new equivalent set was 8.97 (98.65 - 107.62). The highest-ranked probe was within 3.07 WCPM of the grand mean, while the lowest-

ranked probe was within 5.9 WCPM of the grand mean. Given Poncy et al.'s (2005) recommendation that read aloud progress monitoring passage fall within 5 WCPM of the mean of the set, the lowest-ranked probe (i.e., L2PM14, *Wind Power*) was replaced with probe L2PM16, *A Happy House Plant*. This probe was ranked immediately above the fifth passage above the grand mean. This replacement adjusted the overall range of the new passage set to 6.85 (100.88 – 107.73). Furthermore, the highest-ranked probe was now within 3.18 WCPM of the grand mean while the lowest-ranked probe was within 3.67 WCPM of the grand mean. Given these improvements, the six passages immediately above the grand mean and the four passages immediately below were retained for use in Phase Two.

Finally, Table 7 shows the means, standard deviations, and rank-ordering results for DIBELS RTF passages. DIBELS passages were equated based on DORF performance and WCPM means rather than the mean number of words recalled on RTF tasks. As shown in Table 7, passages that were most alike in terms of WCPM were not necessarily the most alike in terms of average number of words recalled during RTF. Potential implications of this discrepancy are discussed in a subsequent chapter.

Table 7. Numerical and Rank Ordering of DIBELS Retell Fluency Probes following Passage Equating

Numerical Order			Rank Order		
DIBELS Probe Number	N	Mean Words Recalled (SD)	DIBELS Probe Number	N	Mean Words Recalled (SD)
L2PM1			L2PM11		
Building Happy Places	27	40.30 (22.79)	*Cooking School*	32	58.19 (26.30)
L2PM2			L2PM2		
Luke Makes His Move	27	52.56 (23.47)	*Luke Makes His Move***	27	52.56 (23.47)
L2PM3			L2PM8		
My Pen Pal	28	32.21 (18.59)	*Dear Diary*	26	52.46 (25.17)
L2PM4			L2PM9		
Life on the River	27	37.85 (18.42)	*Circus Tickets***	25	48.00 (21.70)
L2PM5			L2PM7		
A Day for Trees	32	34.63 (16.76)	*Kim Gets Ready***	32	45.41 (24.84)
L2PM6			L2PM10		
Making Orange Juice	28	32.43 (17.59)	*Bats Are Not Birds*	32	44.72 (21.63)
L2PM7			L2PM13		
Kim Gets Ready	32	45.41 (24.84)	*In Space for an Hour***	26	43.38 (17.81)
L2PM8			L2PM18		
Dear Diary	26	52.46 (25.17)	*Canoe Fun***	26	42.54 (21.33)
L2PM9			L2PM12		
Circus Tickets	25	48.00 (21.70)	*Writing Your Own Book*	27	41.96 (23.94)
L2PM10			L2PM15		
Bats Are Not Birds	32	44.72 (21.63)	*Going to School*	25	41.44 (20.06)
L2PM11			L2PM17		
Cooking School	32	58.19 (26.30)	*A Gift of Chores*	27	40.96 (23.53)
L2PM12			L2PM1		
Writing Your Own Book	27	41.96 (23.94)	*Building Happy Places*	27	40.30 (22.79)

(Table 7 continued)

Numerical Order			Rank Order		
DIBELS Probe Number	N	Mean Words Recalled (SD)	DIBELS Probe Number	N	Mean Words Recalled (SD)
L2PM13			L2PM16		
In Space for an Hour	26	43.38 (17.81)	*A Happy House Plant***	26	39.81 (22.23)
L2PM14			L2PM4		
Wind Power	26	27.04 (21.89)	*Life on the River***	27	37.85 (18.42)
L2PM15			L2PM5		
Going to School	25	41.44 (20.06)	*A Day for Trees*	32	34.63 (16.76)
L2PM16			L2PM20		
A Happy House Plant	26	39.81 (22.23)	*Flower Parts*	28	33.48 (18.08)
L2PM17			L2PM6		
A Gift of Chores	27	40.96 (23.53)	*Making Orange Juice***	28	32.43 (17.59)
L2PM18			L2PM3		
Canoe Fun	26	42.54 (21.33)	*My Pen Pal***	28	32.21 (18.59)
L2PM19			L2PM19		
African Drums	27	31.85 (18.90)	*African Drums***	27	31.85 (18.90)
L2PM20			L2PM14		
Flower Parts	28	33.48 (18.08)	*Wind Power*[a]	26	27.04 (21.89)
Grand Mean (SD)	554	41.19 (22.50)	Grand Mean (SD)	554	41.19 (22.50)

Note: ** indicates passages retained for Phase Two; [a]indicates a passage that was identified through rank-ordering but was then eliminated from the passage set due to having a WCPM score outside of the recommended range of the mean.

Phase Two: Progress Monitoring

Descriptive statistics for the student performance on the three different probe types may be found in Table 8. These data reflect the final number of occasions included in analyses for each probe type following removal of outliers, as well as the minimum and maximum scores achieved on each probe type.

Table 8. Descriptive Statistics for Growth Models

Variable	N	Mean	SD	Minimum	Maximum
R-Maze	255	10.96	5.02	1	25
DORF	255	68.03	23.37	15	125
RTF	253	32.22	16.28	0	78
FRL	32	0.47	0.50	0	1
SPED	32	0.38	0.49	0	1

Note: FRL = Free/Reduced Lunch Status; SPED = Special Education Status

Bivariate correlations for predictors included in growth models are found in Table 9. These correlations for each probe type indicate CBM scores aggregated across all occasions. All CBM probe types were positively correlated with each other, with DORF and R-Maze showing the strongest relationship ($r = .58$, $p < .01$). Furthermore, all CBM probe types were negatively correlated with both free/reduced lunch status and special education status, indicating that students who were eligible for free/reduced lunch or received special education

services scored lower on these measures compared to their counterparts who were not eligible for free/reduced lunch or did not receive special education services.

Table 9. Bivariate Correlations Between Predictors for Growth Model

	R-Maze	DORF	RTF	FRL	SPED
DORF	.58**	1	.35**	-.61**	-.35**
RTF	.23**	.35**	1	-.25**	-.44**
FRL	-.39**	-.61**	-.25**	1	.10
SPED	-.31**	-.35**	-.44**	.10	1

Note: FRL = Free/Reduced Lunch Status; SPED = Special Education Status
** $p < .01$

Growth models. In order to evaluate student growth, separate hierarchical linear growth models were built for each individual CBM probe type. Model building progressed in the sequence described above. Each model included two levels, in which measurement occasions (i.e., time) at level-1 were nested within individual students at level-2. The contributions of student socioeconomic status, as indicated by eligibility for free or reduced lunch, and student special education status were also evaluated by including these variables as predictors at level-2.

R-Maze growth. R-Maze was entered as an outcome variable for the unconditional means model. Results of this model (Table 10) indicated a significant coefficient of 10.96 ($p < .001$), indicating that the grand mean of R-Maze scores across all occasions and all students was different than zero. Furthermore, results for the random effects portion in this model indicate that R-Maze scores vary significantly across students (χ^2 =326.20, df = 31, $p < .001$). Finally, this model resulted in an intra-class correlation (ICC) of 0.548, indicating that 54.8% of the variance in R-Maze scores can be attributed to differences between students.

Table 10. Results of the Unconditional Means Model: AIMSweb R-Maze

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Mean initial status, β_{00}	10.96	0.70	15.75	31	< .001
Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, r_0	14.03	3.75	326.20	31	< .001
Level-1 error, *e*	11.56	3.50			

The unconditional growth model (Table 11) was specified next by adding time (i.e., the "occasion" variable) to the unconditional means model as a random effect. Results of this model estimate an average R-Maze score of 8.58 correct selections on the first occasion of data collection and that scores increased, on average, 0.68 correct selections at each subsequent measurement occasion during the study ($p < .001$). Furthermore, results of random effects show a significant intercept (χ^2 = 154.31, df = 31, $p < .001$) and slope (χ^2 = 47.76, df = 31, $p < .05$),

indicating that students vary significantly on their R-Maze scores at the beginning of the study, and that there was significant variation in their growth rates over the course of the study. These results support the inclusion of time as a random, rather than fixed, effect in the model. The proportional reduction in residual variance from the unconditional means model to the unconditional growth model was calculated using the following formula:

$$\text{Pseudo } R^2 = \frac{\sigma^2 \text{ (unconditional means model)} - \sigma^2 \text{ (unconditional growth model)}}{\sigma^2 \text{ (unconditional means model)}}$$

Results indicate pseudo $R^2 = .294$, suggesting that 29.4% of the within-person variation in R-Maze scores can be explained by time. Furthermore, the deviance in this model was reduced by 63.72, which significantly improved model fit ($\chi^2 = 63.72$, $df = 2$, $p < .001$).

Table 11. Results of the Unconditional Growth Model: AIMSweb R-Maze

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Mean initial status, β_{00}	8.58	0.73	11.80	31	< .001
Mean growth rate, β_{10}	0.68	0.10	7.02	31	< .001
Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, r_{0i}	13.53	3.68	154.31	31	< .001
Growth rate, r_{1i}	0.11	0.33	47.76	31	0.03
Level-1 error, e_{ti}	8.16	2.86			

Finally, student-level variables (i.e., FRL and SPED) were added to the unconditional growth model as level-2 predictors for the initial status and rate of change of R-Maze scores. Table 12 shows results of this model. Estimation of the fixed effects of the model indicate that both FRL status and SPED status were significantly related to R-Maze performance. Specifically, students who were eligible for FRL scored, on average, 4.03 selections lower on their first R-Maze than students who were not eligible for FRL ($p < .001$) and students who received SPED services scored, on average, 4.05 selections lower on their first R-Maze than students who did not receive SPED services ($p < .001$). Furthermore, slope estimates for fixed effects indicate that individual students' growth rates did not differ significantly based on their FRL ($p = 0.63$) or SPED ($p = 0.08$) status. Random effect estimates indicated that there is still residual level-1 variance that could be explained, although such predictors were not measured in this study. Further model specification may also help explain remaining variance in students' initial status. Finally, the addition of FRL and SPED explained less than 1% more variance than the unconditional growth model.

Table 12. Results of the Conditional Model: AIMSweb R-Maze

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Model for initial status, π_{0i}					
Mean initial status, β_{00}	11.86	0.78	15.19	29	< .001
FRL, β_{01}	-4.03	1.05	-3.82	29	< .001
SPED, β_{02}	-4.05	1.08	-3.76	29	< .001
Model for growth rate, π_{1i}					
Mean growth rate, β_{10}	0.51	0.14	3.58	29	.001
FRL, β_{10}	0.09	0.19	0.48	29	.63
SPED, β_{10}	.35	.20	1.79	29	.08

Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, r_{0i}	5.24	2.29	73.55	29	< .001
Growth rate, r_{1i}	0.09	0.30	42.48	29	.05
Level-1 error, e_{ti}	8.16	2.86			

Note: FRL = Free/Reduced Lunch Status; SPED = Special Education Status

DORF growth. Model building for DORF proceeded in much the same way as R-Maze. First, DORF was entered as an outcome variable for the unconditional means model. Results of this model (Table 13) indicated initial status of DORF performance at 68.03 WCPM. Like R-Maze, the intercept for DORF was significant ($p < .001$), indicating that the grand mean of DORF scores across all occasions and all students is different than zero. The random effects estimates of this model showed that DORF scores varied significantly across students ($\chi^2 = 1238.53$, $df = 31$, $p < .001$). Finally, the unconditional means model for DORF resulted in an ICC of 0.832, indicating that 83.2% of the variance in DORF scores can be attributed to differences between students.

Table 13. Results of the Unconditional Means Model: DIBELS Oral Reading Fluency (DORF)

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Mean initial status, β_{00}	68.03	3.87	17.59	31	< .001

Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, r_0	467.04	21.61	1238.53	31	< .001
Level-1 error, e	94.09	9.70			

The DORF unconditional growth model (Table 14) was specified next and again added time to the unconditional means model as a random effect. Results of this model revealed a significant intercept and estimate an initial DORF score of 67.45 WCPM ($p < .001$); however, fixed effect slope estimates for DORF were non-

significant ($b = 0.17$, $p = 0.47$) indicating that, on average, DORF scores did not show a significant rate of change over the course of the study. Results of random effects show a significant intercept ($\chi^2 = 373.52$, $df = 31$, $p < .001$), again indicating that individual student DORF scores vary significantly at the first measurement occasion. Random effects estimates of slope were non-significant ($\chi^2 = 41.25$, $df = 31$, $p > .05$), indicating that there were not significant individual differences in students' growth rates on the DORF probes. The proportional reduction in residual variance from the unconditional means model to the unconditional growth model showed that just 4.2% of the within-person variation in DORF scores can be explained by time. Deviance from the unconditional means to unconditional growth models reduced by just 4.21 after adding time as a random effect and was not a significant improvement in model fit ($\chi^2 = 4.21$, $df = 2$, $p > .05$).

Table 14. Results of the Unconditional Growth Model: DIBELS Oral Reading Fluency (DORF)

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Mean initial status, β_{00}	67.45	3.77	17.90	31	< .001
Mean growth rate, β_{10}	0.17	0.30	0.56	31	0.58
Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, r_{0i}	416.90	20.42	373.52	31	< .001
Growth rate, r_{1i}	0.71	0.84	41.25	31	.10
Level-1 error, e_{ti}	90.19	9.50			

Again, student-level predictors were entered at level-2 in an attempt to explain additional variance. Given that the unconditional growth model indicated that slopes for DORF scores did not vary significantly over the course of the study, the purpose of including student-level variables in this model was to assess whether their relationships with students' initial DORF scores. Student eligibility for FRL and student SPED status were entered simultaneously as fixed effects. Results of this model may be found in Table 15. Estimation of the fixed effects of the model indicate that students' FRL status was significantly related to their initial DORF performance. Specifically, students who qualify for FRL scored an average of 28.53 WCPM below students who do not qualify for FRL on their first DORF probe ($p < .001$). Students who received SPED services initially scored an average of 12.46 WCPM below students who did not receive SPED services ($p < .05$). As expected, slope estimates for all variables were non-significant. Examination of random effects indicates that, like R-Maze, there is still residual level-1 variance in DORF scores that could be explained, although additional potential predictors of interest were

not measured in this study. Finally, the addition of FRL and SPED explained 4.2% more variance in DORF scores than the unconditional growth model.

Table 15. Results of the Conditional Model: DIBELS Oral Reading Fluency (DORF)

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Model for initial status, π_{0i}					
Mean initial status, β_{00}	84.60	3.81	22.18	29	< .001
FRL, β_{01}	-28.53	5.14	-5.55	29	< .001
SPED, β_{02}	-12.46	5.27	-2.36	29	.03
Model for growth rate, π_{1i}					
Mean growth rate, β_{10}	0.25	0.46	0.55	29	.58
FRL, β_{10}	0.28	0.62	0.45	29	.66
SPED, β_{10}	-0.55	0.63	-0.87	29	.39
Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, r_{0i}	168.74	12.99	159.09	29	< .001
Growth rate, r_{1i}	0.80	0.89	40.00	29	.08
Level-1 error, e_{ti}	90.25	9.50			

Note: FRL = Free/Reduced Lunch Status; SPED = Special Education Status

RTF growth. Like R-Maze and DORF, RTF was entered as an outcome variable for the unconditional means model. Results of this model (Table 16) showed a significant mean initial status ($b = 32.22$, $p < .001$), allowing us to reject the null hypothesis that the grand mean of RTF scores is not significantly different than zero.

Table 16. Results of the Unconditional Means Model: DIBELS Retell Fluency (RTF)

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Mean initial status, β_{00}	32.22	2.30	14.02	31	< .001
Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, r_0	156.12	12.49	401.52	31	< .001
Level-1 error, e	97.03	9.85			

Estimates of the variance components for this model suggest that RTF scores vary significantly across students ($\chi^2 = 401.52$, $df = 31$, $p < .001$). An ICC of 0.617 was calculated for the model, indicating that 61.7% of the variance in RTF scores can be attributed to differences between students.

The unconditional growth model (Table 17) for RTF was specified next, again by adding time to the empty model as a random effect. Fixed effects estimates revealed a similar pattern as those for the unconditional growth

model for DORF. Specifically, results showed a significant initial status coefficient of 33.27 words recalled ($p <$ .001) but did not indicate a significant fixed effect slope estimate for RTF ($p = 0.70$), indicating that mean RTF scores did not vary significantly over the course of the study. An examination of the variance components for this model indicates a significant intercept ($\chi^2 = 129.98$, $df = 31$, $p < .001$), and a non-significant slope ($\chi^2 = 40.62$, $df = 31$, $p > .05$). Together, these results suggest that there were individual differences in student RTF performance at the beginning of the study, but that there were not significant differences in individual growth over time. The proportional reduction in residual variance from the unconditional means model to the unconditional growth model was .033, indicating that just 3.3% of the variation in RTF scores in this study can be explained by time; however, deviance from the unconditional means to unconditional growth models was significantly reduced ($\chi^2 = 18.35$, $df = 2$, $p < .001$), indicating that adding time as a random effect improved model fit.

Table 17. Results of the Unconditional Growth Model: DIBELS Retell Fluency (RTF)

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Mean initial status, β_{00}	33.27	2.31	14.36	31	< .001
Mean growth rate, β_{10}	-0.31	0.31	-1.01	31	.32
Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, r_{0i}	130.68	11.43	129.98	31	< .001
Growth rate, r_{1i}	0.67	0.82	40.62	31	.12
Level-1 error, e_{ti}	93.81	9.69			

Finally, student-level predictors were entered at level-2 in an attempt to explain additional variance. Once again, student eligibility for FRL and student SPED status were entered simultaneously as fixed effects in an effort to explain individual differences in initial RTF scores. Results of this model may be found in Table 18. Estimation of the fixed effects of the model indicate that students who qualify for FRL did not differ significantly from students who did not qualify for FRL, either in terms of their initial RTF score ($p = 0.27$) or in terms of their RTF growth over the course of the study ($p = 0.40$). Students who received SPED services scored an average of 13.72 recalled words lower than their non-SPED counterparts on their first RTF probe ($p < 0.01$), but did not differ significantly from non-SPED students in their RTF growth rates ($p = 0.56$). Random effect estimates indicated similar results as those for other CBM probe types in that there is still residual level-1 variance that could be explained. Lastly, adding level-2 predictors resulted in less than a 1% reduction in residual variance.

Table 18. Results of the Conditional Model: DIBELS Retell Fluency (RTF)

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Model for initial status, π_{0i}					
Mean initial status, β_{00}	40.34	2.99	13.49	29	< .001
FRL, β_{01}	-4.55	4.00	-1.14	29	.27
SPED, β_{02}	-13.72	4.09	-3.35	29	.002
Model for growth rate, π_{1i}					
Mean growth rate, β_{10}	0.10	0.49	0.20	29	.85
FRL, β_{10}	-0.55	0.64	-0.86	29	.40
SPED, β_{10}	-0.39	0.65	-0.60	29	.56

Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, r_{0i}	84.05	9.17	87.83	29	< .001
Growth rate, r_{1i}	0.84	0.92	39.55	29	.09
Level-1 error, e_{ti}	93.55	9.67			

Note: FRL = Free/Reduced Lunch Status; SPED = Special Education Status

Predicting comprehension. Descriptive statistics for the prediction model may be found in Table 19. These data reflect average scores across all 32 students included in the study based on the CBM score obtained during the first occasion of data collection.

Table 19. Descriptive Statistics for Prediction Model

Variable	N	Mean	SD	Minimum	Maximum
RCOMP	32	473.97	9.62	456	492
Initial R-Maze	32	7.88	4.58	2	17
Initial DORF	32	70.63	22.18	32	112
Initial RTF	32	33.59	13.04	5	65

Note: RCOMP = Reading Comprehension Score; "Initial" refers to score at first measurement occasion

Bivariate correlations between variable used to predict reading comprehension are detailed in Table 20. These correlations indicated the relationship between variables based on CBM scores from the first occasion of data collection. Like correlations found above in Table 9, R-Maze scores were correlated with both DORF and RTF, and its relationship with DORF was the strongest ($r = .78$, $p < .01$). Unlike the correlations using aggregated scores across all occasions, initial DORF and RTF scores were not significantly related. Furthermore, only R-Maze showed significant negative relationships with both free/reduced lunch status and special education status. For R-Maze,

students who were eligible for free/reduced lunch or receiving special education services tended to score lower on these tasks. For DORF, students who were eligible for free/reduced lunch tended to read fewer words correct per minute, while the relationship between DORF and special education status was non-significant. Finally, students who received special education services tended to recall fewer words on RTF tasks compared to their counterparts who did not receive these services. There was not a significant relationship between RTF and free/reduced lunch status.

Table 20. Bivariate Correlations Between Predictors for Prediction Model

	R-Maze	DORF	RTF	FRL	SPED
DORF	.78**	1	.10	-.64**	-.34
RTF	.38*	.10	1	-.12	-.51**
FRL	-.54**	-.64**	-.12	1	.10
SPED	-.54**	-.34	-.51**	.10	1

Note: FRL = Free/Reduced Lunch Status; SPED = Special Education Status
* $p < .05$; ** $p < .01$

Finally, Table 21 shows the bivariate correlations between students' initial scores on the different CBM probe types and scores on individual WJ-IV reading comprehension subtests, as well as the reading comprehension composite score. Students' initial R-Maze and DORF were significantly related to their scores on the Passage Comprehension and Reading Vocabulary subtests, as well as their composite Reading Comprehension score. Neither R-Maze nor DORF were significantly related to Reading Recall subtests. Initial RTF scores were significantly related to Reading Vocabulary and composite Reading Comprehension scores. All significant correlations indicated positive relationships, suggesting that as students' scores on the different CBM measures increased, their scores on the WJ-IV subtests also increased. The only WJ-IV subtest which was not related to any CBM probe type was the Passage Comprehension subtest.

Table 21. Bivariate Correlations Between CBM Measures and WJ-IV Reading Comprehension Subtests

	R-Maze	DORF	RTF	PCOMP	RECALL	VOCAB	RCOMP
DORF	.78**	1	.10	.73**	.21	.64**	.68**
RTF	.38*	.10	1	.28	.29	.51**	.45*
PCOMP	.83**	.73**	.28	1	.36**	.71**	.89**
RECALL	.34	.21	.29	.36*	1	.06	.65**
VOCAB	.77**	.64**	.51**	.71**	.34	1	.87**
RCOMP	.83**	.68**	.45*	.89**	.65**	.87**	1

Note: PCOMP = Passage Comprehension; RECALL = Reading Recall; VOCAB = Reading Vocabulary; RCOMP = Total Reading Comprehension Score
* $p < .05$; ** $p < .01$

In order to address the second research question as to which CBM type was the best predictor of reading comprehension, a 2-level unconditional model was constructed using RCOMP, or the total reading comprehension

score on the WJ-IV Reading Comprehension – Extended cluster (McGrew et al., 2014) as an outcome variable. Results of this model (Table 22) showed a significant fixed effect coefficient of 473.52 ($p < .001$), indicating that the grand mean of RCOMP scores is significantly different than zero. Estimates of the variance components for this model suggest were non-significant ($\chi^2 = 38.35$, $df = 31$, $p = 0.17$). This finding indicates that RCOMP scores did not vary significantly by school; however, remaining variance at level-1 suggests that the addition of additional time-varying predictors (i.e., CBM scores) could potentially explain more variance.

Table 22. Results of the Unconditional Model: Predicting Reading Comprehension

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Mean initial status, γ_{00}	473.52	1.69	279.58	30	< .001
Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, u_0	17.04	4.13	37.11	30	.17
Level-1 error, r	71.88	8.47			

As a result, students' initial scores for R-Maze, DORF, and RTF were entered simultaneously at level-1 as fixed predictors. Results of this model can be found in Table 23, and showed that R-Maze was the only significant predictor of reading comprehension, ($b = 1.23$, $p < .01$). Furthermore, comparison of the unconditional and conditional models resulted in Pseudo $R^2 = .660$, indicating a 66% reduction in level-1 variance after adding CBM scores as predictors.

Table 23. Results of the Conditional Model: Predicting Reading Comprehension

Fixed Effect	*Coefficient*	*se*	*t-Ratio*	*Approx. df*	*p-value*
Mean initial status, γ_{00}	453.48	4.74	95.66	30	< .001
R-Maze, γ_{10}	1.23	0.40	3.09	28	.004
DORF, γ_{20}	0.08	0.08	1.04	28	.31
RTF, γ_{30}	0.15	0.09	1.75	28	.09
Random Effect	*Variance Component*	*sd*	χ^2	*df*	*p-value*
Initial status, u_0	5.14	2.27	32.68	30	.34
Level-1 error, r_i	24.46	4.95			

DISCUSSION

The purpose of the current study was to identify two sets of equivalent reading CBM passage sets, and then compare their utility in monitoring reading growth and predicting reading comprehension in second-grade students. Field-testing and rank-ordering procedures were used to equate passages in an effort to reduce measurement error. Hierarchical linear modeling was employed to determine how well each probe type (i.e., DORF, Retell, and R-Maze) measured growth over the course of the study, as well as determine which probe type best predicted student performance on the WJ-IV Reading Comprehension – Extended cluster (McGrew et al., 2014). These procedures were carried out in an effort to answer two primary research questions. A discussion of each research question follows, as well as discussion of the research and practical implications of the findings from the current study.

1. After equating passages, which CBM probe type (i.e., R-Maze, DORF, or RTF) is the most sensitive to reading growth in second graders over eight weeks? Additionally, does growth differ depending on certain student characteristics (i.e., free/reduced lunch status or special education services)?

Results of HLM analysis showed that R-Maze was the only CBM probe type that indicated significant rates of change for individual students over the course of the study. These results concur with that of Shin et al. (2000), who found that Maze is sensitive in measuring reading growth in second-grade students. One possible threat to the validity of these results is that the students in the study were unfamiliar with Maze tasks prior to participating. As such, it is possible that the growth estimates found in this study were confounded by students scoring higher on the task as they became more familiar with the structure of the probes and the requirements of the task. Furthermore, student FRL or SPED status did not influence growth rates on R-Maze. This finding is somewhat surprising, particularly for SPED. Previous research (Christ et al., 2010 Shin et al., 2000) has indicated that students receiving SPED services typically show a slower growth rate on reading CBM measures than their peers who do not receive SPED services. A potential explanation for this finding is that SPED services were not specified in this study, and that findings would closer resemble those of other studies if students who had a reading disability and were receiving reading services were differentiated from those who received other services, such as behavioral interventions or speech/language services as part of their special education plan.

The finding that DORF was not an indicator of student growth is somewhat surprising, although it agrees with the Ardoin et al (2013) review indicating that there is not sufficient evidence to promote the use of read aloud

as a progress monitoring tool. While DORF has been shown to be indicative of student reading growth over the course of the year, it is possible that it is less sensitive to short-term changes like those in the current study. It is also possible that field-testing and rank-ordering efforts did not result in sufficient passage equivalence, and that measurement error contributed to these results. Indeed, this explanation is plausible given that Cummings et al. (2014) found that, even after DIBELS Next (Good & Kaminski, 2011) passages were field-tested, significant form effects were still observed.

Additional factors such as familiarity with passages and timing of data collection could also explain some of the results found for DORF. Specifically, unlike R-Maze, DORF was a familiar task for all students included in the study. This may have affected individual students' motivation to perform on these tasks. Indeed, one student was observed to say during the study, "I've read this story before, it's boring." While not an empirical finding, this anecdotal evidence suggests that there may be other factors contributing to observed DORF/RTF scores. Moreover, this study was conducted in the spring, and previous studies have found that second-graders' growth curves in reading fluency have largely stabilized by the end of the year (Kim, Petscher, Schatschneider, & Foorman, 2010). Also, lack of growth may be due to a seasonal effect, given Christ et al.'s (2010) finding that student growth rates on read aloud measures slowed during winter-to-spring compared to fall-to-winter.

Finally, the finding that RTF was not an indicator of growth was expected, and agrees with previous research that RTF does not seem to be an adequate progress monitoring tool. It seems that, while RTF boasts face validity as an indicator of student comprehension and bears similarity to standardized comprehension tasks, variability in both performance and scoring challenge these perceived benefits. Like DORF, it is also possible that passage equivalency efforts were not sufficient, and that variability in probe difficulty also contributed to the non-significant growth findings.

2. Which CBM probe type (i.e., R-Maze, DORF, or RTF) is the best predictor of reading comprehension?

Results of the HLM model used to evaluate the predictive abilities of the different CBM probe types indicated that students' initial R-Maze score had the strongest relationship with the reading comprehension outcome measure. This finding was surprising, and did not support the hypothesis that DORF initial status would be the strongest predictor. Indeed, the correlation between R-Maze and reading comprehension was much higher than expected (r = .83). Although DORF still showed a strong relationship with reading comprehension (r = .68), this

relationship was not a significant predictor in consideration of R-Maze. Moreover, given the wealth of evidence showing DORF as a predictor of reading comprehension, this finding becomes more complicated to interpret. One possible interpretation is that many of the studies showing DORF as a good indicator of reading comprehension used criterion measures other than the Woodcock Johnson, and, more specifically, the WJ-IV Reading Comprehension – Extended cluster (McGrew et al., 2014). This possible explanation comes in light of the reported variability between reading comprehension assessments and which specific skills they measure (Keenan et al., 2008); however, it is nonetheless surprising. In contrast, the finding that RTF did was not as surprising. Although RTF showed a moderate correlation (r = .45) with the comprehension measure, it was not shown to be a significant predictor in consideration of all three probe types used in the study. Combined with findings that RTF was not sensitive to student reading growth, these results add to the existing literature base that question the utility of RTF measures within an RTI framework.

Overall, study results indicated that R-Maze was sensitive to reading growth in at-risk second-graders and was a strong predictor of their performance on a reading comprehension criterion measure. General findings from this study contradict some previous findings regarding the utility of read aloud measures within an RTI framework. Based on the results of this study, it appears that R-Maze could be a useful addition to early screening efforts, and that it may have utility as a progress monitoring tool.

Limitations

Despite the significance of certain findings in this study, there are a number of limitations that are important to address. In particular, these limitations affect the generalization of the results of this study to other populations and measures.

Firstly, participants in the study were limited to second-grade students from a single school district in central Nebraska. The sample also lacked diversity, as the majority of the participants were Caucasian. Other sample characteristics limit the generalizability of results and warrant a note of caution regarding the interpretation of certain results; namely, the limited sample sizes during each phase. Despite having 75 students in Phase One, only 22-32 samples of each individual passage of the available progress monitoring pools were gathered. Gathering additional samples of each probe during field-testing would serve to improve the power of the mean scores for each probe and should result in better passage equivalence. During Phase Two, only 32 students participated. Furthermore, these students came from just four schools. When using HLM, sample size at each level is an

important consideration, and a small sample size at higher levels affects power at lower levels. Although a specific power estimate was not calculated for this study, it is likely underpowered, which affects interpretation of the findings.

In a typical RTI model, progress monitoring is typically employed to track the growth of students receiving an intervention. The current study did not employ an intervention component, and students who were receiving interventions or reading resource instruction were doing so independently of the current study. Future studies could replicate the current study with the addition of an intervention component. Concurrent implementation of an evidence-based reading intervention could help make comparisons between expected growth for students in intervention vs. control conditions.

The current study used second-graders as student participants. It is less common for schools to employ the use of Maze tasks for reading progress monitoring at this grade level, which was evident in participants' initial unfamiliarity with the task. Indeed, results of this study indicate that certain design elements of R-Maze seem to have detracted from its efficient completion. This difficulty was apparent in the study when poorer readers needed multiple demonstrations of task completion prior to Maze administration, as well as the necessity to use amended scoring procedures to correct for a concern of pro-rated scores that were the results of a high error rate. It was also evident in students' lower scores, which were a combination of lower fluency and higher error rates. These concerns complicate interpretation of the findings of the study.

Another limitation included a wide range of IOA for RTF measures. Despite training and practice sessions, IOA on RTF scoring was as low as 33% during Phase Two. A higher rate of passages was evaluated for IOA once this concern became apparent; however, there is still a possibility that RTF scores reported in the study are less accurate than scores for other probes.

Future Directions

Given that reading comprehension becomes a critical component in upper elementary grades, it would be relevant to replicate this study with students at or above fourth grade. Use of an older sample may help reduce some of the limitations in this study, including students having difficulty understanding the concept of the task. Use of an older population would also be warranted given that relationships between reading CBM and reading comprehension seem to shift as students enter upper elementary school.

The current study could also be replicated with more sound passage equivalency efforts, including using a larger sample for establishing mean performance rates and using Euclidean Distance to equate passages. These procedures would be especially helpful for R-Maze passages, as most efforts have been directed toward read aloud up to this point. Specifically, ranges for WCPM scores exist for determining equivalent reading passage sets, but no such criteria exist for R-Maze correct selections.

Furthermore, form effects and measurement error in CBM could be expanded to skills outside of reading, such as early numeracy and mathematics to see if there is inherent variability in different passages.

REFERENCES

Ardoin, S.P. & Christ, T.J. (2009). Curriculum-based measurement of oral reading: Standard errors associated with progress monitoring outcomes from DIBELS, AIMSweb, and an experimental passage set. *School Psychology Review, 38,* 266-283.

Ardoin, S.P., Christ, T.J., Morena, L.S., Cormier, D.C., & Klingbeil, D.A. (2013). A systematic review and summarization of the recommendations and research surrounding curriculum-based measurement of oral reading fluency (CBM-R) decision rules. *Journal of School Psychology, 51,* 1-18. doi: 10.1016/j.jsp.2012.09.004.

Ardoin, S.P., Suldo, S.M., Witt, J., Aldrich, S., & McDonald, E. (2005). Accuracy of readability estimates' predictions of CBM performance. *School Psychology Quarterly, 20,* 1-22. doi:10.1521/scpq.20.1.1.64193.

Ardoin, S.P., Witt, J.C., Suldo, S.M., Connell, J.E., Koenig, J.L., Resetar, J.L., … & Williams, K.L. (2004). Examining the incremental benefits of administering a maze and three versus one curriculum-based measurement reading probes when conducting universal screening. *School Psychology Review, 33,* 218-233.

Arnold, E.M., Goldston, D.B., Walsh, A.K., Reboussin, B.A., Daniel, S.S., Hickman, E., & Wood, F.B. (2005). Severity of emotional and behavioral problems among poor and typical readers. *Journal of Abnormal Child Psychology, 33,* 205-217. doi: 10.1007/s10802-005-1828-9.

Ball, C.R. & Christ, T.J. (2012). Supporting valid decision making: Uses and misuse of assessment data within the context of RTI. *Psychology in the Schools, 49,* 231-243. doi: 10.1002/pits.21592.

Begeny, J.C. & Greene, D.J. (2014). Can readability formulas be used to successfully gauge difficulty of reading materials? *Psychology in the Schools, 51,* 198-215. doi: 10.1002/pits.21740.

Bellinger, J.M., & DiPerna, J.C. (2011). Is fluency-based story retell a good indicator of reading comprehension? *Psychology in the Schools, 48,* 416-426. doi: 10.1002/pits.20563.

Berninger, V.W., Abbott, R.D., Vermeulen, K., & Fulton, C.M. (2006). Paths to reading comprehension in at-risk second-grade readers. *Journal of Learning Disabilities, 39,* 334-351.

Betts, J., Pickart, M., & Heistad, D. (2009). An investigation of the psychometric evidence of CBM-R passage equivalence: Utility of readability statistics and equating for alternate forms. *Journal of School Psychology, 47,* 1-17. doi: 10.1016/j.jsp.2008.09.001.

Bryk, A.S. & Raudenbush, S.W. (1987). Application of hierarchical linear models to assessing change. *Psychological Bulletin, 101,* 147-158. doi:10.1037/0033-2909.101.1.147.

Busch, T.W. & Reschly, A.L. (2007). Progress monitoring in reading. *Assessment for Effective Intervention, 32,* 223-230. doi:10.1177/15345084070320040401.

Cain, K., & Oakhill, J. (2006). Assessment matters: Issues in the measurement of reading comprehension. *British Journal of Educational Psychology, 76,* 697-708.

Catts, H.W., Herrera, S., Nielsen, D. C., Bridges, M. S. (2015). Early prediction of reading comprehension within the simple view framework. *Reading and Writing, 28,* 1407-1425. doi: 10.1007/s11145-015-9756-x.

Chall, J.S. & Jacobs, V.A. (2003). The classic study on poor children's fourth-grade slump. *American Educator, 2,* 14-15.

Christ, T.J. & Ardoin, S.P. (2009). Curriculum-based measurement of oral reading: Passage equivalence and probe-set development. *Journal of School Psychology, 47,* 55-75. doi: 10.1016/j.jsp.2008.09.004.

Christ, T.J., Silberglitt, B., Yeo, S., & Cormier, D. (2010). Curriculum-based measurement of oral reading: An evaluation of growth rates and seasonal effects among students served in general and special education. *School Psychology Review, 39,* 447-462.

Cummings, K.D., Park, Y., & Bauer Schaper, H.A. (2013). Form effects on DIBELS next oral reading fluency progress-monitoring passages. *Assessment for Effective Intervention, 38,* 91-104. doi: 10.1177/1534508412447010.

Daniel, S.S., Walsh, A.K., Golston, D.B., Arnold, E.M., Reboussin, B.A., & Wood, F.B. (2006). Suicidality, school dropout, and reading problems among adolescents. *Journal of Learning Disabilities, 39,* 507-514. doi:10.1177/00222194060390060301.

Decker, D.M., Hixson, M.D., Shaw, A., & Johnson, G. (2014). Classification accuracy of oral reading fluency and maze in predicting performance on large-scale reading assessments. *Psychology in the Schools, 51,* 625-635. doi: 10.1002/pits.21773.

Deno, S.L. (1985). Curriculum-based measurement: The emerging alternative. *Exceptional Children, 52,* 219-232.

Deno, S.L. (2003). Developments in curriculum-based measurement. *The Journal of Special Education, 37,* 184-192. doi:10.1177/00224669030370030801.

Deno, S.L., Fuchs, L.S., Marston, D., & Shin, J. (2001). Using curriculum-based measurement to establish growth standards for students with learning disabilities. *School Psychology Review, 30,* 507-524.

Deno, S.L., Reschly, A.L., Lembke, E.S., Magnusson, D., Callender, S.A., Windram, H., & Stachel, N. (2009). Developing a school-wide progress-monitoring system. *Psychology in the Schools, 46,* 44-55. doi: 10.1002/pits.20353.

Espin, C.A. & Deno, S.L. (1993). Performance in reading from content area text as an indicator of achievement. *Remedial and Special Education, 14,* 47-59. doi:10.1177/074193259301400610.

Espin, C., Wallace, T., Lembke, E., Campbell, H., & Long, J. (2010). Creating a progress-monitoring system in reading for middle-school students: Tracking progress toward meeting high-stakes standards. *Learning Disabilities Research & Practice, 25,* 60-75. doi:10.1111/j.1540-5826.2010.00304.x.

Field, A. (2009). *Discovering statistics using SPSS* (3rd ed.). Thousand Oaks, CA: SAGE Publications Inc.

Fletcher, J.M. & Vaughn, S. (2009). Response to intervention: Preventing and remediating academic difficulties. *Child Development Perspectives, 3,* 30-37. doi:10.1111/j.1750-8606.2008.00072.x.

Fuchs, L.S. (2004). The past, present, and future of curriculum-based measurement research. *School Psychology Review, 33,* 188-192.

Fuchs, L.S. & Fuchs D. (1992). Identifying a measure for monitoring student reading progress. *School Psychology Review, 21,* 45-58.

Fuchs, L.S. & Fuchs, D. (1993). Formative evaluation of academic progress: How much growth can we expect? *School Psychology Review, 22,* 27-48.

Germann, G. (2010). Thinking of yellow brick roads, emerald cities, and wizards. In M.R. Shinn & H.M. Walker (Eds.)., *Interventions for achievement and behavior problems in a three-tier model including RTI* (pp. xiii-xxxv). Bethesda, MD: National Association of School Psychologists.

Glover, T. A., & Albers, C. A. (2007). Considerations for evaluating universal screening assessments. *Journal of School Psychology, 45*, 117–135.

Goffreda, C.T. & DiPerna, J.C. (2010). An empirical review of psychometric evidence for the dynamic indicators of basic early literacy skills. *School Psychology Review, 39,* 463-483.

Good, R.H. & Kaminski, R.A. (Eds.). (2002). Dynamic indicators of basic early literacy skills (6th ed.). Eugene, OR: Institute for the Development of Educational Achievement.

Good, R.H. & Kaminski, R.A. (Eds.). (2011). DIBELS Next Assessment Manual. Eugene, OR: Dynamic Measurement Group. Retrieved from http://dibels.org/next.html.

Graney, S.B., Martinez, R.S., Missall, K.N., & Arciak, O.T. (2010). Universal screening of reading in late elementary school: R-CBM versus CBM Maze. *Remedial and Special Education, 31,* 368-377. doi: 10.1177/0741932509338371.

Graney, S.B., Missall, K.N., Martinez, R.S., & Bergstrom, M. (2009). A preliminary investigation of within-year growth patterns in reading and mathematics curriculum-based measures. *Journal of School Psychology, 47,* 121-142. doi: 10.1016/j.jsp.2008.12.001

Gresham, F., Reschly, D., & Shinn, M.R. (2010). RTI as a driving force in educational improvement: Research, legal, and practice perspectives. In M.R. Shinn & H.M. Walker (Eds.)., *Interventions for achievement and behavior problems in a three-tier model including RTI* (pp. 47-78). Bethesda, MD: National Association of School Psychologists.

Hampton, D.D., Lembke, E.S., Lee, Y., Pappas, S., Chiong, C., & Ginsburg, H.P. (2012). Technical adequacy of early numeracy curriculum-based progress monitoring measures for kindergarten and first-grade students. *Assessment for Effective Intervention, 37,* 118-126. doi: 10.1177/1534508411414151.

Hintze, J.M., & Christ, T.J. (2004). An examination of variability as a function of passage variance in CBM progress monitoring. *School Psychology Review, 33,* 204-217.

Hintze, J.M., Christ, T.J., & Methe, S.A. (2006). Curriculum-based assessment. *Psychology in the Schools, 43,* 45-56. doi: 10.1002/pits.20128.

Hintze, J.M., Shapiro, E.S., Conte, K.L., & Basile, I.M. (1997). Oral reading fluency and authentic reading material: Criterion validity of the technical features of CBM survey-level assessment. *School Psychology Review, 26,* 535-553.

Hoffman, L. (2015). *Longitudinal analysis: Modeling within-person fluctuation and change.* New York, NY: Taylor & Francis.

Hosp, M. K. & Fuchs, L.S. (2005). Using CBM as an indicator of decoding, word reading, and comprehension: Do the relations change with grade? *School Psychology Review, 34,* 9-26.

Howe, K.B. & Shinn, M.M. (2002). *Standard reading assessment passages (RAPs) for use in general outcome measurement: A manual describing development and technical features.* Retrieved from www.aimsweb.com.

IBM Corp. Released 2015. IBM SPSS Statistics for Windows, Version 24.0. Armonk, NY: IBM Corp.

Individuals with Disabilities Education Act of 2004, 20 U.S.C. §1400 *et seq*, and Assistance to States for the Education of Children with Disabilities and Preschool Grants for Children with Disabilities; Final Rule, 71 Fed. Reg. 46540 (Aug. 14, 2006).

January, S.A. & Ardoin, S.P. (2012). The impact of context and word type on students' Maze task accuracy. *School Psychology Review, 41,* 262-271.

Jenkins, J.R., Hudson, R.F., & Johnson, E.S. (2007). Screening for at-risk readers in a response to intervention framework. *School Psychology Review, 36,* 582-600.

Jenkins, J. R., & Jewell, M. (1993). Examining the validity of two measures for formative teaching: Reading aloud and maze. *Exceptional Children*, *59*, 421-432.

Johnston, A.M., Barnes, M.A., & Desrochers, A. (2008). Reading comprehension: Developmental processes, individual differences, and interventions. *Canadian Psychology, 49,* 125-132. doi: 10.1037/0708-5591.49.2.125.

Kavale, K.A., Kauffman, J.M., Bachmeir, R.J., & LeFever, G.B. (2008). Response-to-intervention: Separating the rhetoric of self-congratulation from the reality of specific learning disability identification. *Learning Disability Quarterly, 31,* 135-150.

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.

Kendeou, P., Van den Broek, P., White, M.J., & Lynch, J.S. (2009). Predicting reading comprehension in early elementary school: The independent contributions of oral language and decoding skills. *Journal of Educational Psychology, 101,* 765-778. doi: 10.1037/a0015956.

Kim, Y., 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.

Kim, Y., Wagner, R.K., & Foster, E. (2011). Relations among oral reading fluency, silent reading fluency, and reading comprehension: A latent variable study of first-grade readers. *Scientific Studies of Reading, 15,* 338-362. doi: 10.1080/10888438.2010.493964.

Marcotte, A.M. & Hintze, J.M. (2009). Incremental and predictive utility of formative assessment methods of reading comprehension. *Journal of School Psychology, 74,* 315-335. doi: 10.1016/j.jsp.2009.04.003.

Marston, D., Mirkin, P., & Deno, S. (1984). Curriculum-based measurement: An alternative to traditional screening, referral, and identification. *The Journal of Special Education, 18,* 109-117. doi:10.1177/002246698401800204.

McGrew, K. S., LaForte, E. M., & Schrank, F. A. (2014). Technical Manual. *Woodcock- Johnson IV*. Rolling Meadows, IL: Riverside.

McMaster, K.L., Wayman, M.M., & Cao, M. (2006). Monitoring the reading progress of secondary-level English learners: Technical features of oral reading and Maze tasks. *Assessment for Effective Intervention, 31,* 17-31. doi:10.1177/073724770603100402.

Meneghetti, C., Caretti, B., & De Beni, R. (2006). Components of reading comprehension and scholastic achievement. *Learning and Individual Differences, 16,* 291-301. doi: 10.1016/j.lindif.2006.11.001.

Munger, K.A. & Blachman, B.A. (2013). Taking a "simple view" of the dynamic indicators of basic early literacy skills as a predictor of multiple measures of third-grade reading comprehension. *Psychology in the Schools, 50,* 722-737. doi: 10.1002/pits.21699.

Nation, K., Cocksey, J., Taylor, J.S.H., & Bishop, D.V.M. (2010). A longitudinal investigation of early reading and language skills in children with poor reading comprehension. *Journal of Child Psychology and Psychiatry, 51,* 1031-1039. doi: 10.1111/j.1469-7610.2010.02254.

National Center for Education Statistics. (2015). The Nation's Report Car: 2015 Mathematics and Reading. Washington, DC: Institute of Education Sciences, U.S. Department of Education. Retrieved from http://www.nationsreportcard.gov/reading_math_2015/#reading/acl?grade=4.

National Center on Intensive Intervention. (2012). Review of Progress Monitoring Tools. Website of the U.S. Office of Special Education Programs, Progress Monitoring Technical Review Committee. Retrieved from http://www.intensiveintervention.org/chart/progress-monitoring.

National Institute of Child Health and Human Development. (2000). Report of the National Reading Panel. Teaching children to read: An evidence-based assessment of the scientific research literature on reading and its implications for reading instruction (NIH Publication No. 00-4769). Washington, DC: U.S. Government Printing Office.

National Governors Association Center for Best Practices, Council of Chief State School Officers (2010). Common Core State Standards: English Language Arts. National Governors Association Center for Best Practices, Council of Chief State School Officers, Washington D.C.

Olinghouse, N.G., Lambert, W., & Compton, D.L. (2006). Monitoring children with reading disabilities' response to phonics intervention: Are there differences between intervention aligned and general skill progress monitoring assessments? *Exceptional Children, 73,* 90-106.

Parker, R., Hasbrouck, J.E., & Tindal, G. (1992). The Maze as a classroom-based reading measure: Construction methods, reliability, and validity. *The Journal of Special Education, 26,* 195-218. doi:10.1177/002246699202600205.

Poncy, B.C., Skinner, C.H., & Axtell, P.K. (2005). An investigation of the reliability and standard error of measurement of words read correctly per minute using curriculum-based measurement. *Journal of Psychoeducational Assessment, 23,* 326-338. doi:10.1177/073428290502300403.

Raudenbush, S.W. & Bryk, A.S. (2002). *Hierarchical linear models: Applications and data analysis methods* (2nd ed.). Thousand Oaks, CA: Sage.

Raudenbush, S. W., Bryk, A. S., Cheong, A. S., Fai, Y. F., Congdon, R. T., & du Toit, M. (2011). *HLM 7: Hierarchical linear and nonlinear modeling.* Lincolnwood, IL: Scientific Software International.

Reed, D.K. (2011). A review of the psychometric properties of retell instruments. *Educational Assessment, 16,* 123-144. doi: 10.1080/10627197.2011.604238.

Reschly, A.L., Busch, T.W., Betts, J., Deno, S.L., & Long, J.D. (2009). Curriculum-based measurement oral reading as an indicator of reading achievement: A meta-analysis of the correlational evidence. *Journal of School Psychology, 47,* 427-469. doi: 10.1016/j.jsp.2009.07.001.

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.

Salvia, J., Ysseldyke, J. E., & Bolt, S. (2007). Asse*ssment in special and inclusive education* (10th ed.). Boston, MA: Houghton Mifflin.

Shapiro, E.S. (2013). Commentary on progress-monitoring with CBM-R and decision making: Problems found and looking for solutions. *Journal of School Psychology, 51,* 59-66. doi: 10.1016/j.jsp.2012.11.003.

Shapiro, E.S., Hilt-Panahon, A., & Gischlar, K.L. (2010). Implementing proven research in school-based practices: Progress monitoring within a response-to-intervention model. In M.R. Shinn & H.M. Walker (Eds.)., *Interventions for achievement and behavior problems in a three-tier model including RTI* (pp. 175-192). Bethesda, MD: National Association of School Psychologists.

Shin, J., Deno, S.L., & Espin, C. (2000). Technical adequacy of the Maze task for curriculum-based measurement of reading growth. *The Journal of Special Education,* 34, 164-172. doi:10.1177/002246690003400305.

Shin, J., Espin, C.A., Deno, S.L., & McConnell, S. (2004). Use of hierarchical linear modeling and curriculum-based measurement for assessing academic growth and instructional factors for students with learning difficulties. *Asia Pacific Education Review, 5,* 136-148.

Shinn, M.R. (2002). Best practices in using curriculum-based measurement in a problem-solving model. In A. Thomas & J. Grimes (Eds.). *Best practices in school psychology* (pp. 671-698). Bethesda, MD: National Association of School Psychologists.

Shinn, M.R. (2010). Building a scientifically based data system for progress monitoring and universal screening across three tiers, including RTI using curriculum-based measurement. In M.R. Shinn & H.M. Walker (Eds.)., *Interventions for achievement and behavior problems in a three-tier model including RTI* (pp. 259-292). Bethesda, MD: National Association of School Psychologists.

Singer, J.D. & Willett, J.B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence.* New York, NY: Oxford University Press.

Stanovich, K.E. (1986). Matthew effects in reading: Some consequences of individual differences in the acquisition of literacy. *Reading Research Quarterly, 21,* 360-407. doi:10.1598/RRQ.21.4.1.

Stecker, P.M., Fuchs, L.S., & Fuchs, D. (2005). Using curriculum-based measurement to improve student achievement: review of research. *Psychology in the Schools, 42,* 795-819. doi: 10.1002/pits.20113.

Sugai, G., Horner, R.H., & Gresham, F. (2002). Behaviorally effective school environments. In M.R. Shinn, H.M. Walker, & G. Stoner (Eds.). *Interventions for academic and behavior problems II: Preventive and remedial approaches,* (pp. 315-350). Bethesda, MD: National Association of School Psychologists.

Tilstra, J., McMaster, K., Van den Broek, P., Kendeou, P., & Rapp, D. (2009). Simple but complex: Components of the simple view of reading across grade levels. *Journal of Research in Reading, 32,* 383-401. doi: 10.1111/j.1467-9817.2009.01401.x.

Tichá, R., Espin, C.E., & Wayman, M.M. (2009). Reading progress monitoring for secondary-school students: Reliability, validity, and sensitivity to growth of reading-aloud and Maze-selection measures. *Learning Disabilities Research & Practice, 24,* 132-142. doi:10.1111/j.1540-5826.2009.00287.x.

Tolar, T.D., Barth, A.E., Fletcher, J.M., Francis, D.J., & Vaughn, S. (2014). Predicting reading outcomes with progress monitoring slopes among middle grade students. *Learning and Individual Differences, 30,* 46-57. doi: 10.1016/j.lindif.2013.11.001.

Wanzek, J., Wexler, J., Vaughn, S., & Ciullo, S. (2010). Reading interventions for struggling readers in the upper elementary grades: A synthesis of 20 years of research. *Reading and Writing: An Interdisciplinary Journal, 23,* 889-912. doi:10.1007/s11145-009-9179-5.

Wayman, M.M., Wallace, T., Wiley, H.I., Ticha, R., & Espin, C.A. (2007). Literature synthesis on curriculum-based measurement in reading. *The Journal of Special Education, 41,* 85-120. doi:10.1177/00224669070410020401.

Wiley, H.I. & Deno, S.L. (2005). Oral reading and maze measures as predictors of success for English language learners on a state standards assessment. *Remedial and Special Education, 26,* 207-214. doi:10.1177/07419325050260040301.

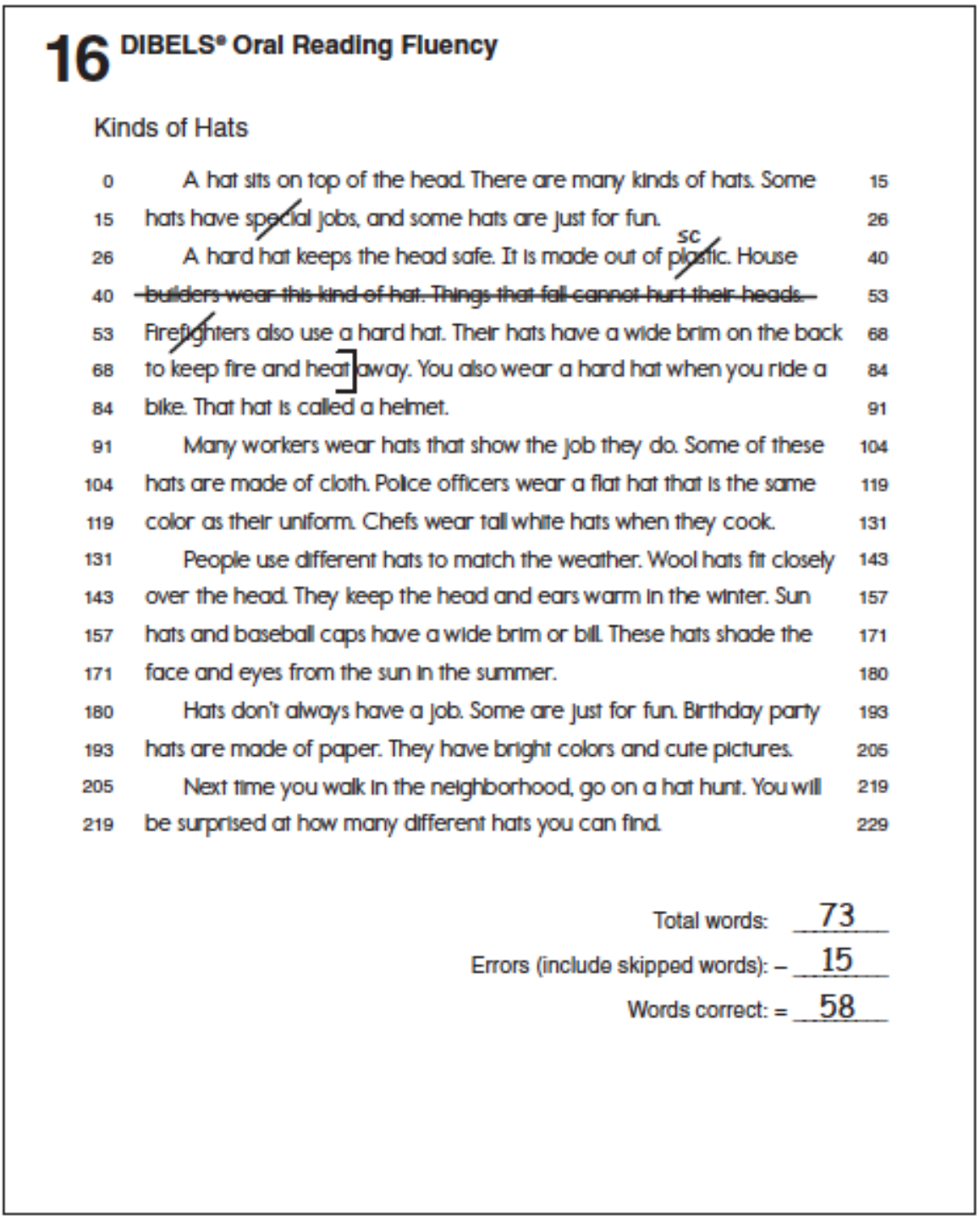
Wise, J.C., Sevcik, R.A., Morris, R.D., Lovett, M.W., Wolf, M., Kuhn, M., … & Schwanenflugel, P. (2010). The relationship between different measures of oral reading fluency and reading comprehension in second-

grade students who evidence different oral reading fluency difficulties. *Language, Speech, and Hearing Services in Schools, 41,* 340-348.

Woltman, H., Feldstain, A., MacKay, J.C., & Rocchi, M. (2012). An introduction to hierarchical linear modeling. *Tutorials in Quantitative Methods for Psychology, 8,* 52-69.

APPENDICES

Appendix A: A standard DIBELS Oral Reading Fluency (DORF) passage



16 DIBELS® Oral Reading Fluency

Kinds of Hats

0	A hat sits on top of the head. There are many kinds of hats. Some	15
15	hats have special jobs, and some hats are just for fun.	26
26	A hard hat keeps the head safe. It is made out of plastic. House	40
40	~~builders wear this kind of hat. Things that fall cannot hurt their heads.~~	53
53	Firefighters also use a hard hat. Their hats have a wide brim on the back	68
68	to keep fire and heat away. You also wear a hard hat when you ride a	84
84	bike. That hat is called a helmet.	91
91	Many workers wear hats that show the job they do. Some of these	104
104	hats are made of cloth. Police officers wear a flat hat that is the same	119
119	color as their uniform. Chefs wear tall white hats when they cook.	131
131	People use different hats to match the weather. Wool hats fit closely	143
143	over the head. They keep the head and ears warm in the winter. Sun	157
157	hats and baseball caps have a wide brim or bill. These hats shade the	171
171	face and eyes from the sun in the summer.	180
180	Hats don't always have a job. Some are just for fun. Birthday party	193
193	hats are made of paper. They have bright colors and cute pictures.	205
205	Next time you walk in the neighborhood, go on a hat hunt. You will	219
219	be surprised at how many different hats you can find.	229

Total words: 73

Errors (include skipped words): – 15

Words correct: = 58

Appendix B: A standard AIMSweb R-Maze passage

Once upon a time there was a merchant whose wife died, leaving him with three daughters.

The two older daughters were good-looking (but, stand, then) very disagreeable. They cared only for (until, themselves, himself) and for their appearance; they spent (palace, wicked, most) of the time admiring their reflections (in, of, turned) a looking glass.

The third and youngest (once, daughter, gate) was quite different from the other (him, two, beast). She was beautiful—so

Appendix C: A standard DIBELS Retell Fluency (RTF) scoring procedure

Passage Goldfish make good pets. They are easy to take care of and do not cost much to feed. Goldfish are fun to watch while they are swimming.

Student response He has a pet goldfish. The fish is easy to take care of. He likes to watch it swim. It is a good pet.

~~0~~	~~1~~	~~2~~	~~3~~	~~4~~	~~5~~	~~6~~	~~7~~	~~8~~	~~9~~	~~10~~	~~11~~	~~12~~	~~13~~	~~14~~	~~15~~	~~16~~	~~17~~	~~18~~	~~19~~	~~20~~	~~21~~	~~22~~	~~23~~	(24)	25
26	27	28	29	30	31	32	33	34	35	36	37	38	39	40	41	42	43	44	45	46	47	48		

Retell Total: 24

How to score

Quality of Response:

(Note: If the student provides only a main idea, it is considered one detail.)

1 Provides 2 or fewer details

2 Provides 3 or more details

3 Provides 3 or more details in a meaningful sequence

(4) Provides 3 or more details in a meaningful sequence that captures a main idea

Appendix D: Procedural integrity checklist for DIBELS Oral Reading Fluency (DORF)

DORF Assessment Accuracy Checklist

Consistently	Needs practice	Does the assessor:
☐	☐	1. Position materials so that student cannot see what is being recorded?
☐	☐	2. State standardized directions exactly as written? ***I would like you to read a story to me. Please do your best reading. If you do not know a word, I will read the word for you. Keep reading until I say "stop." Be ready to tell me all about the story when you finish.*** (Place the passage in front of the student.) Begin testing. ***Put your finger under the first word*** (point to the first word of the passage). ***Ready, begin.*** Begin testing (2nd and 3rd passages). ***Now read this story to me. Please do your best reading. Ready, begin.***
☐	☐	3. Start the timer when the student reads the first word of the passage?
☐	☐	4. Score student responses correctly according to the scoring rules?
☐	☐	5. Use reminder procedures correctly and appropriately?
☐	☐	6. Say the word and put a slash over it if the student fails to say it correctly within 3 seconds?
☐	☐	7. Write "sc" above a previously slashed word if the student self-corrects within 3 seconds?
☐	☐	8. Discontinue if the student does not read any words correctly in the first row of the passage?
☐	☐	9. Place a bracket (]) after the last word the student read before the minute ran out and tell the student to stop?
☐	☐	10. Correctly calculate the total number of words read (correct and errors) and record it on the scoring page?
☐	☐	11. Correctly add the number of errors and record it on the scoring page?
☐	☐	12. Correctly subtract the errors from the total words and record the words correct on the scoring page?
☐	☐	13. Record both scores on the front cover of the scoring booklet?

Appendix E: Procedural integrity checklist for DIBELS Retell Fluency (RTF)

DORF Assessment Accuracy Checklist: Retell

Consistently	Needs practice	Does the assessor:
☐	☐	14. Administer Retell if the student read 40 or more words correct?
☐	☐	15. Remove the passage and then state the standardized Retell directions exactly as written? \ ***Now tell me as much as you can about the story you just read. Ready, begin.***
☐	☐	16. Start the stopwatch after saying ***Begin***?
☐	☐	17. Use reminder procedures correctly and appropriately?
☐	☐	18. Mark the number or words in the student's response and circle the total number of words?
☐	☐	19. Tell the student to stop if he/she is still retelling at the end of one minute?
☐	☐	20. Record the number of correct words at the bottom of the scoring booklet?
☐	☐	21. Record the score on the front cover of the scoring booklet?

Appendix F: Procedural integrity checklist for AIMSweb R-Maze

Appendix A–Checking Out Accuracy in Test Administration

If we use the standardized instructions and score correctly, different examiners should obtain about the same results. To ensure that examiners are consistent in administration and scoring, we recommend "check outs," using the accuracy of implementation rating scale (AIRS) like the one below.

Maze Accuracy of Implementation Rating Scale (AIRS)

Examiner: _____ Date: Observation 1 _____
Observer: _____ Observation 2 _____
Observation 3 _____

X = completed accurately O = incorrect

Step	Observation 1	Observation 2	Observation 3
Distributes Maze so students start when appropriate			
Says standardized directions			
Uses necessary practice test			
Says "Begin"			
Starts stopwatch at correct time			
Monitors for "circling"			
Times accurately			
Records time for prorating			
Stays "Stop"			
Stops stopwatch			
Monitors to ensures students stop			
Collects Mazes			

Appendix G: Institutional Review Board Approval

ACTION ON PROTOCOL APPROVAL REQUEST

Dr. Dennis Landin, Chair
130 David Boyd Hall
Baton Rouge, LA 70803
P: 225.578.8692
F: 225.578.5983
irb@lsu.edu | lsu.edu/irb

TO: Frank Gresham
Psychology

FROM: Dennis Landin
Chair, Institutional Review Board

DATE: January 8, 2016

RE: IRB# 3623

TITLE: An Evaluation of the Utility of Reading Curriculum-Based Measurement as Progress Monitoring Tools and Predictors of Comprehension

New Protocol/Modification/Continuation: Modification

Brief Modification Description: Expand recruitment to include elementary-aged students rather than limiting participants to fourth-grade students.

Review type: Full ____ Expedited __X__ **Review date:** 1/8/2016

Risk Factor: Minimal ___X_____ Uncertain _____ Greater Than Minimal_____

Approved___X____ **Disapproved** _____

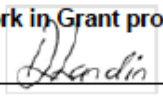
Approval Date: 1/8/2016 **Approval Expiration Date:** 7/15/2016

Re-review frequency: (annual unless otherwise stated)

Number of subjects approved: 250

LSU Proposal Number (if applicable):

Protocol Matches Scope of Work in Grant proposal: (if applicable) _____

By: Dennis Landin, Chairman 

PRINCIPAL INVESTIGATOR: PLEASE READ THE FOLLOWING –
Continuing approval is CONDITIONAL on:

1. Adherence to the approved protocol, familiarity with, and adherence to the ethical standards of the Belmont Report, and LSU's Assurance of Compliance with DHHS regulations for the protection of human subjects*
2. Prior approval of a change in protocol, including revision of the consent documents or an increase in the number of subjects over that approved.
3. Obtaining renewed approval (or submittal of a termination report), prior to the approval expiration date, upon request by the IRB office (irrespective of when the project actually begins); notification of project termination.
4. Retention of documentation of informed consent and study records for at least 3 years after the study ends.
5. Continuing attention to the physical and psychological well-being and informed consent of the individual participants including notification of new information that might affect consent.
6. A prompt report to the IRB of any adverse event affecting a participant potentially arising from the study.
7. Notification of the IRB of a serious compliance failure.
8. **SPECIAL NOTE:**

**All investigators and support staff have access to copies of the Belmont Report, LSU's Assurance with DHHS, DHHS (45 CFR 46) and FDA regulations governing use of human subjects, and other relevant documents in print in this office or on our World Wide Web site at http://www.lsu.edu/irb*

VITA

Haley York is a native of rural southwest Kansas. She completed her undergraduate education at Texas Tech University, earning her Bachelor of Arts in Psychology in December 2009. She began her graduate career at Louisiana State University in August 2010 and received her Master of Arts in Psychology in May 2013. Haley completed her predoctoral internship in central Nebraska as part of the Munroe-Meyer Institute's Rural Integrated Care program. She is currently working as a postdoctoral research associate at the University of Louisville.