CURRICULUM-BASED MEASUREMENT AS AN INTERVENTION: A LITERATURE REVIEW AND META-ANALYSIS

A Dissertation

by

CARA DEMARIS WILLIAMS

Submitted to the Office of Graduate and Professional Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

Chair of Committee,	Yvonne Goddard
Committee Members,	Victor Willson
	Shanna Hagan-Burke
	Yeping Li
Head of Department,	Victor Willson

May 2014

Major Subject: Educational Psychology

ABSTRACT

A two-article dissertation format is provided. The first article is a literature review of Curriculum-based measurement (CBM) as an intervention and has three purposes: a) describe foundational components of CBM; b) explain CBM as an intervention versus an outcome measure; and c) examine connections between CBM and RtI. The second article, a meta-analytic study, addresses CBM in mathematics (CBM-M) as an intervention and examines specific outcomes for students in grades K-12, including those in general education and special education, when detailed feedback was utilized, and when detailed feedback was not incorporated. The three research questions include: (a) What are the effects of implementing CBM-M as an intervention when *digits* correct are assessed for computation and concepts and applications? (b) What are the effects of CBM-M as an intervention when *problems* correct are assessed for computation and concepts and applications? and (c) What are the effects on overall mathematics achievement when CBM-M as an intervention is implemented?

Upon completion of the meta-analysis, results indicated that when digits correct are assessed for computation, all students had a higher statistically significant effect when detailed feedback was utilized. More specifically, students in general education experience higher effects when detailed feedback is used, while students in special education benefit from CBM with or without detailed feedback. No studies were found for addressing concepts and applications with digits correct. When addressing problems correct for computation, all students had the most statistically significant benefit when detailed feedback was incorporated, yet students in general education had the most

benefit. Much more data is needed in the area of problems correct for concepts and applications. From the data gathered, small non-statistically significant effects were found for all students without the inclusion of detailed feedback, yet a negative non-statistically significant effect was found for students in special education. Not enough data was found to assess the use of detailed feedback. In terms of overall mathematical achievement, data was only found for the inclusion of detailed feedback. Results indicated that students in general education achieve small statistically significant effects, while students in special education did not show an effect at all.

Overall, using detailed feedback produced higher statistically significant effects for students in both general and special education. Most research has been conducted in the area of computation for grades 3-6. Much more research is needed in the areas of concepts and applications, overall mathematical achievement, and at the secondary grade levels.

Both articles, the literature review and meta-analytic study, are discussed separately.

DEDICATION

I would like to dedicate, not just my Doctoral Degree, but my entire educational career to my parents. My father, Jerry Cornell Williams, made huge sacrifices to ensure my three brothers and I attended the best schools. My mother, Dorothy DeMaris Williams, taught us to take pride and ownership in all we do. Although my mother is no longer here on Earth, I am certain she would be proud of my accomplishments.

To my daughter, MiKayla: “No dream is too big, and no dreamer is too small.” – DreamWorks Animation ‘Turbo’

ACKNOWLEDGEMENTS

First, I would like to thank God for opening the door to such a wonderful opportunity at Texas A&M University and for giving me the strength and endurance needed to finish my doctoral degree.

Thanks go out to my committee chair, Dr. Yvonne Goddard, and my committee members, Dr. Victor Willson, Dr. Shana Hagan-Burke, and Dr. Yeping Li, for continuous guidance and support throughout the span of my graduate studies. Thank you to my university friends, colleagues, department faculty, and staff for making my time at Texas A&M University a great experience. A special token of gratitude is extended to Dr. Kimberly Vannest for guiding me in the right direction when I felt all was lost.

Last, but certainly not least, I would like to thank my family, friends, and Cedric Isom for supporting me through the long nights, study-filled weekends, and moments of struggle.

TABLE OF CONTENTS

INTRODUCTION

Assessment is an integral part of education and is critical for determining student progress and teacher effectiveness. Whether through formal assessments, such as quizzes or tests, or informal assessments, such as projects or homework, teachers used different forms of assessment to gauge the progression of students throughout the school year. Progress monitoring is a form of assessment named fittingly for the purpose of monitoring academic progress. When using progress monitoring, teachers are able to keep track of student performance on an on-going basis. By monitoring students' ongoing progress, teachers are able to make changes to the instructional curriculum proactively, rather than reacting to unsatisfactory performance on classroom unit and end-of-year assessment results.

One specific form of progress monitoring is called Curriculum-Based Measurement (CBM). While formal and informal assessments may examine a specific skill, CBM is an overarching assessment tool which allows teachers to have a deeper understanding of student progress at a given time in relation to what is expected by the end of the school year. In other words, CBM assesses gains across the entire curriculum, not just one specific skill.

CBM can be used as an outcome measure and as an intervention. When students are assessed periodically as a means of informing teachers of current progress, meaning that students are not privy to their results, CBM is an outcome measure. When CBM is utilized on a consistent basis with student engagement, such as graphing, interpretation of results, or item analysis, CBM is considered an intervention. The main difference between the outcome measure and intervention models of CBM is an outcome measure is just that, the outcome of an administered measure which informs teachers of student deficits, whereas CBM as an intervention focuses on intervening with the students with such strategies as graphical depictions of progress, goal-setting, and explanation of result interpretation in order to improve results by making changes to the curriculum based on the outcome of the administered measure. Using CBM as an intervention is potentially powerful because not only are the teachers informed of student progress and deficit areas, the students are able to participate and experience a sense of ownership in becoming a successful learner. CBM will be discussed in great detail in the literature review portion of this dissertation.

Although CBM has been used in a variety of subjects, the purpose of this dissertation is to understand the current state of the literature of CBM in mathematics. A literature review is presented as the first article, followed by a meta-analytic study. The literature review provides an overview of CBM and presents a current picture of the research status related to this particular topic. More specifically, it focuses on CBM's definition, uses, history, and importance, then connects CBM with Response to Intervention (RtI). Meanwhile, the meta-analytic paper goes deeper by examining outcomes related to using CBM as an intervention in mathematics. Studies in the meta-analytic article incorporated CBM within existing curriculum to evaluate the effectiveness of this progress monitoring method.

In general, the purpose of this dissertation is to answer one main question: What do we know about CBM and in particular, CBM in mathematics, at this time? Once the current state of the literature and research is determined, future research can be conducted in a more methodical fashion.

SURVEY OF THE LITERATURE ON CURRICULUM-BASED MEASUREMENT AS AN INTERVENTION

Progress monitoring has been incorporated into school settings for over 40 years, with increased efforts over the last ten years in response to provisions of the No Child Left Behind Act requiring teachers to implement evidence-based instructional practices (Bolt, Ysseldyke, & Patterson, 2010; Ysseldyke & Bolt, 2007). In addition to deciding what to teach, how to teach, using time efficiently, providing students with practice work, delivering feedback to students, and testing, teachers are now required to manage and monitor student progress (Spicuzza, Ysseldyke, Lemkuil, Kosciolek, Boys, & Teelucksingh, 2001). Lacking a systematic, valid, and reliable method of monitoring student performance and progress at the classroom level can make the task of meeting federal requirements extremely stressful (Ysseldyke & Bolt, 2007). One research-supported approach to gathering formative data is Curriculum-Based Measurement (CBM).

CBM is an instructional approach shown effective in assisting educators with objective data that may be used to record student performance and alter curriculum as needed for students who demonstrate need in both general and special education (Foegen, 2008a; Leh, Jitendra, Caskie, & Griffin, 2007; Spicuzza, et al., 2001). When assisting educators with recording objective data related to student performance and tailored curriculum based on student needs, CBM has shown positive effects for both general and special education (Spicuzza et al., 2001). Although CBM does not identify particular skills students have mastered, overall proficiency spanning the scope of the entire year's curriculum is assessed (Fuchs, Fuchs, Hamlett, & Stecker, 1991). This provides important feedback to teachers about the progress their students are making across the school year. Usually, state mandated assessments do not demonstrate academic gains of low achieving students, but CBM provides an ongoing series of data points for teachers to utilize and incorporate when making instructional decisions (Jiban & Deno, 2007). In addition to allowing students to feel in control of learning, CBM is associated with students becoming highly motivated, as they are able to observe their progress by graphing and goal setting (Brookhart, Andolina, Zuza, & Furman, 2004). When CBM is administered frequently and students are responsible for monitoring their progress, a metacognitive change may occur in which CBM becomes as much intervention as simple progress monitoring. In the next sections, we present the three purposes of this paper: 1) describing the foundational components of CBM; 2) describing CBM as an intervention versus an outcome measure: and 3) examining connections between CBM and Response to Intervention (RtI).

Foundational Components of Curriculum-Based Measurement

The first purpose of this literature review is to describe foundational components included in CBM. In this section, the definition and uses of CBM are discussed first. Next, historical information related to CBM is reviewed, followed by comparing and contrasting CBM with curriculum-based assessment (CBA), and finally, the importance of CBM is presented.

Definition and Uses of Curriculum-Based Measurement

Progress monitoring allows teachers to document student growth toward individualized goals, make instructional changes when documented growth is not on target with the goal, and is a simple way for teachers to identify when students are struggling (Luke & Schwartz, 2007). As a well-documented form of progress monitoring, both fast and dependable, CBM allows teachers to gather academic information pertaining to student performance and progress in the curriculum (Calhoon, 2008; Fuchs, Fuchs, & Zumeta, 2008; Kelly, Hosp, & Howell, 2008).

Teachers may use CBM as a guide when making instructional decisions, which may improve student success (Kelly et al., 2008). Further, CBM assists with screening students for academic problems and evaluating instructional programs (Christ, Scullin, Tolbize, & Jiban, 2008). Teachers are able to screen entire classrooms and "create a database for each student to allow for evaluation of the effectiveness of an individual student's educational program" (Hosp & Hosp, 2003, p. 11). Individualized databases allow teachers to measure student progress often and make instructional decisions to improve individual student achievement (Kelly et al., 2008).

History of Curriculum-Based Measurement

Progress monitoring originally began over thirty years ago with a process known as mastery measurement, in which teachers assessed students one objective at a time based on a hierarchy model from the annual curriculum (Fuchs, 2004). Because teachers believed students were mastering each assessed objective, a false sense of students' progress become apparent once all the skills "mastered" were combined, yet students did not demonstrate mastery in the tested skills (Fuchs, 2004). In other words, mastery of these smaller proficiencies did not generalize to a larger skill set.

In an effort to generalize learning from one skill to the next, the Data-Based Program Modification (DBPM) model was developed (Deno & Mirkin, 1977). The DBPM was a systematic assessment system designed to aid teachers in resource (special education) settings with improving interventions used for students struggling academically. The model was an outline, guiding special education resource teachers on how to use progress monitoring data to make informed educational decisions in regards to the curriculum (Deno & Mirkin, 1977). The DBPM model did not focus on a particular skill, as with isolated skills mastery, but instead showed educators how to use collected progress monitoring data in a more efficient manner However, the validity of DBPM had not been empirically established (Deno, 2003; Fuchs, Deno, & Mirken, 1984).

To validate DBPM, a six-year study (1977-1983) examining the effects of teachers implementing measurement and evaluation procedures routinely to make instructional changes versus teachers using traditional methods, such as sporadic quizzes, assignments, and tests, to monitoring progress was conducted by Stan Deno and colleagues from the University of Minnesota (Deno, 1985; Fuchs et al., 1984). Teachers using measurement and evaluation procedures from the DBPM model achieved higher levels of student success as measured by the Passage Reading Test (PRT), by Fuchs, Deno, and Mirkin (1982), and two Stanford Diagnostic Reading Test subtests: Structural Analysis (SA) and Reading Comprehension (RC) (Deno, 1985; Fuchs et al., 1984). The measurement and evaluation procedures utilized in Deno's study became known as Curriculum-Based Measurement (CBM), and were developed to test the effectiveness of the DBPM special education intervention model (Deno, 1985; Montague, Penfield, Enders, & Huang, 2010).

Deno's work demonstrated that success with basic skills can reliably and validly be assessed frequently with a school's already established curriculum (Deno, 1985). Although special education was the primary environment of concern, CBM now expands far beyond the needs of special populations

> "to screening and identification of students at risk of academic failure, to developing school wide accountability systems, to addressing the problem of disproportionate representation, to evaluation growth in early childhood, to assessing attainment in content area learning, to measuring literacy in students who are deaf, to assessing students who are English language learners (ELL), and to predicting success on high stakes assessments" (Deno, 2003, p. 3).

Implemented for over 20 years, CBM still fulfills its original purpose: providing teachers a way to adjust instruction through technically sound and simple data collection (Shapiro, Keller, Lutz, Santoro, & Hintze, 2006; Stecker, Fuchs, & Fuchs, 2005). First described as "Curriculum-based measurement: The emerging alternative", perhaps the time has come for CBM to now be known as the "validated alternative" (Fuchs, 2004, p. 192).

Curriculum-Based Measurement versus Curriculum-Based Assessment

Curriculum-based assessment (CBA) and curriculum-based measurement (CBM) both provide teachers with assessment results that can be used to monitor student progress and improve instructional programming. Due to the similarity, the two terms are often confused. Although both have similar qualities, there are distinct differences.

CBA, also known as mastery measurement and instructional assessment, assesses skill subsets before instruction on the next skill in a hierarchy (Tucker, 1985; VanDerHeyden, Witt, & Barnett, 2005; Ysseldyke & Bolt, 2007). CBA assesses the "instructional needs of a student based upon the on-going performance within the existing course content in order to deliver instruction as effectively as possible" (VanDerheyden et al., 2005, p. 16). In other words, CBA is used for short-term assessment to determine instructional next-steps, whereas CBM assesses students' progress in a curriculum that spans an entire school year. Since CBM assesses skills acquired over the entire year's curriculum, students are expected to improve over time as exposure to more skills is provided. In this fashion, CBM also examines skill maintenance since previously taught skills continue to be assessed.

On the other hand, CBM, sometimes referred to as a general outcome measure, assesses growth over time with the purpose of monitoring expected knowledge gain by the end of a particular period, such as an entire school year (VanDerheyden et al., 2005; Ysseldyke & Bolt, 2007). CBM is a "standardized methodology that specifies procedures for selecting test stimuli from students' curriculum, administering and scoring tests, summarizing the assessment information, and using the information to formulate instructional decisions in the basic skill areas" (Fuchs & Fuchs, 1988, p. 4).

In general, CBA may be more useful when targeting specific deficit areas, whereas CBM may be preferred when tracking growth over time in a generalized manner is desired (VanDerHeyden et al., 2005). CBA and CBM are consistently cited in research to improve instruction for students at-risk for academic failure (Burns, 2002).

“CBA and CBM must be used on a frequent basis to determine specifically what children know and do not know, to design instruction that addresses skills in need of additional remediation and to show progress in the local curriculum” (Ysseldyke & Bolt, 2007, p. 455).

Importance of Curriculum-Based Measurement

Curriculum-based measurement is important for special and regular education teachers and students. Improved communication between parents, teachers, and students; increased sensitivity to student achievement within short periods of time; improved database of student performance for instructional decisions; ability to compare student progress with that of other classroom peers; and cost effectiveness are all benefits of CBM (Deno, 1985).

Special education programs could greatly benefit from the advantages of CBM (Deno, 1985). For example, CBM provides a means for identifying students for special education services and pinpoints needed changes in instruction for increased academic success (Anderson, Lai, Alonzo, & Tindal, 2011). When screening and monitoring students, regardless of disability or non-disability classification, especially with students at-risk for academic failure, implementing CBM with existing curriculum can be of immense assistance (Anderson et al., 2011). Furthermore, the progress monitoring characteristics embedded within CBM assist teachers with modifying academic interventions based on the needs of each student (Allinder & Oats, 1997).

Although developed to measure the effectiveness of the DBPM special education model, CBM may also benefit general education classrooms (Graney, Missall, Martinez,

& Bergstrom, 2009). Research shows teachers trained to implement CBM are more prone to adapt instructional practices based on data based decisions (Montague et. al., 2010). With increasingly diverse classrooms, teachers in general education will need to adjust, formulate, and improve strategies for enhancing the performance of students with disabilities in the general education setting (Cardona, 2002). Regardless of disability, or non-disability, classification, CBM aids teachers with assessing ongoing performance, providing feedback, focusing on instructional planning, and making major instructional decisions (Cardona, 2002).

Curriculum-Based Measurement as an Intervention versus as an Outcome Measure

Emerging evidence shows CBM may be used as an intervention, not just an outcome measure (Fuchs, Fuchs, & Hamlett, 1989). Frequent monitoring and graphical representation, using time-series, equal-interval graphs, are critical components of CBM (Stecker et al., 2005). Observation of growth over time using graphs can be helpful to teachers and motivating to students. Further, CBM can be used periodically, weekly or bi-weekly, or continuously, daily or hourly (Ysseldyke & Bolt, 2007), thus is flexible in ways that teachers might find helpful. The more frequent these data are collected, the more intensely scrutinized students' progress becomes. This has effects on teachers and students especially when viewing emerging progress graphically. Generally, the more frequently data are collected the more accurate teachers can be in making instructional decisions and the more likely students are to be aware of their progress.

According to Foegen and Morrison (2010) several studies have shown that data gathered through CBM can be used to form a graphical depiction of how students progress throughout the curriculum. The graph created includes an aim line, which displays students' initial level of performance to a goal destination by the school year's end. As students complete the various CBM probes, results are plotted on the graph as new data points. Each data point represents the outcome measure for that particular assessment period. Using the aim line, teachers visually assess students' progress and make instructional decisions (Foegen & Morrison, 2010).

Students are also able to use the visual representations to observe individual progress throughout the school year (Fuchs et al., 1984). Many benefits exist for students involved in monitoring their own CBM progress. Students participating in CBM implementation "(a) more frequently claimed they knew their goals, (b) more often stated their goals, (c) were more accurate in their estimates of whether they would meet their goals, and (d) more typically reported that they relied on data to formulate estimates of whether they would meet goals" (Fuchs et al., 1984, p. 458). The graphs and progress indicators provided while implementing CBM may help to increase student motivation and cause students to work hard at attaining their academic goals (Calhoon & Fuchs, 2003). Effectively, use of frequent CBM probes and continued self-monitoring of academic progress is a metacognitive process that functions as CBM serving as an intervention. Ysseldyke and colleagues (2007) have shown students' attitudes to improve with the use of a progress monitoring system in place. Further, Rafferty and Raimondi (2009) found that students who self-monitored their mathematics performance made further academic gains than when they monitored their time on task, and they preferred monitoring performance over attention.

Using CBM, students are tested over time with equivalent alternate forms (Anderson et al., 2011). The use of alternate forms over a period of time, coupled with equal-interval graphing, is what contributes toward CBM being an intervention. The quantity of alternate forms is determined by the amount of time and frequency CBM is implemented. For example, students assessed twice a week for 13 weeks would need 26 alternate forms, as well as a pre- and posttest. Generally, administration of CBM probes occurs once or twice a week, or biweekly (Calhoon, 2008; Stecker et al., 2005).

A number of CBM probes are premade to purchase or use, but because CBMs are sampled from the curriculum, teachers may create their own probes, as long as standardized guidelines are followed (Kelly et al., 2008). Bryant and Rivera (1997) recommend "(a) selecting long-term goals, (b) measuring behaviors, (c) implementing standardized measurement methods, (d) employing decision making rules that guide instructional evaluation, and (e) accommodating a variety of instructional methods when developing CBM measures" (p. 62). When developing CBM probes, which equivalently measure tasks while integrating the variety of skills essential for proficient year-end performance, teachers can select robust tasks, or systematically sample the set of skills needed for a full year's curriculum (Fuchs et al., 2008). Robust task selection occurs when teachers aim to incorporate generally defined measures not directly parallel to a particular curriculum, but relative to the skill's overall strength and proficiency (Foegen, Jiban, & Deno, 2007). Robust skills include a mixture of components from an academic domain, rather than being derived directly from a specific curriculum (Fuchs, 2004).

Computerized CBM probes are often preferred by teachers. Using computers to assist teachers with managing progress monitoring data and for planning instructional recommendations has been researched for over 18 years (Bolt et al., 2010). Computers help reduce the amount of time teachers spend monitoring student data and increase accuracy, as collecting data by hand can be unreliable and require large amounts of time (Fuchs & Fuchs, 1990; Spicuzza et al., 2001). Using computerized CBM probes and software also adds vital information to the CBM database (Fuchs & Fuchs, 1990). Because of the time savings and improved accuracy, teachers may be more likely to use CBM when available via computer.

Connections between Curriculum-Based Measurement and Response to Intervention

Response to intervention (RtI) is gaining widespread acceptance as a way to identify students who struggle to learn in general education environments and to provide targeted instruction along a continuum of service options based on ongoing data collection and analysis. Advantages of RtI include eliminating poor instruction as a justification for student academic failures, making early intervention a priority, and collecting data frequently and consistently to encourage instructional responsiveness (Powell & Seethaler, 2008). RtI typically entails a three-tiered approach to intervention in which Tier One involves using evidence-based instruction within general education settings and Tier Two requires more intensive, small-group intervention for students who do not respond successfully to Tier One instruction. Students who continue to struggle, despite the more intensive services provided at Tier Two, are provided even more intensive, individualized instruction at Tier Three. Depending upon school, district, or state requirements, Tier Three may or may not involve special education services.

Regardless of Tier, however, formative data are collected for all students so that informed instructional decisions are possible. CBM is often used to examine students' progress in their grade-level curriculum. Because CBM provides repeated snapshots of student progress, teachers are equipped with essential formative data to construct ongoing instructional decisions and timely, judicious adjustments (Stecker, Lembke, & Foegen, 2008). CBM is sensitive to student change, meaningful, and non-demanding of classroom time (Helwig, Anderson, & Tindal, 2002). Powell and Seethaler (2008) point out that CBM is useful in many ways, including using CBM benchmarks to screen and identify suspected at-risk students, setting IEP goals, formulating individualized programs, and monitoring progress within an RtI framework. These authors suggest that CBM can be used to track students' progress at Tier 2 and to determine students' responsiveness-to-intervention at Tier 3 (defined in this case as special education) and help make decisions about exiting students from special education. Notably, tracking student progress on a case-by-case basis effectively aids in predicting student success on high-stakes measures (Montague et al., 2010).

Assessment is a key component of RtI that should occur frequently (Bradley, Danielson, & Doolittle, 2005) and be used to make instructional and special education referral decisions when appropriate (CEC, n.d.; NASDSE, 2006). How frequently assessment should occur and the types of assessments used are debated, though a combined use of summative (universal screening) and formative (progress monitoring) data seems optimal. Whether, and how, to assess all students at the beginning of the school year is still not determined (Fuchs & Fuchs, 2006), though it is advocated (e.g., Burns, Appleton, & Stehouwer, 2007). Options include using end-of-year data from the prior school year or screening all students within the first month of a new school year. Also unclear is when and how continuous monitoring should occur to make determinations about placement in different tiers. In a meta-analysis of RtI research, Burns, Appleton, and Stehouwer (2005) concluded that there is no identified optimal way to assess how best to serve students' needs, though curriculum-based measurement (CBM) has research support to suggest its usefulness in problem-solving models.

Conclusion

Curriculum-Based Measurement is a research-supported tool designed to help teachers make informed instructional decisions so that all students experience academic success. It is short and easy to administer and allows teachers and students to track progress in grade-level curriculum across time. When used frequently, CBM allows teachers and students to examine individual student progress intensively, thus serving as a self-monitoring approach. In fact, Fuchs and colleagues (1984) found that when students self-monitored using CBM data, they knew and were able to state their own academic goals, were more accurate in estimating their ability to meet those goals, and indicated that they used CBM data to make those estimates. In this way, CBM may be viewed as an intervention in which teachers' and students' frequent, intensive academic progress monitoring using CBM data results in improved attitudes toward learning and more academic success. This may be especially helpful when employed as part of an RtI framework.

Despite decades of research support (Baker & Good, 1995; Deno, 1985; Espin & Deno, 1993; Fuchs, Fuchs, & Hamlett, 1993; Fuchs, Fuchs, Mathes, & Simmons, 1997; Kaminski & Good, 1996; Marston & Magnusson, 1998; Ysseldyke & Bolt, 2007; Ysseldyke & Tardrew, 2007), CBM is not often used in practice (Calhoon, 2008; Christ et al., 2008; Deno, 2003; Fore, Burke, & Martin, 2006). If it can be framed as a formative assessment useful for progress monitoring while simultaneously serving as an intervention that may motivate students and result in academic gains, perhaps its worth can be recognized and embraced by educators.

CURRICULUM-BASED MEASUREMENT IN MATHEMATICS AS AN INTERVENTION: A META-ANALYSIS

The National Center for Education Statistics (NCES, 2011) reported only 40% of fourth grade and 35% of eighth grade students display mathematics proficiency; this percentage is much lower for students with disabilities (Foegen, 2008b). Smith, Marchand-Martella, and Martella (2011) categorize students as mathematically proficient when "solid academic performance and demonstrate[ion of] competency over challenging subject matter" is achieved (p. 247). Ultimately, researchers have been prompted to examine student achievement by identifying methods possessing the ability to function with efficiency, document student progress, and inform teachers of instructional effectiveness (Kelly, Hosp, & Howell, 2008).

Students' conceptual deficiencies need to be assessed throughout the school year. Oftentimes, students advance to more difficult coursework despite lacking proficiency at the current level. Mathematics builds upon previously learned skills. When a student's prerequisite skills are deficient, attainment of more complex concepts, such as Algebra or real-life applications, becomes an issue (Foegen, 2008b). Acquiring foundational mathematical concepts is critical, not only for academic success, but for employment, income, and work productivity as well (Rivera-Batiz, 1992).

Per state mandates, students are often assessed once during the school year; however, these high-stakes summative assessments are used for accountability purposes and only provide educators with a one-time snapshot of student achievement (Helwig, Anderson, & Tindal, 2002), and therefore are not useful to inform instruction on an ongoing basis. Research has shown formative assessments to increase student performance (Methe, Hintze, & Floyd, 2008). Formative assessments use data derived from various evaluations to provide teachers, students, and educational stakeholders with instructional feedback (Dunn & Mulvenon, 2009). Teachers often use a type of formative assessment, termed curriculum-based measurement (CBM), to provide ongoing feedback addressing student performance and academic skills.

Teachers are at liberty to create CBM measures by following a systematic proportional sampling of items from the year's curriculum, with each alternate-form probe consisting of the same number of problems and problem types (Fuchs, Fuchs, & Zumeta, 2008). According to Stecker, Lembke, and Foegen (2008), five steps are to be followed with CBM: (a) select appropriate measurement materials, (b) evaluate technical features, (c) administer and score the measure, (d) use data for goal setting, and (e) judge instructional effectiveness.

The National Center on Response to Intervention (2010) listed AIMSweb (grades 2-4), easyCBM (grades K-8), mCLASS (grades K-3), Monitoring Basic Skills Progress (MBSP) (grades 1-6), Orchard Software (grades K-9), STAR (grades 1-12), Vanderbilt RtI Monitor (grades 1-8), Yearly ProgressPro (grades 1-8), and Accelerated Math as progress monitoring tools for mathematics. The majority of these tools requires 1-15 minutes for administration, 10 – 50 alternate forms (although some computer-based tools have unlimited alternate forms), and can be administered to groups or individual students. All tools mentioned above, with the exception of mCLASS and MBSP, are computer-based and address mathematics as a whole, while mCLASS and MBSP have specific forms available for computation only.

The purpose of CBM is to monitor individual student performance and growth rates, through the creation of data based slopes, which in turn assist with implementing instructional changes as needed (Foegen & Morrison, 2010; Fuchs et al., 2008). CBM assists with accurate goal setting for individual students, identification of students who may be at-risk for being unsuccessful on high-stakes assessments, targeting students for intensive instruction, and assisting teachers with systematically adapting their instruction to meet the needs of students (Foegen & Morrison, 2010). Due to the direct assessment nature of CBM, data are less likely to be predisposed to bias, such as gender or socioeconomic status (Stecker et al., 2008). With proper implementation, teachers are able to determine the effectiveness of various instructional strategies within two weeks' time (Kelly et al., 2008).

Identified as an essential component of mathematics, computation CBM has been the primary focus of math assessments, inclusive of addition, subtraction, multiplication, and division of whole, numbers, decimals, and fractions (Fuchs et al., 2008). Concepts and applications are also assessed with CBM and include categories such as "number concepts, numeration, applied computation, geometry, measurement, chart and graphs, and word problems" (Calhoon & Fuchs, 2003, p. 237). Several studies researching computation CBM have incorporated approximately 25 computation problems per alternate-form probe and allowed between 45 seconds and 6 minutes for completion, dependent upon grade level (Calhoon & Fuchs, 2003; Fuchs & Fuchs, 1995; Fuchs,

Fuchs, & Fernstrom, 1993; Fuchs, Fuchs, Hamlett, Phillips, & Bentz, 1994; Fuchs, Fuchs, Hamlett, Phillips, & Karns, 1995; Fuchs, Fuchs, Hamlett, & Stecker, 1991; Fuchs, Fuchs, Hamlett, Walz, & Germann, 1993; Shapiro, Keller, Lutz, Santoro, & Hintze, 2005). Computation CBM probes focus on comprehension of the operation and do not include skills inclusive of problem-solving (Fuchs et al., 2008).

Various CBM tools adopt different scoring procedures. Several computer-based tools calculate scores automatically. Scores may be derived based on the number of problems correct or the number of digits correct. Utilizing the number of digits correct provides credit for answers that are partially correct (Fuchs et al., 1991). Furthermore, using digits correct, in place of problems correct, provides information about the errors students are making when solving particular problems (Shapiro et al., 2005). Assessing errors shines light on the internal thought process students use to work through and address various problems.

When CBM is combined with instructional recommendations, students in both general and special education settings achieve higher academic gains, compared to both CBM without instructional recommendations and not utilizing CBM at all. However, using CBM without instructional recommendations is still more beneficial than not using CBM at all (Fuchs et al., 1991; 1994). Students who are low-achieving, but do not have a disability, appear to benefit most from CBM with instructional strategies, while students who are average-achieving benefit from CBM both with and without instructional strategies, more so than students with learning disabilities (LD) (Fuchs et al., 1994). Students with LD appear to benefit similarly to their non disabled peers from

CBM with or without instructional recommendations (Fuchs et al., 1994). Whether advised by a computerized system or by personnel, instructional recommendations add a vital component to CBM (Fuchs et al., 1991; 1994).

Detailed Feedback and Instruction

CBM is often paired with detailed feedback to help inform teachers of appropriate instructional adjustments. This section provides several examples of programs that provide detailed feedback. These include Accelerated Math (AM), Expert System Instructional Consultation (ExS), peer-assisted learning strategies (PALS), self-monitoring, skills analysis, instructional recommendations, and Task-Focused Goals (TFG). Each of these approaches is discussed in detail in the following paragraphs.

In 1998, Renaissance Learning, Inc. created a computerized CBM system called Accelerated Math (AM) with the ability to match students' skill level, provide individualized practice, score student work, provide instant feedback, and test student proficiency (Spicuzza, Ysseldyke, Lemkuil, Kosciolek, Boys, & Teelucksingh, 2001). Students are pretested using a 15-minute computer adaptive test called STAR Math, which assigns students to appropriate instructional levels (Ysseldyke & Bolt, 2007). All work is performed using paper and pencil, but students record responses on a scan sheet, which is scanned at a computer workstation. Instantly, AM software scores and records student performance, updates teacher record books, provides immediate feedback for the student, generates teacher reports, and creates the next assignment for the student. A daily summary is reported for teachers to specify individualized student progress and to help inform teachers of when intervention is required (Ysseldyke & Tardrew, 2007).

The Expert System Instructional Consultation (ExS) is a computer program designed to attempt reproducing advice experts might provide. ExS requires a coherent network of rules for problem solving in order for the system to imitate the judgment of an expert. In a study utilizing ExS (Fuchs et al., 1991), mathematics instructional experts were nominated by peers based on experience in mathematics at the elementary or middle school level and based on effectiveness in promoting operations, concepts, and applications performance with students who were at-risk for academic failure. Recommendations created for the ExS system to use were

> (a) acquisition instruction using an instructional packet that focused on the concepts underlying the problem type and that relied on modeling, explanation, and self-talk to teach the steps of one of two algorithms, (b) supervised practice with corrective feedback, and (c) structured, timed independent practice" (Fuchs et al., 1991, p. 623).

Peer-Assisted Learning Strategies (PALS) was developed based on the Juniper Gardens' class-wide peer tutoring model as a supplement to existing mathematics curricula. PALS can be used two to three times per week to assist students with extra-individualized practice on skills that have not been mastered. With PALS, students in the same classroom are paired based on skill level (Calhoon & Fuchs, 2003). Modified strategic learning, step-by-step feedback, and frequent verbal and written interactions between students are all included within the PALS framework (Fuchs & Fuchs, 1995).

Self-monitoring provides a record of individual progress and data collection and is designed to allow students to monitor their progress toward goals; it has a history of providing motivation for students (Calhoon & Fuchs, 2003). Although self-monitoring is often used by students, teachers may also benefit from this process by documenting their instructional changes. Responding to written prompts regarding instructional plans set in place and students' progress will allow teachers to keep record of instructional adjustments throughout the school year (Allinder, Bolling, Oats, & Gagnon, 2000).

A skills analysis is a graphed database composed of two parts: (a) summary of each student's current bi-weekly performance, and (b) summary of each student's bi-weekly performance in relationship to the entire school year (Fuchs et al., 1993). Each skills analysis provides teachers with summarized data on which objectives students had not attempted, not mastered, partially mastered, or mastered.

Instructional recommendations are also paired with CBM at times and may included (a) what teachers should teach during whole-class instruction, (b) how to formulate small groups for concentrated instruction on skills most lacking by the students, (c) computer-assisted programs each student should use for the next two weeks, and (d) information addressing students who needed tutoring and which students are able to provide assistance with each particular skill (Fuchs, et al., 1994).

With CBM being attributed to goal attainment, various goal theories may be added to a CBM intervention. Task-Focused Goals (TFG) are founded from the belief that intrinsic motivation is needed for learning, persevering through difficulty, self-regulation, cognitive strategy, deeper word recall processing, and greater active cognitive engagement (Fuchs, Fuchs, Karns, Hamlett, Katzaroff, & Dutka, 1997). With

TFG, students are deemed successful based on improvement, progress made, or mastery (Anderman & Maehr, 1994).

In sum, the literature about CBM encompasses students in both general and special education. CBM measures are available premade or can be created by teachers. Assessment should take between 1-15 minutes and may be done on a computer or through the use of pencil and paper. CBM in mathematics has often been combined with detailed student feedback components and has included the areas of computation, concepts and applications, and overall mathematics achievement.

Purpose and Research Questions

The purpose of the current meta-analysis was to examine studies that implemented curriculum-based measurement in mathematics (CBM-M) as an intervention, not just as a form of measurement. Criteria for an intervention study was defined by routine administration, at least once biweekly for a minimum of 12 weeks and the data were used to inform instructional decisions. Measurement studies administering CBM probes periodically simply use the data for progress indicators. The current meta-analysis will examine three questions in the context of:

- all students in grades K-12
- students in general education
- students in special education
- when detailed feedback was utilized
- when detailed feedback was not incorporated

Specifically, the three research questions are:

(a) What are the effects of implementing CBM-M as an intervention when *digits* correct are assessed for computation and concepts and applications? (b) What are the effects of CBM-M as an intervention when *problems* correct are assessed for computation and concepts and applications? and (c) What are the effects on overall mathematics achievement when CBM-M as an intervention is implemented?

Methods

Data Collection

The Academic Search Complete (EBSCO), Educational Resources Information Center (ERIC) (EBSCO), Linguistics and Language Behavior Abstracts, PsycINFOR 1872-Current (ProQuest), and Sociological Abstracts (ProQuest) were searched for articles using the terms “curriculum-based measure* AND math*”, “progress monitoring AND math*”, “general outcome measure* AND math*”, and “formative assessment AND math*”. Databases were searched in January, scanned for accuracy in March, and searched one final time May to insure all relevant articles were included.

All books, dissertations, non-education journals, and articles written in languages other than English were excluded from the initial search. Articles included in the current meta-analysis were filtered through the following criteria:

1. The article had to be a quantitative study.
2. The quantitative study had to be conducted in the United States.
3. The study could only include students in grades K-12, inclusive of general education, special education, or both.
4. The study had to focus on mathematics achievement.

5. Curriculum-based measurement had to be employed for a minimum of 12 weeks.
6. Curriculum-based measurement had to be implemented at least once biweekly for the minimum of 12 weeks.
7. Pre- and post-achievement data had to be provided.
8. The study had to include a control, contrast, or comparison group.

After all studies were identified, the references of the included studies were scanned using the Scopus database. All relevant references were scanned based on the eight inclusionary categories discussed above. If an article fit all the criteria, the references of this article were also scanned, until all linkages were explored.

The article search performed in January returned 2,782 results. In the March search, 25 articles were added for a total of 2,807. The article search in May returned an additional 93 articles, making the grand total 2,900 articles. Once all books, dissertations, non-education journals, articles written in languages other than English, and duplicate results were excluded from the article search, 531 of the 2,900 articles remained. Table 1 shows the article search process in detail.

Upon completion of initial article filtering based on the inclusion criteria, only 10 met the criteria for the current meta-analysis. The subsequent Scopus search returned another 26 results, bringing the total amount of articles to 557, and of the 26 additional results, two studies were added. Therefore, a total of 12 studies were included in the current meta-analysis. Table 2 demonstrates the article filtration process.

Categorizing Articles

The 12 studies included in the current meta-analysis were coded for particular data. The purpose of coding was to organize and highlight pertinent information encompassed within each study. First, studies were searched for participant grade levels and whether the study included students in special education, general education, or a combination of the two. Secondly, studies were screened for whether computation scores were recorded based on problems or digits correct. The same was assessed for concepts and applications. Studies assessing gains on overall mathematics performance, not specifically computation or concepts and applications, were categorized as "overall" and reported problems correct.

In regards to participant grade levels, only second through twelfth grade was found with 2, 7, 11, 8, 5, 3, 3, 3, 1, 1, and 1 studies found for each of the grade levels, respectively. Of the 12 included studies, six focused on students in general education, four on students in special education, and two studies included students in both general and special education. When addressing mathematical achievement, several studies used more than one method for recording gains and therefore the studies presented more than one effect. For example, of the 12 studies included in the current meta-analysis, four studies only assessed computation using digits correct, two studies assessed computation by using both digits and problems correct, two studies examined computation and concepts and applications by using problems correct, and the four remaining studies only assessed overall mathematics performance using problems correct. Table 3 displays a detailed look at how the articles were categorized.

Statistical Analysis

Once relevant articles were coded, statistical analysis was the next step. Based on the information provided, studies were first categorized into several groups. The groups included: (a) recording of achievement based on *digits correct* and teachers *received* instructional recommendations and/or detailed information addressing student progress (i.e. PALS, detailed skills analysis, ExS), (b) recording of achievement based on *problems correct* and teachers *received* instructional recommendations and/or detailed information addressing student progress, (c) recording of achievement based on *digits correct* where teachers were *not given* instructional recommendations, or detailed information, and (d) recording of achievement based on *problems correct* where teachers *were not* given instructional recommendations, or detailed information. Studies were then categorized again with special education and general education students grouped separately and together. A total of 42 effects were found from the 12 studies included in the current meta-analysis.

Before being able to summarize effect sizes, the differences of the reported pre- and post-mean scores of each study effect were averaged. Standard deviations (SD) were averaged for all experimental and control, comparison, or contrast groups using the following equation:

- Averaged Pre-Post SD = $((SD_{PRE}^2 + SD_{POST}^2)/2))^{0.5}$, where SD_{PRE} is the group SD for the pretest and SD_{POST} is the group SD for the posttest.

Secondly, the SD_{within} was calculated, in order to calculate Cohen's *d* and Hedges *g* effect sizes. SD_{within} is the pooled, or averaged SD, accounting for differences in the groups. If the experimental and control groups had an equal number of participants, the SD for pre- to posttest could be averaged together, but because the groups were different, SD_{within} accounts for the unequal group sizes (Thompson, 2006). Cohen's *d* is a standardized effect size that requires dividing the mean difference of the experimental and control groups by a variance estimate, in this case the pooled SD (Thompson, 2006). Hedge's *g* is an extension of Cohen's *d*, which corrects for sampling bias (Lipsy & Wilson, 2001). The following equations were used to calculate SD_{within}, Cohen's *d*, and Hedge's *g*:

- $SD_{within} = ((((N_E - 1) * SD_E^2 + (N_C-1) * SD_C^2) / (N - 2)))^{0.5}$, where N_E is the total participants in the experimental group, SD_E is the mean standard deviation of the experimental group, N_C is the total participants in the control, comparison, or contrast group, SD_C is the mean standard deviation of the control, contrast, or comparison group, and N is the total participants the experimental and control, contrast, or comparison groups combined.
- Cohen's $d = (\bar{x}_E - \bar{x}_C) / SD_{WITHIN}$, where $\bar{x}_E$ is the standardized mean for the experimental group and $\bar{x}_C$ is the standardized mean for the control, contrast, or comparison group.
- Hedge's $g = d * (1-3 / (4 * N – 9))$, where *d* is Cohen's *d*.

When mean and SD were not reported in the study, ANOVA F-values were used to compute Cohen's *d* using the following equation:

- Cohen's $d = (F\,((N_E + N_C) / (N_E{*}N_C))\,((N_E + N_C) / (N_E + N_C - 2)))^{0.5}$, F is the reported F-value.

The inverse variance weight (ω) of the Hedge's *g* effect size was also calculated in order to compute an overall mean ES and standard error of the mean (S_{mn}). The following equations were used (Lipsey & Wilson, 2001):

- Inverse variance weight (w) $= 2 * N_E * N_C * (N) / (2 * (N)^2 + g^2 * N_E * N_C$, where *g* is the calculated Hedge's *g*.
- Hedge's *g* mean effect size (g_{mn})) $= \Sigma_{wgi} / \Sigma_{wi}$, where *w* is the calculated variance weight, *g* is the calculated Hedge's *g*, and *i* is the value from each individual study.
- Standard error of the mean (S_{mn}) $= (1 / \Sigma_{wi})^{0.5}$

Confidence intervals (C. I.) for *p*-values of 0.10, 0.05, 0.01, and 0.001 were calculated after standardizing the study samples and homogeneity (Q) was analyzed to ensure all sample means derive from the same population. According to Thompson (2006), confidence intervals are "in general, *the best* reporting strategy. The use of confidence intervals is therefore *strongly recommended*" (p. 200). Confidence intervals provide an upper and lower limit, with a determined level of confidence, of where the true-value statistic lies. If the upper and lower limits do not overlap, and do not include 0, the effect size is considered "statistically significant" at the determined level of confidence. When testing homogeneity, if Q has a value of 0, it is considered significant, concluding the sample may have come from heterogeneous distributions (Kline, 2005). A non-significant Q-value means all the effects may have derived from the same distribution with a common mean (Kline, 2005). The following formulas were used to calculate confidence intervals and homogeneity (Lipsey & Wilson, 2001):

- .90 C. I. Upper Limit = (g_{mn}) + 1.64 * (S_{mn}) , where (g_{mn}) is the calculated Hedge's *g* mean effect size and (S_{mn}) is the calculated standard error of the mean.
- .90 C. I. Lower Limit = (g_{mn}) - 1.64 * (S_{mn})
- .95 C. I. Upper Limit = (g_{mn}) + 1.96 * (S_{mn})
- .95 C. I. Lower Limit = (g_{mn}) - 1.96 * (S_{mn})
- .99 C. I. Upper Limit = (g_{mn}) + 2.58 * (S_{mn})
- .99 C. I. Lower Limit = (g_{mn}) - 2.58 * (S_{mn})
- .999 C. I. Upper Limit = (g_{mn}) + 3.29 * (S_{mn})
- .999 C. I. Lower Limit = (g_{mn}) - 3.29 * (S_{mn})
- Homogeneity (Q) = Σ_{wi} (g – (g_{mn})^2

All statistical analyses were run using Microsoft Excel. Table 4 lists all statistical analysis formulas used throughout the meta-analysis.

Detailed feedback was used by 11 of the 12 studies included in the current meta-analysis. Three studies incorporated (AM), one study utilized ExS, one study used instructional recommendations, two study implemented PALS, one study had teachers use self-monitoring, two studies incorporated a skills analysis, and one study included TFG. Each form of detailed feedback was discussed earlier in this paper. Table 5 highlights the duration, frequency, and type of detailed feedback utilized by each of the included 12 studies.

Results

This section addresses results derived from the 12 studies included in the current meta-analysis. Effect sizes will be categorized as "small", "medium" or "large" based on Cohen's (1992) criteria of 0.20, 0.50, and 0.80, respectively. Each question is addressed separately in this section.

Question #1: What are the effects of implementing CBM-M as an intervention when digits correct are assessed for computation and concepts and applications?

- *all students in grades K-12*
- *students in general education*
- *students in special education*
- *when detailed feedback was utilized*
- *when detailed feedback was not incorporated*

Computation with Digits Correct

When students in special and general education were combined, 10 effects were found for CBM-M as an intervention with detailed feedback and eight effects were found for CBM-M as an intervention without detailed feedback when digits correct for computation were assessed. Addressing the 10 effects found for CBM-M as an intervention *with* detailed feedback, an average of 20 students were included in the control groups and 17 students in the treatment groups. A statistically significant overall medium-to-large effect size of g = 0.69 (p < .001; range 0.57 to 0.81) was calculated. Homogeneity was not significant with a $P(Q)$ of 5.03, therefore the distributions most likely derived from a common mean. Of the eight effects incorporated for CBM-M as an intervention *without* detailed feedback in computation, an average of 21 students were in the control groups and 18 students in the experimental groups. The effect size was medium and statistically significant with $g = 0.54$ and a $p < .001$ (range 0.36 to 0.73). Homogeneity was not significant with a $P(Q)$ of 4.63.

In general education, five effects were found for CBM-M as an intervention with detailed feedback and three effects were found when detailed feedback was not used. Of the five effects *with* detailed feedback, an average of 19 students were in the control groups and 15 students in the treatment groups. A statistically significant medium-to large effect of $g = 0.71$ ($p < .001$; range 0.58 to 0.84) was found statistically significant. Homogeneity was not significant with a $P(Q)$ of 3.30. The three effects *without* detailed feedback averaged 21 students in the control groups and 13 students in the treatment groups. A small statistically significant effect of $g = 0.25$ ($p < .10$; range 0.03 to 0.48) was calculated. Homogeneity was not significant with a $P(Q)$ of 7.99.

A total of five effects were found for students in special education when CBM-M as an intervention included detailed feedback and five effects when detailed feedback was not present. Of the five effects *with* detailed feedback, an average of 20 were included in the control groups and an average of 19 students were in the treatment groups. A statistically significant overall medium effect of $g = 0.64$ ($p < .001$; range 0.44 to 0.84) was calculated. Homogeneity was not significant with a $P(Q)$ of 1.26. Of the five effects comprised of CBM-M as an intervention *without* detailed feedback, an average of 21 students were included in the control groups and 21 students in the treatment groups. A medium statistically significant effect of $g = 0.62$ was calculated ($p < .001$; range 0.48 to 0.77). Homogeneity was not significant with a $P(Q)$ of 2.51.

A summary for computation with digits correct can be found in Table 6.

When general and special education students were combined and CBM-M as an intervention was implemented *with* detailed feedback for computation with digits correct, student gains were moderate-to-large and statistically significant. *Without* detailed feedback, students' gains were still moderate and statistically significant, but not nearly as large. These results indicate that CBM-M is effective with all students, compared against not using CBM-M at all. Using detailed feedback will produce a higher statistically significant effect than just using CBM-M alone.

A larger difference in effects was seen when students were separated based on general and special education classifications. Although a slight difference existed in the number of effects to analyze, using detailed feedback resulted in a moderate-to-large statistically significant effect, while not using detailed feedback displayed small *ns* effect in terms of control and experimental groups when examining students in general education. Students in special education exposed to detailed feedback, and those who were not exposed to detailed feedback, attained a medium effect size, which was also statistically significant. Using detailed feedback with students in special education produced a slightly higher effect. These results imply that while CBM-M is effective with all students, students in general education experience higher statistically significant effects when detailed feedback is utilized, but students in special education achieve moderate statistically significant effects *with* or *without* detailed feedback.

Overall, in terms of computation with digits correct assessed, all students experienced comparative positive gains when CBM-M was implemented, when compared with the control groups. Students in general education performed remarkably better when detailed feedback was combined with CBM-M as an intervention, yet students in special education achieved comparably, whether CBM-M was combined with detailed feedback or used alone. All and all, CBM-M as an intervention was most effective with the addition of detailed feedback in computation when digits correct were assessed.

Concepts and Applications with Digits Correct

Not one study was found addressing digits correct for concepts and applications. Future research is desperately needed in this area.

Question #2: What are the effects of CBM-M as an intervention when problems correct are assessed for computation and concepts and applications?

- *all students in grades K-12*
- *students in general education*
- *students in special education*
- *when detailed feedback was utilized*
- *when detailed feedback was not incorporated*

Computation with Problems Correct

When students in general and special education were combined, three effects were found for CBM-M as an intervention with detailed feedback and five effects were found for CBM-M as an intervention without detailed feedback when problems correct for computation were assessed. Addressing the three effects found for CBM-M as an intervention *with* detailed feedback for computation with problems correct, an average of 29 students were included in the control groups and 34 students in the treatment groups. An overall small-to-medium statistically significant effect size of $g = 0.41$ was calculated ($p < .01$; range 0.02 to 0.79). Homogeneity was not significant with a $P(Q)$ of 6.68. Of the five effects incorporated for CBM-M as an intervention *without* detailed feedback in computation, an average of 20 students were in the control groups and 23 students in the experimental groups. The small effect size was statistically significant with $g = 0.35$ ($p < .05$; range 0.08 to 0.62). Homogeneity was also *ns* with a $P(Q)$ of 6.28.

Only one effect was found for students in general education when CBM-M as an intervention included detailed feedback and three effects when detailed feedback was not present. For the single effect *with* detailed feedback, 22 students were included in the control group and 21 students were in the treatment group. The medium effect size was statistically significant with $g = 0.64$ ($p < .05$; range 0.03 to 1.25). Homogeneity was not significant as deemed by the authors (Fuchs et al., 1991). Of the three effects comprised of CBM-M as an intervention *without* detailed feedback, an average of 21 students were included in the control groups and 20 students in the treatment groups. A small statistically significant effect of $g = 0.32$ was calculated ($p < .10$; range 0.03 to 0.62). Homogeneity was not significant with a $P(Q)$ of 7.85.

Special education also had two effects when CBM-M as an intervention included detailed feedback and two effects when detailed feedback was not present. For the two effects *with* detailed feedback, an average of 33 students were included in the control groups and an average of 40 students were in the treatment groups. A small statistically significant effect of $g = 0.34$ was calculated ($p < .10$; range 0.06 to 0.61). Homogeneity was not significant with a $P(Q)$ of 7.85. Of the two effects comprised of CBM-M as an intervention *without* detailed feedback, an average of 20 students were included in the control groups and 29 students in the treatment groups. A small *ns* effect of $g = 0.27$ was calculated. Homogeneity was not significant with a $P(Q)$ of 8.81.

A summary of effects for computation with problems correct can be found in Table 7.

Concepts and Applications with Problems Correct

When students in general and special education were combined, not one study was found for CBM-M as an intervention with detailed feedback and three effects were found for CBM-M as an intervention without detailed feedback when problems correct for concepts and application were assessed. Of the three effects comprised of CBM-M as an intervention *without* detailed feedback, an average of 20 students were included in the control groups and 20 students in the treatment groups. A small *ns* effect of $g = 0.04$ was calculated. Homogeneity was not significant with a $P(Q)$ of 9.92.

Effects for students in general education when CBM-M as an intervention included detailed feedback had not been researched for the area of concepts and applications, but two effects were found when detailed feedback was not present. Of the two effects comprised of CBM-M as an intervention *without* detailed feedback, an average of 20 students were included in the control groups and 20 students in the treatment groups. A small *ns* effect of $g = 0.04$ was calculated. Homogeneity was not significant with a $P(Q)$ of 9.02.

Special education also had just one effect when CBM-M as an intervention included detailed feedback and one effects when detailed feedback was not present. For the single effect *with* detailed feedback, 47 students were included in the control group and 45 students were in the treatment group. A small *ns* effect of $g = 0.00$ was calculated. Homogeneity was not significant as deemed by the authors (Calhoon & Fuchs, 2003). For the single effect comprised of CBM-M as an intervention *without* detailed feedback, 20 students were included in the control group and 20 students in the treatment group. A small *ns* effect of $g = 0.05$ was calculated. Homogeneity was not significant as deemed by the authors (Fuchs et al., 1995).

A summary of effects for concepts and applications when problems correct were assessed can be found in Table 8.

When problems correct were assessed, effects for CBM-M as an intervention were similar to when digits correct were assessed. In computation, although the effects were not equal, comparable averages for control and treatment groups were found *with* and *without* detailed feedback for all students. A medium statistically significant effect was attained *with* detailed feedback and without. These effects matched results found when compared to digits correct being assessed in computation.

Students in general education experienced a higher medium effect when detailed feedback was included than when detailed feedback was omitted. Having a larger effect for the inclusion of detailed feedback was consistent with the effect sizes found for computation with digits correct.

Results for students in special education resulted in a small statistically significant effect when using detailed feedback, while a small non-statistically significant effect was found when detailed feedback was not incorporated. These results imply that while detailed feedback produced higher effects for all students when problems were assessed for computation, students in special education achieved higher effects when digits correct were assessed and detailed feedback was used.

In the area of concepts and applications when problems correct were assessed, effects were not found for CBM-M as an intervention *with* detailed feedback, but all students displayed a very small *ns* effect without detailed feedback. When looking at students in general and special education separately, students in general education achieved a very small *ns* effect *without* detailed feedback. Effects were not found for CBM-M *with* detailed feedback for concepts and applications when problems assessed were examined. Students in special education experienced no effect with the use of detailed feedback and a very small *ns* effect *without* the use of detailed feedback.

In summary, all students achieved higher effects in the area of computation, rather than with concepts and applications, when detailed feedback was provided, regardless of digits or problems correct being assessed. More research is definitely needed in the area of concepts and applications as effects where not found assessing digits correct and few effects were found assessing problems correct.

Question #3: What are the effects on overall mathematics achievement when CBM-M as an intervention is implemented?

- *all students in grades K-12*
- *students in general education*
- *students in special education*
- *when detailed feedback was utilized*
- *when detailed feedback was not incorporated*

A total of 12 effects were found examining student overall mathematics performance *with* detailed feedback, but research had not been conducted for using CBM-M as an intervention *without* detailed feedback. Students in general and special education were combined in the 12 effects with detailed feedback, containing an average of 677 students in the control groups, and 175 students in the experimental groups. The overall effect was small, but significant with $g = 0.22$ ($p < .001$; range 0.12 to 0.32). Homogeneity was not significant with a $P(Q)$ of 1.12.

To separate general and special education from the 12 effects *with* detailed feedback along with CBM-M as an intervention, nine effects were found for general education, while three effects were used for special education. In general education, an average of 893 students were included in the control groups and an average of 226 students in the experimental groups. The overall effect was small, but significant with $g = 0.21$ ($p < .001$; range 0.11 to 0.32). Homogeneity was not significant with a $P(Q)$ of 1.90.

In terms of special education, the three effects had an average of 29 students in the control groups and 22 students in the treatment groups. The results displayed the experimental and control groups were not different with a calculated effect *ns* of g = 0.00. Homogeneity was not significant with a $P(Q)$ of 1.05.

A summary of effects for overall mathematics achievement is displayed in Table 9.

When overall mathematics achievement was examined for all students using CBM-M as an intervention *with* detailed feedback, positive statistically significant gains were achieved for all students and students in general education, but not for students in special education. Effects were not found for CBM-M as an intervention *without* detailed feedback. Students in general education duplicated the results achieved by all students almost exactly. When CBM-M as an intervention *with* detailed feedback was used to examine students in special education, results were of no effect.

Discussion

The purpose of this study was to examine the effects of CBM-M as an intervention on regular and special education students in grades K-12. Meta-analysis of 12 studies showed that computation is not only the most researched area of mathematics in terms of CBM, but also that students in both general and special education achieve the most gains in computation, compared to concepts and applications and overall mathematical achievement, when digits correct are assessed. In this section, a summation of results, implications, and ideas for future research will be discussed.

When assessing the data compiled for all students, general and special education combined, in the area of computation, higher statistically significant gains were discovered with the use of detailed feedback for both digits and problems correct. Data for concepts and applications is lacking, but when all students are assessed, not using detailed feedback with CBM-M as an intervention produced a small effect without statistical significance. There is a possibility that the use of detailed feedback could produce a higher statistically significant effect, but enough research has not been done to allow this conclusion. The same may be true if digits correct were assessed for concepts and application, however, assessing digits correct for concepts and application would be a more tedious process due to the nature of thought process involved with such problems.

In regards to overall mathematics achievement, data were only available with the use of detailed feedback, which returned a statistically significant effect. As stated with concepts and applications, future research would be needed to show that the use of detailed feedback with CBM-M as an intervention when assessing overall mathematics achievement would produce stronger results than if detailed feedback was not used. The same results were found for students in general education in the areas of computation, concepts and application, and overall mathematical achievement.

Students in special education produced similar results to students in general education in terms of computation with digits correct being assessed. However, in regards to computation with problems correct assessed, students in special education displayed statistically significant effects with detailed feedback, but not without. As with students in general education, the use of detailed feedback with CBM-M as an intervention produced higher effects, which were statistically significant. Concepts and applications with problems correct did not produce statistically significant gains for students in special education regardless of whether detailed feedback was used or omitted. For overall mathematics achievement with problems correct assessed, statistically significant gains were not found with the use of detailed feedback. As with all students and students in general education, there is not comparison data available to address how effects would change without the use of detailed feedback.

All three groups of students experienced higher statistically significant effects in the area of computation, rather than with concepts and applications, when detailed feedback was provided, regardless of digits or problems correct being assessed, as had been found in previous research (Fuchs & Fuchs, 1990; Fuchs et al.,1991). However, in the area of computation, all and all, CBM-M as an intervention was most effective with the addition of detailed feedback in computation when digits correct were assessed. Previous research supports these findings (Allinder et al., 2000; Calhoon & Fuchs, 2003; Fuchs & Fuchs, 1990; Fuchs et al., 1994; Fuchs et al., 1991).

Limitations and Future Research

A major limitation of the current meta-analysis is sample size. More research is desperately needed in the area of CBM-M as an intervention with and without detailed feedback for concepts and application, as well as for overall mathematics performance. Furthermore, the majority of studies in the meta-analysis focused on grades 3 – 6. Secondary education is definitely lacking in the area of mathematics research.

Implications

Implications of the current meta-analysis inform teachers to not only use CBM-M as an intervention for computation, concepts, and applications with digits correct, but also to employ instructional decisions and take the time to address detailed feedback. "Teachers who rely on class-wide CBM reports appear to require specific suggestions for how to integrate assessment data with instructional techniques. These finding echo results of earlier CBM studies (e.g., Fuchs, Fuchs, Hamlett, & Ferguson, 1992; Fuchs, Fuchs, Hamlett, & Stecker, 1991)" (Fuchs et al., 1994, p. 535). Implementing continuous progress monitoring, while using the data derived to make instructional decisions, causes students to benefit significantly (Ysseldyke & Bolt, 2007). General and special education teachers "who received instructional consultation along with CBM planned more varied instructional programs and effected better achievement than teachers who relied on CBM but had no access to advice for how to integrate the assessment information into their instructional plans" (Fuchs, et al., 1994, p. 535). According to Bolt, Ysseldyke, & Patterson (2010), progress monitoring can be implemented for over two years and results will continue to improve over time.

Conclusion

This meta-analysis resulted in summarizing the current state of the research on CBM-M as an intervention. Much more research is needed to examine the effects of CBM in mathematics, especially at the secondary level. Implications for teachers involve obtaining detailed feedback regarding student progress to determine next steps for instruction. Just as important is that teachers need to focus on digits correct rather than problems correct because digits correct provide credit for partially correct answers, which in turn gives credit for process and not just the end result (Fuchs & Fuchs, 1990).

CONCLUSION

The purpose of this dissertation was to understand the current state of the literature in regards to CBM, CBM as an intervention, and CBM as an intervention in mathematics. Two articles were presented, a survey of the literature and a meta-analysis. A summary of both articles and topics for future research will be discussed.

The first article pointed out that progress monitoring has been in use for over 40 years within school settings. CBM is a form of progress monitoring which began with the work of Stan Deno and has been utilized by teachers for over 20 years. Both general and special education populations can benefit from frequent monitoring of progress. As an outcome measure, or an intervention, CBM provides teachers with the information needed to make data-based decisions regarding making changes to curriculum in order to aid in enhanced student achievement. As an outcome measure, the teacher, and possibly the students, are able to see growth, whether increasing or decreasing, based on the progress monitoring assessment. When used as an intervention, teachers and students are actively involved in using the assessment data to make changes to curriculum based on data. During an intervention process, data may be presented graphically, itemized, or even discussed on a frequent basis in hopes of attaining a set goal by the end of a specified amount of time. Using CBM as an outcome measure or intervention provides teachers with data which can be used to align students accurately with the respective tier of intervention. In other words, data obtained from CBM can be used to determine on which RtI tier students should be placed at that point in time. Overall, CBM is a research-based progress monitoring method valid for both general and special education settings.

The second article was a meta-analysis of CBM in mathematics as an intervention. The article began by pointing out that computation CBM, compared to concepts and application and overall mathematical achievement, has been the primary focus of mathematical assessments. This is an important finding in itself, indicating that the focus of existing research has been on computation with little attention given to applying mathematical concepts in context. When scoring the computational CBM assessments, digits correct, problems correct, or both digits and problems correct could be used. Furthermore, teachers could use CBM alone or with detailed feedback, such as item analysis, consultation, self-monitoring, instructional recommendations, or peer-assisted learning strategies. Upon completion of the meta-analysis, CBM was shown most effective as an intervention when detailed feedback was incorporated, regardless of whether students were in general or special education. Students performed best in the area of computation when digits correct were assessed. This is likely the case because students were given partial credit for correct numbers in the correct place value, as opposed to missing the entire problem based on one correct number. By receiving partial credit, students are able to see a percentage of success greater than zero, which in turn can initiate intrinsic motivation and a feeling of success within the student. The majority of research has been conducted in computation from grades 3-6.

The findings from these two articles are important because a roadmap of where research in the area of CBM as an intervention in mathematics has not been established.

Based on the knowledge presented in these two articles, researchers can now see the gaps in the literature and decide where they would like to contribute to future findings. As a collective piece, the two articles presented in this dissertation show CBM to be an effective evidence-based strategy for mathematics, especially in computation. Teachers can be confident when using CBM as an intervention in mathematics for computation, especially with the use of detailed feedback and when assessing digits correct for grades 3-6.

Importantly, the articles included in this dissertation demonstrate a definite need in the area of CBM in mathematics as an intervention. Specifically, more research is needed for computation in the secondary grades of 7-12 and with all grades for the areas of concepts and applications and overall mathematical achievement.

REFERENCES

Allinder, R. M. (1996). When some is not better than none: Effects of differential implementation of curriculum-based measurement. *Exceptional Children, 62*(6), 525-535.

Allinder, R. M., Bolling, R. M., Oats, R. G., & Gagnon, W. A. (2000). Effects of teacher self-monitoring on implementation of curriculum-based measurement and mathematics computation achievement of students with disabilities. *Remedial & Special Education, 21*(4), 219-226.

Allinder, R. M. & Oats, R. G. (1997). Effects of acceptability on teachers' implementation of curriculum-based measurement and student achievement in mathematics computation. *Remedial and Special Education, 18*(2), 113-120.

Anderman, E. M. & Maehr, M. L. (1994). Achievement goals in the classroom: Students' learning strategies and motivation processes. *Journal of Educational Psychology, 80*(3), 260-267.

Anderson, D., Lai, C. F., Alonzo, J., & Tindal, G. (2011). Examining a grade-level math CBM designed for persistently low-performing students. *Educational Assessment, 16*(1), 15-34. doi: 10.1080/10627197.2011.551084

Baker, S. K. & Good, R. H. (1995). Curriculum-based measurement of English reading with bilingual Hispanic students: A validation study with second-grade students. *School Psychology Review, 24*(4), 561-578.

Bolt, D. M., Ysseldyke, J., & Patterson, M. M. (2010). Students, teachers, and schools as sources of variability, integrity, and sustainability in implementing progress monitoring. *School Psychology Review, 39*(4), 612-630.

Bradley, R., Danielson, L., & Doolittle, J. (2005). Response to intervention. *Journal of Learning Disabilities, 38*(6), 485-486.

Brookhart, S. M., Andolina, M., Zuza, M., & Furman, R. (2004). Minute math: An action research study of student self-assessment. *Educational Studies in Mathematics, 57*(2), 213-227.

Bryant, B. R., & Rivera, D. P. (1997). Educational Assessment of Mathematics Skills and Abilities. *Journal of Learning Disabilities*, *30*(1), 57-68.

Burns, M. K. (2002). Comprehensive system of assessment to intervention using curriculum-based assessments. *Intervention in School and Clinic, 38*(1), 8-13.

Burns, M. K., Appleton, J. J., & Stehouwer, J. D. (2005). Meta-analytic review of responsiveness-to-intervention research: Examining field-based and research-implemented models. *Journal of Psychoeducational Assessment, 23*(4), 381-394.

Calhoon, M. B. (2008). Curriculum-based measurement for mathematics at the high school level: What we do not know... what we need to know. *Assessment for Effective Intervention, 33*(4), 234-239.

Calhoon, M. B. & Fuchs, L. S. (2003). The effects of peer-assisted learning strategies and curriculum-based measurement on the mathematics performance of secondary students with disabilities. *Remedial and Special Education, 24*(4), 235-245.

Cardona, C. M. (2002). Adapting instruction to address individual and group educational needs in maths. *Journal of Research in Special Educational Needs, 2*(1). DOI: 10.1111/j.1471-3802.2002.00160.x

Christ, T. J., Scullin, S., Tolbize, A., & Jiban, C. L. (2008). Implications of recent research: Curriculum-based measurement of math computation. *Assessment for Effective Intervention, 33*(4), 198-205.

Cohen, J. (1992). A power primer. *Psychological Bulletin, 112*(1), 155-159.

Council for Exceptional Children (CEC) (nd). Response-to-intervention: The promise and the peril. Retrieved on February 23, 2013 from http://www.cec.sped.org/AM/Template.cfm?Section=Home&TEMPLATE=/CM/ContentDisplay.cfm&CONTENTID=7617

Deno, S. L. (1985). Curriculum-based measurement: The emerging alternative. *Exceptional Children, 52*(3), 219-232.

Deno, S. L. (2003). Curriculum-based measures: Development and perspectives. *Assessment for Effective Intervention, 28*(3), 3-12.

Deno, S. L. & Mirkin, P. K. (1977). *Data-based program modification: A manual.* Reston VA: Council for Exceptional Children.

Dunn, K. E. & Mulvenon, S. W. (2009). A critical review of research on formative assessment: The limited scientific evidence of the impact of formative assessment in education. *Practical Assessment, Research & Evaluation, 14*(7), 1-11.

Espin, C. A. & Deno, S. L. (1993). Content-specific and general reading disabilities of secondary-level students: Identification and educational relevance. *Journal of Special Education, 27*(3), 321-337.

Foegen, A. (2008a). Algebra progress monitoring and interventions for students with learning disabilities. *Learning Disability Quarterly, 31*(2), 65-78.

Foegen, A. (2008b). Progress monitoring in middle school mathematics: Options and issues. *Remedial and Special Education, 29*(4), 195-207.

Foegen, A., Jiban, C., & Deno, S. (2007). Progress monitoring measures in mathematics: A review of the literature. *The Journal of Special Education, 41*(2), 121-139.

Foegen, A. & Morrison, C. (2010). Putting algebra progress monitoring into practice: Insights from the field. *Intervention in School and Clinic, 46*(2), 95-103. doi: 10.1177/1053451210375302

Fore III, C., Burke, M., & Martin, C. (2006). Curriculum-based measurement: An emerging alternative to traditional assessment for African American children and youth. *The Journal of Negro Education, 75*(1), 16-24.

Fuchs, L. S. (2004). The past, present, and future of curriculum-based measurement research. *School Psychology Review, 33*(2), 188-192.

Fuchs, L. S., Deno, S. L., & Mirkin, P. K. (1982). *Direct and frequent measurement and evaluation: Effects on instruction and estimates of student progress Research Rep. No. 97).* Minneapolis : University of Minnesota, Institute for Research on Learning Disabilities.

Fuchs, L. S., Deno, S. L., & Mirkin, P. K. (1984). Data-based program modification: A continuous evaluation system with computer software to facilitate implementation. *Journal of Special Education Technology, 6*(2), 50-57.

Fuchs, L. S. & Fuchs, D. (1988). Curriculum-based measurement: A methodology for evaluating and improving student programs. *Diagnostique, 14*(1), 3-13.

Fuchs, L. S. & Fuchs, D. (1990). The role of skills analysis in curriculum-based measurement in math. *School Psychology Review, 19*(1), 6-25.

Fuchs, L. S. & Fuchs, D. (1995). Acquisition and transfer effects of classwide peer-assisted learning strategies in mathematics for students with varying learning histories. *School Psychology Review, 24*(4), 604-627.

Fuchs, D. & Fuchs, L. S. (2006). Introduction to response to intervention: What, why, and how valid is it? *Reading Research Quarterly, 41*(1), 93-99.

Fuchs, L. S., Fuchs, D., & Fernstrom, P. (1993). A conservative approach to special education reform: Mainstreaming through transenvironmental programming and curriculum-based measurement. *American Educational Research Journal, 30*(1), 149-177. doi: 10.3102/00028312030001149

Fuchs, L. S., Fuchs, D., & Hamlett, C. L. (1989). Effects of alternative goal structures within curriculum-based measurement. *Exceptional Children, 55*(5), 429-438.

Fuchs, L. S., Fuchs, D., & Hamlett, C. L. (1993). Technological advances linking the assessment of students' academic proficiency to instructional planning. *Journal of Special Education Technology*, *12*(1), 49-62.

Fuchs, L. S., Fuchs, D., Hamlett, C. L., Phillips, N. B., & Bentz, J. (1994). Classwide curriculum-based measurement: Helping general educators meet the challenge of student diversity. *Exceptional Children, 60*(6), 518-537.

Fuchs, L. S., Fuchs, D., Hamlett, C. L., Phillips, N. B., & Karns, K. (1995). General educators' specialized adaptation for students with learning disabilities. *Exceptional Children, 61*(5), 440-459.

Fuchs, L. S., Fuchs, D., Hamlett, C. L., Stecker, P. M. (1991). Effects of curriculum-based measurement and consultation on teacher planning and student achievement in mathematics operations. *American Educational Research Journal*, *28*(3), 617-641.

Fuchs, L. S., Fuchs, D., Hamlett, C. L., Walz, C., & Germann, S. (1993). Formative evaluation of academic progress: How much growth can we expect? *School Psychology Review, 22*(1), 27-48.

Fuchs, L. S., Fuchs, D., Karns, K., Hamlett, C. L., Katzaroff, M., & Dutka, S. (1997). Effects of task-focused goals on low-achieving students with and without learning disabilities. *American Education Research Journal, 34*(3), 513-543. doi: 10.3102/00028312034003513

Fuchs, D., Fuchs, L. S., Mathes, P., & Simmons, D. (1997). Peer-assisted learning strategies: Making classrooms more responsible to student diversity. *American Educational Research Journal, 34*(1), 174-206.

Fuchs, L. S., Fuchs, D., & Zumeta, R. O. (2008). A curricular-sampling approach to progress monitoring: Mathematics concepts and applications. *Assessment for Effective Intervention, 33*(4), 225-233.

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*(2), 121-142.

Helwig, R., Anderson, L., & Tindal, G. (2002). Using a concept-grounded, curriculum-based measure in mathematics to predict statewide test scores for middle school students with LD. *The Journal of Special Education, 36*(2), 102-112.

Hosp, M. K. & Hosp, J. L. (2003). Curriculum-based measurement for reading, spelling, and math: How to do it and why. *Preventing School Failure, 48*(1), 10-17.

Jiban, C. L. & Deno, S. L. (2007). Using math and reading curriculum-based measurements to predict state mathematics test performance: Are simple one-minute measures technically adequate? *Assessment for Effective Intervention, 32*(2), 78-89.

Kaminski, R. A. & Good, R. H. (1996). Toward a technology for assessing basic early literacy skills. *School Psychology Review, 25*(2), 215-227.

Kelly, B., Hosp, J. L., & Howell, K. (2008). Curriculum-based evaluation and math: An overview. *Assessment for Effective Intervention*, *33*(4), 250-256.

Kline, R. B. (2005). *Principles and practices of structural equation modeling*. New York, NY: The Guillford Press

Leh, J. M., Jitendra, A. K., Caskie, G. I. L., & Griffin, C. C. (2007). An evaluation of curriculum-based measurement of mathematics word problem: Solving measures for monitoring third-grade students' mathematics competence. *Assessment for Effective Intervention, 32*(2), 90-99.

Lipsey, M. W. & Wilson, D. B. (2001). *Practical Meta-Analysis.* Thousand Oaks, CA: Sage Publications

Luke, S. D. & Schwartz, A. (2007). Assessment and accomodations. *Evidence for Education, 2*(1), 1-11.

Marston, D. (1989). *A curriculum-based approach to assessing academic performance: What it is and why do it. In M. R. Shinn (Ed.). Curriculum-based measurement: Assessing Special Children, p. 19-78.* New York, NY: Guilford Press.

Methe, S. A., Hintze, J. M., & Floyd, R. G. (2008). Validation and Decision Accuracy of Early Numeracy Skill Indicators. *School Psychology Review, 37*(3), 359-373.

Montague, M., Penfield, R. D., Enders, C., & Huang, J. (2010). Curriculum-based measurement of math problem solving: A methodology and rationale for establishing equivalence of scores. *Journal of School Psychology, 48*(1), 39-52.

National Association of State Directors of Special Education (NASDSE). (2006). Response to intervention: Policy considerations and implementation: Alexandria, VA.

National Center for Education (2011). *The Nation's Report Card: Mathematics 2011 (NCES 2012-458).* Institute of Education Sciences, U.S. Department of Education, Washington, D.C.

National Center on Response to Intervention (2012). Progress monitoring general outcome measures tools chart. www.rti4success.org

Powell, S. R. & Seethaler, P. M. (2008). Case study #2: Grade three: Math concepts/applications. *National Center on Progress Monitoring*, 1-42.

Rafferty, L. A. & Raimondi, S. L. (2009). Self-monitoring of attention versus self-monitoring of performance: Examining the differential effects among students with emotional disturbance engaged in independent math practice. *Journal of Behavioral Education, 18*(4), 279-299.

Rivera-Batiz, F. L. (1992). Quantitative literacy and the likelihood of employment among young adults in the United States. *Journal of Human Resources, 27*(2), 313-328.

Shapiro, E. S., Edwards, L., & Zigmond, . (2005). Progress monitoring of mathematics among students with learning disabilities. *Assessment for Effective Intervention, 30*(2), 15-32. doi: 10.1177/073724770503000203

Shapiro, E. S., Keller, M. A., Lutz, J. G., Santoro, L. E., & Hintze, J. M. (2006). Curriculum-based measures and performance on state assessment and standardized tests: Reading and math performance in pennsylvania. *Journal of Psychoeducational Assessment, 24*(1), 19-35.

Smith, C. R., Marchand-Martella, N. E., & Martella, R. C. (2011). Assessing the effects of the rocket math program with a primary elementary school student at risk for school failure: A case study. *Education and treatment of children, 34*(2), 247-358.

Spicuzza, R., Ysseldyke, J., Lemkuil, A., Kosciolek, S., Boys, C., & Teelucksingh, E. (2001). Effects of curriculum-based monitoring on classroom instruction and math achievement. *Journal of School Psychology, 39*(6), 521-542.

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*(2), 795-819.

Stecker, P. M., Lembke, E. S., & Foegen, A. (2008). Using progress-monitoring data to improve instructional decision making. *Preventing School Failure, 52*(2), 48-58.

Thompson, B. (2006). *Foundations of behavioral statistics: An insight-based approach*. New York, NY: The Guilford Press

Tucker, J. (1985). Curriculum-based assessment: An introduction. *Exceptional Children 52*(3), 266-276.

VanDerHeyden, A. M., Witt, J. C., & Barnett, D. W. (2005). The emergence and possible futures of response to intervention. *Journal of Psychoeducational Assessment, 23*(4), 339-361.

Ysseldyke, J. & Bolt, D. M. (2007). Effect of technology-enhanced continuous progress monitoring on math achievement. *School Psychology Review, 36*(3), 453-467.

Ysseldyke, J., Spicuzza, R., Kosciolek, S., & Boys, C. (2003). Effects of a learning information system on mathematics achievement and classroom structure. *Journal of Educational Research, 96*(3), 163-173.

Ysseldyke, J. & Tardrew, S. (2007). Use of a progress monitoring system to enable teachers to differentiate mathematics instruction. *Journal of Applied School Psychology*, *24*(1), 1-28. doi: 10.1300/J370v24n01_01

APPENDIX

Table 1

Article Search Results

	Academic Search Complete (EBSCO)	Educational Resources Information Center	Linguistics & Language Behavior Abstracts	PsycINFO 1872-Current (ProQuest)	Sociological Abstracts (ProQuest)	TOTALS
JANUARY						
curriculum-based measure* AND math*	90	193	36	228	38	585
progress monitoring AND math*	179	286	20	149	35	669
general outcome measure* AND math*	400	70	17	337	70	894
formative assessment AND math*	129	312	6	169	18	634
						2782
MARCH						
curriculum-based measure* AND math*	90	193	36	228	38	585
progress monitoring AND math*	183	291	20	150	35	679
general outcome measure* AND math*	407	72	17	339	70	905
formative assessment AND math*	130	314	6	170	18	638
						2807

MAY						
curriculum-based measure* AND math*	92	195	37	236	39	599
progress monitoring AND math*	192	298	22	154	35	701
general outcome measure* AND math*	424	72	18	351	73	938
formative assessment AND math*	135	326	6	177	18	662
						2900

Table 2

Article Filtration Process

	EXCLUDED	REMAINING
		557
Not a qualitative study	199	358
Not conduced in U. S.	80	278
Grades other than K-12	30	248
Not focused on mathematics	82	166
CBM for less than 12 weeks	115	51
CBM less than biweekly	14	37
No pre-post data	9	28
Lacking control, contrast, comparison group	16	**12**

Table 3

Inclusion Studies Categorization

Citation	Grade Levels	GEN	SPED	Comp Digits	Comp Prob	Con/ App Digits	Con/ App Prob	Overall
Fuchs, L.S. & Fuchs, D. (1990)	3-9		X	X	X			
Fuchs, L. S., Fuchs, D., Hamlett, C. L., & Stecker, P. M. (1991)	3-8	X		X	X			
Fuchs, D., Fuchs, L. S., & Fernstrom, P. (1993)	3-6	X	X	X				
Fuchs, L. S., Fuchs, D., Hamlett, C. L., Phillips, N. B., & Bentz, J. (1994)	2-5	X		X				
Fuchs, L. S., Fuchs, D., Hamlett, C. L., Phillips, N. B., & Karns, K. (1995)	2-4	X	X		X		X	
Allinder, R. M. (1996)	3-6		X	X				
Fuchs, L. S., Fuchs, D., Karns, D., Hamlett, C. L., Katzaroff, M., & Dutka, S. (1997)	4	X						X

Allinder, R. M., Bolling, R. M., Oats, R. G., & Gagnon, W. A. (2000)	4		X	X			
Ysseldyke, J., Spicuzza, R., Kosciolek, S., & Boys, C. (2003)	4-5	X					X
Calhoon, M. B. & Fuchs, L. S. (2003)	9-12		X		X	X	
Ysseldyke, J. & Tardrew, S. (2007)	3-10	X					X

Table 4

Statistical Formulas and Descriptions

	Equations
Averaged Pre-Post Standard Deviations	$=((SD_{PRE}^2 + SD_{POST}^2)/2))^{0.5}$
Standard Deviation Within:	$=((((N_E–1)*SD_E^2+(N_C–1)*SD_C^2) / (N-2)))^{0.5}$
Cohen's *d*:	$=(\bar{x}_E - \bar{x}_C) / SD_{WITHIN}$ $=(F((N_E + N_C) / (N_E*N_C)) ((N_E + N_C) / (N_E + N_C - 2)))^{0.5}$
Hedges *g*:	$= d*(1-3/(4*N-9))$
w (variance):	$= 2*N_E*N_C*(N) / (2*(N)^2+g^2*N_E*N_C$
wd	$= g*w$
Hedges *g* mean	$= \Sigma_{WDi} / \Sigma_{Wi}$
Standard Error (mean)	$= (1 / \Sigma_{Wi})^{0.5}$
.90 Confidence Interval (Upper Limit):	$= (g_{mn}) + 1.64 * (S_{mn})$
.90 Confidence Interval (Lower Limit):	$= (g_{mn}) - 1.64 * (S_{mn})$
.95 Confidence Interval (Upper Limit):	$= (g_{mn}) + 1.96 * (S_{mn})$
.95 Confidence Interval (Lower Limit):	$= (g_{mn}) - 1.96 * (S_{mn})$
.99 Confidence Interval (Upper Limit):	$= (g_{mn}) + 2.58 * (S_{mn})$
.99 Confidence Interval (Lower Limit):	$= (g_{mn}) - 2.58 * (S_{mn})$
.999 Confidence Interval (Upper Limit):	$= (g_{mn}) + 3.29 * (S_{mn})$
.999 Confidence Interval (Lower Limit):	$= (g_{mn}) – 3.29 * (S_{mn})$
Homogeneity (Q-test):	$= \Sigma_{wi} (g – g_{mn})^2$

Table 5

Duration, Frequency, and Detailed Feedback

CITATION	DURATION IN WEEKS	FREQUENCY	DETAILED FEEDBACK
Fuchs, L.S. & Fuchs, D. (1990)	15	2x / week	Skills Analysis
Fuchs, L. S., Fuchs, D., Hamlett, C. L., & Stecker, P. M. (1991)	20	>2x / week	Expert System Instructional Consultation
Fuchs, D., Fuchs, L. S., & Fernstrom, P. (1993)	36	1x / week	Skills Analysis
Fuchs, L. S., Fuchs, D., Hamlett, C. L., Phillips, N. B., & Bentz, J. (1994)	25	>1x / week	Instructional Recommendations
Fuchs, L. S. & Fuchs, D. (1995)	25	1x / week	Peer-Assisted Learning Strategy (PALS)
Allinder, R. M. (1996)	16	1x / biweekly	N/A
Fuchs, L. S., Fuchs, D., Karns, D., Hamlett, C. L., Katzaroff, M., & Dutka, S. (1997)	23	1x / week	Task-Focused Goals (TFG) & Self-Referenced Assessment Feedback (SRAF)
Allinder, R. M., Bolling, R. M., Oats, R. G., & Gagnon, W. A. (2000)	20	2x / week	Self-Monitoring
Spicuzza, R., Lemkuil, A., Kosciolek, S., Boys, C., & Teelucksingh, E. (2001)	16	>2x / week	Accelerated Math
Ysseldyke, J., Spicuzza, R., Kosciolek, S., & Boys, C. (2003)	20	>2x / week	Accelerated Math
Calhoon, M. B. & Fuchs, L. S. (2003)	15	2x / week	Peer-Assisted Learning Strategy (PALS)
Ysseldyke, J. & Tardrew, S. (2007)	20	>2x / week	Accelerated Math

Table 6

Computation Results for Digits Correct

Computation-Digits Correct	Detailed Feedback	Detailed Feedback	Detailed Feedback	CBM Only	CBM Only	CBM Only
	CMP-D ALL	CMP-D SPED	CMP-D GEN	CMP-D ALL	CMP-D SPED	CBM-D GEN
# of Effects	10	5	5	8	5	3
Control N Mean	20	20	19	21	21	21
Treatment N Mean	17	19	15	18	21	13
Hedge's *g* Mean	0.69****	0.64****	0.71****	0.54****	0.62****	0.25*
S(Mean)	0.04	0.06	0.04	0.06	0.04	0.14
C. I. - Upper Limit	0.81****	0.84****	0.84****	0..73****	0.77****	0.48*
C. I. - Lower Limit	0.57****	0.44****	0.58****	0.36****	0.48****	0.03*
Probability of Q	5.03	1.26	3.30	4.63	2.51	7.99
Significant $P(Q)$	NO	NO	NO	NO	NO	NO

CBM ONLY = without detailed feedback CMP-D = Computation with Digits Correct ALL = All Students SPED = Students in Special Education GEN = Students in General Education Note: all confidence intervals = .90 unless noted otherwise * = Statistically Significant at $p < .10$ ** = Statistically Significant at $p < .05$ *** = Statistically Significant at $p < .01$ **** = Statistically Significant at $p < .001$

Table 7

Computation Results for Problems Correct

Computation-Problems Correct	Detailed Feedback CMP-P ALL	Detailed Feedback CMP-P SPED	Detailed Feedback CMP-P GEN	CBM Only CMP-P ALL	CBM Only CMP-P SPED	CBM Only CBM-P GEN
# of Effects	3	2	1	5	2	3
Control N Mean	29	33	22	20	20	21
Treatment N Mean	34	40	21	23	29	20
Hedge's *g* Mean	0.41***	0.34*	0.64**	0.35**	0.27	0.32*
S(Mean)	0.15	0.17	0.31	0.14	0.21	0.18
C. I. - Upper Limit	0.79***	0.61*	1.25**	0.62**	0.61	0.62*
C. I. - Lower Limit	0.02***	0.06*	0.03**	0.08**	-0.08	0.03*
Probability of Q	6.68	7.85	N/A	6.28	8.81	7.85
Significant *P*(*Q*)	NO	NO	N/A	NO	NO	NO

CBM ONLY = without detailed feedback CMP-P = Computation with Problems Correct ALL = All Students SPED = Students in Special Education GEN = Students in General Education Note: all confidence intervals = .90 unless noted otherwise * = Statistically Significant at $p < .10$ ** = Statistically Significant at $p < .05$ *** = Statistically Significant at $p < .01$ **** = Statistically Significant at $p < .001$

Table 8

Concepts and Applications Results for Problems Correct

Concepts and Applications Problems Correct	Detailed Feedback CA-P ALL	Detailed Feedback CA-P SPED	Detailed Feedback CA-P GEN	CBM Only CA-P ALL	CBM Only CA-P SPED	CBM Only CA-P GEN
# of Effects	N/A	1	N/A	3	1	2
Control N Mean	N/A	47	N/A	20	20	20
Treatment N Mean	N/A	45	N/A	20	20	20
Hedge's *g* Mean	N/A	0.00	N/A	0.04	-0.05	0.04
S(Mean)	N/A	0.21	N/A	0.18	0.32	0.22
C. I. - Upper Limit	N/A	0.34	N/A	0.34	0.47	0.41
C. I. - Lower Limit	N/A	-0.34	N/A	-0.26	-0.57	-0.32
Probability of Q	N/A	N/A	N/A	9.92	N/A	9.02
Significant *P*(*Q*)	N/A	N/A	N/A	NO	N/A	NO

CBM ONLY = without detailed feedback CA-P = Concepts and Applications with Problems Correct ALL = All Students SPED = Special Education GEN = General Education Note: all confidence intervals = .90 unless noted otherwise * = Statistically Significant at $p < .10$ ** = Statistically Significant at $p < .05$ *** = Statistically Significant at $p < .01$ **** = Statistically Significant at $p < .001$

Table 9

Overall Mathematics Achievement with Problems Correct

Overall Mathematics Achievement-Problems Correct	Detailed Feedback OMA ALL	Detailed Feedback OMA SPED	Detailed Feedback OMA GEN	CBM Only OMA ALL	CBM Only OMA SPED	CBM Only OMA GEN
# of Effects	12	3	9	N/A	N/A	N/A
Control N Mean	677	29	893	N/A	N/A	N/A
Treatment N Mean	175	22	226	N/A	N/A	N/A
Hedge's *g* Mean	0.22****	0.00	0.21****	N/A	N/A	N/A
S(Mean)	0.03	0.17	0.03	N/A	N/A	N/A
C. I. - Upper Limit	0.32****	0.28	0.32****	N/A	N/A	N/A
C. I. - Lower Limit	0.12****	-0.27	0.11****	N/A	N/A	N/A
Probability of Q	1.12	1.05	1.90	N/A	N/A	N/A
Significant?	NO	NO	NO	N/A	N/A	N/A

CBM ONLY = without detailed feedback OMA = Overall Mathematics Achievement ALL = All Students SPED = Special Education GEN = General Education Note: all confidence intervals = .90 unless noted otherwise * = Statistically Significant at $p < .10$ ** = Statistically Significant at $p < .05$ *** = Statistically Significant at $p < .01$ **** = Statistically Significant at $p < .001$

Table 10

Statistical Analysis: Computation for Digits Correct with Detailed Feedback for All Students

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1990*	14.60	4.50	13.75	25.45	0.54	0.53	19	35	54	18.65	195.58	104.38
Fuchs 1991	9.15	5.96	17.02	25.59	0.15	0.14	22	21	43	21.83	14.87	2.13
Fuchs 1993*	11.72	1.49	11.49	10.71	0.92	0.90	21	21	42	11.11	52.11	47.09
Fuchs 1993 A2 C2*	6.46	-1.84	9.91	8.18	0.91	0.88	13	13	26	9.09	42.82	37.88
Fuchs 1993 (B)	6.57	1.49	6.63	10.71	0.57	0.56	21	21	42	8.91	90.87	50.85
Fuchs 1993 (B2) (C2)	5.84	-1.84	6.90	8.18	1.01	0.98	13	13	26	7.57	149.14	146.59
Fuchs 1994 LD (A)*	10.70	8.25	12.29	15.70	0.17	0.16	20	10	30	14.69	3.40	0.55
Fuchs 1994 LA (A)	21.50	12.50	11.54	17.58	0.57	0.55	20	10	30	15.89	4.60	2.54
Fuchs 1994 AA (A)	17.30	11.15	19.34	19.13	0.32	0.31	20	10	30	19.20	6.73	2.10
Allinder 2000*	22.50	10.43	17.57	17.87	0.68	0.67	28	16	44	17.76	204.57	136.50
Mean						0.69	20	17	37		765	531
s(mean)						0.04						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.81	0.79	0.76	0.75					
CI-Lower				0.57	0.60	0.62	0.63					

Table 10 Con't.

Statistical Analysis: Computation for Digits Correct with Detailed Feedback for All Students

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1990*	0.2927	0.1066	1.2756	yes	5.0180	0.0251	no
Fuchs 1991	0.3141	0.0595	1.3218	yes	4.5072	0.0338	no
Fuchs 1993*	0.3178	0.0517	1.3293	yes	2.2933	0.5900	no
Fuchs 1993 A2 C2*	0.4039	-0.1396	1.5122	yes	1.5578	0.1281	no
Fuchs 1993 (B)	0.3178	0.0517	1.3293	yes	1.6388	0.0711	no
Fuchs 1993 (B2) (C2)	0.4039	-0.1396	1.5122	yes	12.4549	0.0000	yes
Fuchs 1994 LD (A)*	0.3975	-0.1204	1.4986	yes	0.9615	0.6187	no
Fuchs 1994 LA (A)	0.3975	-0.1204	1.4986	yes	0.0939	0.4779	no
Fuchs 1994 AA (A)	0.3975	-0.1204	1.4986	yes	0.9825	0.7535	no
Allinder 2000*	0.3220	0.0441	1.3384	yes	0.1448	0.7035	no
				Q	29.6526		
				df	9		
				Prob (Q)	5.0258E-04		NO

Table 11

Statistical Analysis: Computation for Digits Correct with Detailed Feedback for General Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1991	21.45	5.96	17.02	25.59	0.71	0.70	22	21	43	21.83	229.42	159.77
Fuchs 1993 (B)	6.57	1.49	6.63	10.71	0.57	0.56	21	21	42	8.91	143.35	80.22
Fuchs 1993 (B2) (C2)	5.84	-1.84	6.90	8.18	1.01	0.98	13	13	26	7.57	166.51	163.66
Fuchs 1994 LA (A)	21.50	12.50	11.54	17.58	0.57	0.55	20	10	30	15.89	64.07	35.30
Fuchs 1994 AA (A)	17.30	11.15	19.34	19.13	0.32	0.31	20	10	30	19.20	22.76	7.10
Mean						0.71	19	15	34		626.11	446.04
s(mean)						0.04						
				$p < .001$	$p < .01$	$p < .05$	$p < .10$					
CI-Upper				0.84	0.82	0.79	0.78					
CI-Lower				0.58	0.61	0.63	0.65					

Table 11 Con't.

Statistical Analysis: Computation for Digits Correct with Detailed Feedback for General Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1991	0.3146	0.0770	1.3413	yes	0.0588	0.8084	no
Fuchs 1993 (B)	0.3182	0.0692	1.3488	yes	3.3472	0.0711	no
Fuchs 1993 (B2) (C2)	0.4045	-0.1224	1.5320	yes	12.1807	0.0000	yes
Fuchs 1994 LA (A)	0.3981	-0.1030	1.5182	yes	1.6678	0.4779	no
Fuchs 1994 AA (A)	0.3981	-0.1030	1.5182	yes	3.6551	0.7535	no
				Q	20.9095		
				df	4		
				Prob (Q)	3.3002E-04		NO

Table 12

Statistical Analysis: Computation for Digits Correct with Detailed Feedback for Special Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1990*	14.60	4.50	13.75	25.45	0.54	0.53	19	35	54	18.65	21.88	11.68
Fuchs 1993*	11.72	1.49	11.49	10.71	0.92	0.90	21	21	42	11.11	3.38	3.06
Fuchs 1993 A2 C2*	6.46	-1.84	9.91	8.18	0.91	0.88	13	13	26	9.09	26.02	23.02
Fuchs 1994 LD (A)*	10.70	8.25	12.29	15.70	0.17	0.16	20	10	30	14.69	21.96	3.56
Allinder 2000*	22.50	10.43	17.57	17.87	0.68	0.67	28	16	44	17.76	204.57	136.50
Mean						0.64	20	19	39		277.81	177.82
s(mean)						0.06						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.84	0.79	0.76	0.74					
CI-Lower				0.44	0.49	0.52	0.54					

Table 12 Con't.

Statistical Analysis: Computation for Digits Correct with Detailed Feedback for Special Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1990*	0.2915	0.0551	1.2196	yes	0.2476	0.6188	no
Fuchs 1993*	0.3164	0.0006	1.2728	yes	0.2349	0.6279	no
Fuchs 1993 A2 C2*	0.4022	-0.1899	1.4549	yes	1.5560	0.2122	no
Fuchs 1994 LD (A)*	0.3960	-0.1711	1.4418	yes	5.0125	0.0252	no
Allinder 2000*	0.3207	-0.0072	1.2821	yes	0.1513	0.6973	no
				Q	7.2024		
				df	4		
				Prob (Q)	1.2557E-01		NO

Table 13

Statistical Analysis: Computation for Digits Correct without Detailed Feedback for All Students

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs1990 (B)*	9.15	4.50	15.33	25.45	0.24	0.24	19	37	56	19.30	45.95	10.91
Fuchs 1991 (B)	7.63	5.96	20.85	25.59	0.07	0.07	22	20	42	23.46	7.38	0.52
Fuchs 1994 LD(B)*	11.20	8.25	15.21	15.70	0.19	0.18	20	10	30	15.54	10.15	1.87
Fuchs 1994 LA(B)	12.80	12.50	21.54	17.58	0.02	0.02	20	10	30	18.94	3.38	0.05
Fuchs 1994 AA(B)	17.80	11.15	19.38	19.13	0.35	0.34	20	10	30	19.21	26.02	8.76
Allinder 2000 (B)*	10.20	10.43	18.32	17.87	-0.01	-0.01	28	20	48	18.06	5.92	-0.07
Allinder 1996*					0.84	0.82	20	12	32		163.65	133.58
Allinder 1996 (B)*					0.33	0.33	20	26	46		60.94	19.87
Mean						0.54	21	18	39		323.39	175.49
s(mean)						0.06						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.73	0.69	0.65	0.63					
CI-Lower				0.36	0.40	0.43	0.45					

Table 13 Con't.

Statistical Analysis: Computation for Digits Correct without Detailed Feedback for All Students

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs1990 (B)*	0.2869	-0.032	1.118	yes	4.277	0.039	yes
Fuchs 1991 (B)	0.3146	-0.093	1.178	yes	1.651	0.199	no
Fuchs 1994 LD(B)*	0.3936	-0.264	1.349	yes	1.301	0.254	no
Fuchs 1994 LA(B)	0.3936	-0.264	1.349	yes	0.940	0.332	no
Fuchs 1994 AA(B)	0.3936	-0.264	1.349	yes	1.103	0.294	no
Allinder 2000 (B)*	0.2980	-0.057	1.142	yes	1.825	0.177	yes
Allinder 1996*	0.3714	-0.216	1.301	no	12.248	0.000	yes
Allinder 1996 (B)*	0.3028	-0.068	1.153	yes	2.859	0.091	no
				Q	26.205		
				df	7		
				Prob (Q)	4.6299E-04		NO

Table 14

Statistical Analysis: Computation for Digits Correct without Detailed Feedback for General Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1991 (B)	9.15	4.50	20.85	25.59	0.20	0.19	22	20	42	23.46	21.88	4.26
Fuchs 1994 LA(B)	12.80	12.50	21.54	17.58	0.02	0.02	20	10	30	18.94	3.38	0.05
Fuchs 1994 AA(B)	17.80	11.15	19.38	19.13	0.35	0.34	20	10	30	19.21	26.02	8.76
Mean						0.25	21	13	34		51.28	13.07
s(mean)						0.14						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.71	0.62	0.53	0.48					
CI-Lower				-0.20	-0.11	-0.02	0.03					

Table 14 Con't.

Statistical Analysis: Computation for Digits Correct without Detailed Feedback for General Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1991 (B)	0.3102	-0.3721	0.8818	yes	0.0798	0.7775	no
Fuchs 1994 LA(B)	0.3887	-0.5413	1.0511	yes	0.1939	0.6597	no
Fuchs 1994 AA(B)	0.3887	-0.5413	1.0511	yes	0.1746	0.6761	no
				Q	0.4483		
				df	2		
				Prob (Q)	7.9918E-01		NO

Table 15

Statistical Analysis: Computation for Digits Correct without Detailed Feedback for Special Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs1990 (B)*	9.15	4.50	15.33	25.45	0.24	0.24	19	37	56	19.30	45.95	10.91
Fuchs 1994 LD(B)*	11.20	8.25	15.21	15.70	0.19	0.18	20	10	30	15.54	10.15	1.87
Allinder 2000 (B)*	22.50	10.43	18.32	17.87	0.67	0.66	28	20	48	18.06	247.90	162.99
Allinder 1996*					0.84	0.82	20	12	32		163.65	133.58
Allinder 1996 (B)*					0.33	0.33	20	26	46		60.94	19.87
Mean						0.62	21	21	42		528.59	329.22
s(mean)						0.04						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.77	0.74	0.71	0.69					
CI-Lower				0.48	0.51	0.54	0.55					

Table 15 Con't.

Statistical Analysis: Computation for Digits Correct without Detailed Feedback for Special Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs1990 (B)*	0.2883	0.0448	1.2009	yes	6.8207	0.0090	yes
Fuchs 1994 LD(B)*	0.3956	-0.1874	1.4331	yes	1.3013	0.2540	no
Allinder 2000 (B)*	0.2996	0.0198	1.2259	yes	3.2676	0.0707	yes
Allinder 1996*	0.3734	-0.1397	1.3853	no	12.2482	0.0005	yes
Allinder 1996 (B)*	0.3044	0.0093	1.2364	yes	2.8590	0.0909	no
				Q	26.4968		
				df	4		
				Prob (Q)	2.5122E-05		NO

Table 16

Statistical Analysis: Computation for Problems Correct with Detailed Feedback for All Students

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1990*	3.02	0.85	7.61	8.21	0.28	0.27	19	35	54	7.82	12.21	3.34
Fuchs 1991	6.99	1.82	5.56	9.64	0.65	0.64	22	21	43	7.92	10.22	6.55
Calhoon 2003*	2.60	-0.08	6.85	7.48	0.37	0.37	47	45	92	7.18	22.60	8.37
Mean						0.41	29	34	63		45.03	18.26
s(mean)						0.15						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.90	0.79	0.70	0.65					
CI-Lower				-0.08	0.02	0.11	0.16					

Table 16 Con't.

Statistical Analysis: Computation for Problems Correct with Detailed Feedback for All Students

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1990*	0.2876	-0.1717	0.9770	yes	0.2129	0.6445	no
Fuchs 1991	0.3081	-0.2168	1.0213	yes	0.5673	0.4513	no
Calhoon 2003*	0.2107	-0.0132	0.8221	yes	0.0280	0.8671	no
				Q	0.8082		
				df	2		
				Prob (Q)	6.6758E-01		NO

Table 17

Statistical Analysis: Computation for Problems Correct with Detailed Feedback for General Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1991	6.99	1.82	5.56	9.64	0.65	0.64	22	21	43	7.92	10.22	6.55
Mean						0.64	22	21	43		10.22	6.55
s(mean)						0.31						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				1.03	1.45	1.25	1.15					
CI-Lower				-0.39	-0.17	0.03	0.31					

Table 17 Con't.

Statistical Analysis: Computation for Problems Correct with Detailed Feedback for General Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1991	0.3127	0.0094	1.2662	yes	0.0000	1.0000	no
				Q			
				df			
				Prob (Q)			NO

Table 18

Statistical Analysis: Computation for Problems Correct with Detailed Feedback for Special Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1990*	3.02	0.85	7.61	8.21	0.28	0.27	19	35	54	7.82	12.21	3.34
Calhoon 2003*	2.60	-0.08	6.85	7.48	0.37	0.37	47	45	92	7.18	22.60	8.37
Mean						0.34	33	40	73		34.81	11.71
s(mean)						0.17						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.89	0.77	0.67	0.61					
CI-Lower				-0.22	-0.10	0.00	0.06					

Table 18 Con't.

Statistical Analysis: Computation for Problems Correct with Detailed Feedback for Special Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1990*	0.2867	-0.2392	0.9062	yes	0.0483	0.8261	no
Calhoon 2003*	0.2100	-0.0810	0.7516	yes	0.0261	0.8717	no
				Q	0.0743		
				df	1		
				Prob (Q)	7.8514E-01		NO

Table 19

Statistical Analysis: Computation for Problems Correct without Detailed Feedback for All Students

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1990 (B)*	2.35	0.85	4.87	8.21	0.24	0.24	19	37	56	6.19	12.47	2.98
Fuchs 1991 (B)	3.09	1.82	6.93	9.64	0.15	0.15	22	20	42	8.46	10.45	1.54
Fuchs 1995 LD*	6.7	4.95	5.95	5.36	0.31	0.30	20	20	40	5.66	9.89	2.99
Fuchs 1995 LA	8.9	4.45	5.55	5.17	0.83	0.81	20	20	40	5.36	9.24	7.51
Fuchs 1995 AA	7.5	5.75	5.73	4.73	0.33	0.33	20	20	40	5.25	9.87	3.22
Mean						0.35	20	23	44		51.91	18.25
s(mean)						0.14						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.81	0.71	0.62	0.58					
CI-Lower				-0.11	-0.01	0.08	0.12					

Table 19 Con’t.

Statistical Analysis: Computation for Problems Correct without Detailed Feedback for All Students

Effect	**se(mean)**	**Confidence Interval Lower**	**Confidence Interval Upper**	**In CI?**	**Qi**	**Prob Qi**	**Sig?**
Fuchs 1990 (B)›	0.2841	-0.2182	0.9159	no	0.1577	0.6912	no
Fuchs 1991 (B)	0.3112	-0.2775	0.9741	yes	0.4359	0.5091	no
Fuchs 1995 LD›	0.3186	-0.2934	0.9892	yes	0.0234	0.8785	no
Fuchs 1995 LA	0.3186	-0.2934	0.9892	yes	1.9690	0.1606	no
Fuchs 1995 AA	0.3186	-0.2934	0.9892	yes	0.0062	0.9373	no
				Q	2.5921		
				df	4		
				Prob (Q)	6.2822E-01		NO

Table 20

Statistical Analysis: Computation for Problems Correct without Detailed Feedback for General Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1991 (B)	2.35	0.85	6.93	9.64	0.18	0.17	22	20	42	8.46	10.44	1.82
Fuchs 1995 LA	7.7	5.05	5.55	5.17	0.49	0.48	20	20	40	5.36	9.72	4.70
Fuchs 1995 AA	7.5	5.75	5.73	4.73	0.33	0.33	20	20	40	5.25	9.87	3.22
Mean						0.32	21	20	41		30.02	9.74
s(mean)						0.18						
				$p < .001$	$p < .01$	$p < .05$	$p < .10$					
CI-Upper				0.92	0.80	0.68	0.62					
CI-Lower				-0.28	-0.15	-0.03	0.03					

Table 20 Con’t.

Statistical Analysis: Computation for Problems Correct without Detailed Feedback for General Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1991 (B)	0.3109	-0.3038	0.9464	yes	0.2367	0.6266	no
Fuchs 1995 LA	0.3182	-0.3197	0.9615	yes	0.2480	0.6185	no
Fuchs 1995 AA	0.3182	-0.3197	0.9615	yes	0.0000	0.9951	no
				Q	0.4847		
				df	2		
				Prob (Q)	7.8479E-01		NO

Table 21

Statistical Analysis: Computation for Problems Correct without Detailed Feedback for Special Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1990 (B)*	2.35	0.85	4.87	8.21	0.24	0.24	19	37	56	6.19	12.47	2.98
Fuchs 1995 LD*	6.7	4.95	5.95	5.36	0.31	0.30	20	20	40	5.66	9.89	2.99
Mean						0.27	20	29	48		22.36	5.98
s(mean)						0.21						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.96	0.81	0.68	0.61					
CI-Lower				-0.43	-0.28	-0.15	-0.08					

Table 21 Con't.

Statistical Analysis: Computation for Problems Correct without Detailed Feedback for Special Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1990 (B)'	0.2833	-0.3007	0.8301	no	0.0099	0.9206	no
Fuchs 1995 LD'	0.3175	-0.3755	0.9029	yes	0.0125	0.9108	no
				Q	0.0225		
				df	1		
				Prob (Q)	8.8082E-01		NO

Table 22

Statistical Analysis: Concepts and Applications for Problems Correct with Detailed Feedback for Special Education

Effect	**Mean E**	**Mean C**	**SDE**	**SDC**	**d**	**Hedge's g**	**Ctrl N**	**Trmt N**	**N**	**SD_{within}**	**w**	**wg**
Calhoon 2003*	1.23	1.29	8.19	10.63	0.00	0.00	47	45	92	54.86	22.99	-0.02
Mean						0.00	47	45	92		22.99	-0.02
s(mean)						0.21						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.69	0.54	0.41	0.34					
CI-Lower				-0.69	-0.54	-0.41	-0.34					

Table 22 Con't.

Statistical Analysis: Concepts and Applications for Problems Correct with Detailed Feedback for Special Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Calhoon 2003*	4.7935	-9.4526	9.5506	yes	0.1179	0.7313	no
				Q			
				df			
				Prob (Q)			NO

Table 23

Statistical Analysis: Concepts and Applications for Problems Correct without Detailed Feedback for All Students

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1995 LD*	5.00	3.65	6.48	5.89	0.05	0.05	20	20	40	28.55	10.00	0.46
Fuchs 1995 LA	5.20	4.85	4.96	5.27	0.02	0.02	20	20	40	21.94	10.00	0.16
Fuchs 1995 AA	6.70	4.70	6.31	5.66	0.07	0.07	20	20	40	27.79	9.99	0.70
Mean						0.04	20	20	40		29.99	1.32
s(mean)						0.18						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.64	0.52	0.40	0.34					
CI-Lower				-0.56	-0.43	-0.31	-0.26					

Table 23 Con't.

Statistical Analysis: Concepts and Applications for Problems Correct without Detailed Feedback for All Students

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1995 LD*	0.3162	-0.5959	0.6770	yes	0.0000	0.9945	no
Fuchs 1995 LA	0.3162	-0.5959	0.6770	yes	0.0081	0.9281	no
Fuchs 1995 AA	0.3162	-0.5959	0.6770	yes	0.0069	0.9336	no
				Q	0.0151		
				df	2		
				Prob (Q)	9.9246E-01		NO

Table 24

Statistical Analysis: Concepts and Applications for Problems Correct without Detailed Feedback for General Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1995 LA	5.20	4.85	4.96	5.27	0.02	0.02	20	20	40	21.94	10.00	0.16
Fuchs 1995 AA	6.70	4.70	6.31	5.66	0.07	0.07	20	20	40	27.79	9.99	0.70
Mean						0.04	20	20	40		19.99	0.86
s(mean)						0.22						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.78	0.62	0.48	0.41					
CI-Lower				-0.69	-0.53	-0.40	-0.32					

Table 24 Con't.

Statistical Analysis: Concepts and Applications for Problems Correct without Detailed Feedback for General Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1995 LA	0.3162	-0.5970	0.6759	yes	0.0075	0.9309	no
Fuchs 1995 AA	0.3162	-0.5970	0.6759	yes	0.0075	0.9308	no
				Q	0.0151		
				df	1		
				Prob (Q)	9.0233E-01		NO

Table 25

Statistical Analysis: Concepts and Applications for Problems Correct without Detailed Feedback for Special Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1995 LD*	5.00	3.65	6.48	5.89	0.05	0.05	20	20	40	28.55	10.00	0.46
Mean						0.05	20	20	40		10.00	0.46
s(mean)						0.32						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				1.09	0.86	0.67	0.57					
CI-Lower				-0.99	-0.77	-0.57	-0.47					

Table 25 Con't.

Statistical Analysis: Concepts and Applications for Problems Correct without Detailed Feedback for Special Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1995 LD*	3.1628	-6.3565	6.3775	yes	0.0000	1.0000	no
				Q			
				df			
				Prob (Q)			NO

Table 26

Statistical Analysis: Overall Mathematics Achievement for Problems Correct with Detailed Feedback for All Students

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Fuchs 1997 LD (A)*	9.2	9.15	10.07	13.75	0.00	0.00	20	10	30	12.68	6.67	0.03
Fuchs 1997 LA (A)	16.3	7.75	12.23	9.87	0.80	0.78	20	10	30	10.69	6.25	4.86
Fuchs 1997 LD (B)*	12.6	9.15	8.29	13.75	0.28	0.27	20	10	30	12.26	6.61	1.81
Fuchs 1997 LA (B)	12	7.75	12	9.87	0.40	0.39	20	10	30	10.60	6.56	2.56
Spicuzza 2001 NALT-C					0.41	0.41	61	137	198		41.47	16.99
Spiccuzza 2001 NALT-D					0.31	0.31	297	137	434		92.81	28.44
Spicuzza 2001 STAR-C					0.80	0.80	61	137	198		39.53	31.51
Ysseldyke 03 STAR					0.78	0.78	61	157	218		41.39	32.33
Ysseldyke 03 NALT-C					0.40	0.40	61	157	218		43.23	17.36
Ysseldyke 03 NALT-D					0.40	0.40	6385	157	6542		152.95	61.20
Calhoon 2003*	1.4	4.58	11.45	12.47	0.54	0.54	47	45	92	76.47	22.19	11.94
Ysseldyke 07 STAR	6.56	0.42	23.86	24.68	0.02	0.02	1071	1130	2201	801.90	549.82	11.76
Mean						0.22	677	175	852		1009.46	220.77
s(mean)						0.03						
				$p < .001$	$p < .01$	$p < .05$	$p < .10$					
CI-Upper				0.32	0.30	0.28	0.27					
CI-Lower				0.12	0.14	0.16	0.17					

Table 26 Con't.

Statistical Analysis: Overall Mathematics Achievement for Problems Correct with Detailed Feedback for All Students

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1997 LD (A)*	0.3871	-0.7891	0.7874	yes	1.0750	0.2998	no
Fuchs 1997 LA (A)	0.3871	-0.7891	0.7874	yes	0.8696	0.3511	no
Fuchs 1997 LD (B)*	0.3871	-0.7891	0.7874	yes	0.1146	0.7349	no
Fuchs 1997 LA (B)	0.3871	-0.7891	0.7874	yes	0.0015	0.9687	no
Spicuzza 2001 NALT-C	0.1539	-0.2997	0.3066	yes	0.0007	0.9782	no
Spiccuzza 2001 NALT-D	0.1033	-0.1992	0.2067	yes	0.9102	0.3401	no
Spicuzza 2001 STAR-C	0.1539	-0.2997	0.3066	yes	6.0647	0.0138	yes
Ysseldyke 03 STAR	0.1509	-0.2935	0.3005	yes	13.4831	0.0002	yes
Ysseldyke 03 NALT-C	0.1509	-0.2935	0.3005	yes	1.5779	0.2091	no
Ysseldyke 03 NALT-D	0.0808	-0.1545	0.1622	yes	5.5036	0.0190	no
Calhoon 2003*	0.2086	-0.4105	0.4163	yes	0.3910	0.5318	no
Ysseldyke 07 STAR	0.0426	-0.0798	0.0875	yes	81.0809	0.0000	no
				Q	111.0729		
				df	11		
				Prob (Q)	1.1183E-18		NO

Table 27

Statistical Analysis: Overall Mathematics Achievement for Problems Correct with Detailed Feedback for General Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wg
Spicuzza 2001 NALT-C					0.41	0.41	61	137	198		41.47	16.99
Spiccuzza 2001 NALT-D					0.31	0.31	297	137	434		92.81	28.44
Spicuzza 2001 STAR-C					0.80	0.80	61	137	198		39.53	31.51
Fuchs 1997 LA (A)	12	7.75	12.23	9.87	0.40	0.39	20	10	30	10.69	6.56	2.54
Fuchs 1997 LA (B)	12.6	7.75	12	9.87	0.46	0.45	20	10	30	10.60	6.52	2.90
Ysseldyke 03 STAR					0.78	0.78	61	157	218		41.39	32.33
Ysseldyke 03 NALT-C					0.40	0.40	61	157	218		43.23	17.36
Ysseldyke 03 NALT-D					0.40	0.40	6385	157	6542		152.95	61.20
Ysseldyke 07 STAR	6.65	0.42	23.86	24.68	0.02	0.02	1071	1130	2201	801.90	549.82	11.76
Mean						0.21	893	226	1,119		974.27	205.01
s(mean)						0.03						
				p < .001	p < .01	p < .05	p < .10					
CI-Upper				0.32	0.29	0.27	0.26					
CI-Lower				0.11	0.13	0.15	0.16					

Table 27 Con't.

Statistical Analysis: Overall Mathematics Achievement for Problems Correct with Detailed Feedback for General Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Spicuzza 2001 NALT-C	0.1543	-0.0938	0.5139	yes	1.6456	0.1996	no
Spiccuzza 2001 NALT-D	0.1035	0.0070	0.4138	yes	0.8544	0.3553	no
Spicuzza 2001 STAR-C	0.1543	-0.0938	0.5139	yes	13.6052	0.0002	yes
Fuchs 1997 LA (A)	0.3880	-0.5844	0.9960	yes	0.2044	0.6512	no
Fuchs 1997 LA (B)	0.3880	-0.5844	0.9960	yes	0.3593	0.5489	no
Ysseldyke 03 STAR	0.1512	-0.0876	0.5078	yes	13.4831	0.0002	yes
Ysseldyke 03 NALT-C	0.1512	-0.0876	0.5078	yes	1.5779	0.2091	no
Ysseldyke 03 NALT-D	0.0808	0.0520	0.3688	yes	5.5036	0.0190	no
Ysseldyke 07 STAR	0.0428	0.1266	0.2943	yes	19.6488	0.0000	yes
				Q	56.8822		
				df	8		
				Prob (Q)	1.8986E-09		NO

Table 28

Statistical Analysis: Overall Mathematics Achievement for Problems Correct with Detailed Feedback for Special Education

Effect	Mean E	Mean C	SDE	SDC	d	Hedge's g	Ctrl N	Trmt N	N	SD_{within}	w	wd
Fuchs 1997 LD (A)*	9.2	9.15	10.07	13.75	0.00	0.00	20	10	30	12.68	6.67	0.03
Fuchs 1997 LD (B)*	16.3	7.75	8.29	13.75	0.70	0.68	20	10	30	12.26	6.34	4.30
Calhoon 2003*	1.4	4.58	11.45	12.47	-0.27	-0.26	47	45	92	11.98	22.79	-6.00
Mean						0.00	29	22	51		35.80	-1.67
s(mean)						0.17						
							p < .10					
CI-Upper							0.28					
CI-Lower							-0.27					

Table 28 Con't.

Statistical Analysis: Overall Mathematics Achievement for Problems Correct with Detailed Feedback for Special Education

Effect	se(mean)	Confidence Interval Lower	Confidence Interval Upper	In CI?	Qi	Prob Qi	Sig?
Fuchs 1997 LD (A)*	0.3871	-0.7891	0.7874	yes	0.0000	1.0000	no
Fuchs 1997 LD (B)*	0.3871	-0.7891	0.7874	yes	2.8858	0.0894	no
Calhoon 2003*	0.2086	-0.4105	0.4163	yes	1.6250	0.2024	no
				Q	4.5107		
				df	2		
				Prob (Q)	1.0483E-01		NO