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Accelerated Math Evaluation Report

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Accelerated Math Evaluation Report

Progress monitoring has been defined as "a practice that helps teachers use student performance data to continually evaluate the effectiveness of their teaching and make more informed instructional decisions" (Safer & Fleischman, 2005, p. 81). In academics, progress monitoring involves: (1) direct measurement of a student's current level of performance across all critical skill areas using curriculum-based or direct performance measures; (2) determination of desired performance outcomes for each skill area to assure Adequate Yearly Progress (AYP) for the student; (3) establishment of aimlines that define the required pace or rate of skill acquisition necessary to achieve AYP; (4) monitoring and assessing a student's pace or level of skill acquisition at frequent (usually weekly) intervals; and (5) accelerating instruction if achievement is greater than expected or modifying instruction if achievement is inadequate. Professionals engaged in progress monitoring use a variety of measures to track student performance and to assist in instructional decision making when data indicate a need for change (Deno, 2003; Fuchs & Fuchs, 2007; Olinghouse, Lambert, & Compton, 2006). Mastery measurement and curriculum-based assessment are approaches to progress-monitoring with long-standing support.

In mastery measurement, student performance is documented on a series of short-term instructional objectives; when using it, teachers determine instructional sequences for the school year and design and administer criterion-referenced tests to assess progress at each step in the sequence (Kennedy Center, 1992). Curriculum-based assessment (CBA) simply means using direct observation and recording to document performance in the local curriculum as a basis for making instructional decisions (Deno, 1985; Witt, Elliot, Daly, Gresham, & Kramer, 1998). When using CBA, teachers test students speed, proficiency, and/or accuracy across several levels of the curriculum and check their performance against criteria established for determining mastery and making other decisions (Idol, Nevin, & Paolucci-

Whitcomb, 1996). One type of curriculum-based assessment, curriculum-based measurement (CBM), is one of the most widely used, scientifically-validated progress-monitoring methods (Deno, 2003; Safer & Fleischman, 2005; Steckner, undated).

CBM has two distinctive features: (1) proficiency is assessed on all skills represented in the year-long curriculum; and (2) standardized, prescriptive measurement methods are used. Teachers using CBM identify skills in the year-long curriculum, determine the importance of the skills, create 25-30 alternate tests (each sampling the entire curriculum with the same types of problems), regularly administer the tests, graph and analyze performance data, and modify instruction as appropriate (Deno, 2003; Fuchs, Deno, & Mirkin, 1984; Fuchs & Fuchs, 2007; Shinn, 1989; Stecker, undated; Stecker & Fuchs, 2000). CBM is used to identify at-risk students who may need additional services, to help general education teachers plan more effective instruction within their classrooms, to help special education teachers design more effective instructional programs for students who don't respond to the general education program, to document student progress for accountability purposes, and to communicate with parents or others professionals about students' progress (Fuchs & Stecker, undated; Safer & Fleischman, 2005). Distinctions between CBM and mastery measurement are illustrated in Table 1.

According to Fuchs and Fuchs (2007), "[m]ore than 200 empirical studies published in peer-review journals (a) provide evidence of CBM's reliability and validity for assessing the development of competence in reading, spelling, and mathematics and (b) document CBM's capacity to help teachers improve student outcomes [in these areas] at the elementary grades" (p. 1). From our biggest cities to our smallest towns there is common ground--progress monitoring is an evidence-based practice with tremendous promise for improving the lives and academic futures of children:

> When teachers use systematic progress monitoring to track their students' progress in reading, mathematics, or spelling, they are better able to identify students in need of

additional or different forms of instruction, they design stronger instructional programs, and their students achieve better. (Fuchs & Fuchs, 2002, p. 1; Safer & Fleischman, 2005, p. 81)

Accelerated Math (AM: Renaissance Learning, 1999) is a technology-enhanced tool used to customize assignments and monitor progress in math for students in grades 1–12 (cf. Betts, Pickart, & Heistad, 2009; Burns, Dean, & Klar, 2004; Christ & Ardoin, 2009; Christensen Associates, 2005; Francis, Santi, Barr, Fletcher, Varisco, & Foorman, 2008; Gersten et al., 2008; Ysseldyke & Tardrew, 2007). Consistent with widely-recommended and highly-effective response-to-intervention practices, the goal of AM is to generate high-quality data for teachers to use in making important educational decisions. Its computer-based assessments provide time efficiency in quick administration, valid and reliable results for at-risk students, rich data for informing instruction, ready access to data in online databases, and multi-function (e.g., screening, progress monitoring, and outcome) data in single assessments[1]. The *Accelerated Math* (AM) software creates individualized assignments aligned with state standards and national guidelines, scores student work, and generates reports on student progress. Recently listed by the National Center on Response to Intervention (NCRTI) as its first math mastery measurement tool, the system can be used in conjunction with an existing mathematics curriculum to replace other forms of practice and aid teachers in using progress-monitoring data to differentiate instruction. It keeps track of individual students' daily activities on personalized assignments and tests, provides immediate feedback to students and teachers through information

[1]Additional descriptive and technical information is available from the publisher's website (http://www.renlearn.com/am/ and http://www.renlearn.com/RTI/, last reviewed December 2009), the U. S. Department of Education What Works Clearinghouse Intervention Report (http://ies.ed.gov/ncee/wwc/pdf/wwc_accelmath_093008.pdf, last reviewed April 2009), and refereed publications by Nunnery and Ross (2007), Ysseldyke and Bolt (2007), and Ysseldyke and Tardrew (2007).

generated from individual or class diagnostic reports, alerts teachers when students are having difficulty with certain mathematics assignments, and gives teachers the information they need to differentiate and adjust instruction.

According to a What Work Clearinghouse report (2008), the "…extent of evidence for Accelerated Math…[is]…medium to large for math achievement" and the support includes both quasi-experimental research and randomized control trials (p. 1). For example, Spicuzza and Ysseldyke (1999) reported positive effects of this curriculum-based instructional management system during an urban summer school program. In a more comprehensive study, Spicuzza, Ysseldyke, Lemkuil, Kosciolek, Boys, and Teelucksingh (2001) reported statistically significantly greater achievement gains for students who participated in AM than for their peers who did not use the progress monitoring system; and the effects were evident for high-, middle-, and low-performing students. They also found that participation in AM increased the amount progress evaluation and informed feedback experienced by students at all skill levels and improved the communication of thinking and learning strategies to students by teachers. To support their generally positive outcomes, they noted that "further research and replication studies examining the effect of participation with AM for students at different skill levels are needed before conclusions can be made about differential effects of AM across skill levels" (p. 537). In a related study, Ysseldyke, Spicuzza, Kosciolek, Teelucksingh, Boys, and Lemkuil (2003) reported positive outcomes for students enrolled in classrooms using AM as a curriculum enhancement and the greatest effects were observed for students whose teachers implemented the intervention to the greatest degree. Nunnery and Ross (2007) reported the effectiveness of AM for students in grades 6-8 on state-wide assessments. Ysseldyke and Bolt (2007) randomly assigned classrooms to treatment and control conditions. When teachers implemented the program with fidelity and "…when they used the data from the system to manage and differentiate instruction, students gained significantly more than those for whom implementation was limited or nil" (p. 453). Interesting, "[f]ailure to take into account intervention integrity would have made it look like continuous progress monitoring did not enhance math results" (p. 453). Similarly, Ysseldyke and Tardrew (2007) found that the effects of the program were a function of intervention Integrity; in fact, when progress monitoring and instructional management practices were implemented with high fidelity or integrity, the mathematics performance of all students is significantly enhanced.

Accurate assessment of progress in academic content areas is critical to teachers, parents, and administrators because most professionals believe they are predictive of the students' performance on state-wide standardized tests at the end of the school year (McGlinchey & Hixson, 2004; Perie, Marion, & Gong, 2007; Nunnery & Ross, 2007; Ysseldyke & Bolt, 2007; Ysseldyke & Tardrew, 2007). This information may also be used to monitor student growth over time and to improve the quality of teaching through adjustment of curriculum and instructional policies (Fuchs & Fuchs 1993, 2002, 2007; Ysseldyke & Bolt, 2007; Ysseldyke & Tardrew, 2007). The focus of this study was an evaluation of the effects of implementing AM in elementary and junior high schools in Oklahoma.

Method

We conducted a context evaluation (using a records review and summarization of information provided by the cooperating schools) to document the general features within which the research was taking place. We also assisted in the selection of a subset of schools and teachers for site visits so as to be representative of the project as a whole, conducted site visits to complete key informant interviews, observations, and focus groups with participating teachers, and analyzed all training process, implementation fidelity, and intervention outcome data using a randomized field trial.

Participants

Three elementary and two junior high schools in Oklahoma agreed to participate. Demographic characteristics of participating students in elementary school second to fifth grade classrooms were similar across the randomly assigned treatment (n = 18) and control (n = 18) conditions (see Table 2 and 3). Demographics were also similar for randomly assigned treatment (n = 23) and control (n = 23) junior high (grades 6-8) classrooms (see Table 4 and 5). An evidence-based curriculum was used in each school: McDougal Littell *Math* text was used in the junior high schools and *Growing with Math* or *Houghton Mifflin Math* was used in elementary schools.

Procedure

Classrooms of children were randomly assigned to the treatment (AM) and control (the usual practice that was in place prior to the study) conditions. In the junior high school settings, classrooms were randomly assigned at the level of the period. This process was achieved by blocking on both teacher and course content in an effort to create equivalence between the treatment and comparison conditions. A given teacher was assigned several treatment and several comparison periods while considering course content. Given the relatively small number of school buildings and teachers involved in the study, it was not possible to randomly assign at the building or teacher level. In the elementary school settings, classrooms were randomly assigned to treatment and control conditions with grade level. Due to the differences in random assignment methods, the elementary and junior high school data were analyzed separately.

All students had similar levels of experience with the outcome assessments. The STAR Math tests were administered in treatment and control classrooms in fall, winter, and spring while the TerraNova Math tests only were given in the fall and spring. Additionally, in the junior high school study, the TerraNova Algebra test was given to students in the Algebra classes in lieu of the regular TerraNova

Math test given in the fall and spring. The Normal Curve Equivalent (NCE) scores were used as the outcomes for all three measures.

The elementary study involved multiple grade levels (2-5) as did the junior high school study (7-9). The NCE scores offered the advantage of a common scaling across grade levels. Hierarchical Linear Modeling was used to test the effect of the treatment on the outcome measures while nesting students within their classroom/period. Student level control variables included special education placement status and free or reduced lunch status. Student minority status and gender were also entered into the child level models but were not retained as they did not account for any variance in the outcomes once special education status and free of reduced lunch status were already included. Classroom level control variables included proportion of students with special education placements, proportion of students with free or reduced lunch status, and class size. The percentage of the classroom composition made up of males and minority students were also tested but not retained as they did not contribute to the explanatory power of the models.

Fidelity of Implementation

To examine fidelity of implementation effects for the elementary analyses, treatment classrooms where classified using the following decision rules:

- Any class with 75% or more of the students with an average % correct of 75% or greater on all assignments received 1 point.
    - For Grade 2, any class with 75% or more of the class having .50 or more average objectives mastered per week received 1 point.
    - For Grades 3 or higher, any class with 75% or more of the class having 1 or more average objectives mastered per week received 1 point.
- Classes scoring 2 points were rated HIGH.

- Classes scoring 0 points were rated LOW.
- Classes scoring 1 point were classified using additional decision rules.
    - If a Class scored 1 on the Objectives Rating and 0 on the Percent Correct Rating, the class average % correct on all assignments was used to determine the rating. Classes with an average percent correct of 75% or greater were scored HIGH.
    - If a Class scored 1 on the Percent Correct Rating and 0 on the Objectives Rating, the average objectives per week metric was examined. Classes were designated HIGH if the average objectives completed per week was above 1 in the case of grades 3+ or above .5 in the case of grade 2.

Application of these decision rules resulted in nine of the treatment classrooms being classified as low fidelity and nine as high fidelity implementation. Outcomes were compared across these groups as well as across treatment and control classrooms.

Findings

For the elementary school analyses, the results outline intent to treat analyses and analyses with the effect for high implementation in treatment classrooms. For the STAR Math analyses, the treatment and control conditions were equivalent in initial status. There was a statistically significant treatment for monthly growth rate. The control group grew at a rate of .763 NCE points per month, or 6.870 NCE points across the academic year, and this rate was statistically significant. The treatment group grew at a statistically significantly faster rate. The children in this group, on average, grew at a rate of an additional .626 NCE points per month. This translates into a total growth rate of 16.668 NCE points across the academic year. When expressed as effect sizes, or standard deviation units, the control group growth rate was .326 which would be considered a small effect size. The treatment group growth rate as an effect size was .791 which would be considered a large effect, and represents a .465 standard deviation unit advantage in growth rate for the treatment group.

When fidelity of implementation level was added to the elementary school STAR Math models, there was a statistically significant effect on monthly growth rate for the high implementation group. High implementation classrooms grew, on average, at a statistically significant rate that was 1.10 points per month greater than control classrooms. The low implementation classrooms grew, on average, at a rate that was .19 points per month greater than the control group classrooms and this difference was not statistically significant.

For the TerraNova analyses, the control group showed a small decline from fall to spring of 1.856 NCE points across the academic year and this rate was not statistically significant. The treatment group children, on average, made an 3.291 NCE point gain across the academic year. However, this gain was also not statistically significant. There was variability in the size of the gain scores across classrooms on this measure. Therefore we included an analysis that contrasted control classrooms with high and low implementation treatment classrooms. In this analysis, the control group made an average decline of 2.176 NCE points , the low implementation treatment classrooms made an average decline of 2.151 NCE points, and the high implementation treatment classrooms made an average gain of 8.384 NCE points which was statistically significant. These effects translate into the following effect sizes: Control - -1.03, Low Implementation Treatment - -.102, High Implementation Treatment - .398. Therefore, in classrooms where the treatment was more fully implemented, there was a moderately sized advantage for the treatment condition.

For the junior high school analyses, the results reported outline both the intent to treat effects and implementation effects models. Three level growth curve modeling was used to test the treatment effects on the STAR Math measure as it was administered three times. Two level models were used to test the treatment effects on the TerraNova measures as they were administered twice. Gain scores were used as the dependent variables in these models. No treatment effects were found with respect to initial status or monthly growth rate for the STAR Math measure. There were also no statistically significant treatment effects found on the gain scores for either of the TerraNova measures. For the implementation effects models, the treatment variable was entered as two variables: Low implementation and High implementation. These results indicate that the Low implementation group looks similar to the control condition. The High implementation group did show somewhat higher growth rates for all junior high school outcomes; however, these differences were not statistically significant.

Lessons Learned

There are several key findings from this study. First, there was difficulty achieving full implementation in the junior high school settings in this study. There was considerable variability among teachers in the quality of the implementation that was achieved. Second, although there were not statistically significant gains or advantages for the treatment condition for the junior high school settings on either the STAR Math or TerraNova outcome measures, there were small advantages for the high implementation classrooms. Third, in the elementary classrooms there was a statistically significant advantage for the treatment condition as evidenced by faster rates of growth on the STAR Math measures. This finding was consistent across treatment classrooms and grade levels. Fourth, the elementary TerraNova results were positive for the treatment condition, but only in high implementation classrooms where there was an overall moderately sized advantage in growth rate.

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Table 1

Differences between Mastery Measurement and CBM

Mastery Measurement	Curriculum-Based Measurement
▪ Focused on single skill or small set of skills at one point in time.	▪ Focused on large domain of skills over year-long period of time.
▪ Focused on performance in target skills providing little information for use in analysis of retention or generalization.	▪ Focused on performance in collection of skills providing much information for use in analysis of retention and generalization.
▪ Requires shift in assessment each time mastery is demonstrated.	▪ Requires constant focus for assessment across entire year.
▪ Focused on structured hierarchies and skill-oriented approach in which instruction and measurement are tied together.	▪ Focused on effectiveness and performance in which instruction and measurement are not tied together.
▪ Focused on teacher-made criterion-referenced tests with unknown technical adequacy.	▪ Focused on prescribed method for creating, administering, scoring, and using tests that results in technically adequate assessments.

Source. Kennedy Center, 1992.

Table 2

Elementary Treatment and Control Classroom Demographics

Group	Descriptor	Male	Minority	Free and Reduced Lunch	Special Education Placements	Class Size
Treatment (n=18)	Mean	51.94%	36.26%	76.33%	17.30%	16.33
	SD	6.44%	16.31%	11.74%	9.58%	2.32
	Min	38.00%	19.00%	55.00%	0.00%	13
	Max	62.00%	73.00%	95.00%	33.00%	20
Control (n=18)	Mean	50.60%	42.74%	75.22%	19.49%	16.43
	SD	8.34%	17.06%	12.94%	10.96%	3.25
	Min	26.00%	16.00%	53.00%	5.00%	12
	Max	62.00%	79.00%	100.00%	42.00%	26

Table 3

Elementary School Student Characteristics

		n	%
Grade Level	2nd	209	27.39%
	Treatment	82	10.75%
	Control	127	16.64%
	3rd	183	23.98%
	Treatment	123	16.12%
	Control	60	7.86%
	4th	208	27.26%
	Treatment	105	13.76%
	Control	103	13.50%
	5th	163	21.36%
	Treatment	72	9.44%
	Control	91	11.93%
Group	Control	381	49.93%
	Treatment	382	50.07%
Gender	Female	371	48.62%
	Male	392	51.38%
Minority Status	No	465	60.94%
	Yes	298	39.06%
Free and Reduced Lunch	No	184	24.12%
	Yes	579	75.88%
Special Education Placement	No	625	81.91%
	Yes	138	18.09%

Note. n=763.

Table 4

Junior High School Treatment and Control Classroom Demographics

Group	Descriptor	Male	Minority	Free and Reduced Lunch	Special Education Placements	Class Size
Treatment (*n* = 23)	Mean	48.40%	32.27%	34.46%	7.57%	22.61%
	SD	0.11	0.08	.011	0.11	4.19
	Min	28%	20%	16%	0%	15
	Max	67%	50%	61%	34%	29
Control (*n* = 23)	Mean	53.05%	26.67%	28.00%	8.55%	21.65
	SD	0.09	0.08	0.15	0.11	4.99
	Min	35%	14%	4%	0%	11
	Max	67%	42%	56%	44%	30

Table 5

Junior High School Student Characteristics

		n	%
Grade Level	7th	330	32.42%
	Treatment	183	17.98%
	Control	147	14.44%
	8th	340	33.40%
	Treatment	180	17.68%
	Control	160	15.72%
	9th	348	34.18%
	Treatment	174	17.09%
	Control	174	17.09%
Group	Control	498	48.92
	Treatment	520	51.08
Gender	Female	503	49.41
	Male	515	50.59
Minority Status	No	713	70.04
	Yes	305	29.96
Free and Reduced Lunch	No	698	68.57
	Yes	320	31.43
Special Education Placement	No	932	91.55
	Yes	86	8.45

Note. n=1,018.

Table 6

Elementary School STAR Math Performance by Group and Grade Level

Grade	Group	Descriptor	Fall	Winter	Spring
2	Treatment	Mean	48.471	46.706	51.361
		SD	17.635	19.355	19.907
		n	78	67	64
	Control	Mean	44.039	41.625	47.238
		SD	19.009	19.776	22.723
		n	109	96	103
3	Treatment	Mean	41.389	45.884	52.489
		SD	20.141	19.894	19.025
		n	114	108	112
	Control	Mean	43.213	45.069	47.788
		SD	20.926	18.806	22.376
		n	55	49	52
4	Treatment	Mean	42.570	46.163	51.011
		SD	19.698	20.344	22.264
		n	83	86	81
	Control	Mean	40.771	40.324	43.997
		SD	19.350	18.606	23.182
		n	102	92	102
5	Treatment	Mean	44.899	46.074	49.273
		SD	22.659	22.358	23.158
		n	81	68	80
	Control	Mean	41.024	38.212	39.533
		SD	18.960	20.492	22.233
		n	71	69	70
2-5	Treatment	Mean	44.015	46.164	51.156
		SD	20.227	20.346	20.962
		n	356	329	337
	Control	Mean	42.264	41.082	44.709
		SD	19.511	19.454	22.750
		n	340	308	329

Citation: Lambert, R., & Algozzine, B. (2009, December). *Accelerated math evaluation report*. Charlotte, NC: Center for Educational Measurement and Evaluation, University of North Carolina at Charlotte.

Table 7

Elementary School STAR Math Hierarchical Linear Models

		Intercept, Control Group Initial Status	Intercept, Control Group Monthly Growth Rate
Within Student Level	π	45.691	0.763
	se	2.278	0.250
	t	20.058	3.049
	p	0.000	0.003

		Initial Status Free and Reduced Lunch Effect	Initial Status Minority Status Effect	Initial Status Special Education Placement Effect	Growth Rate Free and Reduced Lunch Effect	Growth Rate Minority Status Effect	Growth Rate Special Education Placement Effect
Student Level	β	-1.429	-4.637	-14.726	-0.466	0.117	-0.042
	se	2.053	1.294	2.846	0.221	0.171	0.254
	t	-0.696	-3.585	-5.175	-2.107	0.687	-0.167
	p	0.487	0.001	0.000	0.035	0.492	0.867

		Intercept, Treatment Effect
Classroom Level, Initial Status	γ	-0.017
	se	1.923
	t	-0.086
	p	0.932

		Intercept, Treatment Effect
Classroom Level, Monthly Growth Rate	γ	0.626
	se	0.299
	t	2.090
	p	0.036

Table 8

Elementary School TerraNova Math Performance by Group and Grade Level

Grade	Group		Fall	Spring	Gain
2	Treatment	Mean	53.340	45.580	-7.763
		SD	20.522	14.500	15.838
		n	59	59	59
	Control	Mean	53.260	48.480	-4.781
		SD	18.454	17.575	14.050
		n	73	73	73
3	Treatment	Mean	41.760	53.320	11.557
		SD	18.583	20.099	17.462
		n	79	79	79
	Control	Mean	40.630	52.140	11.514
		SD	16.705	19.643	14.686
		n	35	35	35
4	Treatment	Mean	46.160	48.180	2.020
		SD	19.907	24.007	12.950
		n	50	50	50
	Control	Mean	48.380	46.070	-2.315
		SD	18.816	21.807	14.730
		n	89	89	89
5	Treatment	Mean	50.860	47.490	-3.371
		SD	18.997	21.069	11.263
		n	70	70	70
	Control	Mean	47.080	42.490	-4.588
		SD	18.168	19.325	12.274
		n	51	51	51
2-5	Treatment	Mean	47.950	49.340	1.395
		SD	19.730	19.830	16.440
		n	256	256	256
	Control	Mean	48.460	46.900	-1.557
		SD	18.620	19.930	14.980
		n	248	248	248

Citation: Lambert, R., & Algozzine, B. (2009, December). *Accelerated math evaluation report*. Charlotte, NC:

Center for Educational Measurement and Evaluation, University of North Carolina at Charlotte.

Citation: Lambert, R., & Algozzine, B. (2009, December). *Accelerated math evaluation report*. Charlotte, NC: Center for Educational Measurement and Evaluation, University of North Carolina at Charlotte.

Table 9

Elementary School TerraNova Math Hierarchical Linear Models

Model		Intercept, Control Group Gain	Free and Reduced Lunch	Special Education Placement	
Student Level	β	-1.856	-1.184	-3.017	
	se	1.697	1.617	1.696	
	t	-1.094	-0.732	-1.778	
	p	0.285	0.464	0.075	
		Intercept, Treatment Effect on Gain	Free and Reduced Proportion	Special Education Proportion	Class Size
Classroom Level	γ	3.291	-5.972	-8.693	0.303
	se	2.789	11.435	11.973	0.379
	t	1.180	-0.522	-0.726	0.800
	p	0.249	0.605	0.474	0.431

Table 10

Elementary School TerraNova Math Hierarchical Linear Models with Implementation Effect

Model		Intercept, Control Group Gain	Free and Reduced Lunch	Special Education Placement
Student Level	β	-2.176	-1.184	-3.017
	se	1.672	1.669	1.732
	t	-1.301	-0.709	-1.742
	p	0.205	0.478	0.082

		Low Imp. Treatment Effect on Gain	High Imp. Treatment Effect on Gain	Free and Reduced Proportion	Special Education Proportion	Class Size
Classroom Level	γ	-2.151	8.384	-14.763	-4.263	0.794
	se	2.006	3.666	10.975	11.504	0.304
	t	-1.072	2.287	-1.345	-0.371	2.612
	p	0.294	0.031	0.191	0.714	0.015

Citation: Lambert, R., & Algozzine, B. (2009, December). *Accelerated math evaluation report*. Charlotte, NC:

Center for Educational Measurement and Evaluation, University of North Carolina at Charlotte.

Table 11

Junior High School STAR Math Performance by Group and Grade Level

Grade	Group	Descriptor	Fall	Winter	Spring
7	Treatment	Mean	50.342	51.088	53.838
		SD	20.011	19.999	21.566
		n	168	161	126
	Control	Mean	49.205	48.159	51.625
		SD	16.793	16.399	15.835
		n	135	148	142
8	Treatment	Mean	50.270	52.043	51.660
		SD	20.266	19.354	18.803
		n	169	162	154
	Control	Mean	48.806	50.327	49.696
		SD	19.277	17.556	19.759
		n	151	132	150
9	Treatment	Mean	45.944	46.501	47.463
		SD	16.968	16.035	16.100
		n	151	149	131
	Control	Mean	47.543	45.648	47.043
		SD	17.344	18.051	18.810
		n	151	149	130
7-9	Treatment	Mean	48.957	49.968	50.990
		SD	19.281	18.719	19.041
		n	488	472	411
	Control	Mean	48.493	47.954	49.528
		SD	17.847	17.406	18.275
		n	437	429	422

Note. Scores are expressed as Normal Curve Equivalents.

Table 12

Junior High School STAR Math Hierarchical Linear Models

Citation: Lambert, R., & Algozzine, B. (2009, December). *Accelerated math evaluation report*. Charlotte, NC:

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		Intercept, Control Group Initial Status	Intercept, Control Group Monthly Growth Rate
Within Student Level	π	47.249	0.126
	se	1.617	0.147
	t	29.212	0.857
	p	0.000	0.396

		Initial Status Free and Reduced Lunch Effect	Initial Status Special Education Placement Effect	Growth Rate Free and Reduced Lunch Effect	Growth Rate Special Education Placement Effect
Student Level	β	-6.267	-13.019	0.211	0.163
	se	1.299	2.254	0.133	0.248
	t	-4.823	-5.775	1.588	0.655
	p	0.000	0.000	0.112	0.512

		Intercept, Treatment Effect	Free and Reduced Proportion	Special Education Proportion	Class Size
Classroom Level, Initial Status	γ	1.805	-18.483	-22.653	-0.067
	se	2.291	7.954	9.511	0.233
	t	0.788	-2.324	-2.382	-0.285
	p	0.435	0.025	0.022	0.777

		Intercept, Treatment Effect	Free and Reduced Proportion	Special Education Proportion	Class Size
Classroom Level, Monthly Growth Rate	γ	0.011	0.842	0.316	-0.007
	se	0.212	0.852	1.227	0.024
	t	0.052	0.989	0.258	-0.285
	p	0.959	0.329	0.798	0.777

Citation: Lambert, R., & Algozzine, B. (2009, December). *Accelerated math evaluation report*. Charlotte, NC:

Center for Educational Measurement and Evaluation, University of North Carolina at Charlotte.

Table 13

Junior High School STAR Math Hierarchical Linear Models with Implementation Effects

		Intercept, Control Group Initial Status	Intercept, Control Group Monthly Growth Rate
Within Student Level	π	46.809	0.150
	se	1.597	0.140
	t	29.307	1.067
	p	0.000	0.293

		Initial Status Free and Reduced Lunch Effect	Initial Status Special Education Placement Effect	Growth Rate Free and Reduced Lunch Effect	Growth Rate Special Education Placement Effect
Student Level	β	-6.266	-13.018	0.210	0.159
	se	1.301	2.253	0.133	0.250
	t	-4.816	-5.779	1.577	0.638
	p	0.000	0.000	0.115	0.523

		Intercept, Low Imp. Effect	Intercept, High Imp. Effect	Free and Reduced Proportion	Special Education Proportion	Class Size
Classroom Level, Initial Status	γ	1.605	3.921	-20.294	-22.517	-0.088
	se	2.350	2.920	8.199	10.036	0.241
	t	0.683	1.343	-2.475	-2.244	-0.366
	p	0.499	0.187	0.018	0.030	0.716

		Intercept, Low Imp. Effect	Intercept, High Imp. Effect	Free and Reduced Proportion	Special Education Proportion	Class Size
Classroom Level, Monthly Growth Rate	γ	-0.342	0.180	0.949	0.232	-0.005
	se	0.243	0.227	0.872	1.195	0.024
	t	-1.406	0.795	1.087	0.194	-0.218
	p	0.167	0.431	0.284	0.848	0.829

Table 14

Junior High School TerraNova Math Performance by Group and Grade Level

Grade	Group	Descriptor	Fall	Spring	Gain
7	Treatment	Mean	54.140	51.732	-2.408
		SD	16.637	16.092	10.943
		n	157	157	157
	Control	Mean	54.322	49.622	-4.699
		SD	13.813	14.527	9.924
		n	143	143	143
8	Treatment	Mean	44.961	48.630	3.669
		SD	13.365	14.933	9.739
		n	127	127	127
	Control	Mean	42.948	45.955	3.007
		SD	14.165	16.365	12.948
		n	134	134	134
9	Treatment	Mean	66.067	65.300	-0.767
		SD	10.034	11.250	10.602
		n	30	30	30
	Control	Mean	66.762	65.595	-1.167
		SD	12.666	15.667	14.690
		n	42	42	42
7-9	Treatment	Mean	51.567	51.774	0.207
		SD	16.136	15.878	10.801
		n	314	314	314
	Control	Mean	51.182	50.185	-0.997
		SD	15.964	16.642	12.444
		n	319	319	319

Note. Scores are expressed as Normal Curve Equivalents.

Citation: Lambert, R., & Algozzine, B. (2009, December). *Accelerated math evaluation report*. Charlotte, NC:

Center for Educational Measurement and Evaluation, University of North Carolina at Charlotte.

Table 15

Junior High School TerraNova Math Hierarchical Linear Models

Model		Intercept, Control Group Gain	Free and Reduced Lunch	Special Education Placement	
Student Level	β	-1.533	0.834	1.077	
	se	1.033	0.848	1.737	
	t	-1.484	0.983	0.620	
	p	0.149	0.326	0.535	
		Intercept, Treatment Effect on Gain	Free and Reduced Proportion	Special Education Proportion	Class Size
Classroom Level	γ	1.724	-5.244	13.678	0.257
	se	1.273	5.615	4.892	0.167
	t	1.353	-0.934	2.796	1.545
	p	0.187	0.359	0.010	0.134

Table 16

Junior High School TerraNova Math Hierarchical Linear Models with Implementation Effects

Model		Intercept, Control Group Gain	Free and Reduced Lunch	Special Education Placement
Student Level	β	-1.534	0.834	1.077
	se	1.032	0.848	1.737
	t	-1.487	0.983	0.620
	p	0.149	0.326	0.535

		Intercept, Low Imp. Effect on Gain	Intercept, High Imp. Effect on Gain	Free and Reduced Proportion	Special Education Proportion	Class Size
Classroom Level	γ	1.390	1.983	-5.286	13.694	0.257
	se	1.703	1.365	5.609	5.068	0.168
	t	0.816	1.452	-0.942	2.702	1.531
	p	0.422	0.158	0.355	0.012	0.138

Table 17

Junior High School TerraNova Algebra Scores by Group

Group	Descriptor	Fall	Spring	Gain
Treatment	Mean	37.432	50.696	13.264
	SD	14.803	20.055	18.238
	n	148	148	148
Control	Mean	36.323	49.200	12.877
	SD	14.596	20.402	17.415
	n	130	130	130

Table 18

Junior High School TerraNova Algebra Hierarchical Linear Models

Model		Intercept, Control Group Gain	Free and Reduced Lunch	Special Education Placement
Student Level	β	13.542	-4.852	-0.430
	se	3.816	2.028	4.963
	t	3.548	-2.393	-0.087
	p	0.004	0.018	0.931
		Intercept, Treatment Effect on Gain		
Classroom Level	γ	-0.297		
	se	4.046		
	t	-0.073		
	p	0.943		

Citation: Lambert, R., & Algozzine, B. (2009, December). *Accelerated math evaluation report*. Charlotte, NC:

Center for Educational Measurement and Evaluation, University of North Carolina at Charlotte.

Table 19

Junior High School TerraNova Algebra Hierarchical Linear Models with Implementation Effects

Model		Intercept, Control Group Gain	Free and Reduced Lunch	Special Education Placement
Student Level	β	13.017	-4.852	-0.430
	se	3.378	2.028	4.963
	t	3.853	-2.393	-0.087
	p	0.003	0.018	0.931
		Intercept, Low Imp. Effect on Gain	Intercept, High Imp. Effect on Gain	
Classroom Level	γ	-1.530	3.234	
	se	3.419	3.895	
	t	-0.447	0.830	
	p	0.663	0.424	

Table 20

Elementary STAR Math Hierarchical Linear Models with Implementation Effects

		Intercept, Control Group Initial Status	Intercept, Control Group Monthly Growth Rate
Within Student Level	π	45.703	0.762
	se	2.280	0.251
	t	20.044	3.039
	p	0.000	0.003

		Initial Status Free and Reduced Lunch Effect	Initial Status Minority Status Effect	Initial Status Special Education Placement Effect	Growth Rate Free and Reduced Lunch Effect	Growth Rate Minority Status Effect	Growth Rate Special Education Placement Effect
Student Level	β	-1.300	-4.830	-14.853	-0.495	0.157	-0.013
	se	2.060	1.296	2.830	0.225	0.161	0.248
	t	-0.631	-3.728	-5.248	-2.207	0.976	-0.054
	p	0.528	0.000	0.000	0.027	0.330	0.957

		Low Imp. Treatment Effect	High Imp. Treatment Effect
Classroom Level, Initial Status	γ	0.611	-1.059
	se	2.228	2.542
	t	0.274	-0.416
	p	0.786	0.679

		Intercept, Treatment Effect	Intercept, Treatment Effect
Classroom Level, Monthly Growth Rate	γ	0.185	1.095
	se	0.305	0.361
	t	0.607	3.030
	p	0.544	0.003

Citation: Lambert, R., & Algozzine, B. (2009, December). *Accelerated math evaluation report*. Charlotte, NC: Center for Educational Measurement and Evaluation, University of North Carolina at Charlotte.