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The effects of mathematics instruction using spatial temporal cognition on teacher efficacy and instructional practices

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ABSTRACT

This paper examined the effects of an instructional approach known as Spatial Temporal Mathematics (ST Math) on teacher beliefs about mathematics teaching. Participants were 339 elementary teachers teaching grades 2–5 who were randomly assigned to a control or treatment group. Hierarchical linear modeling was used to determine the effects of the intervention on self-efficacy, outcome expectancy, and instructional practices using scientific reasoning. While the treatment did not yield significant effects in teacher outcomes, our secondary analysis indicated that time on ST Math and the integration of ST Math into daily instructions were positively associated with teacher efficacy and instructional practices using scientific reasoning. Implications of the results on teacher beliefs about mathematics teaching are discussed.

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1. Introduction

Through extensive research on teacher instructional practices, our understanding of effective mathematics teaching and learning has improved markedly, allowing us to provide students with a variety of instructional activities in the classroom. These activities include computer-mediated games and other curricular approaches. However, while the information-technology revolution continues to spread around the globe, the influence of technological change on mathematics instruction is less well understood. We do not know, for example, whether technological innovations can be used to facilitate mathematics instructions and the impact they have on teachers' efficacy and classroom practices. Emerging research is beginning to fill this gap. In this paper we report the effects of a computer-based teaching tool known as Spatial Temporal Mathematics (ST Math) on teacher self-efficacy, outcome expectancy, and instructional practice.

2. Theoretical framework

2.1. Self-efficacy and outcome expectancy

Self-efficacy is defined by Bandura (1977) as beliefs individuals hold about their own abilities to perform a particular kind of task. These beliefs affect the level of effort that individuals exert, their persistence in working through challenges, their resiliency when experiencing failures, and their means of coping with change. Bandura (1997) posited that self-efficacy depends upon the context in which the task is performed—that is, a person may produce different outcomes under different circumstances. For example, while teachers' content knowledge in mathematics affects their instructional practices, those who judge themselves as efficacious in teaching mathematics are expected to be more successful. Having similar content knowledge, teachers who view themselves as inefficacious in teaching mathematics will, other factors being equal, be less effective in the classroom. In this way, individuals who see themselves as capable may come to expect negative outcomes for a given task due to the specific context or environment in which the task must be performed. This phenomenon is referred to as outcome expectations. The distinction between these two concepts can be summarized as follows:

> Perceived self-efficacy is a judgment of one's capacity to accomplish a certain level of performance, whereas an outcome

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expectation is a judgment of the likely consequence such behavior will produce (p. 391)…. In social, intellectual, and physical pursuits, those who judge themselves highly efficacious will expect favorable outcomes, self-doubters will expect mediocre performances of themselves and thus negative outcomes. (Bandura, 1986, p. 392)

The construct of teacher efficacy was first conceived of by the RAND researchers as "the extent to which the teacher believed he or she had the capacity to affect student performance" (Berman, McLaughlin, Bass, Pauly, & Zellman, 1977, p. 137). Teacher efficacy initially measured by responses to two survey items: (1) "If I really try hard, I can get through to even the most difficult or unmotivated students," and (2) "When it comes right down to it, a teacher really can't do much [because] most of a student's motivation and performance depends on his or her home environment." The first item measures a teacher's sense of self-efficacy while the second item assesses a teacher's sense of outcome expectancy. Collectively, these two items describe teacher efficacy, which has been shown to be associated with teacher practice and gains in student proficiency (Berman et al., 1977; Gibson & Dembo, 1984).

Self-efficacy typically precedes outcome expectancy—that is, based on the teacher's sense of self-efficacy, he or she formulates the outcome expectancy of a given task (Tschannen-Moran, Hoy, & Hoy, 1998). Drawing upon Bandura's theory of social learning, Gibson and Dembo (1984) define teacher efficacy (self-efficacy and outcome expectancy) as follows:

> Outcome expectancy would essentially reflect the degree to which teachers believed the environment could be controlled, that is, the extent to which students can be taught given such factors as family background, IQ, and school conditions. Self-efficacy beliefs would indicate teachers' evaluation of their abilities to bring about positive student change. (p. 570)

2.2. Teacher efficacy and instructional practices

Two decades after its inception, Tschannen-Moran et al. (1998) offered a more precise definition for teacher efficacy as a "teacher's beliefs in his or her capability to organize and execute courses of action required to successfully accomplish a specific teaching task in a particular context" (p. 233). This conceptualization accounts for teachers' perceptions of their own competence as well as their assessment of the teaching context. Tschannen-Moran et al. further suggested that teacher efficacy is a malleable trait, one influenced by the teacher's performance and experience.

If teacher efficacy is malleable rather than fixed, it follows that teacher efficacy varies depending upon teacher experience. For elementary pre-service teachers, efficacy for teaching mathematics is in part a function of past experiences with mathematics, instructional strategies, and mathematics anxiety (Gresham, 2009; Swars, 2005; Swars, Daane, & Giesen, 2006). Building on their model, Tschannen-Moran et al. (1998) investigated how teacher efficacy can change over time. They found that pre-service teachers develop efficacy beliefs through coursework and student teaching in the field. For novice teachers (those completing their first year of teaching), efficacy was most associated with stress, commitment to teaching, support, and preparation. The authors noted that "changes in efficacy beliefs among inservice teachers seem to be more difficult to produce and sustain" (Tschannen-Moran et al., 1998, p. 236). In fact, practicing teachers may experience a lower sense of efficacy at the onset of any instructional change, with their teaching efficacy increasing again when they acquire new strategies to cope with the changes and observe an increase in student learning as a result of these changes. These findings are important in setting realistic expectations for how teacher efficacy is likely to change at the onset of any programmatic intervention and can inform ways to provide the proper support for teachers implementing new teaching strategies. Of course, teacher efficacy is not developed only through self-reflection. Ross (1994) found, for example, that teacher efficacy could be enhanced through district-wide professional development using cooperative learning techniques. This study suggested that teachers' knowledge gained from the professional development was associated with positive changes in their efficacy beliefs.

Teacher efficacy is particularly important because it can moderate important variation in teachers' attitudes and behavior. Gibson and Dembo (1984) postulated that teachers who exhibit high self-efficacy and outcome expectancy would have relatively high confidence in their abilities to teach, persist longer, focus on academic instructions, and provide students with constructive feedback. On the other hand, teachers who have low self-efficacy and outcome expectancy would have less confidence in their abilities to be effective teachers and give up easily on being effective. Through classroom observations with a small number of teachers ($N = 8$), Gibson and Dembo (1984) found that low-efficacy teachers spent a greater amount of time focusing on non-academic activities compared to high-efficacy teachers who spent a lesser amount of time on these activities (and thus more time on academic materials). High-efficacy teachers also allocated less time (28%) to small group instruction compared to low-efficacy teachers who spent a greater amount of time on small group instruction (48%). High- and low-efficacy teachers also differed in the feedback they provided to students, with high-efficacy teachers communicating higher expectations and persisting with students through challenging problems. While the small sample used in this study precludes definitive conclusions about the practices exhibited by teachers with varying degrees of efficacy, it does highlight a critical point: teacher efficacy influences the ways teachers interact with students in the classroom thus shaping students' learning experiences in ways that are nearly certain to impact learning.

Teachers influence student learning and development in multiple ways. They directly provide students with content knowledge, but also indirectly shape students' educational experiences that lead to the formation of key aspirations and expectations. These indirect influences can be strong enough to affect student academic attainment. Benner and Mistry (2007) found that teacher expectations for students affect students' own expectations and educational attainment. This shows that the relationship between teacher expectations and students' academic outcomes is mediated by student expectations and self-concept of ability—that is, teacher expectations shape students' expectations and self-concept, which in turn affect their academic performance. Of course, students may not have accurate assessments of teachers' expectations in the classroom. However, Chouinard, Karsenti, and Roy (2007) found that teacher beliefs and expectations, regardless of whether they are accurate, can influence students' beliefs about learning mathematics among secondary school students. This research showed that perceived support from social agents (namely, teachers and parents) affects students' beliefs about mathematics, which affects their achievement goals, and in turn moderates effort in learning mathematics. Teachers, along with parents, influence students' competency beliefs, their attitudes about the utility of mathematics, and their mastery goals and effort in learning mathematics. These findings suggest that while teacher beliefs and expectations may not directly link to student performance, they can shape students' perceptions about their ability to learn, which ultimately affects their achievement. These effects are evident in another study conducted by Lavigne, Vallerand, and Miquelon (2007), which revealed that teachers' support for the development of students' autonomy affects students' beliefs about their own competence and autonomy toward science learning, which then influences their motivation and ultimately their intentions to pursue careers in the field of interest.

2.3. Computer-based instruction supporting teaching and learning

While varying in features, content, and formats, computer-based instruction (CBI) has been found to have an impact on student learning and teacher practice. In an experimental study ($N = 87$) examining the effects of CBI on students' attitudes toward mathematical instruction and problem solving skills, Shyu (1999) found that video-based instruction was positively associated with student achievement. CBI's effects on student achievement were also observed among students with diverse learning needs. Using a quasi-experimental study ($N = 52$) to examine the effects of an integrated computer software program on middle school special education students' performance on the state standardized test, Malouf, Jamison, Carlucci, and Kercher (1990) found the program to have a positive impact on student achievement in mathematics. Similar results were found with gifted and talented students in the CBI program who outperformed their gifted and talented peers enrolled in the standard curriculum (Ysseldyke, Tardrew, Betts, Thill, & Hannigan, 2004). Additional research has investigated how specific features of CBI influence student learning. For example, individually personalized CBI was found to improve students' attitudes toward mathematics and enhance the performance of students with lower-level skills in mathematics (Ku, Harter, Liu, Thompson, & Cheng, 2007). Greater efficiency in learning mathematics (reduced time required to complete exercises) was observed in audio-based CBI compared to text-based CBI (Rehaag & Szabo, 1995). Furthermore, CBI using the spatial contiguity principle has been found to have favorable effects on student achievement compared to the non-spatial contiguous model of CBI (Harter & Ku, 2008).

Extant research suggests that unlike traditional classrooms which are characterized as teacher-centered, classrooms that use CBI are commonly more student-centered and student self directed. When computers are used for instructional purposes, teachers are more likely to see themselves as facilitators of learning and provide students with more personalized attention (Bracey, 1988). In an earlier study, Schofield, Eurich-Fulcer, and Britt (1994) found that while students believed that teachers provided better assistance compared to a computer-based tutor, students preferred to use the computer tutor when available. This study also suggested that CBI improves students' time on task, interest in learning, and motivation. In a more recent study, Frye and Dornisch (2008) discovered that students' perceptions about their teachers are moderated by the use of technology: students' whose math and science teachers more frequently used technology to facilitate instructions were also more likely to rate their teachers as having greater competency in knowledge of the subject area and ability to present content to the class.

2.4. Spatial–Temporal Math

Expanding on the existing research focusing on teacher efficacy and CBI, this paper explores changes in teacher efficacy and practice as the result of a computer-based approach to mathematics instruction known as Spatial Temporal Mathematics (ST Math). ST Math utilizes images to help students develop spatial–temporal cognition that can lead to advanced understanding of mathematical concepts such as fractions, proportions, symmetry, and other arithmetic operations. A randomized experimental design was used to examine the relationships between student participation in the ST Math program and educational outcomes on the California Standards Test (CST), math achievement and ability, and student motivation. Students in each participating grade level (second through fifth grade) were randomly assigned to either a treatment group or a control group. Supervised by their classroom teachers, students in the treatment group received a minimum of two 45-min sessions each week of the ST Math program during regular instruction. Students in the control group experienced their regular mathematics instruction that can be classified as "business as usual." The results of the first year implementation indicate that ST Math had a positive impact on student achievement in mathematics on the state standardized assessment (CST) with the effect size of 0.37 (Rutherford et al., 2010). Complementary to the main study, this paper examines whether ST Math has a similar impact on teacher beliefs about their efficacy and classroom practices.

3. Method

It is common for research in education and other social sciences to have data with hierarchical structure (students nested in classrooms or classrooms nested in schools). In this study, the nesting of classrooms in schools can affect the outcomes of the study (i.e. teachers' beliefs about their practice may vary depending on the composition of school where they work). As the result, variation in teachers' beliefs and attitudes can be found both between teachers within the same school and across schools. Due to the nested structure of the data with teacher at level 1 and school at level 2, we cannot ignore the variability associated with each level of the hierarchy. Given the multi-level structure of the data, with teachers nested in schools, we applied multi-level statistical modeling (Raudenbush & Bryk, 2002; Snijders & Bosker, 1999) to estimate the effects of ST Math on teachers' self-efficacy, outcome expectancy, and instructional practice.

The sample consisted of 339 elementary school teachers teaching grades 2–5 in the western US. The classrooms served a diverse student population with 83% Latino, 6% White, 6% Asian, 2% African American, and 3% Other. Students from low-income families enrolled in free/reduced lunch programs, made up 83% of the student population. English language learners (ELL) made up 61% of the student population. Student achievement data in 2008–2009 indicated that students in this county performed higher than other students in the state in science, mathematics, and language arts. Table 1 provides a summary of student achievement in 2008–2009 and Table 2 describes characteristics of the teacher participants.

3.1. Data sources

A 40-item questionnaire was sent electronically to the elementary teachers in both the treatment and control groups. Teachers in the treatment group were asked to complete 28 additional items describing their implementation of ST Math in their classrooms, beliefs about ST math in improving instruction, and the support they received to implement the intervention. Participants had 2 weeks to complete the online survey. A total of 368 teachers completed the survey. Of those, 29 cases had missing data, resulting in 339 observations represented in the complete data set.

The questionnaire consisted of items describing participants' teaching experience, teacher self-efficacy, teaching outcome expectancy, and instructional practices as related to mathematics. The Mathematics Teacher Efficacy Belief Instrument (MTEBI) was used to evaluate Personal Mathematics Teaching Efficacy (PMTE) and Mathematics Teaching Outcome Expectancy (MTOE). This instrument was developed by Enochs, Smith, and Huinker (2000) to assess self-efficacy and outcome expectancy in mathematics with reliability of 0.88 and 0.75 respectively. Participants graded items on a Likert scale: (1) strongly disagree; (2) disagree; (3) neutral; (4) agree; (5) strongly agree. The items described teachers' *outcome expectancy* in mathematics (e.g., *When a student does*

Table 1
Summary of students scoring at proficient and advanced levels in 2008–2009.

Grade level	County			State		
	Mathematics (%)	Science (%)	Language arts (%)	Mathematics (%)	Science (%)	Language arts (%)
2	70	–	60	63	–	53
3	70	–	50	64	–	44
4	73	–	69	66	–	61
5	63	59	61	57	49	54

Note: Test scores are not available for science in grades 2–4.

Table 2
Characteristics of teachers in the sample (N = 339).

Years	Treatment		Control	
	Total years of teaching	Number of years teaching mathematics	Total years of teaching	Number of years teaching mathematics
1–2 years	5	4	1	1
3–5 years	15	17	10	9
6–10 years	58	64	12	12
11–15 years	75	71	39	41
16–20 years	40	40	14	13
21 years or more	50	47	20	19

better in mathematics, it is often because the teacher exerted a little extra effort) and *self-efficacy* (e.g., *I know how to teach mathematics concepts effectively*). Participants also indicated the extent (very rarely, rarely, sometimes, often, very often) to which they integrated *scientific reasoning* in the classroom (e.g., *make predictions, analyze data, support conclusions with evidence, consider alternative explanations*).

While factor analysis yielded four constructs related to teachers' beliefs and attitudes about mathematics instructions, only three constructs with high reliability were used in the analysis to compare differences between teachers in the treatment and control groups. These three constructs are: (1) Mathematics Teaching Outcome Expectancy (*Cronbach's alpha* = 0.787); (2) Personal Mathematics Teaching Efficacy (*Cronbach's alpha* = 0.853); (3) and integration of scientific reasoning during instruction (*Cronbach's alpha* = 0.889).

3.2. Analysis

Multi-level analysis was used to account for the data structure with teachers (level 1) nested in schools (level 2) (Raudenbush & Bryk, 2002; Snijders & Bosker, 1999). We used hierarchical linear modeling (HLM) to estimate the relationship between teachers' participation in ST Math and self-efficacy, outcome expectancy, and use of scientific reasoning in teaching mathematics. Initial analysis for the unconditional model indicated a small amount of variation in outcome measures across the schools: intra-cluster correlation of 0.009 for teacher efficacy, 0.002 for outcome expectancy, and 0.042 for scientific reasoning. The random-effects approach was used to investigate variation of outcomes across schools, thus any significant effects could be generalized to the larger population beyond the sample schools. This approach is justified by the rationale that information about the sample schools (N = 44) is exchangeable (Snijders & Bosker, 1999). First, an unconditional model was generated to determine variability in teacher outcomes within and between schools. Subsequently, conditional models with random intercepts (intercepts vary across schools) and random slopes (slopes vary across schools) were used to assess how the relationships between ST Math participation and various outcomes varied across schools. Teacher characteristics were described in level 1, school characteristics were captured at level 2.

3.2.1. Independent variables

Level 1:
(1) *Teaching experience:* Number of years of teaching experience in mathematics (1 = 1–2 years; 2 = 3–5 years; 3 = 6–10; 4 = 11–15 years; 5 = 16–20 years; 6 = 21 years or more).
(2) *Time on ST Math:* The number of minutes on ST Math per week.
(3) *Integration of ST Math:* The extent to which teachers integrated ST Math in their daily instruction (1 = Never; 2 = Less than once a week; 3 = Once a week; 4 = A few times a week; 5 = Every day).
(4) *ST Math:* Participation in ST Math (0 = non-ST Math participant; 1 = ST Math participant).

Level 2:
(1) *Percent free/reduced lunch:* Percent of students qualified for free and reduced lunch.
(2) *Percent ELL:* Percent of students identified as ELL.

3.2.2. Dependent variables

(1) *Teaching efficacy:* Teachers' self-efficacy on teaching mathematics (1 = Strongly disagree; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Strongly agree).
(2) *Teaching outcome expectancy:* Teachers' outcome expectancy in terms of their students learning mathematics (1 = Strongly disagree; 2 = Disagree; 3 = Neutral; 4 = Agree; 5 = Strongly agree).
(3) *Scientific reasoning:* The extent to which teachers use scientific reasoning in their math instruction (1 = Very rarely; 2 = Rarely; 3 = Sometimes; 4 = Often; 5 = Very often).

Only classrooms with four or more students were included in the HLM analyses thus reducing the sample size from 339 to 325 teachers in 44 schools. Table 3 provides a summary of level-1 and level-2 predictors.

The following models were used to estimate the relationship between participation in ST Math and teacher outcomes. Teacher characteristics were described in level 1, and school characteristics

Table 3
Descriptive statistics of level 1 and level 2 variables.

Variable name	N	Mean	Standard deviation	Minimum	Maximum
Level-1 Descriptive statistics					
Teaching experience	325	4.11	1.25	1.00	6.00
Time on ST Math	325	65.29	45.59	0.00	210.00
Integration of ST Math	325	2.20	1.51	0.00	4.80
ST Math	325	0.71	0.45	0.00	1.00
Teaching efficacy	325	4.21	0.44	2.54	5.00
Teaching outcome expectancy	325	3.53	0.50	1.63	4.88
Scientific reasoning	325	3.86	0.60	1.75	5.00
Level-2 Descriptive statistics					
Percent free/reduced Lunch	44	83.27	9.93	64.00	100.00
Percent ELL	44	60.80	15.80	27.00	90.00

were captured at level 2. For the hierarchical analysis, the level-1 model was

$$Y_{ij} = \beta_{0j} + \beta_{1j}(X_{ij} - X\ldots) + \beta_{2j}X_{2ij} + r_{ij}$$

where Y_{ij} is the outcome of teacher i in school j ($j = 1,\ldots,44$ schools); β_{0j} is the mean for outcome in school j after controlling for differences in teaching experience and treatment indicator; β_{1j} is the fixed level-1 covariate effect (years of teaching experience); β_{2j} is a treatment-indicator variable (1 = treatment; 0 = control).

The level-2 model was

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_{ij} + \gamma_{02}W_{ij} + u+_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

where W_{1ij} is the percentage of students qualified for free/reduced lunch programs; W_{2ij} is the percentage of students identified as ELL; γ_{00} is the mean outcome in the schools γ_{01} is the free/reduced lunch composition effects; γ_{02} is the English language learners composition effects; γ_{10} is the pooled within-school regression coefficient for the level-1 covariate (years of teaching experience); γ_{20} is the pooled within-school regression coefficient for the level-1 covariate (treatment).

Four models were estimated. The first was an unconditional model for β_{0j}. This resulted in a partition of the total variance in Y_{ij} into its within-school (σ^2) and between-school components (τ_{00}). The second model examined the effects of years of teaching experience on teacher outcomes. Formally,

Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}\ (\text{Teaching Experience}) + r_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

The third model added the treatment indicator as follows:

Level 1:

$$Y_{ij} = \beta_{0j} + \beta_{1j}\ (\text{Teaching Experience}) + \beta_{2j}\ (\text{ST Math}) + r_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + u_{0j}$$

$$\beta_{1j} = \gamma_{10}]$$

$$\beta_{2j} = \gamma_{20}$$

The fourth model included measures specifying the school composition such as the percent of students qualified for free/reduced lunch programs and percent of students identified as ELL.

Level 1:

$$\text{Outcome } i_j = \beta_{0j} + \beta_{1j}\ (\text{Teaching Experience}) + \beta_{2j}\ (\text{ST Math}) + r_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01}\ (\text{Percent FRL}) + \gamma_{02}\ (\text{Percent ELL}) + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

$$\beta_{2j} = \gamma_{20}$$

4. Results

The correlation analysis between program participation and various outcome measures (shown in Table 4) indicated that many factors were weakly associated. However, a strong positive association was found between ST Math participation and the number of ST Math minutes used per week ($r = 0.832$, $p < .001$) suggesting a strong fidelity of implementation. Furthermore, the strong positive correlation between ST Math participation and the integration of ST Math elements into the formal curriculum ($r = 0.790$, $p < .001$) indicated that features of ST Math were being integrated into the formal lessons. Interestingly, time spent on ST Math was also positively associated with integrating features of ST Math in the formal curriculum ($r = 0.863$, $p < .001$). Significant positive associations were also found between teachers' usage of scientific reasoning and Mathematics Teaching Outcome Expectancy ($r = 0.276$, $p < .001$) and Personal Mathematics Teaching Efficacy ($r = 0.576$, $p < .001$). In addition, a positive relationship was detected between Mathematics Teaching Outcome Expectancy and Personal Mathematics Teaching Efficacy ($r = 0.297$, $p < .001$).

We explored these relationships further using multi-level analysis. As shown in Table 5, years of teaching experience ($\gamma_{10} = 0.030$, $se = 0.020$) and treatment condition ($\gamma_{20} = -0.060$, $se = 0.054$) were not statistically related to teacher efficacy. School composition such as the percent of students identified for free/reduced lunch programs ($\gamma_{01} = 0.004$, $se = 0.005$) and percent of students identified as ELL ($\gamma_{02} = -0.002$, $se = 0.003$) did not have significant effects on teacher efficacy.

Table 6 represents the results for teacher outcome expectancy. After controlling for years of teaching experience and school

Table 4
Correlations between various factors ($N = 325$).

	ST Math participation	Personal Mathematics Teaching Efficacy (PMTE)	Mathematics Teaching Outcome Expectancy (MTOE)	Integration of scientific reasoning	Integration of ST Math in class	Time on ST Math
Personal Mathematics Teaching Efficacy (PMTE)	−0.071					
Mathematics Teaching Outcome Expectancy (MTOE)	−0.058	0.297**				
Integration of scientific reasoning	0.023	0.576**	0.276**			
Integration of ST Math in class	0.790**	0.014	0.005	0.098~		
Time on ST Math	0.832**	0.003	−.043	0.072	0.863**	
Number of years teaching mathematics	−0.048	0.075	0.065	0.092~	−0.003	0.014

~ Correlation is significant at 0.10 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

Table 5
Effects of ST Math on teacher efficacy.

Fixed effect	Coefficient	Se	t Ratio
Intercept, γ_{00}	4.250	0.046	91.477
Percent FRL, γ_{01}	0.004	0.005	0.819
Percent ELL, γ_{02}	−0.002	0.003	−0.731
Teaching experience, γ_{10}	0.030	0.020	1.511
Treatment indicator, γ_{20}	−0.060	0.054	−1.109

Random effect	Variance component	df	χ^2	p Value
Mean efficacy, u_{0j}	0.003	41	46.582	0.253
Level-1 effect, r_{ij}	0.191			

Table 6
Effects of ST Math on teacher outcome expectancy.

Fixed effect	Coefficient	Se	t Ratio
Intercept, γ_{00}	3.587	0.052	69.628
Percent FRL, γ_{01}	0.001	0.005	0.209
Percent ELL, γ_{02}	0.003	0.003	1.082
Teaching experience, γ_{10}	0.026	0.022	1.179
Treatment indicator, γ_{20}	−0.080	0.061	−1.309

Random effect	Variance component	Df	χ^2	p Value
Mean efficacy, u_{0j}	0.0001	41	38.150	>.500
Level-1 effect, r_{ij}	0.245			

Table 7
Effects of ST Math on teachers using scientific reasoning.

Fixed effect	Coefficient	Se	t Ratio
Intercept, γ_{00}	3.867	0.065	59.551
Percent FRL, γ_{01}	0.008	0.007	1.166
Percent ELL, γ_{02}	−0.006	0.004	−1.291
Teaching experience, γ_{10}	0.053	0.027	1.941
Treatment indicator, γ_{20}	−0.009	0.073	−0.122

Random effect	Variance component	Df	χ^2	p Value
Mean efficacy, u_{0j}	0.018	41	54.943	0.071
Level-1 effect, r_{ij}	0.342			

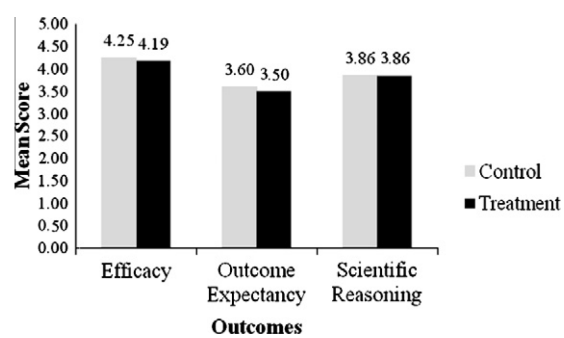

Fig. 1. Average mean scores for teachers' efficacy, outcome expectancy, and teaching practice using scientific reasoning.

composition, the treatment did not have a significant effect on teacher outcome expectancy ($\gamma_{20} = -0.080$, $se = 0.061$). The results also showed that teaching experience ($\gamma_{10} = 0.026$, $se = 0.022$), free/reduced lunch composition ($\gamma_{01} = 0.001$, $se = 0.005$), and ELL composition ($\gamma_{02} = 0.003$, $se = 0.003$) had no effect on teacher outcome expectancy.

As shown in Table 7, the treatment had no effect on teacher practice using scientific reasoning ($\gamma_{20} = -0.009$, $se = 0.073$). However, years of teaching experience had a significant positive effect ($\gamma_{10} = 0.053$, $se = 0.027$) on teacher practice using scientific reasoning. This suggests that teacher practice using scientific reasoning tends to be greater with more years of teaching experience. School composition such as the percent of students eligible of free/reduced lunch programs ($\gamma_{01} = 0.008$, $se = 0.007$), and ELL composition ($\gamma_{02} = -0.006$, $se = 0.004$) were not associated with teacher practice. Fig. 1 provides a summary of results for teacher self-efficacy, outcome expectancy, and instructional practice using scientific reasoning.

While the results indicate that ST Math did not have significant effects on teacher outcomes, our secondary analysis focusing on participants in the treatment group ($N = 231$) showed interesting results. We conducted multiple regression analysis to investigate predictors of outcomes for teachers in the treatment group. First, the combination of variables to predict teacher efficacy from years of teaching experience, time on ST Math, and integration of ST Math in the formal curriculum was statistically significant, $F(3,227) = 5.79$, $p = .001$. Time on ST Math and integration of ST Math into daily instruction significantly predicted teacher efficacy. That is, after controlling for years of teaching experience, teachers who reported greater amounts of time on ST Math were also more likely to report greater levels of efficacy, $\beta = .002$, $t(227) = 1.82$, $p = .070$. Interestingly, integrating ST Math into daily instruction significantly predicted teacher efficacy, $\beta = .143$, $t(227) = 3.39$, $p = .001$. This suggests that teachers who integrate features of ST Math in their daily lessons are also more likely to report greater teacher efficacy. Results are shown in Fig. 2.

Second, years of teaching experience, time on ST Math, and integration of ST Math into daily lessons also predicted outcome

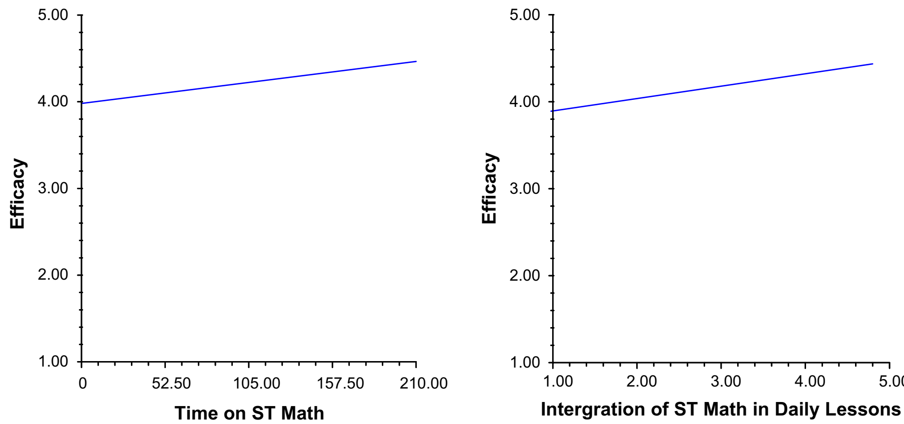

Fig. 2. The relationships between efficacy and time on ST Math and integration of ST math in daily lessons.

expectancy for teachers in the treatment group, $F(3,227) = 5.85$, $p = .001$. Integrating ST Math into the daily lessons significantly predicted teacher outcome expectancy, $\beta = .193$, $t(227) = 3.88$, $p < .001$. This means that teachers who reported integrating features of ST Math in their daily lessons were also more likely to report greater levels of outcome expectancy. Fig. 3 shows the results for this section.

Third, collectively the above three variables also predicted teacher practice using scientific reasoning, $F(3,227) = 10.42$, $p < .001$. Time on ST Math significantly predicted teacher practice, $\beta = .004$, $t(227) = 2.38$, $p = .018$. In other words, teachers who spent more time on ST Math were also more likely to report using scientific reasoning when teaching mathematics. In addition, teachers integrating features of ST Math in their daily lessons also reported using scientific reasoning when teaching mathematics, $\beta = .255$, $t(227) = 4.54$, $p < .001$. Fig. 4 provides the results for this section. Table 8 provides a summary of the findings from our secondary analysis.

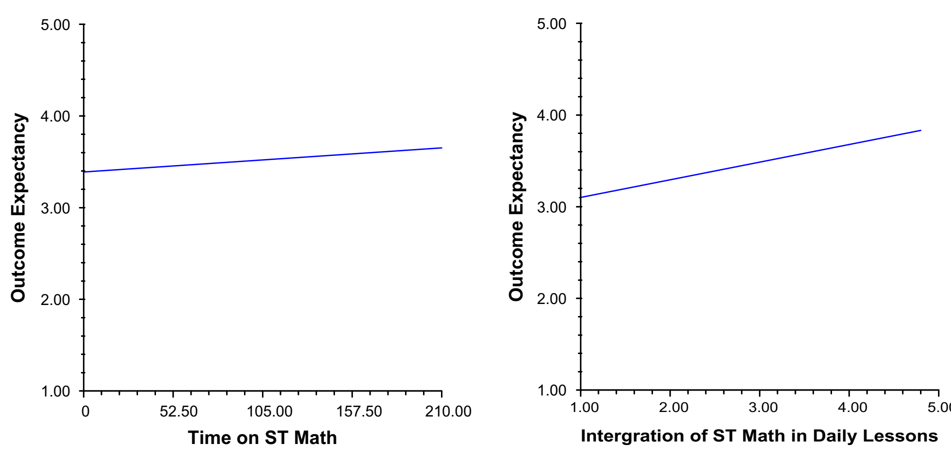

Fig. 3. The relationships between outcome expectancy and time on ST Math and integration of ST math in daily lessons.

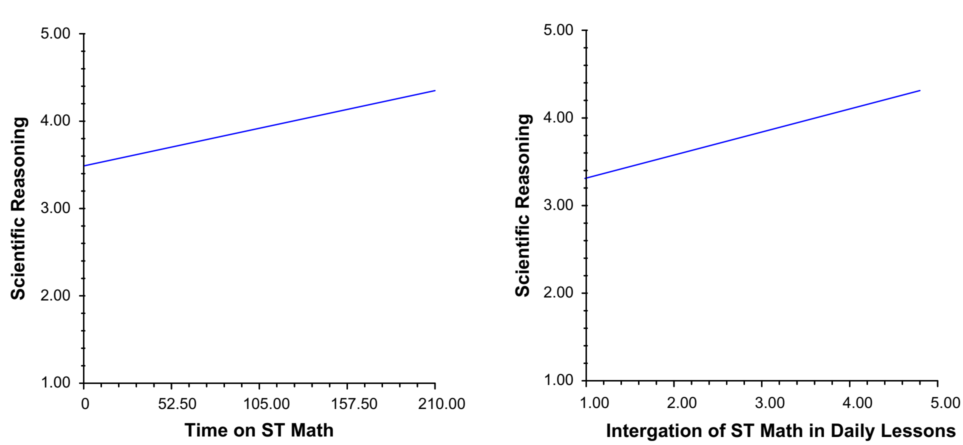

Fig. 4. The relationships between instructional practice using scientific reasoning and time on ST Math and integration of ST Math in daily lessons.

Table 8
Multiple regression analysis summary for teaching experience, time on ST Math, and integration of st math predicting outcome measures ($N = 231$).

Variable	Efficacy		Outcome expectancy		Scientific reasoning	
	β	Se	β	Se	β	Se
Constant	3.60**	.17	2.81**	.20	2.72**	.23
Teaching experience	−0.01	.02	−0.01	.03	−0.01	.03
Time on ST Math	0.01~	.01	0.01	.01	0.01*	.01
Integration of ST Math	0.14**	.04	0.19**	.05	0.26**	.06

~ $p < .10$.
* $p < .05$.
** $p < .01$.

5. Discussion

While ST Math has been shown to have positive effects on student achievement in mathematics after the first year of implementation (Rutherford et al., 2010), these previously reported effects have not included changes to teacher self-efficacy, teaching outcome expectancy, or instructional practices that integrate scientific thinking. However, within the treatment group, we found that the number of hours spent and the integration of ST Math in daily lessons were positively associated with these outcomes. These findings suggest that ST Math can impact teachers' instructional practices. Exposure to the program is likely to be an important factor that mediates the outcomes – that is, a given amount of time is required before changes in teacher efficacy and instructional practices are observed. More generally, the findings of this study provide insight into the potential influence of CBI on teacher beliefs and instructions in mathematics. In the following section, we discuss the implications of these findings in the context of opportunities and challenges that CBI can provide in supporting teaching and learning mathematics. First, we explore the role that teachers play in facilitating ST Math. We then discuss the potential effects of ST Math on teachers' beliefs, attitudes, and instructional practices. Lastly, we address the limitations of the current investigation and provide recommendations for future research.

5.1. Teachers' role in implementing ST Math

Even though participating in the intervention did not change teachers' attitudes, beliefs or instructional practices in teaching mathematics, teachers did report spending more time in the computer lab. This time spent outside of the traditional classroom setting can assist teachers in developing and implementing instructional strategies that may not otherwise be pursued in the traditional classroom setting. ST Math uses simulation and game-based features to engage students in learning mathematical concepts at a pace tailored to their specific learning needs, thus allowing teachers to not only reach students using a different mode of instruction but also to provide them with tailored assistance. This type of instructional advantage was documented in an earlier study using an artificial intelligence computer-based tutoring program for high school students learning geometry proofs. Schofield et al. (1994) noted a change in the social interactions between students and their teacher—teachers giving students more individualized assistance and students having greater control over the kind and amount of help they needed from the teacher. Schofield et al. argued that computer-based instruction did not replace the teacher; instead, it served as an additional resource to facilitate student learning. Students asked for help from their teachers when they felt that the computer's assistance was insufficient. When helping individual students, the teacher was less dictated by the needs of the entire class thus could provide an elaborated explanation for the specific content for individual students. In doing so, the teacher made a shift in the intended audience from whole class instruction to individual focus. This shift inevitably changed the ways in which teachers communicated and delivered content to their students. While similar changes were observed among teachers in the current study, our findings indicated that these changes in student–teacher interactions did not translate to measurable changes in teachers' efficacy and instructional practices using scientific reasoning.

We propose two possible explanations for these results. First, while ST Math offers a different mode of delivery of mathematics content to students, it is not designed for significant impact on teachers' efficacy and instructional practice since the program requires minimal active involvement by teachers while students interact with the program. The adaptive features of ST Math allow for more individualized instruction in which students can work at their own pace. The teacher's primary role is to provide technological and logistical support to students while they engage in the ST Math games. Since a major component of ST Math is increased time spent on computer-based instruction, a form of student engagement that could potentially lead to less time for face-to-face student–teacher interactions. The arrangement could affect teachers' self-efficacy and beliefs about their teaching ability. This hypothesis brings to light the strengths as well as weaknesses embedded in CBI. On the one hand, teachers must consider the positive impact that ST Math can have on student achievement in mathematics, as documented in the main study. On the other hand, teachers experience a shift in their role as the instructor in the classroom from more teacher-centered to less teacher-directed instruction. These two seemingly opposing factors can influence teachers' perceptions about their teaching efficacy. This paradox calls for further investigation on the effects of CBI programs like ST Math on teacher practice. Specifically, it would be useful to compare the results from the survey data to those currently collected by classroom observers. These qualitative data will help us gain insights about how ST Math may facilitate student learning and improve teacher practice in the classroom.

Second, previous research has shown that teachers' efficacy is a malleable factor, one that is influenced by previous learning and teaching experiences (Gresham, 2009; Swars, 2005). More importantly, teachers may experience a decrease in efficacy at the onset of a curricular or instructional change. Teachers' perceptions of self-efficacy increase following their experience of success with the implementation of innovative practices (Stein & Wang, 1988). If this is the case, then it is not surprising to see teachers who implemented ST Math in their first year experience changes in their instructional practices, some of which may have resulted in a decrease in their sense of teacher efficacy. Alternatively, as students spend more time on ST Math, teachers have less time interacting with their students. This decrease in interactions between students and teachers may cause teachers to believe that they play a less important role in assisting students in learning mathematics. However, previous research has shown that students perceived that CBI did not replace the teacher but instead served as an additional resource to facilitate learning (Schofield et al., 1994). Unless it can be shown that positive student–teacher interactions decrease with increased student time on ST Math, and that teachers' efficacy decreases with decreased student–teacher interactions, we can be confident that ST Math does not substitute the role of the teacher in the classroom.

5.2. Potential effects of ST Math on teachers' efficacy and practices

Contrary to the belief that students' time on ST Math may have a negative effect on teacher efficacy, secondary analysis of teachers in the treatment group indicated that time on ST Math and the integration of ST Math in daily lessons were positively associated with teachers' self-efficacy, outcome expectancy, and instructional practices using scientific reasoning. We discuss these findings in the section below.

Teachers whose students spent more time on ST Math reported a higher level of self-efficacy, outcome expectancy, and instructional practices using scientific reasoning, after controlling for years of teaching experience and integration of ST Math in daily lessons. This association may be attributed to changes in teacher-student interactions as a result of CBI. In a study examining high school students' perceptions of teacher competency, Frye and Dornisch (2008) found that math and science teachers who used more technology were perceived by their students as more competent teachers. The authors argued that this association is driven by the "spillover" effect in which students who perceived their teachers as knowledgeable in one area (in this case, technology use) are also more likely to perceive their teachers as knowledgeable in other domains (i.e. teaching mathematics). This perception of teacher competency undoubtedly can affect the ways in which students interact with their teachers, which in turn affects how teachers perceive their teaching efficacy and effectiveness. A similar pattern might apply to teachers implementing ST Math in their classrooms. Like other forms of CBI which have been documented to improve students' motivation (Schofield et al., 1994), attitudes (Ku et al., 2007), and achievement in mathematics (Harter & Ku, 2008; Ku et al., 2007; Rehaag & Szabo, 1995; Shyu, 1999; Ysseldyke et al., 2004), students playing the games embedded in ST Math may experience similar results. In fact, the main study examining the effects of ST Math on student achievement indicated that students using ST Math performed higher on state standardized tests compared to their peers not using ST Math (Rutherford et al., 2010). It is reasonable to suspect that increases in student learning may have been first observed by the classroom teachers, which led to increased teacher efficacy (Stein & Wang, 1988) and subsequently changed teachers' instructional practices to include higher order thinking skills.

Our findings indicated that after controlling for years of teaching experience and time on ST Math, there was a positive significant relationship between integration of ST Math and various outcome measures. Teachers who reported greater integration of ST Math in their daily math lessons were also more likely to report having greater self-efficacy, outcome expectancy, and instructional practices using scientific reasoning. This finding suggests not only that skills students acquired from ST Math transferred into the regular lessons but, perhaps more important, references of ST Math in various contexts positively affect teachers' efficacy and instructional practices. We suspect that teachers' references to ST Math during the regular instructional time can serve multiple purposes. First, those references can help students review concepts introduced in the ST Math games. Second, they allow the teacher to help students make connections between the mathematical concepts taught in the classroom and those presented in ST Math. These two practices can reinforce concepts learned in both ST Math computer lab and the regular classroom, thus improving student learning of mathematics. As student learning increases, the teacher may be more inclined to not only teach the basics but also to elaborate on more complex concepts and integrate higher level thinking skills such as scientific reasoning. Of course, this change in teacher perceptions and practices may vary depending on the students' observed progress, teachers' responsiveness to student learning, and actual instructional modifications exercised by the teacher.

In sum, ST Math has the potential to improve student motivation and interest in the learning task. Seeing this, teachers may be inclined to increase their time on ST Math and make references about ST Math during regular instructional time to further engage students in this content. As a result, students' understanding of mathematics would be expected to improve, which would lead to increased teacher efficacy which in turn would influence teachers to alter their instructional practices. Fig. 5 illustrates the proposed relationships between these larger concepts.

More importantly, these processes signify a shift from teacher-centered to student-centered instructional practices. During ST Math sessions, students interact mostly with the games and only ask for the teacher's assistance when the computer game is unable to provide them the support they need to progress to the next level. The adaptive feature of the ST Math program not only makes learning math an individualized process but also gives students the freedom to request the type and amount of help provided by the teacher. When helping students instead of providing large group instructions as the teacher typically does in the regular classroom, the teacher can provide specific feedback to individual students. During regular math instruction, the teacher can make references to features found in ST Math. While this instruction may be teacher-driven, the explicit connections derived from students' experiences and learning resulted from using ST Math. Since students' skills and knowledge may vary depending on their individual ability, when making these connections teachers must draw on their unique experiences with ST Math. The profound shift from teacher-centered to student-focused instructional practices as a result of CBI should not be underestimated since it carries important implications for effective teaching and learning of mathematics, a topic that deserves further investigation.

5.3. Limitations of the current study

The current study has several limitations. First, while the current research design allows for valid comparisons of differences observed between teachers in the control and treatment groups, data sources obtained from other methods such as teacher interviews and classroom observations during the ST Math computer sessions and regular instructional time would provide more information about how teachers' beliefs and instructional practices may change as a result of ST Math. Second, even though findings of the

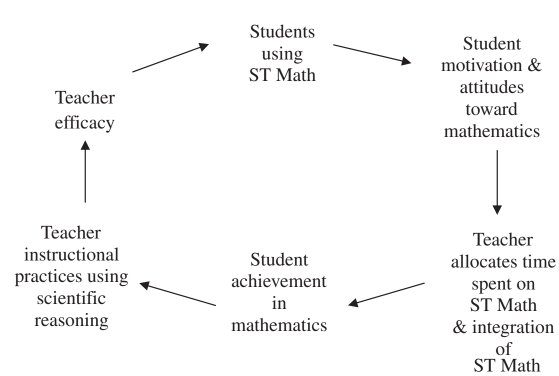

Fig. 5. The relationship between ST Math, student learning, teacher efficacy and instructional practice.

current study contribute to the broader knowledge about the effects of CBI on teacher efficacy and instructional practices, we caution the reader to generalize about the results as they as drawn from a specific intervention focusing on mathematics instruction for second, third, fourth, and fifth grade students. In addition, the external validity or generalizability of the study may be limited by the data available on teacher demographic (years of teaching experience). Given the relatively small sample size, teachers in our sample are likely to be different from teachers in the general population. Third, teacher efficacy and teachers' instructional practices take time to develop and may take an even longer time to change. Longitudinal data collected from this multi-year intervention will allow us to document changes in teacher efficacy and practices over time. Finally, we do not yet fully understand the role that teachers play nor the long-term effects that this type of instruction may have on teachers' beliefs about teaching and learning. Further investigation is needed on how CBI influences the various aspects of teacher practices in the classroom and how the specific features of the intervention may enhance teaching and learning of mathematics.

6. Conclusions

While the implementation of Spatial Temporal Mathematics (ST Math) did not yield significant effects in teachers' self-efficacy, outcome expectancy, and instructional practices using scientific reasoning, our secondary analysis indicated that time on ST Math and the integration of ST Math into daily instructions were positively associated with teacher efficacy and changes in instructional practices. More significantly, these findings highlight the potential impact of computer-based instruction (CBI) on the teaching of mathematics. As technological advancements continue to expand globally, their influence can be observed in national policy discussions and in local educational agencies throughout the US. Consequently, teachers will need to be prepared for the integration of technology-based instruction in their classrooms. These findings suggest that support for building teacher efficacy and instructional practice must be available in order to assist teachers make what will be an inevitable transition to more learner-centered instructional practices.

Acknowledgments

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References

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*, 191–215.

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Englewood Cliffs, NJ: Prentice-Hall.

Bandura, A. (1997). *Self-efficacy: The exercise of control*. New York: W.H. Freeman.

Benner, A. D., & Mistry, R. S. (2007). Congruence of mother and teacher educational expectations and low-income youth's academic competence. *Journal of Educational Psychology, 99*(1), 140–153.

Berman, P., McLaughlin, M., Bass, G., Pauly, E., & Zellman, G. (1977). *Federal programs supporting educational change: Vol. VII. Factors affecting implementation and continuation* (Rep. No. R-1589/7-HEW). Santa Monica, CA: RAND. (ERIC Document Reproduction Service No. 140 432).

Bracey, G. W. (1988). Computers in class: Some social and psychological consequences. *Electronic Learning, 7*, 28.

Chouinard, R., Karsenti, T., & Roy, N. (2007). Relations among competence beliefs, utility value, achievement goals, and effort in mathematics. *British Journal of Educational Psychology, 77*, 501–517.

Enochs, L. G., Smith, P. L., & Huinker, D. (2000). Establishing factorial validity of the mathematics teaching efficacy beliefs instrument. *School Science and Mathematics, 100*, 194–202.

Frye, N., & Dornisch, M. (2008). Teacher technology use and student evaluations: The moderating role of content area. *Journal of Educational Technology Systems, 36*(3), 305–317.

Gibson, S., & Dembo, M. H. (1984). Teacher efficacy: A construct validation. *Journal of Educational Psychology, 76*(4), 569–582. doi:10.1037/0022-0663.76.4.569.

Gresham, G. (2009). An examination of mathematics teacher efficacy and mathematics anxiety in elementary pre-service teachers. *Journal of Classroom Interaction, 44*(2), 22–38.

Harter, C., & Ku, H. (2008). The effects of spatial contiguity within computer-based instruction of group personalized two-step mathematics word problems. *Computers in Human Behavior, 24*(4), 1668–1685.

Ku, H., Harter, C., Liu, P., Thompson, L., & Cheng, Y. (2007). The effects of individually personalized computer-based instructional program on solving mathematics problems. *Computers in Human Behavior, 23*(3), 1195–1210.

Lavigne, G. L., Vallerand, R. J., & Miquelon, P. (2007). A motivational model of persistence in science education: A self-determination theory approach. *European Journal of Psychology of Education, XXII*(3), 351–369.

Malouf, D. B., Jamison, P. J., Carlucci, C. M., & Kercher, M. H. (1990). *Evaluation of instructional model applied to functional math*. Washington, DC: Department of Education.

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

Rehaag, D., & Szabo, M. (1995). An experiment on effects of redundant audio in computer based instruction on achievement, attitude, and learning time in 10th grade math. In *Paper presented at the annual meeting of the association for educational communications and technology,* Anaheim, CA (February).

Ross, J. A. (1994). The impact of an inservice to promote cooperative learning on the stability of teacher efficacy. *Teaching and Teacher Education, 10*(4), 381–394.

Rutherford, T., Kibrick, M., Burchinal, M., Richland, L., Conley, A., Osborne, K., et al. (2010). Spatial temporal mathematics at scale: An innovative and fully developed paradigm to boost math achievement among all learners. In *Paper presented at the annual convention of the American educational research association*, Denver, CO.

Schofield, J. W., Eurich-Fulcer, R., & Britt, C. L. (1994). Teachers, computer tutors, and teaching: The artificially intelligent tutor as an agent for classroom change. *American Educational Research Journal, 31*(3), 579–607.

Shyu, H. (1999). Effects of media attributes in anchored instruction. *Journal of Educational Computing Research, 21*(2), 119–139.

Snijders, T., & Bosker, R. (1999). *Multilevel analysis: An introduction to basic and advanced multilevel modeling*. Thousand Oaks, CA: Sage.

Stein, M. K., & Wang, M. C. (1988). Teacher development and school improvement: The process of teacher change. *Teaching and Teacher Education, 4*, 171–187.

Swars, S. (2005). Examining perceptions of mathematics teaching effectiveness among elementary preservice teachers with differing levels of mathematics teacher efficacy. *Journal of Instructional Psychology, 32*(2), 139–147.

Swars, S., Daane, C., & Giesen, J. (2006). Mathematics anxiety and mathematics teacher efficacy: What is the relationship in elementary preservice teachers? *School Science and Mathematics V, 10*(7), 306–315.

Tschannen-Moran, M., Hoy, A., & Hoy, W. (1998). Teacher efficacy and measure. *Review of Educational Research, 68*, 202–248.

Ysseldyke, J., Tardrew, S., Betts, J., Thill, T., & Hannigan, E. (2004). Use of an instructional management system to enhance math instruction of gifted and talented students. *Journal for the Education of the Gifted, 27*(4), 293–310.