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Keywords

Computer-based learning, Pre-College STEM Contexts, STEM Major choices, and Multilevel Structural Equation Modeling

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Keywords: computer-based learning, pre-college STEM contexts, STEM major choices, multilevel structural equation modeling

Introduction

Many science, technology, engineering, and math (STEM) studies have investigated factors that influence students' STEM major choices at post-secondary institutions, considering the long-standing national problem—the shortage of STEM workers. Most of these studies focused on traditional learning contexts such as math- and science-related learning factors. However, few studies have considered a progressive curriculum or learning activity intertwined with pre-college STEM contexts. Adopting a pre-college STEM-based curriculum with the aim of increasing students' technological literacy has been of great interest recently, particularly as it is still uncommon in K-12 classrooms (National Research Council, 2009).

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In this study, pre-college STEM-based curricula include practical tasks at the K-12 level that are relevant to the STEM job duties, such as technological and engineering skills. This study chose computer-based learning activities as pre-college STEM contexts, given the fact that computing skills will be required for approximately three out of four new STEM occupations by 2020 in the U.S. (U.S. Bureau of Labor Statistics, 2010). Aligned with the importance of computing skills, this study focused on computer-based activities in math classrooms. Additionally, as math teachers play a major role in designing learning materials and instruction, this study aimed to investigate math teacher motivation. A preponderance of studies performed previously focused on math teacher quality based on “observed” credentials, including pedagogical and subject content knowledge, certification status, and teaching experience which is aligned with “a highly qualified teacher” as defined by the federal No Child Left Behind Act of 2001 (NCLB) (Vandervoort, Amrein-Beardsley, & Berliner, 2004; Clotfelter, Ladd, & Vigdor, 2007; Goe, 2007). However, relatively few studies have considered math teachers’ “unobserved” credentials—namely psychological traits. Addressing these issues, the following research questions guide the study:

- To what extent do computer-based learning activities in math classrooms affect a student’s STEM major choice in 4-year post-secondary institutions compared to the traditional learning activities such as individual- and lecture-based learning activities?
- To what extent does the teacher motivation factor affect math performance and self-efficacy across schools and contribute to a student’s STEM major choice?

Literature Review

The literature review section offers a detailed rationale for exploring the two main research questions. This section begins with describing well-documented learning predictors that influence students’ STEM major choices in post-secondary institutions. Subsequently, relevant to the first research question, the second subsection reviews the previous studies that investigated computer-based learning activities. The third subsection describes previous findings on the association between math teacher quality and student achievement in mathematics, paying particular attention to the ways in which the previous studies have defined math teacher quality. Finally, with the summary of the literature review, this study will emphasize the potential contribution to the literature.

Pre-college traditional learning factors influencing students’ STEM major choices

Many studies have considered variables relevant to math and science disciplines, which represent traditional learning contexts, as pre-college learning predictors of STEM major

choices. Scholars agree that student achievement in math and science, enrollment in rigorous math and science courses, and math and science self-efficacy are strong predictors that contribute to students’ STEM major choices in post-secondary institutions.

Regarding math disciplines, it has been well documented that math scores on the Scholastic Aptitude Test (SAT) or American College Testing (ACT) strongly predict students’ STEM major choices in college (e.g., Levin and Wyckoff 1988; Astin & Astin, 1992; Nicholls, Wolfe, Besterfield-Sacre, Shuman, & Larpiattaworn, 2007; Veenstra, Dey, & Herrin, 2008). Concerning student math performance, enrollment in rigorous math courses is a well-known predictor of STEM major selection (e.g., Trusty, 2002; ACT, 2004; Adelman, 2006; Noble, Roberts, & Sawyer, 2006). Equally important, math self-efficacy is also known as a significant cognitive factor that positively affects students’ selection of STEM majors (e.g., Hackett & Betz, 1981; O’Brien, Martinez-Pons, & Kopala, 1999). Self-efficacy refers to an individuals’ confidence in solving math problems, performing math-related tasks, and taking math-related courses (Betz & Hackett, 1983).

Aligned with the math disciplines, student achievement in science is also considered a strong predictor for student selection of STEM majors in post-secondary institutions (e.g., Trusty, 2002; Nicholls, Wolfe, Besterfield-Sacre, & Shuman, 2010; Maltese & Tai, 2011). Similar to the effects of taking advanced math courses, students who take advanced science courses are more likely to enter STEM disciplines in post-secondary institutions (e.g., Muller, Stage, & Kinzie, 2001; Trusty, 2002; Anderson & Kim, 2006; Sahin, Morgan, & Erdogan, 2012). Like the positive relationship between math self-efficacy and STEM major choices, not surprisingly, there is a positive association between science self-efficacy and STEM major selection in college (Luzzo, Hasper, Albert, Bibby, & Martinelli, 1999; Scott & Mallinckrodt, 2005).

In summary, most STEM studies have focused on traditional learning contexts in math and science disciplines, whereas relatively little attention has been paid to pre-college STEM contexts that are considered progressive learning contexts linked to practical STEM tasks. However, some studies focused on pre-college STEM-based curricula including computer-based learning activities. The next section describes these studies.

Computer-based learning activities and student learning outcomes

A curriculum embedded within pre-college STEM contexts is getting attention because of the expectation that such STEM context-based curriculum could increase students’ interest in STEM fields. However, a clear definition of a progressive curriculum has not yet been specified (National Research Council, 2009). As a result, there is no consensus on the effects of pre-college STEM-based curriculum on

student learning outcomes, although the number of studies focusing on this topic is increasing. In these studies, computer-based activities are one of the major learning contexts that exemplify pre-college STEM contexts.

Since the 1990s, computers have been part of our daily lives (Fox, 2003) and subsequently, K-12 classrooms started to adopt computer technology (Ruthven & Hennessy, 2002). Accordingly, there is a growing body of literature on the effects of computer-based learning activities on student learning outcomes. In terms of the student learning outcomes, many studies chose student achievement, but relatively few studies considered the linkage between computer use and STEM major choices.

Several studies used a sample from national or international datasets to explore the effects of computer use on student achievement scores. Recently, Lee (2012) found that computer-based learning activities had positive effects on 12th graders' math achievement scores, using a nationally representative sample from the Educational Longitudinal Study of 2002 (ELS: 2002). Based on the Programme for International Student Assessment (PISA) dataset, Delen and Bulut (2011) revealed the positive effects of information and communication technologies (ICT) on Turkish students' math and science achievement.

In a study utilizing a nationally representative sample from the 2005 National Assessment of Educational Progress (NAEP), Kim and Chang (2010) found mixed results in the effects of computer games on 4th graders' math achievement scores depending on students' demographic characteristics. In this study, computer games yielded positive effects on math achievement scores of non-native English male students, but negative effects on math achievement of English-speaking male students. These findings suggested that the use of the computer in math classrooms can reduce the achievement gap between English language learners and native English-speaking students. Another recent study using the ELS: 2002 revealed that students who frequently used computers for both school and non-school work showed higher math achievement scores (Lee, Brescia, & Kissinger, 2009).

In a study using the NAEP, Wenglinsky (1998) revealed that computer simulation and application software had positive effects on math achievement among both 8th and 4th graders. Middleton and Murray (1999) investigated the relationship between the frequency of teacher technology use and achievement levels of 4th and 5th grade students. This survey response compared 107 fourth and fifth grade teachers to standard achievement test scores of 1,466 fourth and 1,108 fifth grade students in a large South Carolina School District. In the Middleton and Murray study, 5th grade teachers reported a higher level of technology use when compared to 4th grade teachers. This study indicated that 5th grade students taught by the 5th grade teachers showed higher math achievement scores when compared to 4th grade students.

Some recent randomized studies focused on the effects of computer use on student math achievement. Barrow, Markman, and Rouse (2009) showed that computer aided instruction potentially contributed to student achievement in pre-algebra and algebra in U.S. urban school districts with a sufficient computer infrastructure. Banerjee, Cole, Duflo, and Linden (2007) also conducted a randomized study in India and found that among 98 of 122 primary government schools, computer-assisted mathematics instruction improved fourth graders' math achievement. However, some studies showed no significant differences in math achievement between students with or without computer-based learning activities. According to the Institute of Education Science (2010), four studies (Shneyderman, 2001; Smith, 2001; Cabalo, Jaciw, & Vu, 2007; Campuzano, Dynarski, Agodini, & Rall, 2009) employing randomized controlled trials or quasi-experimental designs linked to What Works Clearinghouse (WWC) investigated the relationship between the Carnegie Learning Curricula and Tutor[®] software (CLC & CT[®]S) and math achievement based on a total sample of 1,723 high school students in 27 schools across seven districts. The results of these four studies yielded no significant effects of CLC & CT[®]S on student math achievement among these high school students.

Based on the mixed results, stakeholders have not yet reached a consensus regarding the effects of computer-based learning activities on student learning outcomes. Moreover, few studies have investigated how computer-based learning activities influence STEM major choices.

Math teacher quality and student achievement in mathematics

Several studies have investigated the link between math teacher quality and student math achievement. In terms of defining and measuring math teacher quality, most of these studies considered teachers' observed credentials—that is, teacher pedagogical content knowledge (PCK) and content knowledge (CK), teaching experience, and certification status, based on the definition of “highly qualified teachers” by the federal NCLB (2001) (Vandervot et al., 2004; Clotfelter et al., 2007; Goe, 2007). The federal NCLB states that a highly qualified teacher should have (a) a bachelor's degree, (b) be full certified or licensed, and (c) demonstrate content knowledge in the subject he or she teaches (Smith, Desimone, & Ueno, 2005).

Scholars agree that PCK is a major determinant that shapes teacher quality and consequently, influences student learning (Shulman, 1987; Baumert et al., 2010). In conjunction with PCK, teachers' CK is considered an important indicator of teacher quality. Goe synthesized 22 recent studies and found a positive relationship between CK and student math achievement in 18 out of 22 studies. Based on these studies, CK was often proxied by previous

mathematics course taken, certification status, or degree. Considering CK proxied by teachers' test scores, Clotfelter et al. (2007) investigated the relationship between teachers' SAT or ACT test scores and students' test scores. Clotfelter and colleagues found a significant positive association between teachers' SAT or ACT test scores and students' SAT or ACT test scores. Overall, scholars tended to agree that PCK and CK are the major determinants of teacher quality. However, unlike PCK and CK, there is no agreement among scholars about the effects of teacher certification and teaching experience on student math achievement.

Somewhat inconsistent findings emerged on the relationship between teacher certification and student math achievement. For example, based on a sample of approximately 150,000 students in 9,400 classrooms in the Los Angeles United School District (LAUSD), researchers found no significant difference in math scores between third through fifth graders taught by certified and uncertified teachers (Kane & Staiger, 2005, as cited in Gordon, Kane, & Staiger, 2008). However, Vandevoort et al. (2004) found that among third through sixth graders in 14 Arizona School Districts, students who were assigned to the National Board Certified teachers achieved higher academic scores on the Stanford Achievement Tests in the areas of reading, mathematics, and language arts.

Similarly, the literature suggests mixed findings on the relationship between teaching experience and student math achievement scores. The synthesis study by Goe reported a positive relationship between teaching experience and math at the elementary and middle school levels (i.e., Rowan, Chiang, & Miller, 1997; Cavalluzzo, 2004; Hanushek, Kain, O'Brien, & Rivkin, 2005; Rockoff, 2004). Additionally, the study by Clotfelter et al. (2007) found that teaching experience was a critical factor that contributed to the improved student math scores of all 3rd through 5th grade students in North Carolina. However, Rosenholtz's (1986) study showed that positive effects of teaching experience were effective only during the first five years of teaching, but after five years of teaching, the positive effects seemed to diminish. Similar to the results of the Rosenholtz study, in the meta-analytic study by Goe, two studies (i.e., Rockoff, 2004; Hanushek et al., 2005) showed a positive relationship between student math achievement and teaching experience at the elementary and middle school levels but also only for the first few years. However, three other studies analyzed by Goe (i.e., Harvison & Hanushek, 1992; Gallagher, 2004; Carr, 2006) showed a non-significant relationship between teaching experience and student math achievement. Similarly, using a nationally representative sample of more than 18,000 tenth graders extracted from the National Education Longitudinal Study of 1988, Goldhaber and Brewer (1998) found no significant relationship between teachers' teaching experience and student test scores in math.

Overall, there were mixed results regarding the effect of teacher certification status and teaching experience on student math achievement, while it has been relatively well documented that teachers' PCK and CK are important credentials that define teacher quality. The mixed results regarding teacher credentials suggest that in addition to these "observed" credentials, "unobserved" teacher credentials, namely psychological traits of teachers, might be another essential element that plays a vital role in improving student learning outcomes and shapes teacher quality. In fact, Goe stated that NCLB's definition of teacher quality credentials does not define teacher quality sufficiently; instead, it describes only a minimum standard. Accordingly, the current study investigated teachers' unobserved credentials, particularly the psychological traits and the effects of teacher motivation, given the assumption that teacher motivation ensures a high level of teacher effort to design and implement math instruction. Namely, this study presumes that teacher motivation would be an important determinant of teacher quality beyond the credentials outlined by the NCLB.

Teacher motivation was considered a school-level learning factor, given the extensive body of literature that school organizational contexts influence teachers' motivation (Leithwood, Jantzi, & Steinbach, 1999; Davis & Wilson, 2000; Kelley, Heneman, & Milanowski, 2002; Barnett & McCormick, 2003). Teacher motivation level can change depending on organizational contexts, including principal leadership styles, work conditions, and school culture. In fact, in a survey study conducted by Davis and Wilson (2000) with 660 elementary teachers and their 44 principals, the encouragement of principals, particularly their empowerment of teacher behaviors, positively influenced teacher motivation. A review by Leithwood et al. (1999) indicated that transformational leadership was a critical factor that influences teacher motivation to improve classroom practices and attitudes. Similarly, a semi-structured interview of 4 principals and 11 teachers randomly selected by Barnett and McCormick (2003) showed that principals' transformational leadership, as perceived by the teacher participants, contributed to the enhancement of teacher motivation. Moreover, according to Kelley et al.'s (2002) review of several research studies, school-based performance award programs played an influential role in increasing teacher motivation.

In summary, many scholars have investigated the learning factors influencing students' STEM major choices. Studies showed that in traditional learning contexts, math and science-related learning factors contribute significantly to students' STEM major choices. However, relatively little attention has been paid to pre-college STEM-based curricula, which represents progressive learning activities. This study focused particularly on the effects of computer-based learning activities as pre-college STEM contexts, given the fact that three out of four STEM occupations will demand computing skills by 2020 in the U.S. (U.S. Bureau

of Labor Statistics, 2010). With a particular focus on computer-based learning activities in the math classroom, this study also investigated the relationship between math teacher motivation and student STEM-related learning outcomes (i.e., math performance, math self-efficacy, and STEM major choices), given the assumption that the quality of math instruction potentially depends on teacher motivation levels in terms of design and implementation of new math instruction.

Conceptual Framework

Supported by the conceptual framework of Social Cognitive Career Theory ([SCCT]; Lent, Brown, & Hackett, 1994) (see Figure 1), this study hypothesized that (a) math self-efficacy and math performance would mediate students' selection of STEM majors in 4-year colleges and universities, (b) the selected pre-college math learning activities factors (i.e., computer-, individual-, and lecture-based learning activities) would play an important role in improving math self-efficacy and math performance, and (c) teacher motivation (school-level learning factor) would influence math self-efficacy and math performance linked to students' STEM major choices. As teacher motivation is a school-level learning factor that reflects a contextual factor, teacher motivation falls under "contextual influences" component of the SCCT in this study.

Among many career development theories, SCCT is an appropriate theoretical model to support these hypotheses. As hypothesis (a) indicates, the study focuses on capturing longitudinally the influence of 10th graders' learning experiences on college major choices via 12th graders' math self-efficacy and math performance. Namely, math self-efficacy and math performance are assumed to mediate the college major choices in this study. SCCT includes theoretical components that are aligned with these mediators.

In hypothesis (b), the pre-college math learning activities, including computer-, individual-, and lecture-based learning activities, were chosen according to the pedagogical structure published in the seminal text, *How People Learn: Brain, Mind, Experience, and School* ([HPL]; Bransford,

Brown, & Cocking, 1999, p. 22). As shown in Figure 2, HPL suggest six learning activities, which are technology-, lecture-, skills-, inquiry-, individual-, and group-based learning activities. Among the six learning activities, the study focused particularly on technology-, lecture-, and individual-based learning activities. Two reasons justify the selection of these learning activities. First, a learning activity based on pre-college STEM contexts is a major independent variable; thus, technology-based learning should be chosen. Second, individual- and lecture-based learning activities in HPL, which represent traditional learning activities, should be chosen to look at the extent to which a technology-based learning activity influences the selected learning outcomes (i.e., math self-efficacy, math performance, and STEM major choices) over and above traditional learning activities. Thus, inclusion of inquiry-, skills-, and group-based learning activities would be somewhat irrelevant to the main purpose of the study, keeping in mind that the main purpose of the study is to examine the effects of pre-college STEM contexts on STEM major choices in college. In a different study, the effect of each inquiry-, skills-, and group-based learning activity in math classrooms (considered progressive learning contexts similar to technology-based learning activities) might need to be explored. Additionally, computer-based learning activities in this study represent technology-based learning activities suggested by HPL.

Math teacher motivation was selected as the school-level learning factor, given the literature suggesting that school organizational contexts influence math teacher motivation (Leithwood et al., 1999; Davis & Wilson, 2000; Kelley et al., 2002; Barnett & McCormick, 2003). Math teacher motivation in the study was defined as teachers' comprehensive psychological traits comprising of teachers' attention, values, and enthusiasm toward students' success in mathematics, conceptually framed by the modern expectancy value theory which states that teacher motivation is driven by a teacher's multiple consciousness including teacher efficacy, expectancy, and values (Eccles & Wigfield, 2002).

Beyond teacher motivation, other potential school-level learning factors may influence students' STEM major

Figure 1. Conceptual Model: Social Cognitive Career Theory (Lent, Brown, & Hackett, 1994).

Figure 2. How People Learn: Brain, Mind, Experience, and School (Bransford, Brown, & Cocking, 1999, p. 22).

choices. However, the current study intends to focus exclusively on teacher motivation as the school-level learning factor for the following two reasons. First, the school-level learning factors associated with post-secondary enrollment in both non-STEM and STEM majors have been already discovered by Engberg and Wolniak (2010) using the Educational Longitudinal Study of 2002/06 (which was the same dataset used in the current study). The results showed that the following school-level learning factors affect students' college enrollment: (a) the aspiration of students' family and friends for the students to attend college; (b) students' academic preparation (i.e., taking high-level math courses, total AP courses taken, and high school GPA); and (c) access to parent, peer, and college-linking networks. Engberg and Wolniak indicated that these three school-level learning factors reflect cultural capital theory, human capital theory, and social capital theory, respectively. Based on the results of their study, the three school-level learning factors, namely contextual factors (i.e., cultural, human capital, and social capital), are considered to affect students' college enrollment in either STEM or non-STEM majors. Beyond these three factors, the effect of teacher motivation on math performance, math self-efficacy, and STEM major choices has not been fully understood. Particularly in this study, it is rational to consider teacher-related factors such as teacher motivation because teachers play a critical role in designing and implementing math learning activities (which are chosen as the within-school level factors in the study). Second, methodologically, adding many variables to a proposed model when using multilevel structural equation modeling (used in this study) worsens the model fit (Hox,

2010). Accordingly, this study paid attention exclusively to teacher motivation as the school level factor.

Method

To examine the research questions, this study employed multilevel structural equation modeling (ML-SEM). ML-SEM is an appropriate research method for the current study because we focused on (a) investigating how well the SCCT model fits the proposed model; and (b) demonstrating the direct and indirect effects of the selected math-learning instructions on students' STEM major choices considering the within- and between-school levels (see Figure 3). Importantly, ML-SEM, which is a hybrid model of conventional structural equation modeling and hierarchical linear modeling, would prevent biased structural regression coefficients (Muthén & Satorra, 1989). Compared to conventional and single-level SEM, ML-SEM can provide more accurate and unbiased estimates of population parameters because it takes into account hierarchically nested systems that most educational datasets have (Muthén & Satorra, 1989; Muthén & Muthén, 1998; Kaplan & Ferguson, 1999). As the Educational Longitudinal Study of 2002 (which the current study used) has a nested structure, ML-SEM would be necessary to report unbiased results.

Procedures

In the procedures section, we explain how the proposed model, described in Figure 3, was developed. Specifically, the study describes (a) how latent constructs are identified; (b) the ways in which independent, mediator, and dependent variables are assigned; (c) the extent of intraclass

Figure 3. Multilevel structural model of pre-college math learning instructions and teacher motivation factors on STEM major choices.

correlations; (d) how missing data were treated; and (e) the software for data analysis used.

Identification of latent constructs

In the current study, a factor analysis identified math teacher motivation and math self-efficacy which were classified as latent constructs. The math teacher motivation on students' math learning as obtained from teacher questionnaires is composed of the following three observed indicators with reference to math teachers' perceptions: (a) math teachers' attention to students' success in math; (b) math teachers' attention to teaching methods, and (c) math teachers' enthusiasm toward students' math achievement. These three observed indicators are highly related to each other based on high factor loadings (i.e., 0.77 ~ 0.83) and can be a set of math teacher motivation. Theoretically, these observed indicators can be considered the psychological elements of teacher motivation, which include teacher expectations, efficacy, and attainment value on the positive effects of teachers' attention, teaching methods, and enthusiasm for students' math achievement (e.g., Eccles,

1987; Feather, 1988; Wigfield & Eccles, 1992, 2001). Further, the three observed indicators, which are the responses of math teachers, reflect any one of three cognitive actions (i.e., expectation, efficacy, and attainment value). Moreover, modern expectancy value theory indicates that expectation, efficacy, and value are positively associated with each other. Therefore, the composite value of the three observed indicators, which were identified based on the factor analysis, can be described as teacher motivation.

In the same way, math self-efficacy is well articulated based on the following observed indicators, which yielded high factor loadings (i.e., 0.77 ~ 0.83): (a) students' confidence level on taking math tests, (b) students' confidence level on understanding difficult math texts, (c) students' confidence level on understanding math class, (d) students' confidence level on completing math assignments, and (e) students' confidence level on mastering math class skills. The proposed model featured in Figure 3 has the two latent variables (i.e., teacher motivation and math self-efficacy), which were formed based on the composite values of the observed indicators.

Assignment of independent, mediator, and dependent variables

The proposed model (see Figure 3) shows independent, mediator, and dependent variables. In terms of the SEM, independent variables are called exogenous variables, whereas dependent variables are equivalent to endogenous variables. Mediator variables, which are considered explanatory variables, describe the observed relationship between independent and dependent variables. Table 1 shows how variables were selected as exogenous, mediator, and endogenous variables.

Intraclass correlation

Intraclass correlation (ICC) is referred to as the proportion of the total variability that can be explained as variability between the groups (Heck, 2001). Therefore, high intraclass correlation addresses a significant difference between groups and reflects within group similarity of data values. The range of the intraclass correlation for the dependent variables in the current study is from a low of 0.043 to a high of 0.275. Specifically, the ICC of each dependent variable, the proportion of STEM major choices, Item Response Theory (IRT) math scores in the first

Table 1
Description of the variables in the ELS: 2002.

Variable name	Variable description
<i>Exogenous variables</i>	
Computer-based learning	<i>Base-Year Student Survey Questionnaire:</i> In your current or most recent mathematics class, how often do/did you computers? (BYS29H) 1 = Never; 2 = Rarely; 3 = Less than once a week; 4 = Once or twice a week; 5 = Every day or almost every day
Individual-based learning	<i>Base-Year Student Survey Questionnaire:</i> In your current or most recent mathematics class, how often do/did you review the work from the previous day? (BYS29A) 1 = Never; 2 = Rarely; 3 = Less than once a week; 4 = Once or twice a week; 5 = Every day or almost every day
Lecture-based learning	<i>Base-Year Student Survey Questionnaire:</i> In your current or most recent mathematics class, how often do/did you listen to the teacher lecture? (BYS29B) 1 = Never; 2 = Rarely; 3 = Less than once a week; 4 = Once or twice a week; 5 = Every day or almost every day
Teacher motivation	<i>Base-Year Teacher Survey Questionnaire:</i> When students are successful in achieving intended goals or objectives, it is often attributed to one of the following sources. In your opinion, how important is each source of success? Teacher's attention to the unique interests and abilities of the students (BYTM44D) Teacher's use of effective methods of teaching (BYTM44E) Teacher's enthusiasm or perseverance (BYTM44F) 1 = Extremely Important; 2 = Very Important; 3 = Not Very Important; 4 = Not at all Important <i>Note:</i> The rating scales of these three teacher motivation indicators were reversely coded in the process of data analysis as follows: 1 = Not at all important; 2 = Not very important; 3 = Very Important; 4 = Extremely Important
Base-year math IRT scores	Base-Year Math Item-Response Theory (IRT)-estimated number right scores (F1TXMBIR): The estimated number right score for math is an estimate of the number of items students would have answered correctly if they had responded to all 72 items in the ELS:2002 math item pool
<i>Mediator variables</i>	
Math self-efficacy	First Follow-Up Student Survey Questionnaire: In your current or most recent math class, how often do/did the following statements apply to you? I'm confident that I can do an excellent job on my math tests (F1S18A) I'm certain I can understand the most difficult material presented in my math textbooks (F1S18B) I'm confident I can understand the most complex material presented by my math teacher (F1S18C) I'm confident I can do an excellent job on my math assignments (F1S18D) I'm certain I can master the skills being taught in my math class (F1S18E) 1 = Almost Never; 2 = Sometimes; 3 = Often; 4 = Almost Always
First follow-up math IRT scores	First follow-up Math IRT-estimated number right scores (F1TXM1IR): The estimated number right score for math is an estimate of the number of items students would have answered correctly if they had responded to all 85 items in the ELS:2002 base-year and first follow-up math item pool.
<i>Endogenous variable</i>	
STEM major choices in post-secondary settings	Student's post-secondary major in 2006 (F2MJR2_P) <i>Note:</i> Major fields are coded as the dummy variable; 1 = STEM and 0 = non-STEM

Note. Variable labels in the ELS:02/06 in parentheses.

follow-up, and math self-efficacy, was 0.043, 0.253, and 0.275, respectively. Therefore, there was a large amount of between-school variation in math self-efficacy and IRT math scores, which suggests that the multilevel model was appropriate in this study.

Treatment of missing values

Missing values were imputed based on the Expectation-Maximization (EM) algorithm, using SPSS software, under the assumption of Missing at Random (MAR). Missing at Random, which is the most general assumption in the missing data mechanism (Rubin, 1976), suggests that missing values of variables can be predicted based on available information—observed values of other variables rather than the missing values themselves (Yuan & Bentler, 2001; Lu & Copas, 2004). Based on the fundamental idea of MAR, the missing values of the variables were filled in based on other observed variables. For example, the missing values of the first follow-up on math IRT score were imputed based on other observed variables such as observed indicators of math self-efficacy. In the current study, the approximate proportion of missing values are described as follows: (a) 4.18% of the first follow-up math IRT scores, (b) 5% of individual-based learning, (c) 5.5% of lecture-based learning, (d) 8% of computer-based learning, (e) 17% of teacher motivation, and (f) 25.6% of math self-efficacy. Note that if the percentage missing for a specific variable was more than roughly 20%, it is recommended to use a modern missing data treatment, like the EM algorithm, rather than listwise deletion (Arbuckle, 1996). Among the variables in the study, math self-efficacy had 25.6% missing values, and thus, the study decided to impute the missing values using the EM algorithm rather than listwise deletion.

Data analysis using Mplus 6.1

ML-SEM analysis was conducted using *Mplus* 6.1 (Muthén & Muthén, 2010) and was based on the MLR estimator. The MLR estimator, which allows a non-normality assumption, is widely used when a model includes different types of variables such as binary, ordered categorical, and continuous (Kaplan, 2009). Of note, the data analysis for both within- and between-school levels was performed simultaneously using *Mplus* 6.1.

Samples

The samples were acquired from the Educational Longitudinal Study of 2002/06 (ELS: 02/06). The ELS: 02/06 has longitudinally monitored the transition of a national sample of 10th grade students in 2002 through post-secondary education, employment outcomes, or both. At the three time points (i.e., 2002, 2004, and 2006), the academic status and achievement of these students were collected from multiple populations

including students, their parents, and their teachers who were randomly selected from 750 high schools. At the baseline year (2002), of 17,590 eligible selected sophomores, 15,360 students and 7,140 of their teachers participated in the base-year survey, which suggests that on average, more than two but less than three students had the same math teacher in this dataset (i.e., $15,360/7,140 \approx 2$). The responses of 7,140 teachers in the dataset were linked to student identification numbers. Of the 15,360 students, we extracted 4,357 students from 711 high schools who constantly participated in all three studies (i.e., 2002 base-year study, 2004 first follow-up study, and 2006 second follow-up study), entered 4-year colleges or universities, and declared their majors in the second follow-up year, 2006. Samples were weighted by the weighting variable, F2BYWT, which refers to the second follow-up base-year panel weight (Bozick & Lauff, 2007).

Of the students enrolled in 4-year colleges or universities, 21.5% of students selected STEM majors, whereas 78.5% of students chose non-STEM majors. The categories of the STEM majors in this study were identical to those in a statistical report published by the U.S. Department of Education (Chen & Weko, 2009) (see Appendix A).

Results

First, this section shows the descriptive statistics and correlation between the selected variables followed by addressing the research questions considering both the within- and between-school levels. The first research question examined the relationship between selected within-school learning factors and the likelihood of students to select a STEM major in 4-year colleges and universities as mediated by math performance and math self-efficacy. Specifically, the first research question focused on the extent to which computer-based learning activities, compared to the traditional learning activities (i.e. individual- and lecture-based learning activities), affect students' STEM major choices. The second research question investigated the effects of math teacher motivation on math performance, math self-efficacy, and STEM major choices at the school level.

Table 2 shows the descriptive statistics for each variable and correlations among the variables. Mean and standard deviation of each variable was found in Table 2. Regarding the correlation analyses, individual- and lecture-based learning activities correlated positively with base-year math IRT scores, whereas computer-based learning activities and base year Math IRT scores correlated negatively. Similarly, individual- and lecture-based learning activities had a significant and positive correlation with math self-efficacy, but no significant relationship between computer-based learning activities and math self-efficacy emerged. Math teacher motivation had a significant and negative

Table 2
Descriptive statistics and correlation of the variables.

	1	2	3	4	5	6	7
1. Base-year math IRT Score	1.000	—	—	—	—	—	—
2. First follow up math IRT score	0.864**	1.000	—	—	—	—	—
3. Computer-based learning	-0.157**	-0.135**	1.000	—	—	—	—
4. Individual-based learning	0.170**	0.162**	-0.091**	1.000	—	—	—
5. Lecture-based learning	0.030*	0.021	-0.005	0.148**	1.000	—	—
6. Math self-efficacy	0.285**	0.341**	-0.027	0.094**	0.045**	1.000	—
7. Math teacher motivation	-0.030*	-0.045**	0.012	-0.019	-0.031*	-0.010	1.000
Mean	52.35	58.81	1.65	3.89	4.49	13.76	9.74
Standard deviation	11.84	12.28	1.04	1.30	0.96	3.70	0.85

** $p < 0.01$; * $p < 0.05$.

correlation with base-year Math IRT scores, first follow-up Math IRT scores, and lecture-based learning activities. However, the correlation analyses results would not necessarily show similar pattern with the results from the ML-SEM analyses. In the ML-SEM analyses, all variables within and between school-level affected each other, producing a different relationship between each variable.

Research Question 1: To what extent do computer-based learning activities in math classrooms affect a student's STEM major choice in 4-year post-secondary institutions compared to the traditional learning activities such as individual- and lecture-based learning activities?

Concerning within-school level, math IRT scores during the first follow-up year and math self-efficacy were the mediators that explained the relationship between the selected learning experience factors and students' STEM major choices in 4-year colleges and universities (see Figure 4). The relationship between math IRT scores in the first follow-up year and the selected learning experience factors were examined after controlling for math IRT scores in the base-year, 2002.

Model fit indices (see Table 3) suggest that the model had a good fit. Specifically, the comparative fit index (CFI) was close to 1 (i.e., 0.993) and the root mean square error of approximation (RMSEA) was 0.026, which is less than recommended cut-off value of 0.05.

As shown in Table 3, within-school level, noticeably, computer-based learning activities in math classrooms had a much greater effect on math self-efficacy than did individual- and lecture-based learning activities ($p < 0.001$). All learning factors played significant roles in increasing math self-efficacy; however the significance level of lecture-based learning activities in math was low compared to other math learning activities (i.e., lecture-based, $p < 0.1$; computer-based, $p < 0.01$ and individual-based, $p < 0.05$).

After controlling for math IRT scores in the base-year, individual-based learning activities in math classrooms, "how often reviews work in math class", were substantially

associated with math IRT scores in the first follow-up year ($p < 0.05$). Math IRT scores and math self-efficacy related significantly to STEM major choices in 4-year colleges and universities ($p < 0.001$), whereas math IRT scores demonstrated a larger effect on STEM major choices in 4-year colleges and universities compared to math self-efficacy.

Based on the description of each math learning activity (see Table 1), students who more frequently participated in all selected math learning activities had a higher level of math self-efficacy and were more likely to determine a STEM major in 4-year colleges and universities. Likewise, students who habitually reviewed math materials were more likely to have higher math performance and select STEM majors.

Table 4 shows the indirect effects of the selected learning activities on STEM major choices. Through math self-efficacy, the indirect effect of computer-based learning on STEM major choices was the strongest among the selected learning activities ($p < 0.05$). As mediated by math IRT scores in the first follow-up, the indirect effect of math IRT score in the base-year on STEM major choices was the strongest among the exogenous variables ($p < 0.001$). Furthermore, math IRT score in the base-year yielded the greatest total indirect impact on STEM major choices ($p < 0.001$).

Research Question 2: To what extent does the teacher motivation factor affect math performance and self-efficacy and contribute to a student's STEM major choice?

At the between-school level, math self-efficacy and math performance mediated the relationship between math teacher motivation and students' STEM major choices (see Figure 4).

Math teacher motivation was positively associated with school-level math IRT scores in the first follow-up year when controlling for math IRT scores in the base-year, although the relationship was only marginally significant ($p < 0.1$). Such marginal significance would raise controversy about whether the relationship between the two variables

Figure 4. Standard coefficients for the multilevel structural model of pre-college math learning instructions and teacher motivation factors on STEM major choices.

can have practical significance, as alpha level of 0.1 is generally used as a lenient standard (Noymer, 2008). However, the marginally significant effect of math teacher motivation on student math achievement scores cannot be disregarded. We can assume that this relationship is meaningful and it suffices to say, in practice, math teacher motivation is positively linked to student math achievement scores. Math teacher motivation, which is composed of teachers' perceptions regarding teachers' attention, teaching method, and enthusiasm toward students' math achievement in the current study, had positive effects on students' math performance. This means that student math performance can be improved when students are instructed by math teachers who have greater belief and confidence in teacher attention to pedagogy and enthusiasm for student success in math. Specifically, this result suggests that math teacher motivation is considered an important contextual as well as school-level learning factor that is able to improve student math performance across schools.

Summary

Clearly, with respect to the within-school level, computer-based learning activities in math classes, compared to the individual- and lecture-based learning activities, contributed more to the high proportion of students selecting STEM majors through increasing the effects on math self-efficacy. Additionally, the results revealed a positive relationship between individual-based learning activities and the first follow-up math IRT scores after controlling for the base-year math IRT scores. Regarding between-school level, a positive relationship between teacher motivation and the first follow-up math IRT scores yielded when controlling for the base-year math IRT scores.

The significant and positive effects of all the selected learning activities suggest that individual- and lecture-based learning activities (which reflect traditional learning contexts) should be integrated with computer-based learning activities (which is a progressive learning context). As

Table 3

Multilevel model of STEM major choices in 4-year colleges and universities: standardized model results (direct effect).

Predictor/parameter	Estimate	Two-tailed <i>P</i> -VALUE	S.E.	Est./S.E.
Within-school level (student level)				
<i>STEM major choices on</i>				
First follow-up math IRT scores	0.242***	0.000	0.018	13.762
Math self-efficacy	0.038**	0.017	0.016	2.381
<i>First follow-up math IRT scores on</i>				
Computer-based learning activities	-0.004	0.695	0.010	-0.392
Individual-based learning activities	0.025**	0.011	0.010	2.552
Lecture-based learning activities	-0.005	0.646	0.010	-0.459
Base-year math IRT scores	0.832***	0.000	0.007	115.680
<i>Math self-efficacy on</i>				
Computer-based learning activities	0.693***	0.000	0.010	69.276
Individual-based learning activities	0.030**	0.020	0.013	2.328
Lecture-based learning activities	0.024*	0.077	0.013	1.771
Base-year math IRT scores	0.188***	0.000	0.016	12.079
Between-school level (school level)				
<i>STEM major choices on</i>				
First follow-up math IRT scores	-0.072	0.576	0.128	-0.559
math self-efficacy	0.078	0.432	0.099	0.786
<i>First follow-up math IRT scores on</i>				
Teacher motivation	0.036*	0.070	0.020	1.809
Base-year math IRT scores	0.950***	0.000	0.013	75.327
<i>Math self-efficacy on</i>				
Teacher motivation	0.022	0.648	0.048	0.456
Base-year math IRT scores	0.258***	0.000	0.056	4.559
Model fit indices				
Chi-square = 65.879 (<i>df</i> = 17); <i>p</i> = 0.000; CFI = 0.993, TLI = 0.986, RMSEA = 0.026				

p < 0.1. ** *p* < 0.05. *** *p* < 0.01.

computer-based learning activities exemplify STEM contexts, such integrated curricula is very likely to play an influential role in motivating students' STEM major choices through increasing students' interests in STEM-related tasks.

Beyond the type of math instruction itself, the level of students' involvement in the selected three math learning activities plays an important part in motivating students to prepare for their career in STEM fields, given that the common description of each selected variable is "*how frequently students participate in*" each activity (i.e., computer-, individual-, and lecture-based learning activities). Namely, students themselves should have the determination to be actively involved in the math learning activities. Equally important, at the school level, math teacher motivation should be enhanced, because (a) math teacher motivation significantly affects school level math performance and (b) math teachers play a major role in designing the integrated math instruction and motivating students to be involved in each learning activity.

Discussion

The significant positive relationship between computer-based learning activities and students' STEM major choices in college provides a scientific rationale for promoting pre-college STEM contexts in the K-12 classrooms. Specifically, this study provides evidence that students

who attend math classrooms that integrate computer-based learning activities in the traditional math curriculum are more likely to enter STEM disciplines in college. Nearly three out of four new STEM occupations in the U.S. will require computing skills by 2020 (U.S. Bureau of Labor Statistics, 2010); thus, students with proficient computer skills are more likely to perceive a STEM occupation as a preferable career choice. Noticeably, computer-based learning activities are most likely to encourage math teachers to diversify their instruction and incorporate computer-based curriculum into individual- and lecture-based learning activities (which reflects traditional curriculum). Through individual-based learning activities, students are most likely to be involved in reviewing class notes, textbooks, and other learning materials. Lecture-based learning activities, which are often passively taught by teachers, aim to provide math knowledge and skills.

Along with the significant and positive effects of computer-based learning activities, individual- and lecture-based learning activities also significantly and positively influence student STEM major choices. All the selected learning activities contribute to STEM major choices by optimizing student learning outcomes rather than a single learning activity, which is in line with the HPL theory proposed by Bransford et al. (1999, p.22). Specifically, results from the study showed that each learning activity influenced student STEM learning processes and outcomes. All three learning activities had positive influences on a

Table 4

Multilevel model of STEM major choices in 4-year colleges and universities: standardized model results (indirect effect).

Predictor/parameter	Estimate	Two-tailed <i>P</i> -VALUE	S.E.	Est./S.E.
Within school level (student level)				
<i>Effects from base-year math IRT Scores to STEM major choices</i>				
<i>Total indirect effects</i>	0.209***	0.000	0.015	13.927
<i>Specific indirect effects</i>				
STEM major choices via math self-efficacy				
Base-year math IRT scores	0.007**	0.020	0.003	2.327
STEM major choices via first follow-up math IRT scores				
Base-year math IRT scores	0.201***	0.000	0.015	13.626
<i>Effects from computer-based learning activities to STEM major choices</i>				
<i>Total indirect effects</i>	0.025**	0.026	0.011	2.229
<i>Specific indirect effects</i>				
STEM major choices via math self-efficacy				
Computer-based learning activities	0.026**	0.017	0.011	2.382
STEM major choices via first follow-up math IRT scores				
Computer-based learning activities	−0.001	0.696	0.002	−0.391
<i>Effects from individual-based learning activities to STEM major choices</i>				
<i>Total indirect effects</i>	0.007***	0.004	0.002	2.904
<i>Specific indirect effects</i>				
STEM major choices via math self-efficacy				
Individual-based learning activities	0.001*	0.092	0.001	1.687
STEM major choices via first follow-up math IRT scores				
Individual-based learning activities	0.006**	0.012	0.002	2.522
<i>Effects from lecture-based learning activities to STEM major choices</i>				
<i>Total indirect effects</i>	0.000	0.922	0.003	−0.098
<i>Specific indirect effects</i>				
STEM major choices via math self-efficacy				
Lecture-based learning activities	0.001	0.169	0.001	1.375
STEM major choices via first follow-up math IRT scores				
Lecture-based learning activities	−0.001	0.645	0.003	−0.460
Between-school level (school level)				
<i>Effects from base-year math IRT scores to stem major choices</i>				
<i>Total indirect effects</i>	−0.047	0.683	0.116	−0.408
<i>Specific indirect effects</i>				
STEM major choices via math self-efficacy				
Base-year math IRT scores	0.020	0.447	0.026	0.761
STEM major choices via first follow-up math IRT scores				
Base-year math IRT scores	−0.067	0.576	0.120	−0.559
<i>Effects from teacher motivation to STEM major choices</i>				
<i>Total indirect</i>	−0.001	0.888	0.006	−0.141
<i>Specific indirect</i>				
STEM major choices via math self-efficacy				
Teacher motivation	0.002	0.684	0.004	0.407
STEM major choices via first follow-up math IRT scores				
Teacher motivation	−0.003	0.559	0.005	−0.526
Model fit indices				
Chi-square = 65.879 (<i>df</i> = 17); <i>p</i> = 0.000; CFI = 0.993, TLI = 0.986, RMSEA = 0.026				

* *p* < 0.1. ** *p* < 0.05. *** *p* < 0.01.

student's STEM major choice through math self-efficacy as a mediator, but via math IRT scores as a mediator, only individual-based learning activities contributed to a student's STEM major choice. A small but significant effect of individual-based learning activities on math IRT scores suggests that students should review textbooks, class notes, and other useful math materials frequently. Namely, students themselves should make an effort to learn mathematics, beyond what is taught in the classroom. The efforts of students and teachers should be mutual to produce positive learning outcomes.

Although this study did not show significant effects of computer- and lecture-based learning activities on math IRT scores statistically, these learning activities have been found to be conceptually linked to individual-based learning activities; thus, they can potentially contribute to student math achievement scores. Supported by the pedagogical structure (Bransford et al., 1999, p.22), as previously addressed, a single learning activity cannot provide sufficient opportunities for students to improve learning outcomes. Teachers' lectures are definitely necessary for students to understand class notes, textbooks,

or math learning materials. Moreover, given the well-established literature on the positive relationship between math achievement scores and math self-efficacy (Hackett & Betz, 1989; Pajares & Miller 1994; Pajares & Graham, 1999), computer-based learning activities (which showed a positive association with math self-efficacy in this study) would contribute to increasing math achievement scores. Such potential connections among the learning activities confirm that a blend of diverse learning activities in math curricula with the inclusion of STEM contexts (e.g., computer-based learning activities) can lead to a positive learning outcome such as high enrollment in STEM disciplines in post-secondary institutions. In fact, STEM represents a closely intertwined group of professional fields. Therefore, curricula in any one STEM field could not be well developed without integrating with the others (National Research Council, 2009).

At the school-level, the significant and positive relationship between math teacher motivation and math achievement scores suggests that math teacher motivation, as a psychological trait, should be an important element of a highly qualified teacher. Teacher quality is often determined solely by considering qualifications, whereas psychological traits are often forgotten or neglected in many studies on teacher quality (Béteille & Loeb, 2009). As reviewed previously, teacher motivation level depends largely on school organizational contexts rather than teachers' characteristics, indicating that school-level support can play a major role in determining the level of an unobserved teacher credential – teacher motivation.

Professional development and school organizational contexts can enhance teacher motivation. Nathan et al. (2011) studied the effects of the professional development on teacher beliefs and expectations for the *Project Lead the Way* (PLTW). Nathan and colleagues found that teachers who participated in the professional development expressed higher beliefs and expectations, believing that (a) their pedagogy in science and math play an influential role in engineering fields; and that (b) it is necessary for schools to support students who are interested in STEM fields by providing diverse resources, such as internships, career days, and professional development opportunities. Considering the literature, which suggests that teacher expectations are an essential factor that drives teacher motivation (Eccles & Wigfield, 2002), such professional development is a useful instrument for improving teacher motivation. Importantly, without time, effort, and resource support by school principals, professional development cannot be cultivated in schools (Bryk, Camburn, & Louis, 1999). In addition to the principals' effort to support learning communities, the principals' leadership style (Davis & Wilson, 2000; Barnett & McCormick, 2003) and other organizational contexts (Kelley et al., 2002) are considered helpful factors that

can boost teacher motivation. Not only teacher qualifications per se, but also organizational school contexts play an influential role in determining teacher quality. Although the NCLB standards provide the definition of a highly qualified teacher, organizational contexts (e.g., principal leadership) can degrade teacher quality through supporting a negative school culture of de-motivating teachers.

Besides, the most positive effects of computer-based learning activities in math classroom on STEM major choices informs that non-traditional subjects such as engineering and technology courses can motivate students to prepare for a STEM career. Although many stakeholders agree that STEM contexts should be fully incorporated into the K-12 curriculum to allow students to learn STEM literacy, incorporating these STEM contexts into the curricula at the K-12 level is still in a developing stage (National Research Council, 2009).

Conclusion

All selected learning activities have positive effects on students' STEM major choices as mediated by either math self-efficacy or math performance. Markedly, computer-based learning activities were most likely to increase student math self-efficacy and contribute to students' STEM major selection. These results imply that a combination of various learning activities can optimize student learning gains. Although the extent of contribution and levels of significance of each selected learning activity have different effects on students' STEM major choices, it does not mean that the weakest or non-significant learning activity should be discouraged or neglected in math curricula. Likewise, the strongest and most significant learning activity is not meant to dominate all student learning processes. Fundamentally, the three learning activities relate to each other; therefore, a positive learning outcome can be achieved by synchronizing all three learning activities. In addition to the math instruction facilitated by math teachers, the intensity of students' engagement in these learning activities is essential for enhancing math self-efficacy and encouraging students to select STEM college majors. Beyond the math instruction itself, students should frequently participate in different learning activities.

In summary, a mutual effort between students and teachers should be made to maximize STEM learning outcomes. It is necessary for students to engage in diverse learning activities frequently to increase their math self-efficacy and math performance. Math teachers should develop the math curriculum with a special emphasis on integrating STEM contexts and traditional math learning instruction. Moreover, math teachers should be motivated to design an integrated math curriculum and implement it as a part of their regular instruction. Math teacher

motivation, which reflects math teachers' attention to students and teaching enthusiasm, can improve student math performance. Every student can be proficient in mathematics and identify potential and interest in STEM careers through his or her own efforts as well as teachers' academic support.

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Appendix A. STEM Categorization and Major Fields of Study in ELS 2002/06

STEM Categorization	ELS: 02/06
Mathematics	Mathematics and statistics
Agricultural/natural sciences	Agriculture/natural resources/related Science technologies/technicians
Physical sciences	Physical sciences
Biological sciences	Biological/biomedical sciences
Engineering/engineering technologies	Engineering technologies/technicians Mechanical/repair technologies
Computer/information sciences	Computer/information sciences/support technicians

Note. STEM categorization is adopted from “Statistics in brief (Chen & Weko, 2009)” published by the U.S. Department of Education.