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Why Students Choose STEM Majors: Motivation, High School Learning, and Postsecondary Context of Support

Xueli Wang
University of Wisconsin-Madison

This study draws upon social cognitive career theory and higher education literature to test a conceptual framework for understanding the entrance into science, technology, engineering, and mathematics (STEM) majors by recent high school graduates attending 4-year institutions. Results suggest that choosing a STEM major is directly influenced by intent to major in STEM, high school math achievement, and initial postsecondary experiences, such as academic interaction and financial aid receipt. Exerting the largest impact on STEM entrance, intent to major in STEM is directly affected by 12th-grade math achievement, exposure to math and science courses, and math self-efficacy beliefs—all three subject to the influence of early achievement in and attitudes toward math. Multiple-group structural equation modeling analyses indicated heterogeneous effects of math achievement and exposure to math and science across racial groups, with their positive impact on STEM intent accruing most to White students and least to underrepresented minority students.

KEYWORDS: STEM participation, college major choice, social cognitive career theory, multiple-group SEM

Introduction

Without question, America's ability to maintain its global competitiveness within science, technology, engineering, and mathematics (STEM) fields is an issue of national importance. Often framed in the context of human capital (National Science Board, 2010), discussions of the critical issues facing the nation's STEM infrastructure center on a recognized need

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XUELI WANG is an assistant professor in the Department of Educational Leadership and Policy Analysis at the University of Wisconsin-Madison, 270-H Education Building, 1000 Bascom Mall, Madison, WI 53706-1326; e-mail: *xwang273@wisc.edu*. Her research interests include participation in STEM fields of study and pathways and success of students beginning at community colleges.

for building STEM workforce capacity (National Academies 2005 "Rising Above the Gathering Storm" Committee, 2010). Support for this cause has been levied through investments in educational programming, many of which are focused on postsecondary education.

The demand for graduates in STEM fields continues to grow at a relatively rapid rate. According to the National Science Foundation (2010), the employment rate in science and engineering fields rose an average of 3.3% annually between 2004 and 2008 compared to an average 1.3% annual increase in employment in all occupations, and this estimated growth rate is consistent with long-term national trends (U.S. Department of Labor, 2007). By 2018, 9 of the 10 fastest growing occupations that require at least a bachelor's degree will depend on significant math or science training, and many science and engineering occupations are predicted to grow faster than the average rate for all occupations (Lacey & Wright, 2009; National Science Board, 2010).

These data document the need for greater participation of qualified college graduates in the STEM workforce. However, the supply side of the STEM pipeline still reports a serious shortage of students pursuing STEM disciplines (Fox & Hackerman, 2003). While the national demand for motivated students to enter postsecondary STEM fields is at its highest, high school seniors' interest in and readiness for pursuing these majors have been sluggish (ACT, 2006). American postsecondary institutions are therefore facing an unprecedented need to increase the number of students who study in STEM disciplines.

Of particular concern in the discussion on broadening STEM participation is the underrepresentation of racial minorities, women, and students of low socioeconomic status (SES; e.g., Anderson & Kim, 2006; Herrera & Hurtado, 2011; National Academies 2005 "Rising Above the Gathering Storm" Committee, 2010; National Science Foundation, 2006, 2010; Schultz et al., 2011). An overwhelming body of research has also suggested that underrepresented racial minorities, women, and students of low SES persist at lower rates in STEM fields of study than their White, male, and more socioeconomically advantaged counterparts (e.g., Bailyn, 2003; Blickenstaff, 2005; Kulis & Sicotte, 2002). It has been established that college majors create differential opportunities for social mobility and that college graduates from STEM fields attain higher occupational earnings and social status positions associated with these professions compared to many other fields (Russell & Atwater, 2005). In this sense, the differential participation rates in STEM fields are particularly detrimental because they adversely affect those underrepresented students' long-term social mobility, thus perpetuating socioeconomic inequality (Carter, 2006). Therefore, the shortage of these students successfully pursuing and completing studies in STEM disciplines continues to be a significant concern for educators, policymakers, and researchers alike.

Although these rising calls have generated a fair amount of empirical interest, most research concentrates on persistence and attainment among students who have already entered STEM fields. Not enough attention has been paid to factors relevant to interest in and entrance into STEM fields, which are arguably the first critical steps into the STEM pipeline. Given the previously discussed pressing concerns facing STEM education nationally, it is pivotal to provide rigorous academic programs and support mechanisms that prepare students, especially members of traditionally underrepresented groups, to enter these challenging and important fields of postsecondary study. Needless to say, this educational endeavor will rely on collective, concerted, and well-informed efforts by the nation's educational institutions. A decision to pursue a STEM major is a longitudinal process that builds during secondary education and carries into postsecondary studies. A full picture of this process is best realized through incorporating the effects of these two levels of education since they both shape students' entrance into STEM. Treating secondary and postsecondary education effects in isolation would severely limit the ability to fully make sense of this phenomenon. As such, theoretically based work from a holistic, K–16 perspective is needed to better understand boosters and barriers to students' entrance into STEM fields of study. Toward that end, a theoretical model of STEM participation is proposed and tested in this study focusing on both secondary and postsecondary factors. Particular attention is also given to the potentially varying effects of these factors among different student subpopulations by analyzing multiple-group structural equation models based on race, gender, and SES.

Background Literature and Theoretical Framework

Research on STEM Education

STEM education has garnered close scholarly attention. Numerous studies have revealed the disproportionately high attrition rates of women and minorities and the bachelor's degree completion gap in STEM disciplines at 4-year institutions across the nation (e.g., Anderson & Kim, 2006; Huang, Taddese, & Walter, 2000; Seymour & Hewitt, 1997). In addition to the gender and racial disparities in STEM persistence and completion, researchers also have highlighted theoretical reasons that students persist or leave a STEM field of study, such as early exposure to and proficiency in math and science (Adelman, 1998, 1999, 2006; Anderson & Kim, 2006); high school curriculum (Elliott, Strenta, Adair, Matier, & Scott, 1996); advanced courses in math and science (Ellington, 2006); information early in the career search process (Holland, 1992); the types of opportunities, experiences, and support students receive in college (e.g., M. J. Chang, Sharkness, Newman, & Hurtado, 2010; Seymour & Hewitt, 1997); institutional selectivity (M. J. Chang, Cerna, Han, & Sáenz, 2008; Eagan, 2009; Strayhorn, 2010); faculty quality and diversity (Brainard, Metz, & Gillmore, 1993; Leach, 2010); and classroom experiences (Cabrera, Colbeck, & Terenzini, 2001).

Despite the wealth of research on persistence and completion in STEM fields, less focus has been given to entrance into postsecondary STEM disciplines. Existing research does reveal that the choice to pursue STEM fields is affected by math- and science-related interest and self-assessment (e.g., Seymour & Hewitt, 1997), math and science completed during high school (e.g., Ethington & Wolfle, 1988; Maple & Stage, 1991), social background (Ware & Lee, 1988), and parental education (Gruca, Ethington, & Pascarella, 1988). The most comprehensive national study to date on students who enter STEM was conducted by Chen and Weko (2009). Utilizing three Institute of Education Sciences (IES) longitudinal data sets, the authors found that the percentage of students entering STEM fields was higher among male students, younger students, students financially dependent on family, Asian/Pacific Islander students, foreign students, or those who spoke a language other than English as a child, and students with more advantaged family background and stronger academic preparation than their counterparts. However, given the descriptive nature of the study, factors influencing STEM entrance beyond demographics were barely examined. Another recent study (Crisp, Nora, & Taggart, 2009) found that students' decisions to declare a STEM major and earn a STEM degree at a Hispanic-serving institution were influenced by their gender, ethnicity, SAT math score, and high school class rank percentile. Despite these commendable empirical efforts, relatively less is known at the national level about why students enter STEM fields.

Overall, research on STEM education represents substantial empirical efforts to form a better understanding of the underlying factors that influence student success along the STEM pipeline. Yet few academic studies using nationally representative samples have dealt with the very first step of STEM participation: why students enter STEM majors. The primary focus of existing studies based on national samples revolves around students who have already chosen a STEM major (e.g., M. J. Chang et al., 2008, 2010; Eagan, 2009). Furthermore, while abundant data exist to indicate the low enrollment and high attrition rates in STEM fields of racial minorities, women, and students of low SES, little is known in regard to how factors influencing STEM entrance work differently or similarly across these subgroups of students.

Aside from the imperative need for adding to the empirical knowledge base on STEM entrance, research in this vein also calls for a new theoretical framework that holistically and longitudinally captures supports and barriers to students choosing STEM majors. Indeed, as previously noted, a small body of research has looked at the issue of STEM enrollment, yet these studies either are heavily focused on secondary school and background influences (Maple & Stage, 1991; Tyson, Lee, Borman, & Hanson, 2007) or solely deal with the fit between postsecondary disciplinary environments and students' interests (Olitsky, 2012; Toker & Ackerman, 2012), often in isolation of each other. Although these studies are well grounded in prior literature, their theoretical considerations provide limited insight illustrating one or only a few aspects of the issue and do not explicitly account for the developmental and longitudinal nature of a student's interest in and decision to pursue a particular field of postsecondary study. In addition, important postsecondary supports and barriers such as financial aid, academic interaction, and remediation that could influence STEM entrance after students enroll in college are seldom addressed in those frameworks. Recognizing these research gaps and the lack of a comprehensive framework on STEM entrance in the literature, this study draws on a theoretical model with an intentional emphasis on the secondary-postsecondary nexus of the STEM pathway that accounts for the holistic and longitudinal nature of STEM entrance. A detailed discussion of this framework follows.

Theoretical Framework

The theoretical model (Figure 1) integrates the social cognitive career theory (SCCT) and prior literature on factors closely related to college students' academic choices and outcomes. In this model, students' intent to major in STEM is affected by their 12th-grade math achievement, exposure to math and science courses, as well as math self-efficacy beliefs, all of which are subject to the influence of prior achievement in and attitudes toward math. Students' STEM intent in turn affects their actual choice of STEM fields of study. In addition, entrance into STEM fields also is directly influenced by postsecondary context of supports and barriers. To be specific, postsecondary supports include academic interaction, financial aid, college readiness in math and science, graduate degree expectations, and enrollment intensity. Among postsecondary barriers are remediation (taking remedial courses in math, reading, and writing) and external demands such as having children and the number of work hours. A more detailed description of the model's theoretical grounding and supporting literature follows.

Based on Bandura's (1986) general social cognitive theory, SCCT underscores the interrelationship among individual, environmental, and behavioral variables that are assumed to undergird one's academic and career choice (Lent & Brown, 2006). Key factors in SCCT include self-efficacy beliefs, outcome expectations, interests, environmental supports and barriers, as well as choice actions (Lent, Sheu, Gloster, & Wilkins, 2010). SCCT offers an appropriate theoretical lens to study the issue of STEM choice (Lent, Brown, & Hackett, 1994, 2000) and has been applied in a small number of studies on STEM-related academic choice intentions (e.g., Betz & Hackett, 1983; Byars-Winston, Estrada, Howard, Davis, & Zalapa, 2010; Hackett, Betz, Casas, & Rocha-Singh, 1992; Lent, Lopez, & Bieschke, 1993; Lent, Lopez, Lopez, & Sheu, 2008). Although this set of studies suggests the validity of SCCT as an explanatory framework for understanding STEM interests

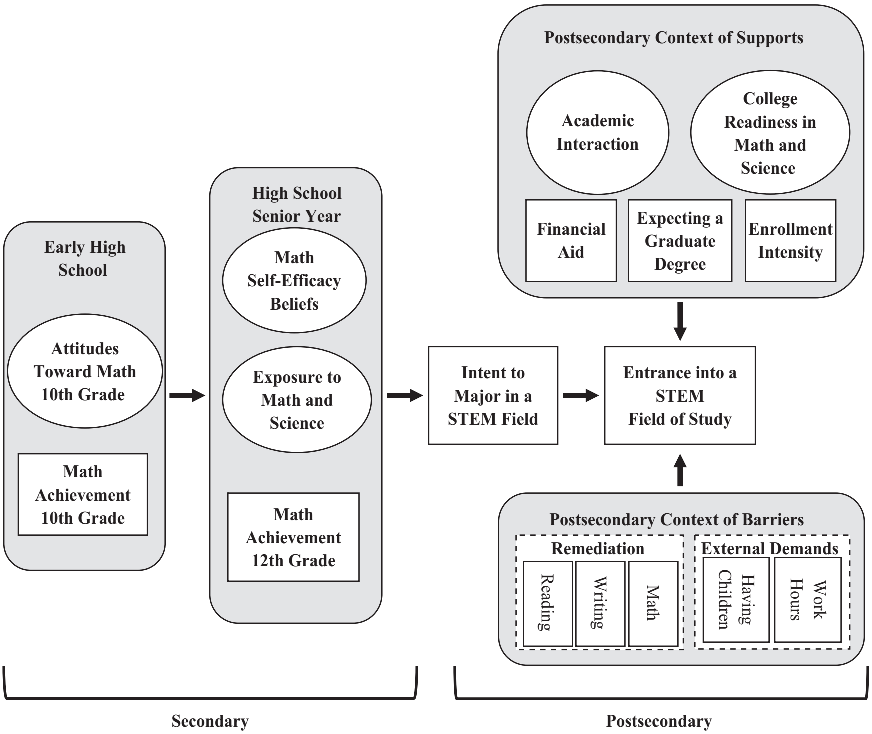

Figure 1. **Theoretical model for the study.**

and choices, they are largely limited by cross-sectional designs and single-institution data (Lent et al., 2010). Based on a national longitudinal database, this study incorporates the key constructs of SCCT to build a conceptual model of STEM participation and capture the nature of the relationships among the theoretical variables over time.

SCCT posits that determination to produce a particular choice can be explained as a result of interests and goals. Therefore, choosing a STEM major is hypothesized to be influenced by students' intent to pursue these fields upon postsecondary entry. Meanwhile, based on SCCT, interest in a choice action is subject to self-reference belief and learning experiences. Given the fundamental importance of early math experience in future STEM education (e.g., Adelman, 1999; Bowman, 1998; Marshall, McGee, McLaren, & Veal, 2011; National Science Board, 2004), STEM intent can thus be argued as a product of motivational attributes and learning as related to math at the secondary level. More specifically, this intent is related to high school seniors' math achievement, exposure to math and science courses, and math self-efficacy beliefs (i.e., individuals' confidence in their ability to successfully perform or accomplish math tasks or problems; Hackett & Betz, 1989; Pajares & Kranzler, 1995). Furthermore, these three elements are shaped by early math achievement and attitudes, especially in light of the longitudinal and developmental nature of achievement in and attitudes toward math (Eccles, 1994; Trusty, 2002).

SCCT also highlights the role of environmental supports and barriers in determining choice actions. In a postsecondary setting, students' pursuit of STEM as an academic goal responds to contextual supports and barriers—social, academic, or financial. Students transitioning into postsecondary education navigate a series of demands, such as the need for financial resources, academic integration into college, and various external demands. The outcomes of this process might present either supports or barriers and thus impact students' academic choice behavior. Therefore, the proposed conceptual model also includes a number of supports and barriers in this transition process, discussed in the following paragraphs.

Postsecondary supports are represented by academic interaction, college readiness in math and science, financial aid receipt, expecting a graduate degree, and enrollment intensity. Academic interaction between students and other college socialization sources, such as faculty and academic advisors, positively influences numerous student outcomes (Astin, 1993; J. C. Chang, 2005; Terenzini, Pascarella, & Blimling, 1999). Such interactions may provide necessary support for students to clarify and confirm their choice of major field of study. Also, as K–12 assessments are not always in perfect alignment with the academic requirements of postsecondary institutions (Goldrick-Rab, Carter, & Winkle-Wagner, 2007), once in college, students' perceptions of the extent to which their high school math and science courses have prepared them for college-level work may influence their decision to pursue STEM. Students who feel that they are college-ready in the areas of math and science may favorably consider a STEM major. In addition, the receipt of financial aid affects students' academic choices (e.g., DesJardins, Ahlburg, & McCall, 2006; Ishitani & DesJardins, 2002) and in particular may positively influence students' choice of a STEM major (Kienzl & Trent, 2009).

The conceptual model also includes enrollment intensity and graduate degree expectations. Enrollment intensity—whether students enroll full-time or less than full-time—often indicates the amount of time and psychological energy students devote to their educational experience (Wang, 2009) and is positively linked to a number of postsecondary outcomes (Berkner, Cuccaro-Alamin, & McCormick, 1996). Also, degree aspirations are strongly related to educational choices and outcomes (Carter, 2002; Pascarella & Terenzini, 2005; Wang, 2013). Although not necessarily providing direct, tangible structural support to STEM entrance, these two elements may indicate the level of students' psychological commitment to their studies and should be accounted for in understanding student entrance into STEM majors.

In regard to postsecondary barriers to STEM entrance, the proposed theoretical model includes remediation and external demands. For many students, remediation is a necessary part of the curriculum (Pascarella & Terenzini, 2005). However, research on the effect of enrolling in remedial courses has produced mixed results (Adelman, 1999; Bahr, 2008; Bailey & Alfonso, 2005; Long, 2005). In examining the relationship between remediation and student choice of STEM, this study will provide targeted, context-based research evidence regarding the effectiveness of remediation in sustaining students' academic aspirations. In addition, the external demands that students may need to deal with, for example, having dependent children and working long hours, may redirect them from pursuing challenging fields of study such as STEM. Together, these initial college experiences at students' first postsecondary institution are presumed to directly shape their decisions to pursue STEM fields of study.

As previously argued, sociodemographic differences are of critical importance in STEM-related research (Crisp et al., 2009), and persistent gender and racial gaps in the STEM pipeline remain (Anderson & Kim, 2006; Clewell & Campbell, 2002; Dowd, Malcom, & Bensimon, 2009). This warrants the need for STEM-related research to take such background differences into consideration. In this study, the proposed theoretical framework is assessed separately across racial, gender, and SES groups (more details provided in the methods and results sections of the article). This approach not only helps evaluate the framework's applicability across student subpopulations, but also illuminates how the proposed relationships in the model may differ based on race, gender, and SES.

Research Questions

Guided by the conceptual framework, this study examines the direct and indirect influences of high school exposure to math and science, achievement and motivational attributes as related to math, and initial postsecondary experiences on entrance into STEM fields of study in college. Specifically, this research addresses the following interlocking questions:

Research Question 1: What are the relationships among high school exposure to math and science, achievement and motivational attributes as related to math, intent to pursue STEM upon entry into postsecondary education, and entrance into STEM fields of study?

Research Question 2: Taking into account the relationships described in Question 1, how are students' initial postsecondary education experiences, such as academic interaction, receipt of financial aid, and remediation, related to STEM entrance?

Research Question 3: How do these relationships vary by race, gender, and SES?

Methods

Data Source and Sample

Data for this study came from the Education Longitudinal Study of 2002 (ELS:2002), which was designed to study the transition of young people from high school into postsecondary education and the workplace. ELS:2002 started with a nationally representative cohort of high school sophomores. The sample was then augmented in the first follow-up study in 2004 to represent high school seniors. In 2006, roughly 2 years after high school, the second follow-up study collected data on access to postsecondary institutions, choices of enrollment and college major, and other aspects of college experience. Given its focus on the transition from high school to postsecondary education, ELS:2002 was an appropriate data set for this study. To fully understand student learning, motivation, interest, and choice as related to STEM majors, it is necessary to follow the same individuals from secondary to postsecondary education. The longitudinal data from ELS:2002 provided a thorough empirical description of student experiences relevant to STEM education in high school and early years of college. (For complete information on ELS:2002, see http://nces.ed.gov/surveys/els2002/.)

This study focused on the spring 2004 high school graduates who had enrolled in a postsecondary institution by 2006. Of approximately 14,000 members of the 2004 senior cohort, about 12,500 (89.3%) responded to the second follow-up interview. For the purpose of this study, an initial total of 6,300 (out of 12,500 eligible) students who reported postsecondary attendance at a 4-year institution by 2006 were retained. Among these students, roughly 19.3% intended to major in STEM upon entering college while 80.7% were interested in other fields of study; 15.4% (out of all 6,300 4-year enrollees) declared a major in a STEM field by 2006, compared to 84.6% who chose other disciplines or had not declared a major. All analyses were weighted using the appropriate ELS panel weight (F2F1WT).

Measures

This section summarizes variables that were included in the study based on the theoretical model. The main outcome, entrance into STEM, was a dichotomously coded variable based on the survey item that asked respondents' field of study during the 2006 ELS second follow-up interview. The focal mediating variable was intent to pursue a STEM field, measured by whether the most likely postsecondary field of study students considered upon postsecondary entry was in a STEM discipline.

Five variables at the secondary school level were included:[1] (a) exposure to math and science courses, measured by the number of units in mathematics and science technologies that students took; (b) 12th-grade math achievement, measured by math standardized test scores at the 12th grade;[2]

(c) 12th-grade math self-efficacy beliefs, measured by five items—each on a 4-point Likert scale—that represented students' self-efficacy beliefs in areas such as taking math tests, mastering math skills, and completing math assignments; (d) 10th-grade math achievement, measured by math standardized test scores at the 10th grade (see Note 2); and (e) 10th-grade attitudes toward math, measured by three items—each on a 4-point Likert scale—that represented students' perceived enjoyment and importance of math.

Although these variables measured during high school offered some insight into student learning in math and science, they did not indicate fully how well such learning prepared students for college-level work. To provide a more comprehensive picture that went beyond course-taking and achievement, a latent variable at the college level was included that measured college readiness in math and science: the extent to which college students believed that their high school math and science courses prepared them for college-level work.

Also included to represent postsecondary context of supports and barriers were: academic interaction, receipt of financial aid, enrollment intensity, graduate degree expectations, remediation, and external demands. Academic interaction was measured by the frequency of interacting with faculty about academic matters, meeting with advisors about academic plans, and working on coursework at school libraries. Receipt of financial aid was a dichotomous variable based on students' first-year aid status. Enrollment intensity was measured by a dichotomous variable indicating whether students' college enrollment was full-time or not. Similarly, the variable measuring graduate degree expectations was dichotomous: coded 1 if students expected to earn a graduate degree and 0 otherwise. Remediation included three dichotomous variables: whether students took remedial courses to improve reading, writing, and math skills. Representing external demands were (a) one dichotomous variable measuring whether students had dependent children and (b) a continuous variable measuring the average number of weekly hours students worked for pay. Table 1 lists the names, descriptions, and ELS labels of all variables used in the study. In the table, each latent construct and its corresponding indicators also are specified.

Analysis

Descriptive Analysis

First, descriptive statistics were computed and disaggregated by the sample's background characteristics. These descriptive statistics provided a general profile of the ELS 2004 high school senior cohort's participation in STEM fields of study 2 years after high school graduation, and helped identify any variation in STEM intent and entrance across sociodemographic variables.

Table 1
List of Variables in the Study

Variable Name	Description	Education Longitudinal Study Label
Endogenous variable		
Entrance into STEM fields of study (STEM)	Respondent's 2006 major field of study is in STEM fields; 1 = yes, 0 = no	Recoded from F2MAJOR2
		F2MAJOR4
Mediating variable		
Intent to major in a STEM field (INTENT)	Field of study respondent would most likely pursue when beginning at the first postsecondary institution is in STEM fields; 1 = yes, 0 = no	Recoded from F2B15
12th-grade math achievement	High school senior math standardized score	F1TXMSTD
12th-grade math self-efficacy beliefs[a]	Can do excellent job on math tests	F1S18A
	Can understand difficult math texts	F1S18B
	Can understand difficult math class	F1S18C
	Can do excellent job on math assignments	F1S18D
	Can master math class skills	F1S18E
	Items based on 4-point Likert scales with 4 indicating *almost always* and 1 indicating *almost never*	
High school exposure to math and science courses[a]	Units in mathematics from high school transcript	F1RMAT_C
	Units in science from high school transcript	F1RSCI_C

(continued)

Table 1 **(continued)**

Variable Name	Description	Education Longitudinal Study Label
Exogenous variable		
10th-grade math attitudes[a]	Gets totally absorbed in math	BYS87A
	Thinks math is fun	BYS87C
	Mathematics is important	BYS87F
	Items based on 4-point Likert scales with 4 indicating *strongly agree* and 1 indicating *strongly disagree*	
10th-grade math achievement	High school sophomore math standardized score	BYTXMSTD
Postsecondary context of supports and barriers		
Academic interaction[a]	Talk with faculty about academic matters outside of class	F2B18A
	Meet with advisor about academic plans	F2B18B
	Do coursework at library	F2B18C
	Items based on 3-point scales with 3 indicating *often* and 1 indicating *never*	
College readiness in math and science[a]	High school math prepared for college	F2B17A
	High school science prepared for college	F2B17B
	Items based on 3-point scales with 3 indicating *a great deal* and 1 indicating *not at all*	
Financial aid receipt	Offered financial aid first year at college; 1 = yes, 0 = no	F2PS1AID
Enrollment intensity (FULLTIME)	1 = full-time, 0 = less than full-time	Recoded from F2PSIFTP
Expecting to earn a graduate degree (GRADEXP)	Whether respondent expected to earn a graduate degree; 1 = yes, 0 = no	Recoded from F2STEXP
Remediation	Took remedial reading; 1 = yes, 0 = no	F2B16A

(continued)

Table 1 **(continued)**

Variable Name	Description	Education Longitudinal Study Label
	Took remedial writing; 1 = yes, 0 = no	F2B16B
	Took remedial math; 1 = yes, 0 = no	F2B16C
External demands	Whether has biological children; 1 = yes, 0 = no	F2D03
	Hours worked weekly (WRKHRS)	F2C26R
		F2C31R
Demographic variables		
Race	Underrepresented minorities, Asian American, and White	Recoded from F1RACE
Socioeconomic status (SES)	The SES variable is quartile coding of the composite variable measuring SES in ELS:2002. This composite variable was constructed based on five equally weighted, standardized components: father's/guardian's education, mother's/guardian's education, family income, father's/guardian's occupation, and mother's/guardian's occupation (Source: ELS:2002 Electronic Codebook).	F1SES1QR
Gender	Respondent's gender (male or female)	F1SEX

[a] A latent variable.

Confirmatory Factor Analysis

Following the descriptive analysis, a two-step modeling approach was adopted. First, the measurement part of the model was examined. If the measurement model was acceptable, then the full structural equation model was analyzed where the measurement and structural parts of the model were simultaneously estimated (Kline, 2011).

A confirmatory factor analysis (CFA) was performed to analyze the proposed measurement model that explicitly specified the latent factors and their corresponding indicator items (Figure S1 in the online version of the journal). Five latent constructs were measured: 10th-grade attitudes toward math, 12th-grade math self-efficacy, high school exposure to math and science, college readiness in math and science, and academic interaction. At this step, fit statistics of the measurement model were assessed, and convergent validity was checked by examining the standardized factor loadings—the estimated correlations between individual factors and their corresponding indicators (Kline, 2011). In addition, multiple-group CFA were performed to evaluate whether the measurement model held across subsamples.

Structural Equation Modeling

Following CFA, the proposed conceptual model was tested using structural equation modeling (SEM). Figure 2 is a depiction of the structural part of the SEM diagram based on the theoretical model.

In mathematical form, the path structure in this study was postulated by five simultaneously estimated regression equations. The first three equations examined how 12th-grade math self-efficacy, exposure to math and science, and 12th-grade math achievement were each influenced by 10th-grade math achievement and attitudes toward math. The fourth equation investigated how students' intent to major in STEM was affected by 12th-grade math self-efficacy, exposure to math and science, and 12th-grade math achievement. The final regression equation examined how students' decisions to enter into STEM fields of postsecondary study were affected by their intent to major in STEM fields, college readiness in math and science, and postsecondary context of supports and barriers (e.g., academic interaction, receipt of financial aid, expectation of graduate degree, enrollment intensity, remediation experience, and external demands). Moreover, students' 12th-grade math achievement was included in the final equation because math ability might have a direct effect on students' eventual entrance into STEM fields.[3] In addition, given the strong relationship between math achievement and math self-efficacy (Pajares, 1996; Pajares & Kranzler, 1995; Pajares & Miller, 1994), the SEM model specified that these two 12th-grade variables were correlated and this relationship was accounted for in the SEM analysis by estimating the residual covariance between these two variables.[4]

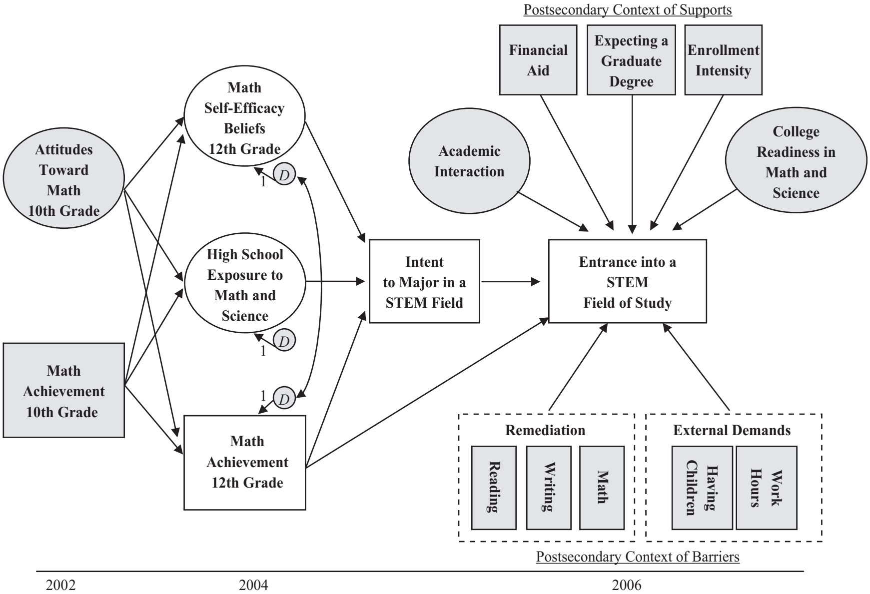

Figure 2. **Diagram of proposed structural model for the structural equation modeling analysis.**

Note. To conserve space, the measurement part of latent factors (depicted as circles in Figure 2) is omitted from the path structural diagram. Exogenous variables are shaded; others are endogenous variables. Note that endogenous variables, 12th-grade math self-efficacy, exposure to math and science, math achievement, and STEM intent, serve as both a dependent and an independent variable. *D* = disturbance term of the corresponding endogenous variable.

The analyses were conducted using M*plus* 6.1, a statistical software package capable of SEM analysis that uses a mixture of different types of variables (Kaplan, 2009; Kupek, 2006; Muthén & Muthén, 1998–2010). In addition, M*plus* contains statistical tools that accommodate complex survey design features such as survey weights and the clustering nature of ELS:2002. Given the binary nature of the outcome variable in the fourth and fifth equations previously described, probit regression models were conducted for those two regression equations using the weighted least square with adjustment in mean and variance (WLSMV) estimator. When using the WLSMV estimator, the difference in chi-square values is not distributed as chi-square, so the DIFFTEST option in M*plus* was used to obtain a correct chi-square difference test between the baseline and nested models (Muthén & Muthén, 1998–2010, p. 553).

Following Byrne (1998), the following fit indices were used to assess overall model fit: chi-square (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Fit Index (TLI), and root mean square error of approximation (RMSEA).

Multiple-Group Analysis: Testing for Structural Invariance

Following the full-sample SEM analysis, multiple-group analyses were employed to examine whether the hypothesized model was equivalent across subgroups. Specifically, this part of the study drew upon three sets of analyses respectively based on race (Whites, Asians, and underrepresented minorities[5]), gender (females and males), and SES (quartiles) and tested for structural weight invariance across subgroups within each of these three sociodemographic categories. Because this study focused on the structural pattern of the model (i.e., the underlying mechanism affecting students' entrance into STEM fields of study), the model invariance tests concentrated on the equivalence of structural path parameters across different groups.

To illustrate, in the gender-based multiple-group analysis, a baseline model was first fitted—a multiple-group model with only factorial equality constraints across gender, where the structural weights (i.e., regression coefficients) were freely estimated across the male and female groups. Then, another multiple-group model was estimated with cross-group constraints where all structural weights across males and females were constrained to be equal. Next, a structural invariance test was conducted based on the corrected chi-square difference ($\Delta\chi^2$) test that compared the baseline model with the constrained-equal model. Through this test, if the corrected chi-square difference statistic did not reveal a significant difference between the models, then it would be concluded that the model had structural weight invariance across gender groups. However, if non-invariance was indicated by a significant $\Delta\chi^2$ statistic, then structural weights (i.e., regression coefficients) were gradually constrained to be equal across gender groups to determine whether group differences could be attributable to any of the structural weights. If any constrained parameters (i.e., structural weights) were found to be gender-invariant as suggested by insignificant $\Delta\chi^2$ statistics, then they would be constrained, cumulatively, in subsequently more restrictive models. On the contrary, a significant $\Delta\chi^2$ statistic would suggest that the given parameter was not equivalent across gender groups; therefore, it would be freely estimated in the subsequent models for invariance tests (Byrne, 2010; Kline, 2011). Race- and SES-based multiple-group analyses were carried out in the same fashion.

Indirect Effects

In this study, intent to major in STEM served as a mediator variable that transmitted the effects of variables at the secondary level onto entrance into STEM majors. In addition, 12th-grade math self-efficacy, exposure to math and science, and math achievement were hypothesized to mediate the influence of 10th-grade math achievement and attitudes toward math on intent to major in STEM. These indirect paths from high school variables to STEM intent and to STEM entrance were estimated and the associated indirect effects were calculated and tested for statistical significance using M*plus*'s MODEL INDIRECT command.

Missing Data

As is common with survey research, some of the variables included in the study had missing data. In this study, M*plus*'s full information maximum likelihood (FIML) estimation was applied to handle missing data for the variables that were treated as dependent by the software. Listwise deletion was used to deal with the missingness in the exogenous observed variables. Before performing listwise deletion, the data set that contained cases to be deleted was compared with the data set that included cases not subject to listwise deletion. It was observed that the distributions of variables in both were quite similar. As a result, about 660 cases were removed from the analysis, resulting in the final analytic sample size of about 5,650.

Results

Descriptive statistics are presented in Table 2 to provide a comprehensive picture of entrance into STEM majors based on student background characteristics. The sample's correlation matrices and means and standard deviations for each measure are provided in Tables S2-S5 in the online version of the journal. A discussion of the CFA and SEM model fit and the results from multiple-group analyses follows. This section concludes with a description of the substantive results in light of the three research questions.

Results of Confirmatory Factor Analyses

The CFA analyses based on the whole sample as well as on racial, gender, and SES subsamples indicated that the measurement model fit the data well.[6] RMSEA values in all models were well below the .05 cut-off point and their 90% confidence interval upper bounds were all below .08, indicating a good fit (Hooper, Coughlan, & Mullen, 2008; MacCallum, Browne, & Sugawara, 1996). CFI and TLI values were all above .95, again suggesting a good fit (Schreiber, Stage, King, Nora, & Barlow, 2006). All of the standardized factor loadings were above .4 and significant at $p < .001$, suggesting good convergent validity of the measurement model (Kline, 2011). These fit indices and factor loadings are presented in Table S1 in the online journal.

Results of Multiple-Group SEM Analyses

Prior to multiple-group analyses, the SEM model was analyzed based on the whole sample, and fit indices suggested excellent model-to-data fit (line

Table 2

Descriptive Statistics of Demographic Characteristics of the Sample, Unweighted and Weighted

	Total *N*		STEM Intent (2004)				STEM Entrance (2006)			
			Intended to Major in STEM		Did Not Intend		Declared a STEM Major		Did Not Declare a STEM Major	
	N	Wtd *N*	*N* (%)	Wtd *N* (%)	*N* (%)	Wtd *N* (%)	*N* (%)	Wtd *N* (%)	*N* (%)	Wtd *N* (%)
Total	6,300	1,560,050	1,220 (19.3)	302,860 (19.4)	5,090 (80.7)	1,257,180 (80.6)	970 (15.4)	240,670 (15.4)	5,330 (84.6)	1,319,370 (84.6)
Gender										
Female	3,440	851,200	370 (10.9)	92,630 (10.9)	3,060 (89.1)	758,580 (89.1)	350 (10.2)	87,320 (10.3)	3,080 (89.8)	763,880 (89.7)
Male	2,870	708,840	840 (29.3)	210,240 (29.7)	2,030 (70.7)	498,610 (70.3)	620 (21.6)	153,360 (21.6)	2,250 (78.5)	555,490 (78.4)
Race/ethnicity										
White	4,050	996,660	720 (17.7)	183,290 (18.4)	3,340 (82.3)	813,370 (81.6)	560 (13.9)	143,360 (14.4)	3,490 (86.1)	853,300 (85.6)
Asian	750	181,240	200 (26.7)	44,300 (24.4)	550 (73.3)	136,940 (75.6)	180 (24.0)	42,220 (23.3)	570 (76.0)	139,020 (76.7)
Underrepresented minorities										
Black	660	166,090	140 (20.8)	35,170 (21.2)	530 (79.2)	130,920 (78.8)	110 (17.2)	30,840 (18.6)	550 (82.8)	135,250 (81.4)
Hispanic	520	135,480	100 (18.7)	25,860 (19.1)	430 (81.3)	109,620 (80.9)	70 (12.8)	14,470 (10.7)	460 (87.2)	121,000 (89.3)
American Indian	30	6,920	10 (25.0)	1,390 (20.0)	20 (75.0)	5,540 (80.0)	0 (7.1)	240 (3.5)	30 (92.9)	6,680 (96.5)
Multiracial	280	73,660	50 (18.5)	12,870 (17.5)	230 (81.5)	60,800 (82.5)	40 (14.9)	9,540 (13.0)	240 (85.1)	64,120 (87.0)
Socioeconomic status										
Lowest quartile	700	173,830	160 (22.2)	37,250 (21.4)	550 (77.8)	136,580 (78.6)	90 (12.4)	20,150 (11.6)	620 (87.6)	153,680 (88.4)
Second quartile	1,050	268,580	180 (17.4)	47,940 (17.9)	870 (82.6)	220,640 (82.1)	140 (13.0)	34,610 (12.9)	910 (78.0)	233,970 (87.1)
Third quartile	1,620	398,640	270 (16.8)	69,080 (17.3)	1,350 (83.2)	329,560 (82.7)	230 (14.2)	56,240 (14.1)	1,390 (85.8)	342,400 (85.9)
Highest quartile	2,930	719,000	600 (20.6)	148,590 (20.7)	2,320 (79.4)	570,410 (79.3)	520 (17.6)	129,670 (18.0)	2,410 (82.4)	589,330 (82.0)

Note. The analytical *N*s are rounded to the nearest 10 according to Institute of Education Sciences (IES) guidelines. The sum of subgroups may not equal to the total in the table due to rounding. Wtd = weighted.

1 of Table 3). Multiple-group SEM analyses were then conducted for racial, gender, and SES groupings. Three sets of statistics and model fit indices were derived from this series of analyses and are presented in Table 3. For example, in the race-based multiple-group analysis, the hypothesized model was initially fitted to the White, Asian, and underrepresented minority (URM) samples separately. The fit statistics for the White-only model were $\chi^2(275)$ = 1,063.85, relative χ^2 = 3.87, CFI = 0.980, TLI = 0.977, RMSEA = 0.028 (line 2 of Table 3); Asian fit statistics were $\chi^2(275)$ = 417.67, relative χ^2 = 1.52, CFI = 0.974, TLI = 0.970, RMSEA = 0.028 (line 3); and URM fit statistics were $\chi^2(275)$ = 528.44, relative χ^2 = 1.92, CFI = 0.978, TLI = 0.975, RMSEA = 0.026 (line 4). The fit indices suggested that the model fit each racial group well. Thus, all racial groups were combined together and simultaneously fitted to the data to become the multiple-group baseline model.

The racial multiple-group baseline model also fit the data well: $\chi^2(881)$ = 1,987.54, relative χ^2 = 2.26, CFI = 0.979, TLI = 0.978, RMSEA = 0.026 (line 5). In the next step, all of the 21 structural weights (i.e., regression coefficients) were constrained equally across racial groups to examine structural weight invariance across racial groups. The result of the corrected chi-square difference test was statistically significant ($p < .05$), which suggested that one or more of the parameters were non-invariant across racial groups (line 6). Thus, instead of constraining these 21 parameters all at once, parameters were constrained one by one to identify the source of non-invariance found in the previous step. When the regression coefficient for the path from *10th-grade math achievement* to *12th-grade math self-efficacy* was constrained equal across racial groups, the result of the corrected chi-square difference test was statistically significant, meaning that the regression coefficient of this path was one of the sources of structural non-invariance across racial groups (line 7). Similarly, non-invariance was found when the regression coefficient for the following paths was constrained equally across racial groups: from *exposure to math and science* to *intent to major in STEM* (line 8) and from *12th-grade math achievement* to *intent to major in STEM* (line 9).

Furthermore, steps were taken to identify precisely where the non-invariance of these three structural weights existed between specific pairings of racial groups by performing partial constraints (i.e., selecting only two of the three racial groups to be constrained equal at a time). Non-invariance was found for all three pairs of comparison: White and Asian, Asian and URM, and URM and White. Therefore, all three structural weights were freely estimated across all racial groups in the model. Subsequent invariance tests showed that there was no structural non-invariance caused by the remaining 18 structural weights.

The middle and lower sections of Table 3 display the model fit statistics and multiple-group structural invariance test results for gender and SES groupings, respectively. No structural non-invariance was found in the

Table 3

Racial, Gender, and Socioeconomic Status (SES) Multiple-Group Structural Weight Invariance Tests

	Model	Description	χ^2 (*df*)	Relative χ^2 (χ^2/df)	Corrected $\Delta\chi^2(\Delta df)$	Comparative Fit Index	Tucker-Lewis Fit Index	Root Mean Square Error of Approximation
1	Single-group structural equation modeling (n = 5,650)		1,383.23 (275)	5.03	—	.982	.979	.027
	Racial groups							
2	White		1,063.85 (275)	3.87	—	.980	.977	.028
3	Asian		417.67 (275)	1.52	—	.974	.970	.028
4	Underrepresented minorities		528.44 (275)	1.92	—	.978	.975	.026
5	Baseline (factorial constrained)		1,987.54 (881)	2.26	—	.979	.978	.026
6	All structural weights constrained	21 coefficients	2,002.84 (923)	2.17	75.05 (42)**	.980	.979	.025
7	Constrained *10th-grade math achievement* ⟶ *12th-grade math self-efficacy*	1 coefficient	1,990.68 (883)	2.25	8.28 (2)*	.979	.978	.026
8	Constrained *Exposure to math and science* ⟶ *Intent to major in STEM*	1 coefficient	2,002.60 (883)	2.27	4.00 (2)***	.979	.978	.026
9	Constrained *12th-grade math achievement* ⟶ *Intent to major in STEM*	1 coefficient	1,991.43 (883)	2.26	7.57 (2)*	.979	.978	.026
10	All other 18 weights constrained (FINAL MODEL)	18 coefficients	1,979.15(917)	2.16	35.39 (36)	.980	.980	.025
	Gender groups							
11	Male		795.27 (275)	2.89	—	.981	.978	.027
12	Female		863.54 (275)	3.14	—	.981	.978	.026
13	Baseline (factorial constrained)		1,681.42 (578)	2.91	—	.981	.979	.026
14	All structural weights constrained	21 coefficients	1,671.16 (599)	2.79	28.79 (21)	.982	.981	.025
	SES groups							
15	SES first quartile		392.94 (275)	1.43	—	.974	.970	.026
16	SES second quartile		472.17 (275)	1.72	—	.978	.975	.028
17	SES third quartile		573.71 (275)	2.09	—	.981	.978	.027
18	SES fourth quartile		781.25 (275)	2.84	—	.983	.980	.026
19	Baseline (factorial constrained)		2,291.35 (1,184)	1.94	—	.981	.980	.026
20	All structural weights constrained	21 coefficients	2,308.68 (1,247)	1.85	71.40 (63)	.982	.981	.025

Note. A significant $\Delta\chi^2$ value indicates that the estimate is non-invariant across groups.
*$p < .05$. **$p < .01$. ***$p < .001$.

multiple-group analyses based on gender and SES, which indicated that the hypothesized model can be operated equally across different subgroups within gender or SES.

Final SEM Model

Through these detailed analyses, it became clear that a multiple-group model based on race, where the paths from *10th-grade math achievement ⟶ 12th-grade math self-efficacy, exposure to math and science courses ⟶ intent to major in STEM*, and *12th-grade math achievement ⟶ intent to major in STEM* were freely estimated for all racial groups while all other structural weights were constrained equal, was the most reasonable and viable model. This final model fit the data, χ^2 (917) = 1,979.15, relative χ^2 = 2.16, CFI = 0.980, TLI = 0.980, RMSEA = 0.025, and was slightly better in fit than the baseline model. As for the parameter estimates, Table 4 displays the direct and indirect effect estimates (both unstandardized and standardized) from this final multiple-group model based on race. Changes in predicted probabilities (CP) are also reported for significant coefficients in equations modeling *STEM intent* and *STEM entrance*.

Figure 3 presents the final model with statistically significant paths highlighted, and the coefficient estimates are also denoted along with the paths.

The following summarizes specific results from the final model by addressing the questions pursued in this study.

> *Research Question 1:* What are the relationships among high school exposure to math and science, achievement and motivational attributes as related to math, intent to pursue STEM upon entry into postsecondary education, and entrance into STEM fields of study?

Intent to pursue STEM was significantly and positively influenced by 12th-grade math self-efficacy, the effect of which remained the same among all subgroups. The effect of high school exposure to math and science on STEM intent was statistically significant and positive across all racial groups, but was the smallest among underrepresented minority students. Math achievement at the 12th grade was positively associated with intent to pursue STEM fields among White students and underrepresented minorities, but was null for Asian students.

Through intent to major in STEM, all three 12th-grade variables also indirectly and positively affected actual choice of STEM majors after college entry, except that 12th-grade math achievement did not show any significant indirect effect among Asian students. Furthermore, 12th-grade math achievement showed a significant direct effect on STEM entrance. Also, it should be noted that all three 12th-grade variables were significantly and positively influenced by 10th-grade math achievement and attitudes, both of which exerted significant indirect effects on STEM intent and STEM entrance.

Table 4

Unstandardized and Standardized Estimates of Direct and Indirect Effects: Final Structural Equation Modeling (SEM) Model

	White				Asian				URM			
Model and Effect	Unstandardized	*SE*	Standardized	***CP***[a]	Unstandardized	*SE*	Standardized	***CP***[a]	Unstandardized	*SE*	Standardized	***CP***[a]
Direct effects												
Math self-efficacy beliefs ON												
10th-grade attitudes toward math	0.737***	.064	.377		(=)		.420		(=)		.437	
10th-grade math achievement	0.073***	.007	.281		.044**	.014	.232		.066***	.010	.319	
Exposure to math and science ON												
10th-grade attitudes toward math	0.175***	.018	.407		(=)		.326		(=)		.350	
10th-grade math achievement	0.015***	.002	.271		(=)		.270		(=)		.252	
12th-grade math achievement ON												
10th-grade attitudes toward math	0.893***	.101	.118		(=)		.098		(=)		.112	
10th-grade math achievement	0.810***	.010	.807		(=)		.836		(=)		.833	
Intent to major in STEM ON												
Math self-efficacy beliefs	0.101***	.021	.154	.034	(=)		.153	.027	(=)		.169	.036
Exposure to math and science	1.398***	.174	.468	.515	.838***	.235	.386	.287	.331**	.118	.164	.124
12th-grade math achievement	0.029***	.006	.169	.010	.008	.008	.061		.016*	.007	.127	.006
STEM entrance ON												
Intent to major in STEM	1.120***	.072	.764	.331	(=)		.701	.325	(=)		.723	.410
12th-grade math achievement	0.017***	.005	.069	.003	(=)		.083	.003	(=)		.087	.007
Academic interaction	0.131**	.050	.072	.024	(=)		.092	.023	(=)		.097	.051
College readiness in math and science	0.167***	.051	.132	.032	(=)		.294	.031	(=)		.110	.065
Financial aid receipt	0.308**	.102	.077	.043	(=)		.074	.041	(=)		.081	.111
Graduate degree expectation	0.385***	.100	.104	.051	(=)		.101	.048	(=)		.114	.137
Full-time enrollment	–0.135	.285	–.013		(=)		–.013		(=)		–.020	
Remedial reading	–0.084	.170	–.016		(=)		–.020		(=)		–.018	
Remedial writing	–0.131	.160	–.030		(=)		–.035		(=)		–.033	
Remedial math	0.070	.148	.016		(=)		.018		(=)		.019	

(continued)

Table 4 **(continued)**

Model and Effect	White Unstandardized	White *SE*	White Standardized	White ***CP***[a]	Asian Unstandardized	Asian *SE*	Asian Standardized	Asian ***CP***[a]	URM Unstandardized	URM *SE*	URM Standardized	URM ***CP***[a]
Having dependent children	–0.332*	.163	–.050	–.045	(=)		–.053	–.043	(=)		–.059	–.119
Hours worked weekly	–0.001	.006	–.005		(=)		–.004		(=)		–.005	
Indirect effects												
STEM ←Intent ← Efficacy	0.113***	.024	.118		(=)		.107		(=)	.024	.122	
STEM ←Intent ← Exposure math/ science	1.567***	.195	.358		.947***	.269	.273		.371**	.134	.119	
STEM ←Intent ← Math achievement (12th)	0.032***	.007	.129		.009	.009	.042		.018*	.008	.092	
STEM ←Intent ← ○ ←Math attitudes (10th) (sum)	0.385***	.045	.205		.256***	.050	.138		.164***	.030	.105	
via ○ Efficacy	0.083***	.018	.044		(=)		.045		(=)	.018	.053	
via ○ Exposure	0.274***	.038	.146		.165***	.049	.080		.065**	.024	.041	
via ○ Math achievement (12th)	0.029***	.007	.015		.008	.008	.004		.016*	.007	.010	
STEM ←Intent ← ○ ← Math achievement (10th) (sum)	0.058***	.006	.234		.026***	.007	.134		.028***	.007	.145	
via ○ Efficacy	0.008***	.002	.033		.005**	.002	.025		.007***	.002	.039	
via ○ Exposure	0.024***	.004	.097		.015***	.004	.074		.006**	.002	.030	
via ○ Math achievement (12th)	0.026***	.005	.104		.007	.007	.035		.015*	.006	.077	
Intent ← Efficacy ←Math attitudes (10th)	0.075***	.016	.058		(=)		.064		(=)		.074	
Intent ← Efficacy← Math achievement (10th)	0.007***	.001	.043		.004**	.002	.036		.007***	.002	.054	
Intent ← Exposure ←Math attitudes (10th)	0.244***	.034	.191		.146***	.042	.126		.058**	.021	.057	
Intent ← Exposure ← Math achievement (10th)	0.022***	.003	.127		.013***	.004	.104		.005**	.002	.041	

(continued)

Table 4 **(continued)**

Model and Effect	White				Asian				URM			
	Unstandardized	*SE*	Standardized	***CP***[a]	Unstandardized	*SE*	Standardized	***CP***[a]	Unstandardized	*SE*	Standardized	***CP***[a]
Intent ← Math achievement (12th)←Math attitudes (10th)	0.026***	.006	.020		.007	.007	.006		.014*	.006	.014	
Intent ← Math achievement (12th)← Math achievement (10th)	0.023***	.005	.136		.006	.006	.051		.013*	.006	.106	

Note. URM = underrepresented minorities; (=) = estimate constrained equal across groups. Two out of the five models depicted in this table have a dichotomous outcome variable: intent to major in STEM (1 = intend to major in STEM, 0 = did not intend to major in STEM) and STEM entrance (1 = entered into a STEM major, 0 = did not enter into a STEM major). For these two equations, probit models were conducted in M*plus*. Although the probit regression coefficients obtained from these analyses can show whether a particular independent variable has a positive or negative effect on the probability that the dependent variable (e.g., intent to major in STEM) takes the value of 1, these coefficients are not as intuitive as those of a linear regression. To translate the probit regression coefficients to probability values, the following formula (Muthén & Muthén, 1998–2010) was adopted:

$$P(y=1|X)=F(a+b*X)=F(-t+b_1*x_1+b_2*x_2+\ldots),$$

where F is the standard normal distribution function, a is the probit regression intercept, $\mathbf{b}$ is the probit regression coefficients, t is the probit threshold, and $t = -a$. Building upon this formula, to present probit estimates more intuitively, Table 4 includes change in predicted probability for each significant probit regression coefficient in the STEM intent and STEM entrance models. This value was obtained through the following steps: First, compute P (y = 1 | $\mathbf{x}$) with all continuous independent variables set to their mean values and discrete independent variables set to their mode values to represent a typical case for a student. Then, to determine the impact of a unit change in a continuous independent variable x_j on P (y = 1), x_j is set equal to $\bar{x}+1$, and P (y = 1 | $\mathbf{x}$) is recomputed with all other independent variables held at the same values as in the typical case (i.e., other things being equal). The first probability value is then subtracted from the second probability value, and this difference is the impact of a unit change in x_j when all other independent variables are held at their mean or mode values. For the binary independent variables in the models (e.g., financial aid receipt and expecting a graduate degree), the procedures are similar except that the binary x_j variable is set to 0 in the first step and then to 1 in the second step.

[a]CP = change in probability (when outcome = 1), calculated with all other independent variables set to their mean (for continuous variables) or mode (for discrete variables) value and reported for statistically significant direct effects in the intent to major in STEM and STEM entrance models only.

*$p < .05$. **$p < .01$. ***$p < .001$.

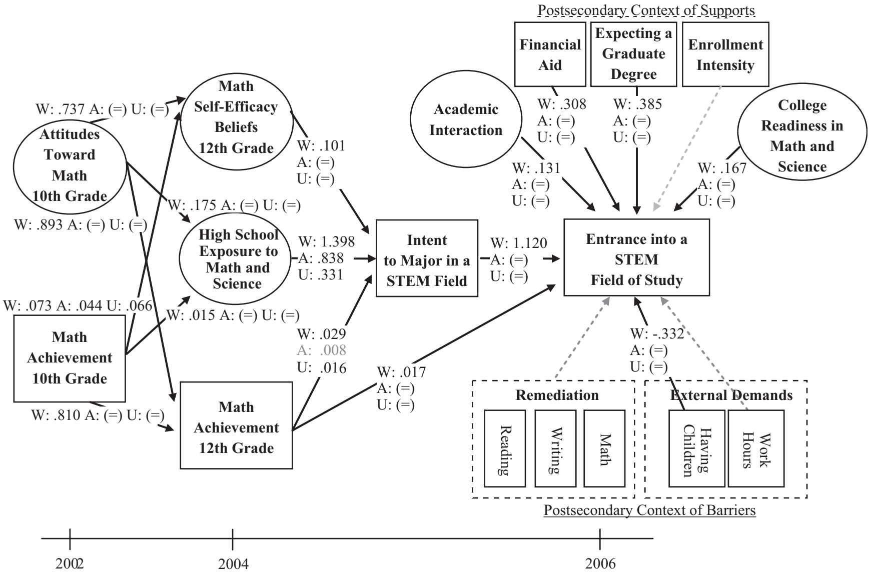

Figure 3. **Results of final multiple-group structural equation modeling (SEM) model based on race.**

Note. W = White; A = Asian; U = underrepresented minorities; (=) = estimate was constrained equal across groups. Insignificant paths are in gray.

> *Research Question 2:* Taking into account the relationships described in Question 1, how are students' initial postsecondary education experiences, such as academic interaction, receipt of financial aid, and remediation, related to STEM entrance?

Intent to pursue STEM and several postsecondary latent and observed variables showed direct effects on STEM entrance. Specifically, choosing a STEM major was positively associated with intent to major in STEM, academic interaction, college readiness in math and science, receiving financial aid, and expecting to earn a graduate degree. As for external demands, having dependent children significantly and negatively affected STEM entrance while number of weekly work hours did not have any significant effect. Receiving remediation and being enrolled full-time did not show any influence on STEM entrance. None of these effects differ significantly across racial, gender, and SES groups.

> *Research Question 3:* How do the modeled effects vary based on gender, race, and SES?

The potentially varying effects of the modeled factors were examined through conducting multiple-group SEM analyses based on race, gender, and SES. These analyses indicated that the proposed theoretical model generally held well and was stable across various racial, gender, and SES groups. Significant differences in structural weights were found in the multiple-group model based on race. Specifically, the effect of 12th-grade math achievement on intent to major in STEM was significant for White and underrepresented minority students, but was nonsignificant for Asian students. In practical terms, for White students, a 1-point increase from the mean in math achievement scores would result in a .010 increase in the probability of their intending to major in STEM. For underrepresented minority students, this change in the probability of STEM intent was .006 and for Asian American students there would be no significant change.

While significantly affecting STEM intent of all students, exposure to math and science had the largest impact on White students and the smallest effect on underrepresented minority students. In practical terms, among White students, when their exposure to math and science increased by 1 point above the mean of this factor score, the increase in the probability that the students would intend to major in STEM was .515. This increase in the probability of STEM intent would be .287 for Asian students and only .124 for underrepresented minority students. In addition, the overall significant and positive effect of 10th-grade math achievement on 12th-grade math self-efficacy was most substantial for underrepresented minorities, followed by White students and Asian students. That is, a 1 standard deviation increase in 10th-grade math achievement score was associated with .281 standard deviation increase in the math self-efficacy factor score among White students, .232 standard deviation increase among Asian students, and .319 standard deviation increase among underrepresented minority students.

Discussion

As one of the first studies that applies the social cognitive career theory to study a nationally representative high school cohort's entrance into college STEM majors, this research takes advantage of a unique, rich national data set to holistically explore supports and barriers to STEM entrance. Results point to important secondary and postsecondary factors influencing entrance into STEM disciplines. In addition, pivotal racial differences are uncovered by this study in terms of how early math-related attitudes and math and science learning influence STEM choice. A closer examination of these results reveals a number of important findings worthy of further discussion.

Math and Science Learning at the Secondary Level

High school preparation in math and science plays a critical role in developing student interest in pursuing a STEM field of study and influencing entrance into STEM majors. Math and science learning in K–12 education has been central to the research and discussion on broadening the STEM pipeline. In particular, selection and completion of math and science courses during high school are essential in developing students' predispositions toward choosing a STEM major in college (Blickenstaff, 2005).

The influence of high school learning as related to math and science, however, is multifaceted. Many prior studies focused solely on math achievement when examining the influence of high school experience on student interest and entrance into STEM fields (e.g., Crisp et al., 2009; Porter & Umbach, 2006). This study, however, shows that the effect of students' exposure to math and science courses is even stronger than that of math achievement, which was once deemed the single best predictor of students' future STEM entrance. This finding implies that in order to boost high school students' interest in pursuing STEM fields of study, an earlier introduction and exposure to math- and science-related courses could be an effective method. This means that students' interest in pursuing STEM could be an evoked response to direct exposure to these courses.

On the other hand, math achievement still indicates a significant, persistent effect on STEM intent (with the exception of Asian students whose STEM goals and resulting persistence may originate prior to 12th grade[7]) and subsequent enrollment in STEM majors. This warrants continued policy focus on improving math achievement of students. When it comes to structuring and engaging students in math and science courses, particular attention should be given to college readiness. As clearly indicated in this study, students who perceive their high school math and science courses to have adequately prepared them for college work are likely to choose a STEM major. In light of these findings, a stronger alignment between high school offerings and academic expectations at the college level represents a promising step toward promoting greater student interest and entrance into STEM fields of postsecondary study.

The Importance of Motivational Beliefs

Motivation clearly matters in STEM-related interest and choices. The study's four motivational attributes, (a) attitudes toward math, (b) math self-efficacy beliefs, (c) intent to pursue STEM fields of study, and (d) aspiration to earn a graduate degree, all demonstrate a significant and positive direct or indirect link to STEM entrance. From the pre-college perspective, positive attitudes toward math (e.g., being interested in the subject and recognizing its importance) at an early age positively influence later math achievement, math and science course-taking, and math self-efficacy beliefs, all of which are the cornerstone of fostering intent to pursue STEM and eventually choosing these disciplines. While prior research has suggested that positive attitudes toward math are fundamental to students' persistence and success in math learning (Hackett & Betz, 1989; Singh, Granville, & Dika, 2002), this study offers additional empirical evidence linking these attitudes with college students' choice of STEM majors. The results illuminate *how* these early attitudes affect STEM intent and entrance through their influence on 12th-grade factors that are critical for future STEM choice and success, thus highlighting the importance of cultivating students' positive attitudes toward math from early on. In conjunction with prior research (Bairaktarova & Evangelou, 2012; Marshall et al., 2011), this study's findings present viable approaches such as resorting to learning strategies that make math education enjoyable and educating students about the significance and long-term benefits of good math skills.

Math self-efficacy beliefs also play a significant and positive role in shaping STEM intent, and through intent, math self-efficacy has a strong indirect effect on actual STEM entrance. Similar to previous research that examined the link between math self-efficacy and STEM choice (e.g., Scott & Mallinckrodt, 2005), this study demonstrates that students with stronger math self-efficacy beliefs are more likely to intend to major in STEM fields upon college entrance. While this finding supports the argument for promoting positive math self-efficacy beliefs among all students, it should be noted that math self-efficacy often is discussed in relation to gender (Sadker & Sadker, 1994). That is, male students are more self-efficacious in math than female students despite comparable achievement (Eccles, 1994; Pajares, 2005; Watt, 2006). Multiple-group analysis in this study shows that there is no gender difference in terms of how math self-efficacy works to influence students' STEM intent. This suggests that improving female students' math self-efficacy may also help cultivate stronger interest in pursuing STEM among female students with equivalent achievement in math as their male counterparts. To make this happen, it is particularly important to further address the gender bias in STEM discussion (Clewell & Campbell, 2002), which may adversely affect female students' math self-efficacy beliefs.

In addition to self-efficacy, other key motivational factors in SCCT that influence choice actions include outcome expectations and interests (Lent et al., 2010). In this study, STEM intent is used as a proxy for outcome expectations and interests and is the biggest positive effect of all on the choice action of interest: choosing a STEM major. This result aligns well with SCCT, which stipulates that an individual's intention to engage in a certain activity (in this case choosing a major in STEM fields) helps organize, guide, and sustain the individual's efforts over a period of time.

This study also shows that expecting to earn a graduate degree is positively associated with STEM entrance. Perhaps those who are graduate school aspirants tend to be a more select and motivated group who are successful in establishing a stable, long-term academic plan and who are better prepared to take on challenging fields of study such as STEM.

Postsecondary Supports and Barriers

Postsecondary Supports

The first year of college is critical for students' STEM choice, especially when contextual supports in the form of interaction with faculty and academic advisors and receipt of financial aid are present. For all students, academic interaction seems to encourage entrance into STEM fields of study. These interactions may help students better integrate themselves into the college environment and also assist them in better aligning their academic aspirations with actual choices. From an advising perspective, helping current and potential STEM aspirants declare a STEM major early in their college careers is critical to minimizing additional time, funds, and opportunity costs spent in pursuing a degree (Frehill, 1997). As previously discussed, the socialization process may help reinforce one's academic and career choices. Also, in the context of SCCT, such interactions serve as the contextual support that helps individuals persist in alignment with their goals.

Financial aid's positive link to STEM entrance highlights the importance of financial resources as another form of postsecondary support for students pursuing STEM majors. It should be noted that given the correlational nature of the analysis, this association can be interpreted in both directions: that financial aid leads students to choose a STEM major or that students in STEM majors are more likely to receive financial aid. Nonetheless, it seems undeniable that financial resources provide the much needed support for students to succeed in STEM fields of study. Students pursing STEM disciplines tend to spend more time studying than students in other fields (Arum & Roksa, 2011; Brint, Cantwell, & Saxena, 2012). Therefore, receiving financial aid may help relax financial constraints and allow them to allocate enough time and energy to study and engage in greater interaction with faculty and advisors, thus meeting the academic challenges associated with majoring in STEM fields. In fact, a recent study by Kienzl and Trent (2009) showed that receiving financial aid helped socioeconomically underrepresented students enter high-cost STEM fields at a large public research university. Results from this research based on national data echo Kienzl's and Trent's finding and further reveal that the positive effect of financial aid applies across racial, gender, and SES groups.

Postsecondary Barriers

In regard to variables representing postsecondary barriers, only being a parent negatively affects STEM entrance, while remediation and number of weekly work hours do not show any significant impact. Given that the study's sample reached their early 20s in 2006, students who entered parenthood by that time likely had children of a very young age. This presents constraints such as having demanding child care responsibilities and navigating a challenging schedule that may prevent them from enrolling in courses in perfect alignment with their academic aspirations. These added challenges may prevent students who are parents from choosing a STEM major.

The null effect of working hours may be due to the possible differential effect of employment on college students' academic experience and choices, as evidenced in more recent studies on college student employment. It is possible that students who work an "optimal" amount of hours and in employment related to their academic interest gain skills (e.g., time management and work-study balance) that help them make viable academic plans and decisions (Dundes & Marx, 2006; Ehrenberg & Sherman, 1987). On the other hand, working excessive hours and in areas isolated from one's academic work may put students at a disadvantage (Bean & Metzner, 1985). These potential varying effects of work hours may thus result in an overall null effect of employment on STEM entrance. In a similar way, the nonsignificant effect of remediation is likely due to the differential outcomes of students' remedial experience—with positive outcomes of taking remediation and negative ones cancelling each other out—that leads to an overall null impact on STEM entrance.

Racial Differences Underlying STEM Entrance

For recent high school graduates, racial backgrounds still largely impact the way in which high school math and science learning is linked to STEM aspirations, with underrepresented minorities experiencing the least gain in their intent to purse a STEM field through coursework exposure in math and science. This result suggests that the effect of high school exposure to math and science courses on STEM intent is heterogeneous, accruing more to White students and least to underrepresented minorities.

The identification of this heterogeneous effect in regard to exposure to math and science courses indicates that the well-documented racial disadvantage in STEM participation cannot simply be resolved by offering more math and science to underrepresented minority students alone. Rather, more research is needed to understand how math and science education can better serve underrepresented minority students and what additional factors contribute to these students' STEM-related aspirations and choices. One of the findings from this study suggests that math self-efficacy, a common positive influence on STEM intent, is influenced by early math achievement to a greater extent among underrepresented minority students than among White and Asian students. This result is alarmingly important in that if the current racial disparity in math achievement is not addressed early enough, its adverse impact on future achievement of underrepresented minorities will be compounded by its detrimental effect on math self-efficacy beliefs. This will further discourage underrepresented minorities to pursue and succeed in STEM fields. On the other hand, this finding also implies that interventions addressing math achievement of underrepresented racial minorities should be implemented early on and if effective, may have large impacts on these students' math self-efficacy beliefs, thus promoting their STEM interest and entrance. With these results, the current study pinpoints the importance of paying attention to the potentially heterogeneous impacts of various policies and practices when targeting underrepresented minorities in expanding the STEM pipeline.

Pathway to STEM Majors: Holistic and Complex

Last but not least, the process leading to entrance into STEM fields of study is complex; numerous influences—individual, psychological, contextual, and social—act together to shape, develop, and sustain one's interest and eventually turn it into an actual choice. This study sets out to disentangle these influences and their effects on STEM choice by adopting a holistic perspective that draws upon the integration of SCCT and relevant literature on STEM education. Although this study does not account for all of the complexities, its findings suggest that SCCT is a viable framework for understanding STEM choice behaviors, especially when secondary STEM-related learning experience is added to the model. Consistent with SCCT and for all students, choosing a STEM major largely is dependent on their intrinsic motivational attributes, such as math attitudes, math self-efficacy beliefs, and interest in entering STEM. These observations, along with the finding that aspiring to earn a graduate degree turns out to influence students' STEM entrance, suggest that students' pathways to STEM can be substantially explained by their overall educational motivation and aspirations. Students also respond to postsecondary supports and barriers, such as academic interaction, receiving financial aid, and having dependent children, when making choices in regard to STEM as a major field of study.

In addition, by utilizing multiple-group SEM analyses to gauge impact heterogeneity, this study illuminates the differential processes leading up to entrance into STEM majors among racial groups. An important finding that emerges from this study is that the race-based inequitable participation in STEM fields of study may be partially explained by the disparity in student intent to major in STEM as a direct outcome of their pre-college learning experiences in math and science: Although exposure to math and science courses positively increases the likelihood of being interested in STEM majors for all students, this positive impact accrues most to White students and least to underrepresented minority students.

Limitations of the Study and Directions for Future Research

The Study's Limitations

This study's findings should be considered in conjunction with several important limitations. First, although the study relies on rich longitudinal data from a nationally representative sample, the use of an extant data set poses conceptual and analytical constraints. One such constraint is the time window covered by ELS:2002, which followed students from 10th grade to 2 years after high school graduation. As delineated at various points in this article, motivational beliefs, learning, and achievement in math formed earlier in a child's education have enduring effects on his or her future STEM-related aspirations and choices. Although to the extent possible, the study incorporates variables that speak to these early effects, similar variables from the middle school or elementary school years are simply not available given the design of ELS:2002. Therefore, relevant pre–high school influences were not addressed in the study. Instead, variables from 10th grade were used as proxies of earlier influences. Similarly, this study focuses on choosing a STEM major roughly within 2 years of college. Some students may still be exploring their major fields of interest during this time frame, and others might switch into STEM disciplines later on. These dynamics were not explored given the data available for the study. Therefore, it is impossible to explore the long-term effects of the secondary and postsecondary variables on students' entire progress through the STEM pipeline.

Also, variables of interest in existing data sets are not always measured in ways the researcher would have desired. For example, self-efficacy beliefs are central to SCCT, which serves as the guiding theoretical framework for this study. While ELS:2002 contains survey items that measure math self-efficacy adequately, multiple measures of STEM-related self-efficacy such as science self-efficacy *in addition to* math self-efficacy would help disentangle the complex nature of STEM learning. ELS does not include data for developing such multiple measures, so this study relies on math self-efficacy as a proxy for STEM self-efficacy beliefs, which limits the robustness of the data in support of the theory.

On a similar note, intent to major in STEM fields of study is measured at one point in time, gauging students' interest in choosing a STEM major upon entering postsecondary education. The one-time snapshot nature of this measure limits the study's ability to provide insights into how postsecondary institutions may help develop students' intent to choose a STEM field over time. In addition, the lack of earlier measures of students' intent to major in STEM prohibits the study from assessing the potential impact of these earlier aspirations for a STEM college career on high school students' attitude toward math and math achievement.

Another limitation relates to the lack of causal inference, given the use of extant survey data and SEM. ELS:2002 provides observational data that did not involve any random assignment of students to any of the independent variables, such as financial aid receipt or high school exposure to math and science. Although SEM goes beyond the traditional regression analysis in that it accounts for the temporal, complex relationships among latent and observed variables, it is still an exploration of various correlations.

While plausible explanations for the findings are discussed based on theory and prior research, none of the relationships described in this article should be interpreted as causal.

Directions for Future Research

This study points to several directions for future research. Although studies on STEM-related issues have proliferated in the past decade, disentangling the reasons for STEM participation remains a complex challenge, especially when determining whether the factors are dependent on sociodemographic backgrounds and/or within the control of the educator. Integrating variables at the secondary and postsecondary levels, this study accounts for a longitudinal process of STEM choice and tackles effect heterogeneity based on race, gender, and SES. However, a number of questions remain to be answered in future research. First, the finding surrounding math self-efficacy needs further investigation to understand more completely the mechanism through which it works in support of interest in STEM fields and future STEM choice, especially among female students. How does math self-efficacy or, better yet, STEM self-efficacy interact with various socialization sources and social perceptions regarding the gender role in career- and major-related choices to affect students' actual STEM choices? Which one of the sources of self-efficacy is the most theoretically and practically viable way to help promote STEM-related self-efficacy: mastery experience, vicarious experience, social persuasions, or physiological factors?

Furthermore, given the persistent, enduring effect of high school exposure to math and science courses, as well as math achievement, finding the best possible way to teach those courses, especially accounting for racial differences in the ways in which these effects are transmitted, will continue to dominate the central stage of STEM discussion. Also important to note, rigorously designed experimental or quasi-experimental studies may represent the best approach for scaling up promising interventions: An experimental design, by randomly assigning students to an intervention, can establish the true effectiveness of a program aimed at promoting STEM participation. Alternatively, quasi-experimental research, often by adopting a rigorous approach to creating comparison groups, can also estimate (although not as reliably as true experiments can) causal effects of a STEM intervention or practice.

Equally important, the first year in college can be critical, and as evidenced in this study, a number of postsecondary variables are related to entrance into STEM fields of study. Of particular note are the positive effects of both receiving financial aid and academic interaction on STEM entrance. These relationships need to be further studied—ideally through original, targeted data collection—to understand how they affect STEM entrance. Such nuanced understanding may aid in the development of policy interventions that truly can make a difference.

Conclusion

This study addresses the vital secondary-postsecondary nexus in STEM entrance, an issue often reflected in policy discussions but seldom systematically examined in empirical research, especially from a longitudinal approach. Given the rising national attention to promoting seamless movement through the STEM pipeline among students of diverse backgrounds, continued policy focus will be given to participation of traditionally underrepresented groups. To support this policy priority, a comprehensive knowledge of the barriers and facilitators to entering these fields of study is of paramount importance.

Following a holistic view of the issue of inequity in STEM participation, this study uncovers the impact of critical motivational, secondary learning, and postsecondary variables on STEM entrance and establishes the social cognitive career theory as a viable conceptual model for future STEM-related research. Furthermore, results from this study illuminate important racial differences in how pre-college learning and motivation exert their influence on students' intent to major in STEM. In light of these findings, educational policy and interventions aimed at developing STEM-related perceptions, attitudes, and aspirations among underrepresented minority students will benefit from a deeper understanding of the potentially heterogeneous effects of variable educational experiences. Together, results from this study offer new theoretical and empirical knowledge that informs policy and practice intended to promote equitable participation in STEM fields of postsecondary study.

Notes

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[1]Following the suggestion made by one of the reviewers, two sets of high school variables were also analyzed as additional covariates in the structural equation modeling (SEM) model: (a) family background including first-generation status (1 = first-generation college student; 0 = continuing generation) and language background (1 = English is native language; 0 = English is not native language) and (b) high school context variables including percentage of the school's students that qualify for free/reduced-price lunch, percentage of minority students in the school, student-teacher ratio of the school, high school type (dummy coded into Catholic, other private, and public as the referent group), and urbanicity of the school (dummy coded into suburban, rural, and urban as the referent group). Analysis of these added covariates indicated that none of them had a statistically significant relationship to STEM entrance and the effects of variables already in the model did not change substantially.

[2]The mathematics test standardized score was a T-score created by a transformation of the IRT (item response theory) theta (ability) estimate, rescaled to a mean of 50 and standard deviation of 10, from the cognitive assessments in Education Longitudinal Study of 2002 (ELS:2002). The standardized T-score provides a norm-referenced estimate of achievement relative to the population (spring 2002 10th graders and spring 2004 12th graders, respectively) as a whole (Source: ELS:2002 Electronic Codebook).

[3]After the full analysis, a series of interaction terms were added to this final regression equation. These interaction terms were created between *intent to major in a STEM field* and variables indicating postsecondary context of supports of barriers to assess the potential interaction effects between intent and postsecondary context variables. Results showed that none of the interaction terms was statistically significant.

[4]In M*plus*, the residual covariance between math achievement and math self-efficacy at 12th grade was estimated by adding the "WITH" statement between these two variables.

[5]Underrepresented minorities include African Americans, Hispanics, Native Americans, and multiracial students. In the literature highlighting inequitable participation in STEM education by race, three key racial and ethnic groups, African Americans, Hispanics, and Native Americans, are often analyzed together in comparison to their White and Asian counterparts. STEM-related research and data on students who identify their race/ethnicity as "multiracial" are scarce and in this sense they are also underrepresented. Also, if each race category were to represent a distinct group, the multiple-group SEM analysis would become challenging to conduct and interpret. In addition, the small numbers of Native American and multiracial students make it difficult to analyze them separately. Given these theoretical and analytical considerations, these racial/ethnic groups were combined as the underrepresented minorities in STEM.

[6]As a regular practice, the chi-square value is almost always presented in studies that involve confirmatory factor analysis (CFA) and SEM (Kline, 2011). However, because the chi-square test is sensitive to sample size (Kenny, 2011; Schumacker & Lomax, 2004), it might erroneously suggest a poor fit by rejecting the null hypothesis in studies with large sample sizes like this. As a result, other fit indices such as Comparative Fit Index (CFI) and Tucker-Lewis Fit Index (TLI) are more relevant to this study. Also reported is the relative chi-square, alternatively referred to as the normed chi-square, which equals the chi-square value divided by the degrees of freedom. Some scholars argue that this index might be less sensitive to sample size, but the guidelines about acceptable maximum values vary, ranging from less than 2 (e.g., Ullman, 2001) to less than 5 (e.g., Schumacker & Lomax, 2004).

[7]For Asian American students, 12th-grade math achievement did not emerge as a significant factor associated with their STEM intent. Asian Americans are well represented in STEM fields (Anderson & Kim, 2006; May & Chubin, 2003), and this high representation may well be a result of Asian students' stronger aspirations to pursue math- and science-related careers at a very young age, a level unmatched by any other racial groups (National Science Foundation, 1994). This early interest, although not accounted for in this study given the limitation of the data, may have largely translated into their STEM intent independent of their 12th-grade math achievement.

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