Modeling Entrance Into STEM Fields of Study Among Students Beginning at Community Colleges and Four-Year Institutions

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Abstract (150-200 words)

To address research and policy concerns regarding the expansion of the STEM education pipeline, the critical first step of choosing STEM fields of postsecondary study among students should precede discussions on persistence, completion, and employment outcomes. However, relevant empirical evidence remains surprisingly scarce. Theoretically grounded research targeting this gap is thus much warranted. This study tests a theoretical model of STEM participation that examines factors shaping the decision to pursue these fields of study among students entering community colleges and four-year institutions using a nationally representative sample of high school graduates from 2004. Applying the social cognitive career theory and multi-group structural equation modeling analysis, this study highlights a number of findings that may point to specific points of intervention along students' educational pathway into STEM. This study further reveals important heterogeneity in the effects of high school and postsecondary variables based on where students start their postsecondary education: community colleges or four-year institutions.

Keywords (4-6)

Community college students, STEM education, choice of major, social cognitive career theory, multi-group structural equation modeling

Modeling Entrance Into STEM Fields of Study Among Students Beginning at Community Colleges and Four-Year Institutions

Over the past few decades, the educational pipeline of science, technology, engineering, and mathematics (STEM) fields has been a key preoccupation for researchers and policy-makers. Demand remains high for college graduates in these particular fields as their skills are pivotal to promoting health outcomes and national economic and security interests. Employment in STEM fields has been rising at a higher rate than that for employment in all occupations (National Science Foundation, 2010; U.S. Department of Labor, 2007). However, despite this pressing need to ensure greater participation in the STEM workforce, the supply side of the pipeline still experiences a serious deficit (Hall, Dickerson, Batts, Kauffmann, & Bosse, 2011). On the one hand, the growth in the number of college students entering STEM fields of study does not keep pace with the STEM labor market demand (CPST, 2007; Lowell & Regets, 2006); on the other hand, there is indication that high school graduates' interest in and readiness for STEM fields of study have been declining (ACT, 2006). Given the need to attract more high school graduates into these specific postsecondary areas of study, research devoted to understanding the influences on students' academic choices in regard to postsecondary STEM majors is essential.

Empirical work in this vein, however, should not center solely on students attending four-year colleges and universities as studies on choice of college majors and fields of study have generally been conceived. As widely acknowledged, STEM participation of traditionally underrepresented groups such as women, first-generation students, low-income college students, and racial minorities, especially African

Americans, Hispanics, and American Indians, still presents cause for concern (e.g., Anderson & Kim, 2006; National Academies 2005 "Rising Above the Gathering Storm" Committee, 2010; Smyth & McArdle, 2004). For many members of these underrepresented student populations, community colleges serve as an entry point to postsecondary education (e.g., Bailey, Leinbach, Scott, Alfonso, Kienzl, & Kennedy, 2004; Dowd, 2008; Wang, 2009) and represent a unique opportunity in the preparation of a future STEM workforce that reflects the diversity of the U.S. population (Dowd, 2011). In this sense, much of the effort in broadening STEM participation, particularly among underprivileged student groups, will rely on the nation's community colleges. Therefore, research that deals with the STEM pipeline should not overlook these institutions.

Recent studies have begun to explore the state of STEM education in community colleges, especially regarding female students' underrepresentation among STEM-related associate degree earners (Hagedorn & DuBray, 2010) and possible reasons for this underrepresentation such as a lack of emotional and institutional support (e.g., Hardy & Katsinas, 2010; Lester, 2010), self-concept (Starobin & Laanan, 2005), and interaction with faculty (Starobin & Laanan, 2008). However, current empirical research on STEM education at the postsecondary level mainly focuses on four-year institutions, whereas community colleges and their students are underrepresented in the literature.

In general, there is very little empirical research regarding specific factors influencing entrance into STEM fields among college students. The barriers and boosters to students' choice of STEM fields at both community colleges and four-year institutions are unclear. As a result, knowledge is scant on how to broaden participation in these explicit areas of study among college students, particularly those who begin at community colleges.

To understand what influences college students to enter majors in STEM fields, this study proposes and tests a theoretical model that examines factors shaping the decision to pursue STEM fields of study among students entering community colleges and four-year institutions using a nationally representative sample of high school graduates from 2004.

Theoretical Framework and Related Literature

In order to situate the current study within relevant theory and existing literature, this section describes a career development theory, namely the Social Cognitive Career Theory (SCCT) that represents a viable conceptual framework for studying choice of STEM fields of study in postsecondary education. Pertinent prior higher education literature is also discussed in conjunction with this framework to provide the theoretical underpinning for the study.

Social Cognitive Career Theory (SCCT)

Adapted from Bandura's (1986) general social cognitive theory, SCCT theorizes an individual's career interest, choice, and performance processes (Lent, Brown, & Hackett, 1994). SCCT illustrates how individuals guide their career development through cognitive-personal factors and how these factors are linked to personal background (also referred to as person inputs) and environmental supports and barriers. Specifically, SCCT focuses on three social cognitive mechanisms that drive career development: self-efficacy, outcome expectations, and personal goals. Self-efficacy is an individual's judgment of his or her own ability to complete an action required of a certain type of performance. Outcome expectations are beliefs about the consequences of performing a specific behavior. Personal goals are a person's intention to engage in a certain activity or to produce a particular result. Goals organize, guide, and sustain a person's efforts over a period of time without external influence.

SCCT asserts that an individual's career goals are consistent with their interests, self-efficacy, and outcome expectations. Self-efficacy and outcome expectations are modeled to affect career goals and choices directly and indirectly via interests. Environmental supports and barriers influence career goals as well. These career goals, along with background and contextual factors, then determine career choice actions (Lent, Brown, & Hackett, 1996).[1]

Although Lent et al. (2002) employed the term "career" in developing SCCT, they argued that this framework is as relevant to academic development, primarily because models of academic and career choice and success share similar causal mechanisms, and academic development dovetails with career development. In this sense, SCCT includes "conceptually and developmentally related processes of academic interests, choices, and performances" (p. 264). This is especially true with postsecondary study in STEM fields, as a credential in STEM is the typical path to careers in STEM related professions (Langdon, McKittrick, Beede, Khan, & Doms, 2011).

In recent years, SCCT has been applied to practice and research in regard to expanding the STEM pipeline. Many empirical studies guided by SCCT focus on academic goals and achievement in math and science among middle- and high- school students. For example, self-efficacy in math/science was found to be related to math/science outcome expectations and together predicted math/science career interests

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[1] For a complete description of SCCT, refer to Lent et al. (1994, 2002).

and goals among Mexican American middle school students (Navarro, Flores, & Worthington, 2007). A study investigating educational pathway choice of Australian students found that a variable pattern of interactions between vocational interest, self-efficacy, and achievement could predict student career path behavior (Patrick, Care, & Ainley, 2011). Similarly, a longitudinal study of high school students revealed evidence that career planning and exploration are determined mostly by self-efficacy and goals but also by varied influences of personality and contextual and biographic variables (Rogers & Creed, 2011).

To a limited extent, scholars have also applied SCCT to examine STEM choice and persistence in a postsecondary context. Lent, Brown, Schmidt, Brenner, Lyons, and Treistman (2003) studied engineering students enrolled in a predominantly white university and found that key constructs in SCCT successfully predict academic goals and persistence over three semesters. Similar studies conducted at two historically black universities confirmed SCCT as a viable model predicting choice and persistence in engineering majors (Lent et al., 2005). Byars-Winston and Fouad (2008) focused on the contextual supports and barriers as posited by SCCT and found that parental involvement and perceived career barriers both influence college students' math/science goals. Moreover, in a study based on data from the 2004 Freshmen Survey and 2008 College Senior Survey administered by the Cooperative Institutional Research Program (CIRP), Herrera and Hurtado (2011) applied SCCT and analyzed factors predicting the retention of STEM career aspirations of underrepresented minority students in comparison to those of White students.

Overall, these studies point to the utility of SCCT in understanding STEM success in postsecondary education. However, this theory still receives minimal attention among higher education scholars interested in studying STEM issues. In addition, no prior research has applied SCCT in examining relevant STEM research topics pertaining to community college students. Extending this theoretical lens to research on postsecondary STEM issues therefore affords depth and complexity, both conceptually and analytically, that are well suited for studying the multifaceted process of student choice into STEM fields of postsecondary study.

Conceptual Framework and Supporting Literature

The conceptual framework (Figure 1) guiding this study builds upon SCCT and relevant prior literature. It should be noted that although SCCT includes various factors and highlights numerous causal relationships among the variables included in the framework, this study focuses on constructs and relationships within SCCT that are most theoretically relevant to the nexus between high school learning to postsecondary STEM choices based on existing literature on STEM education and college student success. Therefore, although the proposed model draws upon SCCT, it is a more parsimonious model and is therefore not necessarily a direct and complete application of the original SCCT model. Specifically, this study incorporates the core constructs of SCCT: self-efficacy, interest and goals, contextual supports and barriers, person inputs, and choice actions related to STEM areas of study. Learning experiences in high school are also added to the model. In summary, the model theorizes that students' self-efficacy and learning experiences during high school affect their interest and goals in terms of choosing a STEM major, which in turn influence actual choice of STEM disciplines. As students move into postsecondary education, STEM choice is also subject to contextual supports and barriers as well as person inputs. A more detailed description of the model follows.

[Insert Figure 1 about here.]

Self-efficacy is a central social cognitive construct in SCCT and is theorized to strongly influence one's career interest. Prior literature also suggests that self-efficacy affects individuals' academic and occupational behaviors during adolescence and early adulthood (Schunk & Miller, 2002). For example, research has found that academic self-efficacy is a critical factor of one's choice of major and academic success in higher education (Porter & Umbach, 2006). In particular, self-efficacy beliefs of math proficiency may be associated with choice of major in STEM fields (Betz & Hackett, 1983; Scott & Mallinckrodt, 2005).

Although SCCT does not distinctively identify learning as a key factor in shaping academic and career interests and choices, it would be reasonable to hypothesize that high school learning affects interest and choice surrounding postsecondary majors. Existing research has also suggested that students' academic experience and preparation in math and science during high school are the cornerstone of their later interest and enrollment in STEM disciplines (Lent, Brown, & Hackett, 2000; Staniec, 2004).

After enrolling in college, a number of contextual influences may come into play in terms of which major areas of study students actually choose, especially given that students are not required to declare their major upon admission. Within the SCCT framework, these factors may become contextual supports that facilitate students in choosing certain fields of study or circumstantial barriers that pull students away from certain majors. Several such environmental factors are established by prior literature as those shaping students' academic experience in college and are thus plausible influences on choice of STEM fields including: academic integration into college (Astin, 1993; Chang, 2005; Lamport, 1993; Terenzini, Pascarella, & Blimling, 1999), perceived academic readiness for college (Millar, 2010; Rosenbaum, 2001), taking remedial courses (Adelman, 2006; Attewell, Lavin, Domina, & Levey, 2006; Bahr, 2008; Bailey & Alfonso, 2005; Long, 2005; Pascarella & Terenzini, 2005), receiving financial aid (DesJardins, Ahlburg, & McCall, 2006; Ishitani & DesJardins, 2002), and having external demands which may distract students from studying, especially among community college students (Bryant, 2001; Kane & Rouse, 1999).

Finally, person inputs including several demographic and control variables are part of the conceptual model. Gender, ethnicity, and socioeconomic status (SES) are the most widely inquired variables that are likely to influence one's choice of major. Indeed, in STEM fields it is observed that males, Asian or Asian Americans, White students, and students from more favorable socioeconomic backgrounds are overrepresented, regardless of where they start postsecondary education: community colleges or four-year institutions (e.g., Heinze & Hu, 2009). Nonetheless, research findings are not conclusive in the sense that after controlling for other influential factors, demographic differences tended to be attenuated (Porter & Umbach, 2006).

In summary, the conceptual model for the study theorizes a repertoire of factors that influence students' choice of STEM fields of postsecondary study. Based on SCCT and prior higher education literature, this model examines possible trajectories of students' selection of STEM-related fields of study while taking into account relevant influential factors and their interrelationships. Thus, the analysis will unveil the most salient factors, which would allow researchers and policy-makers to focus more accurately on these pivotal variables when recruiting prospective students into STEM areas of study.

Methods

Data and Sample

Data used for this study drew upon the first and second follow-up surveys of the Education Longitudinal Study of 2002 (ELS:2002), a national, longitudinal survey designed to study high school students' transition from secondary into postsecondary education. Sponsored by the National Center for Education Statistics (NCES) of the Institute of Education Sciences (IES), ELS:2002 provides data pertaining to survey participants' high school and postsecondary experiences, as well as their transition to and success in postsecondary education and the workforce. The baseline survey of ELS:2002 was completed in 2002, when the participants were high school sophomores. The first follow-up survey was conducted in 2004, when most participants were high school seniors. Participants' high school transcript data were added to the database at this stage of data collection. The second follow-up survey was completed in 2006, effectively two years after high school graduation for most survey participants. New data collected pertains to individuals' postsecondary enrollment and experiences, social and economic return of education, and newly acquired adult roles (e.g., family formation).

The sample of the study includes students who participated in both the first and second follow-up interviews of ELS:2002 and who had enrolled in a community college or four-year institution by 2006 (N=9,770). This sample was further divided into two analysis groups: (a) students whose first postsecondary institutions are four-year institutions (about 6,300; 65%) and (b) those who attend community colleges as their first postsecondary institutions (about 3,470; 35%). Due to the cluster sampling design of ESL:2002, all analyses were weighted using the appropriate panel weight (F2F1WT) and therefore the results generalize to the population of spring 2004 high school graduates who attended postsecondary education through either a four-year institution or a community college within two years of high school graduation.

Measures

Dependent and independent variables of the study were chosen based on the proposed conceptual framework and included the following:

The key dependent variable, STEM choice, is a dichotomous variable recoded from the survey item indicating respondents' major field of study during the second follow-up in 2006. This variable was coded one if a student had declared a major field of study in STEM disciplines[2] and zero otherwise. The main mediating variable in the model is students' interest and goals in choosing a STEM field of study, measured by whether students thought of a STEM discipline as the most likely field of study when entering college. Math self-efficacy was measured by five Likert-type items regarding high school seniors' self-efficacy beliefs in taking math tests, mastering math skills, and completing math assignments. Learning experiences in the conceptual model were represented by two high school independent variables: (a) exposure to math and science courses, measured by the total number of units in mathematics and science technologies during

[2] Based on an NCES report authored by Chen and Weko (2009), the following fields of study were categorized as STEM in ELS:2002: mathematics and statistics, agricultural/natural resources/related, biological/biomedical sciences, physical sciences, science technologies/technicians, engineering technologies/technicians, mechanical/repair technologies, and computer/information sciences/support technicians.

high school; and (b) high school math preparation, measured by the standardized math test score a student receives during the first follow-up.

Postsecondary contextual supports and barriers were operationalized by the following: academic integration, math and science readiness for college (as students perceived themselves once in college), external demands, receipt of financial aid, number of remedial subjects, and enrollment intensity. Person inputs included demographic variables such as gender, race/ethnicity, socioeconomic status, language spoken, and first-generation status. In addition, an educational outcome expectation variable was included: graduate degree expectation. Table 1 provides a detailed description of the variables used in the study.

[Insert Table 1 about here.]

Analytical Approaches

The main analytical approach to this research is structural equation modeling (SEM), which defines both latent and observed variables while testing the direct and indirect links and their directions among variables used in a study (Byrne, 2010; Kaplan, 2009; Kline, 2011). For the purpose of testing the hypothesized model and examining whether the proposed model is equivalently applicable for both groups of students (i.e., those who began at four-year institutions and those who started at community colleges), a multi-group SEM analysis was conducted.

Generally speaking, SEM is a combination of a measurement model and a structural model. As the measurement part of the SEM analysis, a confirmatory factor analysis (CFA) was first conducted to measure on the latent variables in the proposed model. CFA accounts for indicator variables' measurement errors by capturing them into the residual terms in the model (Kline, 2011). Five latent variables were measured in this study: (a) math self-efficacy, (b) exposure to math and science courses in high school, (c) academic integration in college, (d) math and science readiness for college, and (e) external demands. The indicator variables of the corresponding latent factors are described in Table 1. The factor loadings of indicator variables and fit statistics of measurement model such as chi-square (χ^2), root-mean-square error of approximation (RMSEA), Comparative Fit Index (CFI), and Tucker-Lewis Fit Index (TLI), were examined.

After measuring latent variables, the structural part of the model was added to form the full structural equation model (see Figure 2). Practically, the structural part of SEM is a path analysis of a series of related regression equations with theoretical linkages among endogenous, exogenous, and mediating variables. In this study, the structural model was represented by two regression equations. Specifically, the first regression equation investigated how students' interest in choosing a STEM field of study was affected by the three high school variables: (a) math self-efficacy beliefs, (b) exposure to math and science courses, and (c) high school math preparation. Then, the second regression equation explored how students' actual selection of a STEM field was influenced by their initial interest, high school math preparation, postsecondary supports and barriers (such as academic integration, math and science readiness for college, external demands, financial aid receipt, number of remedial subjects, and enrollment intensity), as well as person input variables (such as gender, race/ethnicity, graduate degree expectation, first native language, and first-generation status). In the hypothesized model, students' interest in choosing STEM was functioned as the mediating variable to convey the indirect effects of the aforementioned three high school variables on students' STEM choice.

Moreover, the model also posited that high school math preparation had a direct effect on students' entrance into a STEM major.

In conducting the SEM analysis, a one-sample, full structural equation model was initially fitted to the data. The same model was then fitted to the community college and four-year groups separately, followed by a set of multi-group SEM analyses, described below.

Structural Path Invariance Tests

In order to examine whether the proposed model and its structural path coefficients are equivalent across both student groups (those beginning at community colleges and those beginning at four-year institutions), a series of structural path invariance tests were conducted. Because students entering community colleges and four-year institutions are likely to be different in backgrounds, academic preparation, and educational aspirations, as well as to experience different institutional environments given the contrasting educational configurations offered by two-year and four-year institutions, the modeled variables might exert effects differently on student interest and choice regarding STEM fields of study.

An invariance test on each structural weight (i.e., path regression coefficient) across the community college and four-year groups was conducted in the following way: The chi-square statistic of a baseline model where all structural weights were freely estimated was compared to the chi-square statistic of a nested model where only the given structural weight was constrained equal. Through this test, if the chi-square difference statistic ($\Delta\chi^2$) does not reveal a significant difference between the models, then it can be concluded that the structural path being tested is invariant across the two groups of students; a significant chi-square difference statistic ($\Delta\chi^2$), on the other hand, would suggest that the structural path exerts different effects on the two groups.

Following these invariance tests, individually found invariant parameters were constrained to be equal and those individually found non-invariant parameters were freely estimated across groups in the final multi-group, constrained model. All the SEM analyses were conducted using M*plus* 6.1, a statistical package capable of modeling a variety of SEM analyses using a mixture of continuous and categorical data collected from a complex sampling design (Muthén & Muthén, 1998-2010), as in this study. Also, due to the fact that many variables in the study are ordered-categorical (i.e., ordinal), the mean and variance adjusted weighted least squares (WLSMV) estimator is preferred (Kline, 2011), which is also the default estimator in M*plus* when SEM analysis involves ordinal variables.

Missing Data

Missing data in this study were handled by using multiple imputation, which is considered one of the advanced and viable methods in dealing with missing data (Schafer & Graham, 2002). Multiple datasets were generated that replace missing observations with a set of plausible values. Each of these datasets were then analyzed using standard procedures for analyzing complete data, parameter estimates were averaged over these analyses, and standard errors were computed using the average of the standard errors over the set of analyses and the between analysis parameter estimate variation (Horton & Lipsitz; 2001; Rubin,1996). Berglund (2010) pointed out that a small to moderate number (3-10) of imputations is enough to achieve the desired multiple imputation efficiency (Rubin, 1987). The number of imputations selected in this study is five. Given the multi-group approach used in the study, data imputation was done for the community college and four-year groups separately.

Limitations of the Study

A few important limitations of the study should be noted before discussing the results. First of all, as an extant dataset, ELS:2002 does not necessarily measure all the variables used in the study the way the researcher would have preferred. For example, in the original SCCT, interest and goals that eventually lead to the choice action are separate developmental stages with interest affecting goals. It would be desirable to capture these two constructs separately and to examine the interrelationships among them and the choice action (in this study choice of a STEM field of study), which would lend even greater insight into the developmental processes underlying students' motivation and choice as related to STEM areas of postsecondary study. Unfortunately, distinctive measures of interest in STEM disciplines and related goals are not available in ELS:2002 and as a result, this study had to resort to a single measure to approximate students' interest and goals in regard to majoring in STEM.

In addition, although entrance into STEM fields of postsecondary study is a critical initial step along the STEM pipeline, this study acknowledges that persistence and eventual completion of these majors are pivotal in supplying qualified graduates into the STEM workforce or graduate education. Given the scope of the study and that ELS:2002 followed students only two years post high school graduation, issues of college persistence and completion in STEM were not addressed. For similar reasons, transfer behaviors, especially among community college beginners, were not accounted for in this analysis. Therefore, it should be noted that the outcome of this study focuses on student choice related to STEM disciplines and it could be possible that students switched institutions by the time they declared a major field of study.[3] Because of the said issues, although the ultimate outcome in the SCCT framework is attainment given the academic or career choice, this study was able to focus only on the part of the model that has choice action as the outcome.

Last but not least, although sometimes referred to as "causal modeling," SEM still explores correlations instead of causal relationships. Therefore, the findings of this study do not imply causal explanations.

Results

Table 2 provides a summary of the weighted and unweighted descriptive statistics of the data. There were about 9,770 student records in the sample of the study: 4,490 (46%) male and 5,280 (54%) female. White students accounted for 61% of the analytical sample, Asian Americans accounted for 12%, and the remaining 27% were underrepresented minorities. Students' SES was classified into four quartiles and its distribution from lowest to highest quartiles were 16%, 20%, 26%, and 38% respectively.

There were 16% of the students who were interested in choosing a STEM field of study upon entering college and 13% actually chose a STEM discipline. More details of student characteristics are available in Table 2.

[Insert Table 2 about here.]

Additionally, detailed demographic breakdowns are presented for students who were interested in a STEM field of study (Table 3) and those who entered one (Table 4).

[Insert Table 3 about here.]

[Insert Table 4 about here.]

[3] Less than 10% of the study's sample transferred or switched postsecondary institutions by 2006.

Results of Confirmatory Factor Analysis on the Measurement Model

The confirmatory factor analysis measured five latent factors described in the measurement part of the model. Table 5 presents the fit statistics and factor loadings of the indicator variables of the measurement model based on the entire sample. It should be noted that although the proposed measurement model has a significant chi-square value, $\chi^2(94) = 1{,}666.430$, $p = 0.000$, chi-square values are sensitive to sample size and may mistakenly reject a well fitted model, especially given the large sample size of this study. Therefore, other relative fit indices should also be examined (Kline, 2011; Schumacker & Lomax, 2004). The RMSEA was 0.041, which was below the 0.05 cut-off point (Hooper, Coughlan, & Mullen, 2008; MacCallum, Browne, & Sugawara, 1996). A smaller RMSEA value indicates a better model to data fit. The CFI and the TLI were 0.986 and 0.982, respectively. Both of these comparative fit indices were above the 0.95 cut-off point (Schreiber, Stage, King, Nora, & Barlow, 2006). As the value of CFI or TLI approaches to 1.0, model fit is getting better. The unstandardized and standardized factor loadings and their levels of significance also suggest that the proposed measurement model fits the data adequately.

[Insert Table 5 about here.]

Results of SEM Analyses and Structural Path Invariance Tests

Table 6 displays the results of a set of SEM analyses and a series of structural path invariance tests. The initial one-sample SEM analysis showed a reasonable model-to-data fit, RMSEA = 0.042, CFI = 0.931, TLI = 0.922. The model was then fitted to the community college and four-year student data individually. The model fits the separate datasets slightly better as indicated by the lower RMSEA and higher CFI and TLI values.

Next, the multi-group SEM analysis was conducted by fitting the model to the two groups of data simultaneously. This multi-group model was used as the baseline model for the subsequent analyses of structural path invariance tests. The baseline model also fits the data adequately well, RMSEA = 0.035, CFI = 0.948, TLI = 0.943.

[Insert Table 6 about here.]

Eighteen individual parameter invariance tests were conducted. The results of these tests are presented in the lower section of Table 6. Five path coefficients were found non-invariant individually, and the remaining 13 coefficients were invariant across student groups. Therefore, in the final multi-group model, the 13 invariant path coefficients were constrained-equal across the two student groups. The final constrained model fits the data better in comparison to the baseline model, RMSEA = 0.034, CFI = 0.948, TLI = 0.944.

Parameter Estimates of the Final SEM Model

The estimated unstandardized and standardized structural path coefficients for the final multi-group model are presented in Table 7.

[Insert Table 7 about here.]

All three high school independent variables: (a) math self-efficacy beliefs, (b) exposure to math and science courses, and (c) high school math preparation showed statistically significant effects on four-year beginners' interest in choosing a STEM field of study. When compared in standardized terms, exposure to math and science and math preparation seemed to have more substantial effects than math self-efficacy beliefs. However, these three variables' impact on two-year beginners' interest in STEM were not as substantial as those observed in their counterparts. In particular, exposure to math and science courses was not a significant factor in predicting two-year beginners' interest in STEM. Nonetheless, math self-efficacy beliefs appeared to be the strongest influence on two-year beginners' interest in STEM, followed by math preparation.

Two postsecondary variables exerted differential effects on students beginning at community colleges and those starting at four-year institutions. Academic integration had a significant and positive effect on four-year beginners' choice of STEM majors, while its effect was significant but negative on two-year beginners' STEM entrance. Similarly, receiving financial aid had a significant and positive effect on four-year beginners' STEM entrance; but it reported no effect on two-year beginners' STEM entrance. Other variables were invariant (thus constrained-equal) across the two student groups. Therefore, their effects on students' STEM choice were modeled to have the same effects across groups. Specifically, students' interest in STEM, math and science readiness for college, and high school math preparation all had significant and positive effects on both two- and four-year beginners' STEM choice. Moreover, as compared in standardized terms, students' interest in STEM fields had the strongest influence on their actual choice of a STEM field.

Of the person input variables, being female was negatively associated with STEM choice. Being Asian or a member of underrepresented minorities was positively associated with choosing STEM areas of study compared to being White. Furthermore, students who expected to earn a graduate degree were more likely to participate in STEM majors than those who did not.

Finally, the three high school variables also had indirect effects on STEM choice through the mediating variable (i.e., STEM interest). The indirect effects of math self-efficacy, exposure to math and science courses, and high school math preparation on students' STEM choice are presented in Table 7 as well. Although the mediating variable worked invariantly across groups, the high school variables exert non-equivalent effects on STEM interest across groups. As a result, their indirect effects on STEM choice were also non-equivalent across the community college and four-year groups. Consistent with their effects on the mediating variable, the three high school variables' indirect effects on STEM entrance were also weaker for students beginning at community colleges. Figure 2 displays the final multi-group SEM model with significant paths highlighted.

[Insert Figure 2 about here]

Discussion

This study integrates a career development theory and prior scholarship in higher education to investigate factors shaping student interest in and choice of STEM fields of postsecondary study. Particular attention is directed toward understanding the potentially different ways in which the modeled factors exert their effects across two distinct student populations: students beginning at community colleges and those who start at four-year institutions. The study's analyses indicate that overall, STEM-related interest and choice are well captured by the proposed model; furthermore, salient differences have been uncovered in terms of how the effects of various motivational, background, and environmental factors operate based on the level of first postsecondary institutions students attended. What follows is a more detailed discussion of these results, and where applicable, their implications for policy and directions for future research.

What Matters in High School

An overarching finding from this study is that high school learning and motivation in relation to math and science have long-term effects on the development of STEM interest, which carries over to postsecondary studies and leads to actual enrollment in these fields. From a developmental perspective, academic and career related interests and self-beliefs are the cornerstones for future choice actions. Prior research has also indicated that high school learning experience in math and science is predictive of future STEM persistence and attainment among students attending four-year institutions (e.g., Crisp, Nora, & Taggart, 2009).

What is unclear from existing literature is how these important high school variables influence students seeking entry into postsecondary education through a community college. In this study, although high school exposure to math and science courses and math preparation appear to be strong influences on four-year beginners' STEM interest, their impact on two-year beginners' STEM interest are not as salient, with exposure to math and science courses not showing any effect. These observations suggest that even with the same amount of contact with relevant coursework or the equivalent level of math preparation, students who are four-year college bound are more likely to translate the impetus afforded by high exposure to math and science and high achievement in math into real interest in selecting a STEM discipline, compared to their counterparts heading to two-year colleges. Considering the complexity associated with community college entrants' academic and career intentions, expectations, and goals (Bailey, Jenkins, & Leinbach, 2005; Cohen & Brawer, 2008; Laanan, 2003), and in light of this study's findings, it is reasonable to believe that the developmental process underlying community college entrants' STEM pathways is more nuanced and multifaceted than that of high school graduates destined for four-year colleges and universities. Given the inherent differences noted previously between these two groups of students, substantial distinction seems to also exist in the process of cultivating interest in choosing a particular academic field. Therefore, future research is warranted to further explore how STEM-related interest and choice behaviors develop among community college entrants.

Cultivating STEM Interest

STEM interest has the strongest association with students' actual choice of a STEM field of study, and it works equivalently across both community college and four-year students. This finding aligns well with the SCCT framework where existing interest transforms into an action when suitable opportunities and conditions occurred. Consequently, it is not surprising that the influence of STEM interest on STEM entrance works consistently for everyone despite differing groups. Given that interest in choosing STEM is clearly the most prominent force behind the actual choice of a STEM discipline, cultivating students' interest in these particular areas of study is naturally an intervention point for policy and practice aimed at widening the STEM pipeline. Given the study's results, improving math learning, strengthening math self-efficacy beliefs, and introducing students to more math and science offerings seem to be obvious approaches.

On the other hand, these "obvious" implications may readily apply to the more select, four-year college bound students, but not to the same extent as those heading to community college who are largely racial minorities, first-generation college students, and academically disadvantaged (Cohen & Brawer, 2008). In particular, the findings of this study revealed that taking more math and science courses during high school does not help cultivate interest in STEM among high school graduates entering community colleges. Given the previously described disadvantages of students who attend community colleges, additional empirical and practical efforts should be expanded on improving the effectiveness of high school math and science courses in promoting and sustaining STEM interest of traditionally underprivileged students. In addition, in light of the finding that student perceived math and science readiness for college positively impacts choice of STEM fields illuminates the importance of building a seamless alignment between secondary and postsecondary STEM offerings and assessment. STEM-aspiring high school graduates should be provided with the type of knowledge, skills, and competencies needed for postsecondary STEM success in addition to being informed of and prepared for the academic challenges they might encounter once enrolled.

Postsecondary STEM Choice: Supports and Barriers

Among the factors representing postsecondary supports and barriers related to STEM choice, academic integration and receiving financial aid exhibit differential effects across two-year and four-year student groups. It is intriguing to observe that while showing a significant and positive impact on STEM choice among four-year college students, academic integration has a significant negative effect on community college entrants' STEM entrance. This raises the question as to why taking initial interest into account, the "academically integrated" student is more likely to enter STEM in a four-year setting while it is the opposite for a similar student beginning at a community college.

Before exploring possible answers to this question, it should be mentioned that college students, including those undecided, tend to associate academic majors with future educational, career, and social attainment (Gordon & Steele, 2003; Song & Glick, 2004). Baccalaureate and graduate degrees in STEM disciplines as well as employment in these areas often afford relatively higher educational, social, or economic success compared to other fields (Melguizo & Wolniak, 2011). Therefore, for a student following the traditional four-year college—graduate school or four-year college—labor market trajectory, these disciplines may represent desirable options implying future success in education or career. Meanwhile, it is also true that STEM disciplines at four-year institutions, identified as either “hard applied” or “hard pure” fields (Austin, 1990), are known for their challenging academic standards including competitive grading (Herrera & Hurtado, 2011). In this sense, interested students may shy away from these fields if they are not academically integrated into the campus environment despite their STEM aspirations, and academically integrated students may be more ready to take on these demanding areas of study.

In a community college environment, however, students’ choice of STEM fields and associated considerations may be less straightforward, which may help explain the seemingly counter-intuitive effect of academic integration. A substantial number of students enter community colleges expecting to transfer to a four-year institution. The transfer aspiring students, especially if they are recent high school graduates, are a motivated group more likely to engage in academically integrative experiences such as interacting with faculty and advisors (Deil-Amen, 2011; Wang, 2009). At the same time, these students often do not have to complete an associate degree or declare a major in order to transfer to a baccalaureate institution. Therefore, even those transfer bound students who are interested in future STEM majors at four-year institutions may not have the need to declare a STEM area of study.

In addition, given the status differences between community colleges and four-year institutions (Dowd, 2011), STEM areas in community colleges do not necessarily enjoy the same high prestige as they do in four-year colleges and universities. Moreover, compared to other program offerings in two-year colleges, these disciplines may not lead to financially secure and rewarding jobs. The latter assumption has significant implications for students not interested in transferring. Among students seeking job training or immediate employment after completing a certificate, an associate degree, or even just a number of courses, those who are educationally integrated and have navigated the community college system adequately may be practically normed toward a non-STEM field such as accounting, business, or nursing that hold more promising job prospects.[4] In either case, the transfer aspiring students or the employment-oriented students could be academically integrated but do not select STEM fields of study.

In light of this finding, it may be important to support and strengthen the collaborations between community colleges' STEM programs and local employers in STEM fields as well as to develop seamless upward transfer pathways in these disciplines, so that choosing a STEM area of study may readily entail real prospect for future educational and career attainment for community college students. At the same time, additional targeted research would offer more convincing insights into the interesting pattern of results surfacing from this study.

Similar to the result in regard to academic integration, receiving financial aid has differential effects on students based on where they begin postsecondary education. Although financial aid receipt has a significant positive effect on four-year beginners' STEM choice, it has no effect on community college students. For students pursuing a bachelor's degree in a STEM fields, financial aid may help them reduce the need to work and focus on study, which is important given the amount of time and stringent grading

[4] Data from the National Center for Education Statistics (Snyder & Dillow, 2011) also confirmed that business, health professions, and liberal arts/transfer programs are among the most popular fields of study among community college students who declare major fields of study.

system often found in these disciplines (Arum & Roksa, 2011). In this sense, financial aid may facilitate entrance into STEM for four-year college students who might otherwise find a baccalaureate degree in these specific areas of study less feasible to pursue due to time and financial constraints. In a community college setting, for reasons discussed previously, selection of STEM may not be a necessary step toward transfer or may not imply immediate opportunities for high status jobs; therefore, financial aid may benefit students aspiring to non-STEM fields as much, if not more, as it would for those choosing STEM.

A number of other findings from this study are also worth noting. Female students beginning at both community colleges and four-year institutions are less likely to enter a STEM field of study. Consistent with prior studies (e.g., de Cohen & Deterding, 2009; Song & Glick, 2004), this result once again pinpoints the gender disparity in participation in STEM pipelines. Furthermore, Asian Americans and members of underrepresented minorities are more likely to choose STEM compared to White students. This finding, considered in conjunction with the much smaller proportion of underrepresented minorities completing STEM degrees, further underlines the high attrition rates of underrepresented minorities from STEM fields (Burke & Mattis, 2007). Although these students may aspire to or enter STEM majors at similar or even higher proportions compared to their White counterparts, their low completion rates speak to something quite alarming along the educational journey of these students. Needless to say, more intensive efforts are called for to provide women and underrepresented minorities with sufficient preparation and support along with focused research on the wide range of dimensions of the educational experiences in STEM of these students.

Conclusion

The past few decades have witnessed continued national demand for college graduates in STEM fields of postsecondary study. Therefore, how to increase the number of college students majoring in the STEM disciplines becomes an imperative question spanning secondary and postsecondary education. Empirical inquiries into factors related to entrance into these areas of study among students beginning at both community colleges and four-year institutions will in many ways inform educational policy and practices. Toward that end, this research advances a model of STEM participation among two student groups—community college and four-year institution entrants—based on a nationally representative sample of high school graduates of spring 2004. Applying SCCT, this study reveals a number of findings that may illuminate specific points of intervention along students' educational pathway into STEM. More importantly, utilizing multi-group SEM analysis, this study revealed important heterogeneity in the effects of high school and postsecondary variables based on where students start their postsecondary education: community colleges or four-year institutions. In particular, for recent high school graduates beginning at four-year institutions, facilitating the secondary-postsecondary STEM pathway seems more straightforward by strengthening academic integration and providing financial aid. However, entrance into STEM fields of study among students beginning at community colleges appears to be a more complex process that needs to be further understood. It should be noted that in recent years, increasing national attention has been paid to the role of community colleges in expanding the STEM pipeline in order to meet the social and economic need for a more diverse STEM workforce. However, the transfer pathways in STEM are insufficient to meet the national demands and must be expanded (Dowd, 2011). Prominent researchers and policy makers have called for concerted efforts to improve STEM education in community colleges as well as to foster transfer pathways in these disciplines between community colleges and four-year institutions (National Research Council and National Academy of Engineering, 2012). In general, future experimental inquiries and evidence-based policy interventions are needed to further support STEM aspiring students to enter, persist in, and graduate from these challenging and vital fields of postsecondary study.

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Table 1

List of variables

Variable	Description
Dependent Variable	
STEM choice	Respondent's 2006 major field of study is in STEM. 1=yes, 0=no
Mediating Variable STEM interest	Respondent's self-reported most likely field of study upon entering college is in STEM. 1=yes, 0=no
Independent Variable Math self-efficacy	Latent variable measured by: 1. Can do excellent job on math tests 2. Can understand difficult math texts 3. Can understand difficult math class 4. Can do excellent job on math assignments 5. Can master math class skills *Items based on 4-point Likert scales: 4 indicating "almost always" and 1 indicating "almost never"*
High school exposure to math and science courses	Latent variable measured by: 1. Units in high school math 2. Units in high school science
High school math preparation	High school math standardized score
Academic integration in college	Latent variable measured by: 1. Talk with faculty about academic matters outside of class 2. Meet with advisor about academic plans 3. Work on coursework at school library 4. Use the web to access school library for coursework *Items based on 3-point scales:3 indicating "often" and 1 indicating "never"*
Math and science readiness for college	Latent variable measured by: 1. High school math prepared for college 2. High school science prepared for college *Items based on 3-point scales:3 indicating "a great deal" and 1 indicating "not at all"*
External demands	Latent variable measured by: 1. Whether has biological children, 1=yes, 0=no 2. Whether is married, 1=yes, 0=no 3. Weekly work hours
Receiving financial aid	Offered financial aid 1st year at college, 1=yes, 0=no
Number of Remedial Subjects	Number of remedial subjects in reading, writing, and math
Enrollment intensity	1=full-time, 0=part-time
Expecting a graduate degree	Respondent expected to earn a graduate degree, 1=yes, 0=no
Demographic Variables	
Gender	1=female, 0=male
Race	Underrepresented minorities[a], Asian American, with White being the reference category
Socioeconomic Status	Socioeconomic status quartile
English as the First Language	English is the respondent's first native language. 1=yes, 0=no
First-Generation	Respondent is the first in family to go to college. 1=yes, 0=no

[a] Underrepresented minorities include African Americans, Hispanics, and American Indians, and multi-racial students.

Table 2

Summary of demographic characteristics of the sample, by level of first institutions

	Four-Year Institution				Community College				Total			
	N	%	Weighted	W%	N	%	Weighted	W%	N	%	weighted	W%
Gender												
Male	2,870	45.5	708,844	45.4	1,620	46.7	412,559	47.5	4,490	45.9	1,121,403	46.2
Female	3,440	54.5	851,202	54.6	1,850	53.3	456,161	52.5	5,280	54.1	1,307,363	53.8
Total	6,300	100.0	1,560,046	100.0	3,470	100.0	868,720	100.0	9,770	100.0	2,428,766	100.0
Race/Ethnicity												
American Indian	30	0.4	6,922	0.4	30	0.7	7,934	0.9	50	0.5	14,856	0.6
Asian	750	11.9	181,239	11.6	380	10.8	36,546	4.2	1,130	11.5	217,786	9.0
Black	660	10.5	166,087	10.6	430	12.3	112,319	12.9	1,090	11.2	278,406	11.5
Hispanic	520	8.3	135,477	8.7	600	17.3	169,452	19.5	1,130	11.5	304,929	12.6
Multi-Racial	280	4.5	73,660	4.7	150	4.3	28,345	3.3	430	4.4	102,005	4.2
White	4,050	64.3	996,660	63.9	1,890	54.5	514,124	59.2	5,940	60.8	1,510,784	62.2
Socio-economic Status												
Lowest quartile	700	11.2	173,826	11.1	820	23.7	219,776	25.3	1,520	15.6	393,602	16.2
Second quartile	1,050	16.7	268,578	17.2	950	27.3	236,176	27.2	2,000	20.4	504,754	20.8
Third quartile	1,620	25.7	398,640	25.6	950	27.4	244,460	28.1	2,570	26.3	643,101	26.5
Highest quartile	2,930	46.4	719,001	46.1	750	21.6	168,308	19.4	3,680	37.6	887,309	36.5
Interest in a STEM major	1,220	19.3	302,861	19.4	350	10.1	89,622	10.3	1,570	16.0	392,483	16.2
Entrance into a STEM major	970	15.4	240,673	15.4	250	7.2	59,994	6.9	1,220	12.5	300,667	12.4
Receiving financial aid	4,420	70.1	1,087,460	69.7	1,440	41.4	371,996	42.8	5,850	59.9	1,459,456	60.1
Enrolled full-time	6,030	95.6	1,489,844	95.5	2,430	70.0	608,822	70.1	8,460	86.5	2,098,666	86.4
Expecting a graduate degree	3,530	56.0	866,933	55.6	890	25.8	226,760	26.1	4,420	45.3	1,093,693	45.0
English as the first language	5,440	86.2	1,341,285	86.0	2,770	80.0	716,566	82.5	8,210	84.0	2,057,851	84.7
First-generation	860	13.6	212,189	13.6	920	26.6	246,632	28.4	1,780	18.2	458,821	18.9

Note. Per IES guidelines, the analytical N's should be rounded to the nearest 10. Therefore, the sum of subgroup N's may not add up to the total due to rounding.

Table 3

Summary of demographic characteristics of students interested in STEM, by level of first institutions

	Four-Year Institution				Community College				Total			
	N	%	Weighted	W%	N	%	Weighted	W%	N	%	Weighted	W%
Interest in a STEM major	1,220	19.3	302,861	19.4	350	10.1	89,622	10.3	1,570	16.0	392,483	16.2
Gender												
Male	840	69.2	210,236	69.4	270	76.6	68,790	76.8	1,110	70.9	279,026	71.1
Female	370	30.8	92,625	30.6	80	23.4	20,831	23.2	460	29.1	113,457	28.9
Race/Ethnicity												
American Indian	10	0.6	1,385	0.5	0	0.6	713	0.8	10	0.6	2,098	0.5
Asian	200	16.5	44,301	14.6	50	12.8	4,806	5.4	250	15.7	49,106	12.5
Black	140	11.4	35,166	11.6	40	12.3	11,775	13.1	180	11.6	46,941	12.0
Hispanic	100	8.1	25,856	8.5	60	16.0	14,093	15.7	150	9.8	39,949	10.2
Multi-Racial	50	4.3	12,865	4.2	10	3.1	2,668	3.0	60	4.0	15,533	4.0
White	720	59.2	183,289	60.5	190	55.3	55,567	62.0	910	58.3	238,856	60.9
Socio-economic Status												
Lowest quartile	160	12.8	37,246	12.3	80	22.5	19,295	21.5	240	15.0	56,541	14.4
Second quartile	180	15.1	47,942	15.8	80	21.9	19,401	21.6	260	16.6	67,343	17.2
Third quartile	270	22.5	69,080	22.8	110	31.1	28,228	31.5	380	24.4	97,308	24.8
Highest quartile	600	49.6	148,594	49.1	90	24.5	22,698	25.3	690	44.0	171,291	43.6
Receiving financial aid	870	71.5	216,595	71.5	140	40.2	32,616	36.4	1,010	64.5	249,211	63.5
Enrolled full-time	1,170	96.5	291,496	96.2	240	69.5	63,239	70.6	1,420	90.5	354,735	90.4
Expecting a graduate degree	730	59.8	179,925	59.4	110	30.2	26,407	29.5	830	53.1	206,333	52.6
English as the first language	1000	82.2	251,843	83.2	280	80.9	77,503	86.5	1,280	81.9	329,346	83.9
First-generation	180	14.4	43,475	14.4	90	25.4	23,241	25.9	260	16.9	66,716	17.0

Note. Per IES guidelines, the analytical N's should be rounded to the nearest 10. Therefore, the sum of subgroup N's may not add up to the total due to rounding.

Table 4

Summary of demographic characteristics of students entering a STEM major, by level of first institutions

	Four-Year Institution				Community College				Total			
	N	%	Weighted	W%	N	%	Weighted	W%	N	%	Weighted	W%
Entrance into a STEM major	970	15.4	240,673	15.4	250	7.2	59,994	6.9	1,220	12.5	300,667	12.4
Gender												
Male	620	63.7	153,355	63.7	180	71.7	43,862	73.1	800	65.4	197,217	65.6
Female	350	36.3	87,318	36.3	70	28.3	16,132	26.9	420	34.6	103,450	34.4
Race/Ethnicity												
American Indian	0	0.2	243	0.1	0	0.8	994	1.7	0	0.3	1,237	0.4
Asian	180	18.7	42,222	17.5	40	16.7	4,266	7.1	220	18.3	46,488	15.5
Black	110	11.8	30,836	12.8	20	9.2	6,247	10.4	140	11.2	37,083	12.3
Hispanic	70	6.9	14,474	6.0	30	12.0	8,762	14.6	100	7.9	23,236	7.7
Multi-Racial	40	4.3	9,540	4.0	10	5.2	3,056	5.1	60	4.5	12,597	4.2
White	560	58.1	143,357	59.6	140	56.2	36,669	61.1	710	57.7	180,027	59.9
Socio-economic Status												
Lowest quartile	90	9.0	20,149	8.4	60	23.5	14,327	23.9	150	12.0	34,476	11.5
Second quartile	140	14.1	34,611	14.4	60	25.5	15,208	25.3	200	16.5	49,819	16.6
Third quartile	230	23.7	56,242	23.4	70	27.5	16,364	27.3	300	24.5	72,606	24.1
Highest quartile	520	53.2	129,671	53.9	60	23.5	14,095	23.5	580	47.1	143,766	47.8
Receiving financial aid	730	74.9	180,472	75.0	110	45.0	26,544	44.2	840	68.8	207,016	68.9
Enrolled full-time	950	97.5	233,532	97.0	200	80.1	50,528	84.2	1,150	93.9	284,059	94.5
Expecting a graduate degree	650	67.3	160,682	66.8	70	29.5	17,859	29.8	730	59.5	178,541	59.4
English as the first language	780	80.1	193,792	80.5	200	78.1	48,782	81.3	970	79.7	242,574	80.7
First-generation	110	11.4	27,764	11.5	70	26.3	15,946	26.6	180	14.5	43,710	14.5

Note. Per IES guidelines, the analytical N's should be rounded to the nearest 10. Therefore, the sum of subgroup N's may not add up to the total due to rounding.

Table 5

Results of confirmatory factor analysis on the measurement model

	b		*S.E.*	*Std.*		*S.E.*
χ^2 = 1666.430						
df = 94						
RMSEA = 0.041						
CFI = 0.986						
TLI = 0.982						
Factors and Indicators						
Math self-efficacy beliefs						
Do excellent job on math tests	1.000		--	0.883	***	0.005
Understand difficult math texts	1.127	***	0.034	0.904	***	0.004
Understand difficult math class	1.047	***	0.029	0.892	***	0.005
Do excellent job on math assignments	0.913	***	0.027	0.864	***	0.007
Can master math class skills	1.008	***	0.027	0.884	***	0.005
Exposure to math and science courses						
Units in high school math	1.000		--	0.650	***	0.018
Units in high school science	1.170	***	0.064	0.663	***	0.019
Academic integration in college						
Talk with faculty	1.000		--	0.647	***	0.014
Meet with advisor	1.001	***	0.054	0.647	***	0.013
Do coursework at library	0.993	***	0.049	0.644	***	0.012
Use the web to access school library	1.046	***	0.054	0.663	***	0.014
Math and science readiness for college						
HS math prepared for college	1.000		--	0.844	***	0.028
HS science prepared for college	0.429	***	0.066	0.559	***	0.020
External demands						
Whether has biological children	1.000		--	0.207	***	0.045
Whether is married	0.690	***	0.201	0.145	***	0.042
Weekly work hours	50.042	**	18.007	0.961	***	0.162

Std. = Standardized estimate
*** $p < 0.001$, ** $p < 0.01$

Table 6

SEM model fit statistics and results of structural path invariance tests

Model	χ^2	*df*	$\Delta\chi^2$ *p-value*	$\Delta\chi^2$ Test (α=0.05)	RMSEA	CFI	TLI
One sample (N = 9,770)	5615.107	307	--	--	0.042	0.931	0.922
Four-Year Institution Group (N = 6,300)	2765.833	307	--	--	0.036	0.955	0.949
Community College Group (N = 3,470)	1729.023	307	--	--	0.037	0.932	0.922
Baseline model	4435.937	639	--	--	0.035	0.948	0.943
Individual path coefficient constrained							
Path to STEM Interest							
Math Self-Efficacy	4409.561	640	0.000	Non-Invariant	0.035	0.948	0.943
Exposure to Math and Science Courses	4446.088	640	0.001	Non-Invariant	0.035	0.948	0.943
High School Math Preparation	4441.985	640	0.014	Non-Invariant	0.035	0.948	0.943
Path to STEM Choice							
Interest in a STEM Major	4434.610	640	0.249	Invariant	0.035	0.948	0.943
Academic Integration	4440.042	640	0.043	Non-Invariant	0.035	0.948	0.943
Math and Science Readiness for College	4433.967	640	0.160	Invariant	0.035	0.948	0.943
High School Math Preparation	4437.978	640	0.153	Invariant	0.035	0.948	0.943
Receiving Financial Aid	4445.271	640	0.002	Non-Invariant	0.035	0.948	0.943
External Demands	4435.640	640	0.586	Invariant	0.035	0.948	0.943
Number of Remedial Subjects	4433.287	640	0.104	Invariant	0.035	0.948	0.943
Enrolled Full-time	4434.667	640	0.260	Invariant	0.035	0.948	0.943
Expecting a Graduate Degree	4438.644	640	0.100	Invariant	0.035	0.948	0.943
Female	4438.162	640	0.136	Invariant	0.035	0.948	0.943
Asian	4435.563	640	0.541	Invariant	0.035	0.948	0.943
Underrepresented Minorities	4435.809	640	0.721	Invariant	0.035	0.948	0.943
Socioeconomic Status	4436.053	640	0.733	Invariant	0.035	0.948	0.943
English as the First Language	4434.466	640	0.225	Invariant	0.035	0.948	0.943
First-Generation	4434.685	640	0.263	Invariant	0.035	0.948	0.943
Final model							
13 Invariant Path Coefficients Constrained	4427.826	652	0.836	Invariant	0.034	0.948	0.944

Table 7

Path coefficients of the final multi-group SEM based on level of first postsecondary institutions

	Four-Year Institution				Community College			
Path	*b*		*S.E.*	*Std.*	*b*		*S.E.*	*Std.*
STEM Interest								
Math Self-Efficacy	0.067	***	0.017	0.107	0.064	*	0.027	0.113
Exposure to Math and Science	0.667	***	0.104	0.282	0.144		0.091	0.083
High School Math Preparation	0.037	***	0.004	0.290	0.012	*	0.005	0.102
STEM Choice								
STEM Interest	1.113	***	0.080	0.709	(constrained equal)			
Academic Integration	0.141	*	0.059	0.066	-0.220	**	0.075	-0.141
Receiving Financial Aid	0.282	**	0.093	0.074	-0.025		0.127	-0.008
Adequacy of HS Preparation for College	0.115	*	0.050	0.084	(constrained equal)			
External Demands	0.013		0.046	0.009	(constrained equal)			
High School Math Preparation	0.014	**	0.005	0.067	(constrained equal)			
Number of Remedial Subjects	-0.018		0.037	-0.011	(constrained equal)			
Enrolled Full-time	0.083		0.118	0.010	(constrained equal)			
Expecting a Graduate Degree	0.202	**	0.078	0.057	(constrained equal)			
Female	-0.848	***	0.080	-0.243	(constrained equal)			
Asian	0.334	**	0.130	0.062	(constrained equal)			
Underrepresented Minorities	0.208	*	0.101	0.051	(constrained equal)			
Socioeconomic Status	0.023		0.042	0.014	(constrained equal)			
English as the First Language	-0.140		0.107	-0.028	(constrained equal)			
First-Generation	0.014		0.108	0.003	(constrained equal)			
<u>Indirect Effects</u>								
STEM Choice								
Math Self-Efficacy	0.062			0.063	0.058			0.065
Exposure to Math and Science	0.618			0.167	0.136			0.049
High School Math Preparation	0.035			0.171	0.011			0.059

Std. = Standardized estimate
*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

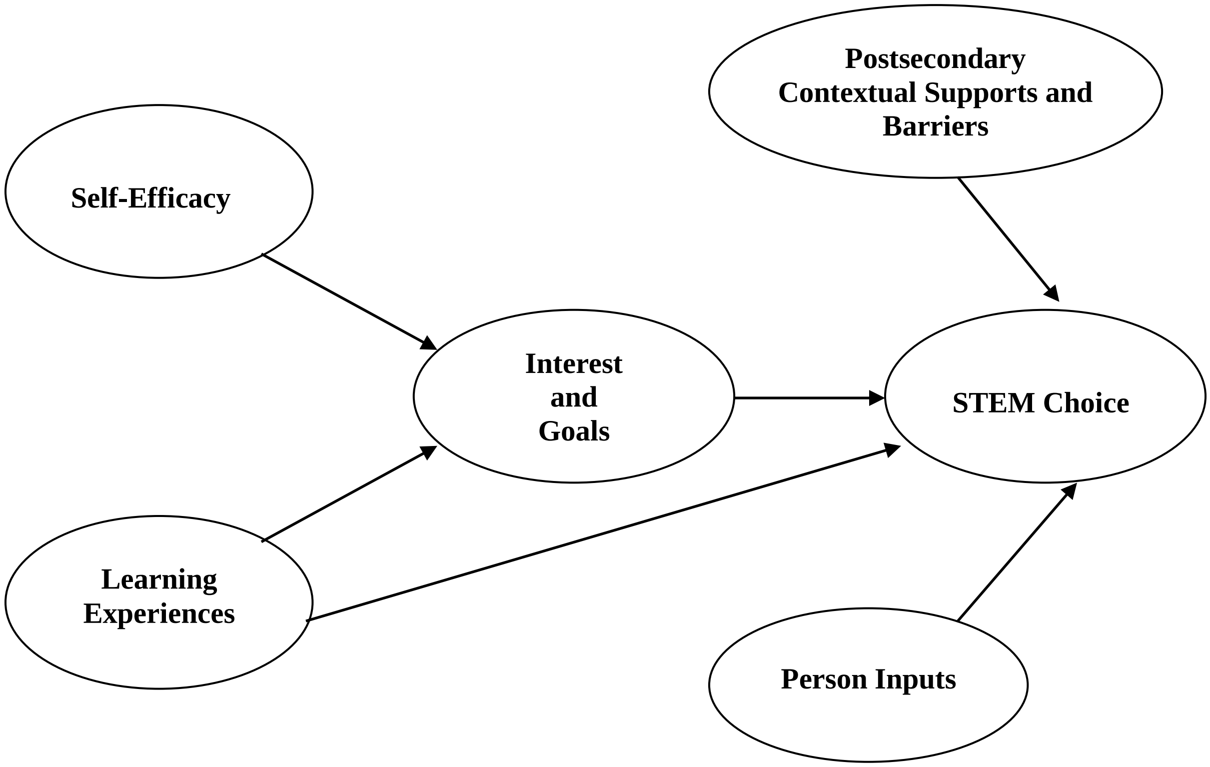

Fig. 1 The study's conceptual model.

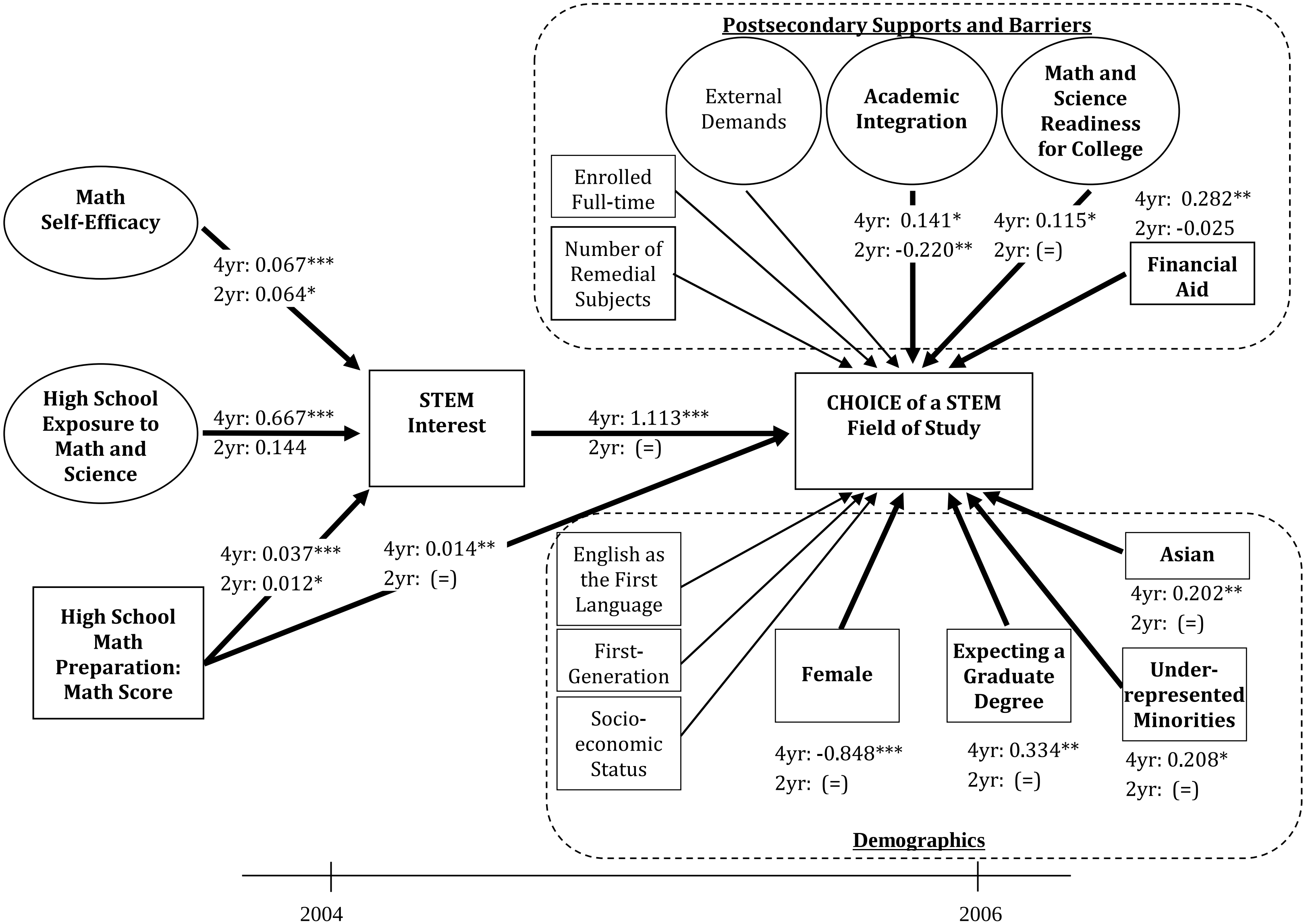

Fig. 2 Final multi-group structural equation modeling results.
4yr: Four-year institution, 2yr: Community college. (=) indicates that the path coefficient is constrained equal across the two groups.
Significant paths are highlighted in bold. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$