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

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Abstract In this study, a theoretical model is tested to examine factors shaping the decision to pursue STEM fields of study among students entering community colleges and four-year institutions, based on a nationally representative sample of high school graduates from 2004. Applying the social cognitive career theory and multi-group structural equation modeling analysis, this research highlights a number of findings that may point to specific points of intervention along students' educational pathway into STEM. This study also 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. For example, while high school exposure to math and science courses appears to be a strong influence on four-year beginners' STEM interest, its impact on community college beginners' STEM interest, albeit being positive, is much smaller. In addition, college academic integration and financial aid receipt exhibit differential effects on STEM entrance, accruing more to four-year college students and less to those starting at community colleges.

Keywords Community college students · STEM education · Choice of major · Social cognitive career theory · Multi-group structural equation modeling

Over the past few decades, the educational pipeline of science, technology, engineering, and mathematics (STEM) fields has been a key preoccupation for researchers and policymakers. 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

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et al. 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 and 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 postsecondary areas of study, research devoted to understanding the influences on students' academic choices in regard to postsecondary STEM majors is essential.

It is important to note that there are a number of insightful studies providing valuable information on STEM education, many of which focus on interest and persistence in and completion of four-year STEM majors (e.g., Herrera and Hurtado 2011; Herrera et al. 2011; Hurtado et al. 2012). Nonetheless, in general there are still few empirical studies that deal with the actual point of entry into STEM disciplines and the specific factors influencing *entrance* into STEM fields of study among college students. As a result, the barriers and boosters to students' choice of STEM majors are unclear and knowledge is scant on how to broaden participation in these areas of study among college students.

In addition, empirical work in this vein should not focus solely on students attending four-year institutions as prior studies on choice of college major 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 and Kim 2006; National Academies 2005 "Rising Above the Gathering Storm" Committee 2010; Smyth and McArdle 2004). For many members of these underrepresented student populations, community colleges serve as an entry point to postsecondary education (e.g., Bailey et al. 2003; 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 and diversifying STEM participation will rely on the nation's community colleges. This point also holds true for minority-serving institutions, many of which are two-year colleges (Benitez 1998; Dayton et al. 2004; Laden 2001). Therefore, research that deals with the STEM pipeline should not overlook community colleges. 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.

To understand what influences college students to enter majors in STEM fields, this study 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 disciplines 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 et al. 1994, 2002). 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 individuals' 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 et al. 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 et al. 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 and goals among Mexican-American middle school students (Navarro et al. 2007). A study investigating educational pathway choice of Australian students showed that a variable pattern of interactions between vocational interest, self-efficacy, and achievement predicted student career path behavior (Patrick et al. 2011). Similarly, a longitudinal study of high school students revealed evidence that career planning and exploration were determined mostly by self-efficacy and goals but also by varied influences of personality and contextual and biographical variables (Rogers and Creed 2011).

To a limited extent, SCCT has also been applied to examine STEM choice and persistence in a postsecondary setting. Lent et al. (2003) studied engineering students enrolled in a predominantly white university and found that key constructs in SCCT successfully predicted 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

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

goals. Moreover, in a study based on data from the 2004 Freshmen Survey and the 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 choice of STEM majors. In addition, no prior research has applied SCCT in examining relevant STEM research topics pertaining to community college students. Traditionally, research surrounding STEM choice and college major choice in general has primarily relied on Holland's (1973, 1985) theory of career choice that emphasizes the compatibility between personalities and environments (e.g., Allen and Robbins 2008; Pike 2006; Porter and Umbach 2006; Smart et al. 2000). While Holland's theory is instrumental in pointing to the importance of congruence between personalities and environments in making career and academic choices, it does not directly address students' inputs other than personalities, such as their demographic backgrounds, self-efficacy, and educational plans for the future. In addition, regarding academic major choice, "environments" are often discussed solely as disciplinary characteristics of major fields of study, whereas other potential supports or barriers external to students, such as affordability and multiple responsibilities of students are neglected.

Students' choice of major fields of study, however, is more complex than a simple consideration of fit between personalities and disciplinary environments. Other factors indubitably come into play when selecting a major, which calls for a more comprehensive theory to account for the complexity that surrounds major choice. Many of the student input and environmental factors not accounted for by Holland's theory are conceptually depicted by SCCT. Extending this theoretical lens to research on postsecondary STEM issues therefore affords depth and complexity, both conceptually and analytically, that is well suited for studying the multifaceted process of student choice of STEM fields of postsecondary study.

Conceptual Framework and Supporting Literature

The conceptual framework (Fig. 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 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 much 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. Additionally, learning experiences in high school and college readiness are added to the model. In summary, the model hypothesizes that students' self-efficacy and learning experiences during high school affect their interest and goals in terms of choosing a STEM major as well as their college readiness, which in turn influence their actual choice of STEM disciplines. STEM choice is also subject to contextual supports and barriers as well as person inputs. A more detailed description of the model follows in Fig. 1.

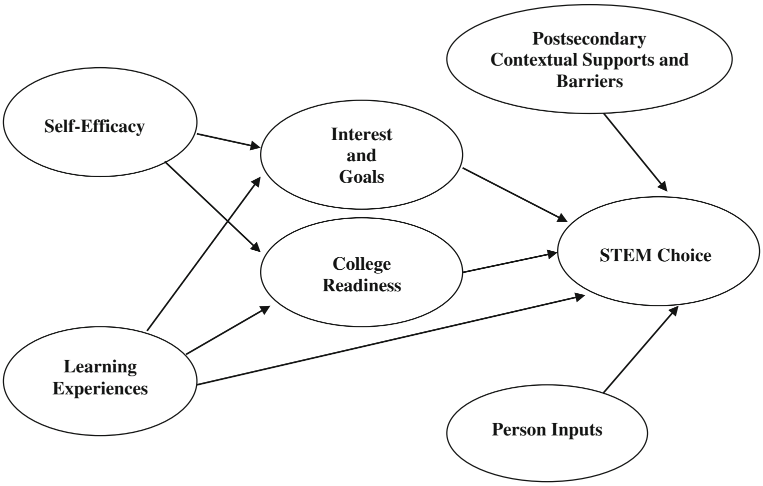

Fig. 1 The study's conceptual model

Self-efficacy is a central 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 and 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 and Umbach 2006). In particular, self-efficacy beliefs of math proficiency are hypothesized to associate with choice of major in STEM fields (Betz and Hackett 1983; Scott and Mallinckrodt 2005).

Although SCCT does not distinctively identify learning as a key factor in shaping academic and career interests and choices, it is reasonable to hypothesize that high school learning affects interests and choices 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 et al. 2000; Staniec 2004). In addition, as an outcome of high school learning, perceived college readiness may influence students' choice of major (Millar 2010; Rosenbaum 2001), and readiness in math and science in particular may be related to students' decision to choose STEM majors (Adelman 1998; Wang 2012).

After enrolling in college, a number of contextual influences may come into play in terms of which major areas of study students would actually choose, especially given that students are not required to declare their major upon admission. Within the SCCT framework, these postsecondary factors may become either contextual supports that facilitate students in choosing certain fields of study or circumstantial barriers that pull students away from specific majors. Several such environmental factors are established by prior literature as those shaping students' academic experience in college and thus may have plausible influences on choice of STEM fields. These elements include (a) academic integration into college (Astin 1993; Chang 2005; Lamport 1993; Terenzini et al. 1999); (b) enrolling in remedial courses (Adelman 2006; Attewell et al. 2006; Bahr 2008; Bailey and Alfonso 2005; Long 2005; Pascarella and Terenzini 2005); (c) receiving financial aid (DesJardins et al. 2006; Ishitani and DesJardins 2002); and (d) having external demands which may distract students from studying (Bryant 2001; Kane and Rouse 1999).

Finally, demographic characteristics and educational expectations are important person inputs in the proposed conceptual model. Gender, ethnicity, and socioeconomic status (SES) are the most widely inquired variables that are likely to influence one's choice of major (Maple and Stage 1991; Porter and Umbach 2006; Ware and Lee 1988). Indeed, in STEM fields it is observed that males, 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 and 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 and Umbach 2006). As to educational expectations, they may also influence one's choice of major, given that higher expectations are associated with selection of a math or science major among students (Ware and Lee 1988).

In summary, the conceptual model for the study hypothesizes a number of interrelationships among a repertoire of factors that influence students' entrance into 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. Explicitly stated, the following hypothesized relationships are examined in this study: (a) STEM interest is positively associated with math self-efficacy beliefs, high school exposure to math and science, and high school math achievement, and all three are interrelated with each other; (b) these three high school variables are also positively related to students' perceived math readiness for college; (c) high school exposure to math and science in particular has a positive effect on students' perceived science readiness for college; (d) STEM interest and perceived math and science readiness for college all in turn influence students' choice of a STEM field of study; (e) STEM choice is also affected by postsecondary context of supports (academic integration and financial aid) and potential barriers (remediation, being married, having children, and working hours); and (f) person inputs (race, gender, SES, and educational expectations) also shape STEM choice.

It should be noted that, 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 differential institutional environments given the contrasting educational configurations offered by two-year and four-year institutions, the aforementioned hypothesized relationships are assessed across these two groups of students. Thus, the analysis will unveil the most salient factors for both beginning community college students and their four-year counterparts, which would allow researchers and policymakers 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 into 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 2 years after high school graduation for most survey participants. New data collected pertained to individuals' postsecondary enrollment and experiences, social and economic return of education, and newly acquired adult roles (e.g., family formation).

The study's sample included 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: students whose first postsecondary institution was a four-year college or university (about 6,300; 65 %) and those who attended a community college as their first postsecondary institution (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, was 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 a STEM discipline[2] and zero otherwise. The main mediating variables in the model included students' interest in choosing a STEM field of study and their perceived math and science readiness for college. STEM interest was measured by whether students thought of a STEM discipline as the most likely field of study to pursue when entering college. Math readiness for college and science readiness for college were each measured by a 3-point scale indicating students' perceived adequacy of their high school math and science for college-level work. In terms of the high school level independent variables, 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: exposure to math and science courses, measured by the total number of units in mathematics and science technologies during high school, and high school math achievement, measured by the standardized math test score a student received during the first follow-up.

Postsecondary contextual supports and barriers were operationalized by the following: academic integration, receipt of financial aid, number of remedial subjects, and external demands. Person inputs included demographic variables such as gender, race/ethnicity, SES, as well as graduate degree expectations. Table 1 provides a detailed description of the

[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.

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
Math readiness for college	High school math prepared for college
Science readiness for college	High school science prepared for college
	Items based on 3-point scales: 3 indicating "a great deal" and 1 indicating "not at all"
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 achievement	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"
Married	Whether is married, 1 = yes, 0 = no
Having children	Whether has biological children, 1 = yes, 0 = no
Work hours	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
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
SES	Socioeconomic status quartile

[a] Underrepresented minorities include African American, Hispanic, American Indian, and multi-racial students

variables used in the study. These variables were selected based on the previously described conceptual framework and literature in relation to STEM education and college success, which underscore high school learning and components of SCCT such as interest and goals, contextual supports and barriers, and person inputs.

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 the 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.

As the measurement part of the SEM analysis, a confirmatory factor analysis (CFA) was first conducted to measure the latent variables in the proposed model. Three latent variables were measured in this study: (a) math self-efficacy; (b) exposure to math and science courses in high school; and (c) academic integration in college. The indicator variables of the corresponding latent factors are described in Table 1. The factor loadings of indicator variables and fit statistics of the 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 the latent variables, the structural part of the model was added to form the full structural equation model (see Fig. 2 in the Result section). 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 four regression equations. Specifically, the first two regression equations investigated how students' interest in choosing a STEM field of study and their perceived math readiness for college were each affected by the three high school variables: (a) math self-efficacy beliefs; (b) exposure to math and science courses; and (c) high school math achievement. Then, the third regression examined the effect of high school exposure to math and science on perceived science readiness for college. Finally, the fourth regression equation explored how students' actual selection of a STEM field was influenced by their initial interest, high school math achievement, math readiness for college, science readiness for college, postsecondary supports and barriers (such as academic integration, financial aid receipt, number of remedial subjects, and external demands), as well as person input variables (such as gender, race/ethnicity, SES, and graduate degree expectations).

In conducting the SEM analysis, initially a one-sample, full structural equation model was 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 with structural path invariance tests, described below.

Structural Path Invariance Tests

In order to examine whether the modeled variables exert effects equivalently on student interest and choice regarding STEM fields of study across both student groups (i.e., those beginning at community colleges and those beginning at four-year institutions), a series of structural path invariance tests were conducted. In simple terms, invariance tests examine whether the proposed structural model and the hypothesized relationships among variables can be applicable equivalently to different populations (i.e., four-year and two-year student groups in this 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 to be the same across the community college and four-year groups. Through this test, if the chi-square difference statistic ($\Delta\chi^2$) did not reveal a significant difference between the models, then it could be concluded that the structural path being tested was the same 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 exerted significantly different effects on the two groups.

Following these invariance tests, individually found invariant parameters were constrained to be the same and those individually found non-invariant parameters were freely estimated across community college and four-year college student groups in the final multi-group 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 and 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 was used (Kline 2011).

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 and Graham 2002). Multiple datasets were generated that replaced 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 and 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 was five. Given the multi-group approach used in the study, data imputation was conducted separately for the community college and four-year groups.

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 between them and the choice action (in this study, choice of a STEM major), 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 in and eventual completion of these majors are also 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 2 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 focused 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 SCCT 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. Of the total sample, 16 % of students were interested in choosing a STEM field of study upon entering college, and 13 % eventually chose a STEM discipline. More details of student characteristics are available in Table 2.

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).

Results of Confirmatory Factor Analysis

The CFA measured three 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 had a significant chi-square value, $\chi^2(41) = 977.863$, $p = 0.000$, 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 indices such as RMSEA, CFI, and TLI should be examined as primary fit indices (Kline 2011; Schumacker and Lomax 2004). A smaller RMSEA value indicates a better model to data fit (Hooper et al. 2008; MacCallum et al. 1996) and a CFI or TLI value closer to 1 suggests a good fit (Schreiber et al. 2006). The RMSEA was 0.048, which was below the 0.05 cut-off point. The CFI and the TLI were 0.991 and 0.988, respectively. All these indices showed a good fit between the measurement model and the data. The unstandardized and standardized factor loadings and their levels of significance also suggested that the proposed measurement model fit the data adequately.

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 = 0.954, TLI = 0.947. The model was then fitted to the community college and four-year student data individually. The model fit the separate

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

Table 2 Summary of demographic characteristics of the sample, by level of first institution

	Four-year institution				Community college				Total			
	N	%	Weighted	W %	*N*	%	Weighted	W %	*N*	%	Weighted	W %
Gender												
Male	2,870	45.5	708,840	45.4	1,620	46.7	412,560	47.5	4,490	45.9	1,121,400	46.2
Female	3,440	54.5	851,200	54.6	1,850	53.3	456,160	52.5	5,280	54.1	1,307,360	53.8
Total	6,300	100.0	1,560,050	100.0	3,470	100.0	868,720	100.0	9,770	100.0	2,428,770	100.0
Race/ethnicity												
American Indian	30	0.4	6,920	0.4	30	0.7	7,930	0.9	50	0.5	14,860	0.6
Asian	750	11.9	181,240	11.6	380	10.8	36,550	4.2	1,130	11.5	217,790	9.0
Black	660	10.5	166,090	10.6	430	12.3	112,320	12.9	1,090	11.2	278,410	11.5
Hispanic	520	8.3	135,480	8.7	600	17.3	169,450	19.5	1,130	11.5	304,930	12.6
Multi-racial	280	4.5	73,660	4.7	150	4.3	28,350	3.3	430	4.4	102,010	4.2
White	4,050	64.3	996,660	63.9	1,890	54.5	514,120	59.2	5,940	60.8	1,510,780	62.2
SES												
Lowest quartile	700	11.2	173,830	11.1	820	23.7	219,780	25.3	1,520	15.6	393,600	16.2
Second quartile	1,050	16.7	268,580	17.2	950	27.3	236,180	27.2	2,000	20.4	504,750	20.8
Third quartile	1,620	25.7	398,640	25.6	950	27.4	244,460	28.1	2,570	26.3	643,100	26.5
Highest quartile	2,930	46.4	719,000	46.1	750	21.6	168,310	19.4	3,680	37.6	887,310	36.5
Interest in a STEM major	1,220	19.3	302,860	19.4	350	10.1	89,620	10.3	1,570	16.0	392,480	16.2
Entrance into a STEM major	970	15.4	240,670	15.4	250	7.2	59,990	6.9	1,220	12.5	300,670	12.4
Receiving financial aid	4,420	70.1	1,087,460	69.7	1,440	41.4	372,000	42.8	5,850	59.9	1,459,460	60.1
Expecting a graduate degree	3,530	56.0	866,930	55.6	890	25.8	226,760	26.1	4,420	45.3	1,093,690	45.0

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 institution

	Four-year institution				Community college				Total			
	N	%	Weighted	W %	*N*	%	Weighted	W %	*N*	%	Weighted	W %
Interest in a STEM major	1,220	19.3	302,860	19.4	350	10.1	89,620	10.3	1,570	16.0	392,480	16.2
Gender												
Male	840	69.2	210,240	69.4	270	76.6	68,790	76.8	1,110	70.9	279,030	71.1
Female	370	30.8	92,630	30.6	80	23.4	20,830	23.2	460	29.1	113,460	28.9
Race/ethnicity												
American Indian	10	0.6	1,390	0.5	0	0.6	710	0.8	10	0.6	2,100	0.5
Asian	200	16.5	44,300	14.6	50	12.8	4,810	5.4	250	15.7	49,110	12.5
Black	140	11.4	35,170	11.6	40	12.3	11,780	13.1	180	11.6	46,940	12.0
Hispanic	100	8.1	25,860	8.5	60	16.0	14,090	15.7	150	9.8	39,950	10.2
Multi-racial	50	4.3	12,870	4.2	10	3.1	2,670	3.0	60	4.0	15,530	4.0
White	720	59.2	183,290	60.5	190	55.3	55,570	62.0	910	58.3	238,860	60.9
SES												
Lowest quartile	160	12.8	37,250	12.3	80	22.5	19,300	21.5	240	15.0	56,540	14.4
Second quartile	180	15.1	47,940	15.8	80	21.9	19,400	21.6	260	16.6	67,340	17.2
Third quartile	270	22.5	69,080	22.8	110	31.1	28,230	31.5	380	24.4	97,310	24.8
Highest quartile	600	49.6	148,590	49.1	90	24.5	22,700	25.3	690	44.0	171,290	43.6
Receiving financial aid	870	71.5	216,600	71.5	140	40.2	32,620	36.4	1,010	64.5	249,210	63.5
Expecting a graduate degree	730	59.8	179,930	59.4	110	30.2	26,410	29.5	830	53.1	206,330	52.6

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 institution

	Four-year institution				Community college				Total			
	N	%	Weighted	W %	*N*	%	Weighted	W %	*N*	%	Weighted	W %
Entrance into a STEM major	970	15.4	240,670	15.4	250	7.2	59,990	6.9	1,220	12.5	300,670	12.4
Gender												
Male	620	63.7	153,360	63.7	180	71.7	43,860	73.1	800	65.4	197,220	65.6
Female	350	36.3	87,320	36.3	70	28.3	16,130	26.9	420	34.6	103,450	34.4
Race/ethnicity												
American Indian	0	0.2	240	0.1	0	0.8	990	1.7	0	0.3	1,240	0.4
Asian	180	18.7	42,220	17.5	40	16.7	4,270	7.1	220	18.3	46,490	15.5
Black	110	11.8	30,840	12.8	20	9.2	6,250	10.4	140	11.2	37,080	12.3
Hispanic	70	6.9	14,470	6.0	30	12.0	8,760	14.6	100	7.9	23,240	7.7
Multi-racial	40	4.3	9,540	4.0	10	5.2	3,060	5.1	60	4.5	12,600	4.2
White	560	58.1	143,360	59.6	140	56.2	36,700	61.1	710	57.7	180,030	59.9
SES												
Lowest quartile	90	9.0	20,150	8.4	60	23.5	14,330	23.9	150	12.0	34,480	11.5
Second quartile	140	14.1	34,610	14.4	60	25.5	15,210	25.3	200	16.5	49,820	16.6
Third quartile	230	23.7	56,240	23.4	70	27.5	16,360	27.3	300	24.5	72,610	24.1
Highest quartile	520	53.2	129,670	53.9	60	23.5	14,100	23.5	580	47.1	143,770	47.8
Receiving financial aid	730	74.9	180,472	75.0	110	45.0	26,540	44.2	840	68.8	207,020	68.9
Expecting a graduate degree	650	67.3	160,682	66.8	70	29.5	17,860	29.8	730	59.5	178,540	59.4

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	SE	Std.	SE
$\chi^2 = 977.863$				
df = 41				
RMSEA = .048				
CFI = .991				
TLI = .988				
Factors and indicators				
Math self-efficacy beliefs				
Do excellent job on math tests	1.000	–	.883***	.005
Understand difficult math texts	1.128***	.034	.904***	.004
Understand difficult math class	1.049***	.029	.892***	.005
Do excellent job on math assignments	.916***	.027	.865***	.007
Can master math class skills	1.006***	.027	.884***	.005
Exposure to math and science courses				
Units in high school math	1.000	–	.675***	.022
Units in high school science	1.085***	.074	.639***	.023
Academic integration in college				
Talk with faculty	1.000	–	.651***	.014
Meet with advisor	.982***	.055	.644***	.013
Do coursework at library	.984***	.050	.645***	.013
Use the web to access school library	1.029***	.056	.661***	.014

b factor loading estimate, *SE* standard error, *Std.* standardized estimate

*** $p < .001$

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 subsequent analyses of structural path invariance tests. The baseline model also fit the data adequately well: RMSEA = 0.035, CFI = 0.967, TLI = 0.963.

Twenty-two individual parameter invariance tests were conducted. The results of these tests are presented in the lower section of Table 6. Eight path coefficients were found non-invariant individually and the remaining 14 coefficients were invariant across student groups. Therefore, in the final multi-group model, the 14 invariant path coefficients were fixed to be the same across the community college and four-year groups. The final model fit the data well, RMSEA = 0.035, CFI = 0.967, TLI = 0.964.

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.

All three high school independent variables, (a) math self-efficacy beliefs; (b) exposure to math and science courses; and (c) high school math achievement showed statistically significant effects on four-year beginners' interest in choosing a STEM field of study, with math achievement exerting a marginally significant effect ($p < .10$). When compared in standardized terms, exposure to math and science seemed to have the most substantial effect, followed by math self-efficacy beliefs and math achievement. However, high school

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 ($\alpha = 0.05$)	RMSEA	CFI	TLI
One sample ($N = 9{,}770$)	4442.618	240			.042	.954	.947
Four-year institution group ($N = 6{,}300$)	2175.192	240			.036	.971	.967
Community college group ($N = 3{,}470$)	1352.733	240			.037	.958	.951
Multi-group baseline model	3506.252	501			.035	.967	.963
Individual path coefficient constrained							
STEM interest							
Math self-efficacy	3488.532	502	.000	Non-invariant	.035	.967	.964
Exposure to math and science courses	3518.447	502	.000	Non-invariant	.035	.967	.963
High school math achievement	3505.062	502	.275	Invariant	.035	.967	.963
Math readiness for college							
Math self-efficacy	3513.217	502	.008	Non-invariant	.035	.967	.963
Exposure to math and science courses	3506.140	502	.738	Invariant	.035	.967	.963
High school math achievement	3508.539	502	.130	Invariant	.035	.967	.963
Science readiness for college							
Exposure to math and science courses	3495.404	502	.001	Non-invariant	.035	.967	.964
STEM choice							
Interest in a STEM major	3505.633	502	.431	Invariant	.035	.967	.963
Academic integration	3514.628	502	.004	Non-invariant	.035	.967	.963
Math readiness for college	3506.441	502	.664	Invariant	.035	.967	.963
Science readiness for college	3542.991	502	.000	Non-invariant	.035	.967	.963
High school math achievement	3506.879	502	.428	Invariant	.035	.967	.963
Receiving financial aid	3511.503	502	.022	Non-invariant	.035	.967	.963
Expecting a graduate degree	3548.240	502	.000	Non-invariant	.035	.967	.963
Number of remedial subjects	3504.639	502	.204	Invariant	.035	.967	.963
Female	3508.526	502	.132	Invariant	.035	.967	.963
Asian	3504.430	502	.177	Invariant	.035	.967	.963
Underrepresented minorities	3505.325	502	.336	Invariant	.035	.967	.963
SES	3507.235	502	.321	Invariant	.035	.967	.963
Married	3509.284	502	.082	Invariant	.035	.967	.963
Having children	3509.179	502	.087	Invariant	.035	.967	.963
Weekly work hours	3505.072	502	.277	Invariant	.035	.967	.963
Final model[a]							
14 Invariant path coefficients constrained	3512.691	515	.954	Invariant	.035	.967	.964

[a] Fourteen of the 22 path coefficients found invariant in the chi-square difference tests were constrained to be equaled across four-year institution and community college groups in the final model

variables' impact on two-year beginners' interest in STEM was not as substantial. In particular, exposure to math and science courses was a marginally significant factor in predicting two-year beginners' interest in STEM and exerted a substantially smaller effect.

Table 7 Path coefficients of the final multi-group SEM based on level of first postsecondary institutions

Path	Four-year institution students			Community college students		
	b	SE	Std.	*b*	SE	Std.
STEM interest						
Math self-efficacy	.071***	.017	.121	.065*	.028	.116
Exposure to math and science	.781***	.115	.342	.189+	.107	.105
High school math achievement	.007+	.004	.050	(=)		.053
Math readiness for college						
Math self-efficacy	.089***	.013	.159	.142***	.017	.237
Exposure to math and science courses	.346***	.052	.158	(=)		.181
High school math achievement	.019***	.003	.132	(=)		.128
Science readiness for college						
Exposure to math and science courses	.598***	.080	.278	.568***	.090	.307
STEM choice						
Interest in a STEM major	1.140***	.083	.701	(=)		.700
Academic integration	.112+	.059	.052	−.164*	.065	−.108
Math readiness for college	−.056	.058	−.033	(=)		−.037
Science readiness for college	.235***	.057	.136	.082	.072	.052
High school math achievement	.017**	.006	.070	(=)		.075
Receiving financial aid	.381***	.097	.097	−.059	.137	−.018
Expecting a graduate degree	.528***	.100	.145	.039	.170	.010
Number of remedial subjects	−.071+	.041	−.042	(=)		−.049
Female	−1.036***	.080	−.288	(=)		−.311
Asian	.536***	.118	.096	(=)		.065
Underrepresented minorities	.019	.101	.005	(=)		.005
SES	.086*	.038	.049	(=)		.055
Married	.669**	.216	.079	(=)		.079
Having children	−.112	.154	−.019	(=)		−.017
Weekly work hours	−.009	.006	−.032	(=)		−.056
Sum of indirect effects						
STEM choice						
Math self-efficacy	.063		.066	.055		.061
Exposure to math and science	.721		.195	.063		.056
High school math achievement	.123		.057	.045		.040
Correlations						
Math self-efficacy with exposure to M & S	.287***	.030	.313	.260***	.039	.251
Math self-efficacy with math achievement	4.972***	.323	.347	4.316***	.514	.315
Exposure to M & S with math achievement	1.519***	.115	.415	1.211***	.148	.284
Math readiness with science readiness	.448***	.018	.448	.402***	.023	.402

(=) indicates that the path coefficient is constrained equal across the two student groups

b path coefficient estimate, *SE* standard error, *Std* standardized estimate

*** $p < .001$, ** $p < .01$, * $p < .05$, + $p < .10$

Although math self-efficacy showed a significantly positive effect on two-year college students' STEM interest, this effect was weaker and less significant compared to that on four-year college students. Nonetheless, for entering community college students, math self-efficacy beliefs still appeared to be the strongest influence on interest in STEM, followed by exposure to math and science and math achievement. The marginally significant, positive effect of high school math achievement was the same across community college and four-year college students.

The three high school independent variables (math self-efficacy, exposure to math and science, and math achievement) were all significant and positive predictors of students' perceived math readiness for college. Science readiness for college was significantly and positively associated with exposure to math and science courses. In regard to variables hypothesized to influence STEM entrance, students' interest in STEM and high school math achievement had significant and positive effects on students' STEM choice, and the effects were equivalent across the community college and four-year groups. Moreover, as compared in standardized terms, of all variables, students' interest in STEM fields had the strongest influence on their actual choice of a STEM field. As for perceived readiness for college, science readiness for college had a positive effect on STEM entrance among students beginning at four-year institutions, but exerted no impact on community college entrants. Perceived math readiness for college did not turn out to have a significant impact on choosing a STEM field of study for both student groups.

Two postsecondary variables exerted differential or even contrasting effects on STEM choice for 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 choice. 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 postsecondary variables were invariant (thus fixed to be the same) across the community college and four-year student groups. Specifically, STEM entrance was negatively associated with the number of remedial subjects and positively linked to being married. Weekly working hours and having children did not influence STEM choice.

Of the person input variables, being female was negatively associated with STEM choice. Being Asian was positively associated with choosing STEM areas of study compared to being White. STEM entrance was also significantly and positively influenced by SES. All these effects based on gender, race, and social background were equivalent between community college and four-year college student groups. On the other hand, expecting a graduate degree was associated with a stronger likelihood to enter STEM majors among the four-year group, whereas no relationship was found between graduate degree expectations and STEM entrance among community college students.

Finally, the three high school variables also had indirect effects on STEM choice through the mediating variables (i.e., STEM interest, math readiness for college, and science readiness for college). The indirect effects of math self-efficacy, exposure to math and science courses, and high school math achievement on students' STEM choice are presented in Table 7 as well. 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. Additionally, the correlations between math self-efficacy, high school exposure to math and science, and high school math achievement, along with that between math readiness and science readiness for college are

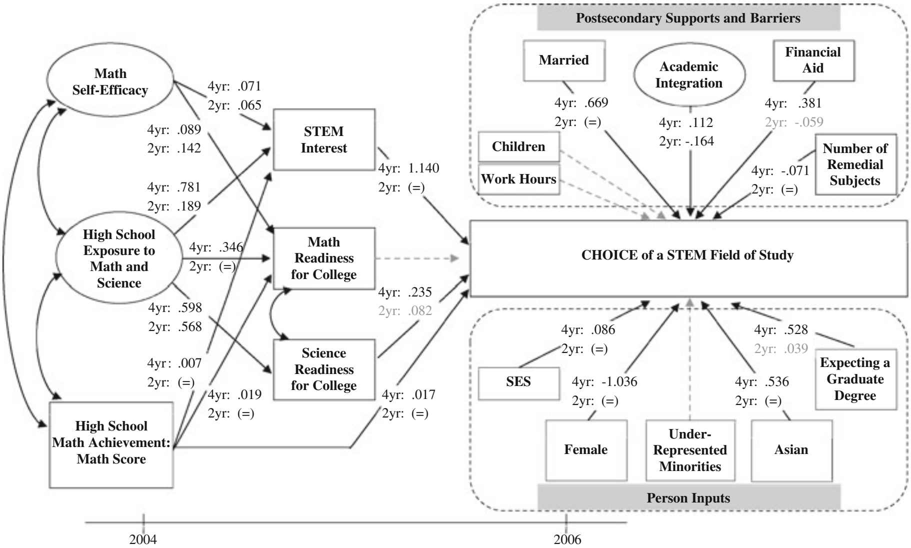

Fig. 2 Structural part of final multi-group SEM results. *4 yr* four-year institution, *2 yr* community college. (=) indicates that the path coefficient is constrained equal across the two student groups. Insignificant paths with $p > .10$ are in *gray color*

reported in Table 7. Figure 2 displays the final multi-group SEM model with significant paths denoted with their corresponding unstandardized path coefficients.

Discussion

This study integrates a career development theory, namely SCCT, 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 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 STEM fields. From a developmental perspective, academic- and career-related interests and self-belief 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 et al. 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 appears to be a strong influence on four-year beginners' STEM interest, its impact on two-year beginners' STEM interest is not as salient, with exposure to math and science courses showing a much smaller effect for community college students. This suggests that even with the same amount of contact with relevant coursework, four-year college bound students are more likely to translate the impetus afforded by exposure to math and science into 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 et al. 2005b; Cohen and 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. Additional research is needed to further understand the process of cultivating community college beginners' interest in choosing a specific academic field. Particularly, more empirical studies are warranted to explore how STEM-related interest and choice behaviors develop among community college entrants.

Contrary to this study's hypothesis, students' perceived math readiness for college is not a significant influence on STEM entrance. Perceived science readiness for college only matters for four-year students' STEM choice while exerting no impact on community college students. The non-significant effect of math readiness could be due to the fact that both the direct and indirect effects of high school math achievement on STEM choice are already accounted for in the model, thus attenuating any potential effect of math readiness. As for the finding in regard to perceived science readiness for college, it clearly points to the importance of building a seamless alignment between secondary and postsecondary science offerings to facilitate entrance into STEM fields among four-year college students. However, the null effect of science readiness among beginning community college students further indicates the need for additional research that examines which high school factors precisely shape these students' STEM interests and choices.

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 occur (Lent et al. 2000, 2005). 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 STEM is clearly the most prominent force behind the actual choice of a STEM discipline, cultivating students' STEM interest 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 are obvious approaches.

Given this study's findings, these implications apply to students entering both community colleges and four-year institutions; however, it is important to note again that the significant effect of exposure to math and science on STEM interest is smaller among those heading to community colleges. Considering the fact that community college bound students are largely racial minorities, first-generation college students, and academically disadvantaged (Cohen and Brawer 2008), this finding suggests that these traditionally underprivileged students, who are seriously needed to enhance the diversity of the STEM pipeline, do not benefit as much as their four-year counterparts from high school coursework in math and science in developing their STEM interest. It highlights the importance of improving the effectiveness of high school math and science courses in promoting STEM interest among traditionally disadvantaged students, so that the already significant impact of course exposure to math and science may become even more sizable. It is also plausible that additional factors that were unaccounted for in this study contribute to the cultivation of STEM interest of these community college bound students. In either case, this finding means that additional empirical efforts should be expanded in further understanding the heterogeneous effect of exposure to math and science on STEM interest.

Postsecondary Supports and Barriers to STEM Choice

Among the factors representing postsecondary supports and barriers related to STEM choice, academic integration exhibits differential effects across two-year and four-year student groups. For students at four-year institutions, academic integration is positively related to choosing a STEM major. Traditionally, STEM disciplines at four-year institutions are identified as either “hard applied” or “hard pure” fields (Austin 1990) and are known for their challenging academic standards including competitive grading (Herrera and Hurtado 2011). In this sense, STEM majors at four-year institutions may attract students who are not only interested, but are also academically integrated enough to be ready to take on these demanding areas of study. The finding in this study pertaining to four-year college students’ STEM choice supports this rationale.

It is intriguing to observe that while showing a significant and positive impact on STEM choice among four-year college students, academic integration as measured in this study has a significant negative effect on community college beginners’ STEM entrance. This raises the question as to why after 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.

This mixed result may not necessarily mean that academic integration per se negatively affects community college students’ STEM choice. Instead, it is possible that this result is an artifact of the different meanings of academic integration at four-year institutions and community colleges and how academic integration is measured in this study. On a baccalaureate campus, opportunities for academic integration often arise when students contact faculty, advisers, and peers for academic purposes beyond the classroom (Astin 1993; Kuh 2003; Hu and Kuh 2002). In community colleges, which are primarily commuter campuses, however, integration is predominantly promoted through information networks that are developed through formal classroom structures (Karp et al. 2008) and in-class interactions (Deil-Amen 2011). The academic integration measure afforded by data in ELS:2002 focuses on integration behaviors outside the classroom and may thus leave out the in-class integrative experiences of community college students, which leads to the conflicted result.

It is also possible that despite students’ academic integrative experiences such as seeking academic support and services outside of the classroom, they may ultimately prove ineffective at the community college level (Bailey et al. 2005a), thus negatively impacting STEM entrance. Nonetheless, future research on the relationship between college integration and STEM choice should employ quantitative and/or qualitative measures that more closely depict the different and more fluid form of integration of community college students, thus offering 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 field, 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 system often found in these disciplines (Arum and 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 STEM fields less feasible to pursue due to time and financial constraints.

In a community college setting, financial aid may not have an impact on STEM entrance for various reasons. First, many students attending these institutions already work and have a tendency of paying for their own tuition (Nakajima 2008). As a result, financial aid may not necessarily hold the same appeal as it would at a four-year college or university. Second, although community colleges have low tuition rates, a fair amount of their student population may be of lower SES. With this thought in mind, some types of aid may be viewed as a financial burden, especially if the student has lower earnings expectations (Malcolm and Dowd 2012). Another potential reasoning behind the finding is that even if community college students receive financial aid, it may not be sufficient to cover all expenses and an unmet need remains (Dowd and Coury 2006). Consequently, gaps in financial resources may not have an effect on STEM entrance.

Consistent with the hypothesized relationship in the theoretical model, the number of remedial subjects represents a barrier to STEM entrance for both community college and four-year college students. Although remedial courses are an attempt to assist underprepared students for subsequent advanced studies (Hagedorn and DuBray 2010), such a process can prove arduous and time-consuming to the point that students may desert their STEM aspirations and goals (Hagedorn and DuBray 2010; Hagedorn and Lester 2006), thus preventing eventual STEM entrance.

This study does not find working hours and having children exerting any effect on STEM choice. On the other hand, being married in fact turns out to be a support instead of a barrier to STEM entrance. Married students who are interested in STEM fields may benefit from emotional, financial, and other forms of support from their spouse when making choices in regard to their major field of study. Although there is no direct prior empirical evidence in support of this finding, there exists research showing that being married may reflect a more serious attitude and commitment toward studies in conjunction with less financial pressures if a spouse remains working (e.g., Kohen et al. 1978), and that being married can provide college students with emotional and motivational support (Leppel 2002).

STEM Choice in Relation to Person Inputs and Educational Expectations

As for person inputs, 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 and Deterding 2009; Song and Glick 2004), this result once again pinpoints the gender disparity in STEM participation. Students of higher SES are more likely to enter STEM fields compared to those from less favorable backgrounds (Tyson et al. 2007). Furthermore, Asian Americans are more likely to choose STEM compared to White students (Crisp et al. 2009), while underrepresented racial minorities did not have a particular advantage or disadvantage in entering STEM fields in comparison to their White counterparts (Anderson and Kim 2006; Riegle-Crumb and King 2010). 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 and Mattis 2007). Although these students may aspire to or enter STEM majors at similar rates 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, low-income students, and underrepresented minorities with sufficient preparation and support along with focused research on the wide range of dimensions of these students' educational experiences in STEM fields. In particular, recent research has begun to explore reasons behind underrepresentation of women and minorities in STEM at both community colleges and four-year institutions (e.g., Hagedorn and DuBray 2010; Hardy and Katsinas 2010; Lester 2010; Perna et al. 2009; Seymour 1995; Starobin and Laanan 2005, 2008; Towns 2010; Xu 2008). Faculty support is one effort that is a constant issue permeating this area of research. Xu (2008) pointed out the shortage of female faculty members in STEM fields that leads to a lack of support or mentor role for female students who wish to pursue a STEM major. The case is identical for underrepresented minority students and the same logic applies (Towns 2010). For future research, more qualitative and mixed-methods inquiry is needed to provide additional insights that may not be apparent in quantitative data and for making sense of the sometimes equivocal findings from quantitative analyses.

Finally, among four-year college students, expecting a graduate degree is positively associated with STEM entrance while this relationship does not hold among community college students. It is highly likely that two-year college students with graduate degree aspirations possess clearly defined goals and plans in regard to upward transfer. However, these students do not always enter a STEM major. As Cohen and Brawer (2008) noted, transfer education in community colleges has traditionally focused on the liberal arts. Consequently, if students wish to transfer to a four-year institution to eventually earn a graduate degree, they may be more likely to enroll in non-STEM, liberal arts programs as a result of the liberal arts focus of many transfer curricula offered at two-year institutions. Nonetheless, as efforts to create more transferable credits in all disciplines continue to grow (Boswell 2004; Ignash and Townsend 2000; Roksa and Keith 2008; Townsend 2001), opportunities lie in expanding the STEM transfer pathways to better serve students seeking to pursue advanced STEM degrees but beginning at community colleges.

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 pathways into STEM. Furthermore, by utilizing multi-group SEM analysis, this study uncovers 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, the conceptual model appropriately accounts for factors shaping their STEM entrance, both substantively and from the perspective of model-to-data fit. Based on the results, facilitating these students' secondary-postsecondary STEM pathway seems more straightforward by strengthening high school learning, cultivating STEM interest, strengthening postsecondary academic integration, and providing financial aid. On the other hand, entrance into STEM fields of study among community college students appears to be a more complex process that needs to be further understood.

It is important to note that, although the result patterns in regard to disparities in STEM do not vary significantly across community colleges and four-year institutions, underrepresented racial minorities attend two-year colleges in numbers disproportionately larger than their enrollment in postsecondary education in general. With this in mind, broadening STEM participation at community colleges has important equity implications (Dowd 2011).

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 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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