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Who Chooses the E in STEM?

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Abstract: *Science and technology are at a critical juncture, not only in the United States, but globally with regard to the increasing lack of interest and subsequent decline in the entrance of students into science, technology, engineering, and mathematics (STEM) related careers. With studies taking place on an international scale to determine how best to attract students from all backgrounds and demographics, much work is needed to understand the dynamics at play that might predict a trajectory towards STEM careers based on factors such as student preparation, motivation, and exposure to STEM. Therefore, the purpose of this study is to model and validate predictors that might determine student interest, readiness, and entrance into an engineering ("E") track of STEM-related careers. Looking specifically at a statistically representative sample of the U.S. population, this study uses data from the National Longitudinal Study of Adolescent Health (Add Health) to model, with multilevel methods, a comparison between the factors that link with an engineering career pathway to those factors that link to a non-engineering STEM pathway out of the entire cohort of STEM students. The findings suggest that the overwhelming differentiating factor is associated with gender.*

Introduction

The reduction of students entering the science, technology, engineering, and mathematics (STEM) education pipeline is certainly not just a problem in the United States, but rather a global phenomenon facing many developed nations. With the challenges that exist around the world today, such as the ever increasing water shortage, the need for more robust and efficient sources of energy, and the demand for restored infrastructure, the need could not be more pressing to recruit and educate a more diverse, inclusive pool of talented individuals with the skills and passion to help meet these daunting challenges (Doshi et al., 2007). Among the STEM disciplines, engineering, by its very nature, is a social endeavour capable of assisting society in solving these problems of international scale. However, there appears to be a growing misalignment between the level of urgency that exists and the availability of a steady, diverse supply of engineers to develop and implement groundbreaking solutions (Chubin et al, 2005).

From observation, this is a critical issue most prominent in developed nations in regards to the recruitment and retention of engineers. It would seem as though developing nations are operating on a different playing field because they are eager to create and sustain a globally competitive economy. As a result, their push to succeed is a cultural phenomenon and therefore their students are more motivated to make contributions in areas such as science and engineering because they see the value as being an improvement in their economic and social status. Developing countries see the relevance in changing their business and educational infrastructure to support this endeavour. Take for example Singapore, where the government is investing billions of dollars in support of a world class research and development enterprise. China and India, two large and ever growing economies have the population and the cultural values aligned with foreseeable growth in science and engineering.

Understanding this, what are the factors that influence whether students choose to pursue STEM (and in this case, engineering) majors leading them to participate in engineering-related careers? Is there some combination of variables (e.g. preparation, motivation, and exposure) that contribute to these decisions and how does the interconnectivity of these variables play out across demographics? The study presented here is an exploration of how preparation, motivation, and exposure (PME) variables influence whether students elect to choose STEM in college, and to identify which students among the STEM majors elect to choose engineering. The goal is to shed more light on why certain students successfully pursue engineering degrees.

This study was conducted using survey data from the Add Health database, a comprehensive, longitudinal analysis of American students based on social and behavioural factors evaluated over a ten year span. To date, much of the research literature available has presented little data about the interconnectivity of PME. There have been studies examining these variables in isolation, but very few investigations have tackled the complex nature of PME as a working system in the context of understanding student achievement in STEM (Crisp et al., 2009). The Add Health database provides a unique opportunity to explore this complex relationship by examining student factors that may contribute to a trajectory into STEM-related careers. A comparison is also made between the factors that contribute to success in STEM in the U.S. and the United Kingdom, a region with similar complexities experiencing challenges in the education, recruitment, and retention of engineers.

Literature Review

Developing a framework for which to study the relationship between the three classifications within PME first requires an understanding of the variables in the context of previously documented research. The following is a comprehensive look at each variable and describes the role and impact each plays with respect to student achievement in STEM.

Preparation

Students' courses of study in the middle grade years in the U.S. are fairly streamlined allowing all students to partake in the same curriculum. Burkam, Lee, and Smerdom (1997) concluded that middle grade science was a weak predictor of science achievement, but that the number and types of courses taken became stronger predictors of achievement in high school. They followed up with the notion that U.S. students have considerable latitude to choose among science courses to fulfill their two or three course science requirements for graduation eligibility, and that these courses range in varying degree of intensity, topic, and difficulty. It was also pointed out that some students may have even elected not to take any science courses during a particular academic year. If this concept is explored using gender differences high school girls continued to elect fewer advanced mathematics and science courses than boys, according to prior research (Catsambis, 1994; Greenfield, 1996; Oakes, 1990).

Berryman (1983) and Oakes (1990) both made reference to inadequate academic preparation as a major component that placed a barrier on student achievement in the sciences. Both studies described what has been labelled as a sorting mechanism, or tracking, where courses taken prior to college dictated who accessed training beyond the elementary, middle, and high school years of schooling in science, mathematics, and engineering (SME) related fields. This issue is often exacerbated for many African American, Native American, and Latino students (particularly in urban areas) who fall behind in SME subjects, even as early as in elementary school. Looking beyond the primary years at the college level, Bonous-Hammarth (2001) explored the retention of SME majors by examining patterns of attrition from SME during a four-year period and the transfer of students from non-SME majors into SME majors. Results indicated that of the target samples, African American, Native American, and Latino students were the majority of SME students changing majors and the minority of new entrants into SME (Bonous-Hammarth, 2001). This has contributed to the under-representation of African Americans and Latinos in science or engineering occupations (National Science Foundation, 2006).

Motivation

A few studies point to middle childhood as an influential time because of the development of behavioural habits that are critical for solidifying health and competence; and in terms of skills development, middle childhood is a time when the basis for personal identities and self-esteem are being reinforced (Erikson, 1982). Other studies have focused on the role of self beliefs in adolescent choices, such as expectancies and values which are strong predictors of academic- and sport-related choices (Eccles et al., 1995). Some findings have noted specific instances of girls' intentions to enrol in elective mathematics and science courses being associated with their interest and belief about the importance of these subjects, and also report that the actual number of mathematics and science courses taken in high school might very well be predicted by girls' associated task values (e.g. interest, feelings of importance) but not their mathematics self-concepts (Joyce and Farenga, 2000). But in general, the level of individual competencies based on experiences is a key barometer for determining interest levels in a given domain and has an impact on whether one chooses further exploration (Blustein and Flum, 1999). What is still not clear in the literature is how choices and beliefs relate to each other in a longitudinal fashion (Simpkins et al., 2006).

To this end, task values and their links to achievement motivation must be understood in the context of individuals' intentions or goals, according to Nicholls (1989). Nicholls described two types of student motivation: task oriented and ego oriented. Students who are task oriented tend to report more satisfaction with learning and believe that hard work, cooperation, and trying to understand lead to success in school. However, ego oriented students are more likely to rely on trying to beat others and impress their teachers to succeed in school (Nolen & Haladyna, 1990). Whether students chose to pursue science-related activities might be correlated to how students operate within these two domains (Nolen, 1988).

In sum, one may draw a correlation between task orientation versus ego orientation and the impact each might have on success in science. But it should be stressed that neither orientation can predict, with certainty, whether students will or will not transition into a STEM major and career. It would seem, however, that students who fall into a task oriented category would have a higher propensity for pursuing science-related activities than ego oriented students because they are motivated by interest rather than peer-driven competition. Perceptions of ability in science, or more specifically science self concept, have been shown to be related to attitudes toward science. In other words, students who have positive regard for their ability to learn and understand science also report positive attitudes toward science (George, 2000).

Motivation as described above is linked to self efficacy, and in turn might serve as an important career development mechanism influencing the educational and career decisions, achievement behaviour, and career adjustments (Lent et al., 1991). Mathematics achievement in relation to self efficacy is often used as the litmus test for measuring academic interests in science-related courses due to the fact that mathematics skills are prerequisite to participation in a large array of scientific and technology-based fields (Hackett & Betz, 1981). Conclusions have been further drawn to include that mathematics self efficacy is influenced by prior mathematics performance (Hackett, 1985). Findings from one analysis offered suggestion that past successful experience in a particular domain (e.g. performance in mathematics) may promote self efficacy, and that confidence in one's performance will correspondingly enhance interest in that domain, motivating one to be further exposed and make choices to pursue related educational and career activities (Lent et al., 1991).

As in the U.S., mathematics is a significant motivational barrier in the U.K. preventing many students from progressing in science, and in engineering in particular. One case in point, a major problem noted by the School of Technology at the University of Glamorgan, revealed that many local schools in the region have been unable to sustain sufficient numbers of mathematics students to justify numerous course offerings. As a result, only one school was nominated to offer a particular advanced course, creating a logistical challenge for many students and further decreasing their desire to select advanced mathematics. This has had an impact on the number of prepared students enrolling at the university as well as those that withdraw from courses all together (Bowen et al., 2007). The issue of self efficacy presents itself in this latter statement because those that drop courses ultimately do not feel competent enough to persevere which, again, leads to decreasing interest.

Exposure

Multiple and sustained opportunities for students to experience and engage in STEM related activities has a positive impact on their overall outlook and choices, guiding a trajectory into STEM careers. According to Rowe (1977), the value of early and extensive exposure to science influences decisions students (and from her research, African American students) make about science professions. This is, of course, not unique to just African American students and can be applied to all student populations where research shows that all ethnic groups have equally positive attitudes and similar aspirations for STEM careers (Crisp et al., 2009). However, particular attention can be drawn to students of colour given the fact that they lag behind their white counterparts in STEM across the board in terms of exposure to college preparatory courses (Simpson, 2001). And again, looking at gender, there is evidence to suggest that differences in science-related experiences at the formal level extend into informal learning environments, where girls are less likely to engage in out-of-school activities than boys. Girls potentially miss out on the many kinds of skills developed in these levels of activities (e.g. science fairs) where students can explore, assemble, and tinker that afford opportunities to enhance interest and success in science (Greenfield, 1996; Jones, 1997; Rennie, 1987).

Another factor defined under the umbrella of exposure is access to a positive mentor relationship. Mentoring relationships, be they community-based or industry-based, have been shown to play a vital role for many students interested in pursuing various occupational goals (Klaw & Rhodes, 1995; Dori & Tal, 2000). According to their findings, mentors may stimulate improved attitudes toward school achievement, academic ability, and school performance. This leads to a greater sense of value and expectations to achieve future goals (Rhodes et al., 2000). Studies have also shown that students who have a parent(s) that is involved in a STEM-related career have a greater tendency to be motivated to participate as well, and that this relationship can play a vital role in the choices students make about college attainment and careers (Maple & Stage, 1991). One study links this situation to what is described as a ‘comparative advantage’, but makes the distinction that ability and school effects may supersede home background when focusing on science and mathematics achievement (Van de Werfhorst et al., 2003).

Applying this same line of thinking to the impact on the field of engineering, the lack of exposure in elementary, middle, and high school years is believed to be having a major impact not only in the United States, but elsewhere around the world. For example, in the United Kingdom, there are studies and reports about the decreasing proportion of engineering undergraduates due to limited knowledge among young people about what the field entails, a decline in the number of students studying advanced mathematics, low participation of women, and a decline in the number of students opting for technical entry into industry (DfEE, 2000; Roberts, 2002). Perception matters: students in the U.K., much like their counterparts in the U.S., base their perceptions of engineering careers on what they assume to be lower level, manual occupations. This limited view explains why many students elect to chose alternative degree courses and career pathways (Bowen et al., 2007; Hodgkinson & Hamill, 2006).

Given the literature, this investigation contributes new insight into the relationship between PME and STEM outcomes in three capacities. First, the current literature has examined student attitudes and motivation, formal and informal learning environments, achievement, peer groups, and gender differences as some of the major variables that can contribute to success in STEM. While all of these variables make contributions in their respective silos, this study seeks to explain how all of these factors work together in a way that jointly influences how students transition through the STEM education pipeline. Second, while previous studies have attempted to explore why certain students choose STEM majors and careers, this study offers clear explanations for why and who chooses STEM and, among those, engineering degrees. Finally, this paper employs a dataset new to this field in order to draw multi-faceted conclusions based on a nationally representative sample of United States high school students.

Data & Methods

Data

To examine the relationship between PME and the selection of E-majors within STEM college outcomes, this study uses data from Add Health, which was initiated in 1994 to examine how adolescents' social contexts influence health and risk behaviours. The datasets contain thousands of variables on adolescents' families, schools, neighbourhoods, and peers. The first wave, with in-school surveys, in-home interviews, parent surveys, and school administrator surveys, was conducted with 7th to 12th graders between 1994 and 1995. The second wave, with in-home interviews and school administrator surveys was conducted in 1996. The third wave, with an in-home interview, was conducted in 2001-2002 when respondents were 18-26 years old. This evaluation uses data from all waves.

The sample of students was drawn from a clustered random sample of 80 high schools out of a sampling frame of 26,666 schools containing an 11th grade. Schools were clustered based on size, school type, urbanicity, region, and percent white. One feeder school for each participating high school was randomly selected in probability proportional to size when a feeder existed. In the 145 participating schools, 90,118 students completed the initial questionnaire. A sample of students stratified by gender and grade was then chosen to complete the in-home interviews. A total of 20,745 respondents participated in the first in-home wave out of the 27,000 selected, a 77% response rate. The first wave of in-home interviews included oversamples of several key groups: saturated schools (in which all students in the school were selected), disabled, Blacks from well-educated families, Chinese, Cuban, Puerto Rican, and adolescents living together (twins, full- and half-siblings, non-related adolescents, and siblings of twins). One parent of each participating student was solicited for a Wave I survey, and 17,670 replied, for an 85% response rate. 14,738 students participated in Wave II in-home interviews, and 15,197 participated in Wave III in-home interviews.

To supplement the limited educational data in Add Health, the Adolescent Health and Academic Achievement (AHAA) study began in 2001 with the collection of high school transcripts. Researchers collected transcripts for 12,237 Add Health subjects based on the more than 1,200 schools they last attended. This investigation uses students' overall grade-point averages as calculated by AHAA researchers based on transcript data.

Variables

Table 1 presents the means and standard deviations for all dependent and independent covariates implemented in this investigation for three relevant samples. The first set of means and standard deviations is for the entire sample of students in the Add Health database for whom relevant data are available. The second sample includes only those students from within the first sample who graduated with a STEM college major. The third sample includes only those students from within the second sample who graduated with an E major (that is, out of all possible STEM majors). The analysis in this study utilizes all three samples.

Outcome measures. The first outcome variable to be used in this investigation is binary: a 1 indicates if a student had graduated as a STEM major in college, and a 0 indicates otherwise. Students could identify more than one major in college in the survey. Thus, if a student graduated with a STEM major in addition to a second major, he or she would also be identified as a STEM major. The determination of those college majors deemed as belonging to STEM was conducted based on the academic classification codes assigned to each major in the database. Majors that fell into science, technology, engineering, mathematics, or a hybrid of these four disciplines were considered to be STEM majors. A list of STEM majors included in the dataset is available upon request.

Table 1

Descriptive Statistics for Three Samples: Add Health Sample, Students who Select STEM Majors in the Add Health Sample, and Students within the STEM Sample who Select an E Major

	Add Health Sample		STEM Majors in Add Health Sample		E Majors from STEM Majors Sample	
	Mean	***SD***	**Mean**	***SD***	**Mean**	***SD***
N	2,120		597		144	
Preparation						
Highest high school science	4.37	*1.27*	5.27	*0.96*	5.21	*1.08*
Highest high school math	6.08	*1.95*	7.60	*1.46*	7.58	*1.50*
Cumulative high school science GPA	2.26	*0.97*	3.00	*0.80*	2.93	*0.91*
Cumulative high school math GPA	2.17	*0.94*	2.88	*0.86*	2.86	*0.92*
Motivation						
Desire to attend college	4.37	*1.07*	4.84	*0.53*	4.72	*0.75*
Parental interest in academic grades	0.90	*0.30*	0.92	*0.26*	0.89	*0.32*
Parental interest in teachers	0.68	*0.47*	0.67	*0.47*	0.68	*0.47*
Parental interest in non-coursework	0.88	*0.32*	0.91	*0.28*	0.90	*0.30*
Exposure						
STEM club	0.06	*0.23*	0.15	*0.35*	0.19	*0.39*
Mother in STEM career	0.05	*0.22*	0.06	*0.23*	0.07	*0.25*
Father in STEM career	0.12	*0.33*	0.20	*0.40*	0.24	*0.43*
Mentor in STEM career	0.75	*0.43*	0.80	*0.40*	0.81	*0.39*
Demographic & Academic Information						
Male (1 = 100%)	0.50	*0.50*	0.47	*0.50*	0.79	*0.41*
Black (1 = 100%)	0.22	*0.42*	0.15	*0.36*	0.15	*0.36*
Latino (1 = 100%)	0.19	*0.39*	0.12	*0.33*	0.15	*0.36*
Other (1 = 100%)	0.19	*0.39*	0.27	*0.44*	0.33	*0.47*
Family Income (thousands)	46.64	*52.51*	59.04	*46.35*	57.92	*38.78*
PVT	99.99	*15.27*	107.23	*13.19*	108.60	*11.96*

A second outcome variable employed is also binary and distinguishes samples 2 and 3 in Table 1: a 1 indicates if a student had graduated as an E major within the set of students who chose from the pool of STEM majors in college. Analogous to the construction of the previous outcome variable, a 1 indicates E selection within STEM, and a 0 indicates otherwise. In other words, 0 suggests students have selected science, technology, or mathematics majors. As before, students could identify more than one major in college in the survey. Thus, if a student graduated with more than one STEM major, it was still possible to identify if one of those majors were E. A list of E majors included in the dataset is available upon request.

Preparation variables. This study has parsed-out the relevant input variables into the PME classification described above. To address preparation for a STEM-related career, this study evaluates the highest course completed while in high school in science and math. The scale of this measure is 1, being an introductory course, to 6 being an extremely advanced course.

Second, cumulative high school science and mathematics grade point average (GPA) were included as a gauge of STEM success. Grade point averages are reported on a continuous scale from 0 to 4, with 4 being an A average.

Motivation variables. Table 1 also presents independent variables relating to the degree to which a student is academically motivated. First, students' desire to attend college is defined by their wave I response to the question of how much they want to attend college on scale of 1 to 5, with 1 = low and 5 = high.

A student's interpretation of parental interest in his or her school life is defined by three binary variables: first, if a student felt that a parent was interested in his or her academic grades; second, if a student felt that a parent was interested in his or her teachers; and third, if a student indicated that his or her parents were interested in other non-coursework related aspects of his or her schooling experience.

Exposure variables. As depicted in Table 1, there are four variables relating to STEM exposure. First, a binary variable indicates whether a student had participated in a STEM-related extracurricular club at school, such as a computer or science club. Second, two binary variables indicate if a mother or father's career was STEM-related. Finally, an indicator if a student had a non-parental mentor in a STEM-related career.

Additional variables. This study employed a standard set of student academic and demographic variables. These included indicators for self-reported race and ethnicity, sex, and age at Wave I. Finally, an additional variable captures family socioeconomic status (SES). Income is defined as the natural logarithm of the parents' self-reported income (in thousands of dollars) from the Wave I parent survey.

To account for student ability, this study employed two measures. First, scores on the Add Health Picture Vocabulary Test (PVT) were included. The test was an 87-item, multiple-choice, computerized, abridged version of the Peabody Picture Vocabulary Test (Dunn & Dunn, 1981) administered to students at the start of the Wave I interview. Raw scores were standardized by age.

Methods

After assembling and appending data from the various Add Health data files, the analysis first excluded all observations for which data on the dependent variable (science or mathematics GPA) was missing for the first analysis or not having information on college major for the second analysis. For descriptive analyses, survey means included the appropriate Add Health transcript survey weights. Means are compared using t-tests for independent samples. The multiple linear regressions also used survey-weighting techniques and also the proper Add Health data weights, as provided in the dataset.

A first analysis implements a logistic regression model in which selection into a STEM college major is regressed on the span of independent variables from Table 1. The examination of the STEM outcome is based on a measure as to whether a student had graduated college with a STEM-related major. Hence, the intention of this first analysis tests for significant PME factors that may be related, in general, to these measures. A second analysis also implements a logistic regression model in which E selection is regressed on the span of independent variables from Table 1. The examination of E as an outcome tests if significant PME relationships exist within the subset of students who selected to pursue an E degree within STEM.

Results

Predicting STEM College Majors

The first set of analyses examined the extent to which PME variables could predict if students had selected a STEM-related major in college. Table 2 presents odds ratios and their significance values and standard errors for a logistic regression predicting college STEM major selection based on preparation in science (Table 3 presents an analogous model for math)

Having included science GPA as a predictor, the logistic regression model portrays two significant results relating to STEM college major selection. Both high school science GPA and high school science preparation positively predict STEM major selection. In other words, students with higher preparation in high school science are much more likely to select a STEM major in college.

Table 2

Odds Ratios, Based on Logistic Regressions of STEM Major Selection (Science Model)

	Odds Ratio	Standard Error
Preparation		
Highest high school science	1.440 ***	0.14
Cumulative high school science GPA	2.207 ***	0.27
Motivation		
Desire to attend college	1.869 *	0.53
Parental interest in academic grades	0.402 **	0.14
Parental interest in teachers	0.952	0.23
Parental interest in non-coursework	3.091 *	1.58
Exposure		
STEM club	1.098	0.49
Mother in STEM career	1.194	0.71
Father in STEM career	1.186	0.32
Mentor in STEM career	1.176	0.27
Demographic & Academic Information		
Male	2.098 ***	0.42
Black	0.770	0.25
Latino	0.543	0.25
Other	1.340	0.44
Family Income	1.003 +	0.00
PVT	0.991	0.01
n	2,048	

*Notes: ***p<0.001; **p<0.01; *p<0.05; + p<0.10; Controls for grade level are incorporated but not presented.*

Motivation is also statistically significantly related to the likelihood of selecting a STEM major. Students who have a higher motivation to attend college are more likely to select a STEM major than are students with lower motivation. It appears, then, that college motivation is associated with STEM college major selection. Interestingly, students who had parents who were interested in non-coursework school activities are three times as likely to select a STEM college major than are students whose parents were not interested in non-coursework high school activities. On the other hand, students whose parents showed an interest in their grades are less likely to select a STEM major.

In terms of exposure to STEM vis-à-vis adult figures, none of the predictor variables are statistically significant. Demographic variables indicate that being male is related to a higher probability of selecting a STEM major in college. The odds ratio indicates males have a 2-to-1 likelihood of selecting a STEM major compared to females. Income is marginally significantly related to the probability of selecting a STEM major: students who come from families with higher incomes tend to have a higher probability of selecting STEM majors.

When preparation variables related to science are replaced with those related to mathematics, a similar interpretation is portrayed in Table 3. A higher high school mathematics GPA and more advanced coursework both increase the likelihood of selecting a STEM major in college. In other words, students with increasingly higher high school preparation in mathematics are more likely to select a STEM-related course of study in college.

Table 3

Odds Ratios, Based on Logistic Regressions of STEM Major Selection (Math Model)

	Odds Ratio	Standard Error
Preparation		
Highest high school math	1.194 +	0.13
Cumulative high school math GPA	1.944 ***	0.27
Motivation		
Desire to attend college	1.939 *	0.53
Parental interest in academic grades	0.387 **	0.13
Parental interest in teachers	1.012	0.25
Parental interest in non-coursework	2.822 **	1.50
Exposure		
STEM club	1.173	0.49
Mother in STEM career	1.182	0.66
Father in STEM career	1.247	0.36
Mentor in STEM career	1.174	0.28
Demographic & Academic Information		
Male	1.982 ***	0.41
Black	0.782	0.27
Latino	0.610	0.25
Other	1.392	0.46
Family Income	1.003	0.00
PVT		
n	2,051	

*Notes: ***p<0.001; **p<0.01; *p<0.05; + p<0.10; Controls for grade level are incorporated but not presented.*

Motivation and exposure variables also exhibit similar interpretations as in the previous logistic regression model. A higher motivation to attend college is related to a higher likelihood of selecting a STEM major. Students who identified their parents as having an interest in non-coursework school activities have a higher probability of selecting a STEM major, though a parental interest in grades is related to a lower probability of STEM major selection. High school exposure parameters again do not yield statistical significance in their relationship to college STEM major choice.

Finally, as for demographic variables, being male is related to a higher probability of selecting a STEM major in college. However, in the case of this model relating to mathematics preparedness, neither race nor income is related to the probability of selecting a STEM major.

Predicting E Majors

The second set of analyses examined the extent to which PME variables differed in their prediction for those students who had selected an E major versus those who selected an S, T, or M major. Table 4 presents odds ratios and their significance values and standard errors for a logistic regression model predicting E major selection based on preparation in science. Table 5 presents odds ratios predicting E major selection based on preparation in mathematics.

Table 4

Odds Ratios, Based on Logistic Regressions of E Major Selection (Science Model)

	Odds Ratio	Standard Error
Preparation		
Highest high school science	1.911 +	0.65
Cumulative high school science GPA	1.164	0.31
Motivation		
Desire to attend college	1.619	1.30
Parental interest in academic grades	0.191 *	0.15
Parental interest in teachers	0.434	0.23
Parental interest in non-coursework	14.637 +	20.72
Exposure		
STEM club	0.507	0.59
Mother in STEM career	0.139 +	0.14
Father in STEM career	1.347	0.96
Mentor in STEM career	2.423	1.69
Demographic & Academic Information		
Male	7.778 ***	3.86
Black	2.556	1.99
Latino	1.952	1.54
Other	1.812	1.09
Family Income	0.984 +	0.01
PVT		
n	597	

*Notes: ***p<0.001; **p<0.01; *p<0.05; + p<0.10; Controls for grade level are incorporated but not presented.*

Table 5

Odds Ratios, Based on Logistic Regressions of E Major Selection (Math Model)

	Odds Ratio	Standard Error
Preparation		
Highest high school math	0.981	0.20
Cumulative high school math GPA	1.190	0.36
Motivation		
Desire to attend college	1.762	1.33
Parental interest in academic grades	0.211 *	0.16
Parental interest in teachers	0.430	0.24
Parental interest in non-coursework	11.596 +	14.66
Exposure		
STEM club	0.601	0.72
Mother in STEM career	0.152 +	0.15
Father in STEM career	1.444	0.99
Mentor in STEM career		
Demographic & Academic Information		
Male	8.536 ***	4.06
Black	3.247	2.57
Latino	1.466	1.18
Other	2.287	1.21
Family Income	0.986 +	0.01
PVT	1.021	0.03
n	597	

*Notes: ***p<0.001; **p<0.01; *p<0.05; + p<0.10; Controls for grade level are incorporated but not presented.*

Given the outcomes of the coefficients across both mathematics and science subjects, it is possible to interpret both models simultaneously. Taken together, these results have a slightly differing interpretation than they did in the previous set of analysis. Here, the PME variables lack meaningful statistical significance. What this suggests, then, is that those factors that significantly predicted the probability of choosing a STEM major do not differentiate students once within STEM. Thus, while PME measures did significantly relate to the probably of choosing to enter STEM, these same measures did not predict entrance into E.

What does differentiate E students from other STEM students, however, is gender. Of those students who selected STEM majors, gender statistically significantly relates to those who chose E majors. In other words, even after examining measures relating to PME as well as other demographic information in the model, it is only student gender that shines through as having a differential prediction on the types of students that select E (as opposed to other science, technology, and mathematics majors). The results show across both science and mathematics preparation models, that of the students that selected a STEM major, males are much more likely to select an E discipline than are females. What this suggests, then, is that out of all students electing STEM majors, only gender plays a statistically significant role in predicting the types of students entering into E fields. The fact that males disproportionately outnumber females in engineering is of no surprise. However, the model shows that motivational and exposure variables at the pre-college level (parental interest in non-course work (i.e. STEM-related clubs), mentorship, and parents involved in STEM) contribute significantly to male pursuit of STEM majors and their selection of engineering specialties.

Discussion

The use of the Add Health database provided a unique opportunity to explore a dataset new to the engineering education field due to its multidimensional assessment of student factors within the context of social and academic behaviours. Because the Add Health database is a comprehensive collection of longitudinal student data, we were able to evaluate for each of the two outcomes (STEM major and E major) based on the interconnectivity of the variables of PME. We were able to run separate analyses for both outcomes to determine, in particular, who among the STEM cohort elected to pursue an engineering course of study.

Our analysis of preparation indicates that students with higher levels of science and mathematics preparation tend to have a higher probability of STEM entrance compared to students with much lower levels of preparation. This supports studies that show students that take more advanced courses feel more confident about their abilities and tend to have a stronger sense of self efficacy, thus performing better and maintaining a higher level of achievement in chosen subject areas (Lent et al., 1991). This is also aligned with the findings that have shown an association between interest and associated values or expressed feelings of importance (Dick and Rallis, 1991; Eccles et al., 1995; Joyce and Farenga, 2000). In other words, students that elect to take higher levels of science and mathematics courses and perform well are motivated to pursue related courses of study in college and beyond.

Examining the exposure variables, the combination of all selected variables equated to a lack of statistical significance impact on STEM or E selection. This may suggest that STEM mentorship plays a greater role in pre-college than in college itself. In one particular study conducted on mentoring interventions for adolescents, it was revealed that mentoring in the form of parental relationships as well as that from an outside adult figure can have a positive impact on student achievement (Rhodes et al., 2000). The study also concluded that mentoring can influence both cognitive and behavioural dimensions of adolescents' approach to school. This notion supports the claims made by our research which suggests that these forms of exposure are significant predictors for high school STEM success. And the argument about the role and impact of comparative advantage might indeed be a contributing factor, in that students who come from families with higher incomes and parents involved in STEM tend to have a higher probability of selecting STEM majors according to our findings. The reasoning behind this might have much to do with access to significant resources that would support such a trajectory.

If students choose to pursue STEM beyond high school, P and M appear to have the greatest impact. Once students fall within a college STEM cohort, the differentiating factor that influences pursuit of engineering appears to be associated with gender where males substantially outnumber females. Socialization has been linked to the reasoning behind this effect, being that males are more often influenced to pursue science and mathematics than females overall. In the field of engineering, males are more attracted to the discipline because of interest and exposure; whereas females are more likely to pursue other disciplines, such as the life sciences (Greenfield, 1996). In addition, the combination of negative self concept and the lack of role models for females adversely influence their attitudes and participation in science-related activities, thus leading to a decline in the level of courses taken throughout the education pipeline (George, 2000). These findings are clearly aligned with many of the studies that have been conducted in the United Kingdom, where the gender issue is of major concern (Hodgkinson & Hamill, 2006).

What this study has ultimately done is shed light on demographic diversity in STEM, and contributed insight into the complexities involved in developing an inclusive, skilled engineering workforce to meet the challenges of the 21st century global economy. A more thorough understanding of how PME work in concert to attract and guide students into particular career pathways is strongly needed, and this paper aids in this important research effort. There is clear evidence from this investigation that supports findings that show the significance of early participation in STEM through both formal and informal learning experiences, particularly for students from underrepresented groups. Also, incorporating more engineering fundamentals into primary and secondary curriculum would expose more students to the field of engineering. Nonetheless, it is evident from this study that the early impact of PME increases the probability of students pursuing STEM in college and beyond.

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