Connecting Math Attitudes with STEM Career Attainment Using a Three-Step Latent Class Analysis Approach

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A recent report prepared by the President's Council of Advisors on Science and Technology (PCAST, 2012), suggests that in order for the United States to remain competitive in the science, technology, engineering, and mathematics (STEM) fields, it must produce approximately one million more STEM professionals than currently projected over the next decade. This is about 34% annually more than current rates (PCAST, 2012). Although there is a strong urgency for producing more STEM professionals, there has been a lack of STEM career seekers, especially among women, underrepresented minorities (National Science Foundation (NSF), 2013) and English Language Learners (ELLs).

ELLs have become one of the largest growing populations in the United States. In 2011-2012, there were approximately 4.4 million ELL students, or an estimated 9.1% of the total number of public school students in the United States (Kena, Aud, Johnson, Wang, Zhang, Rathbun, Wilkinson-Flicker, & Kristapovich, 2014). This is higher than the 4.1 million ELL students in 2002-2003 or 8.7% of the estimated number of public school students in 2002-2003 (Kena et al., 2014). This population is expected to grow at a rapid rate, where it estimated that by the year 2030, there will be approximately 40% of school-aged children will be an English Language Learner (Thomas & Collier, 2002). Studying ELLs is of interest because while they are a quickly growing population in the United States, there has been very little research conducted specifically in ELLs pursuing STEM fields.

What is known about this population is that ELLs are a diverse group of individuals whose varied linguistic, economic, and cultural backgrounds present unique needs and assets for the school and the community (Kanno & Harklau, 2012). Research thus far has focused on secondary outcomes such as studying ELLs' opportunities to learn mathematics in high school (Mosqueda, 2012); ELLs' academic achievement and coursetaking patterns in high school

(Callahan, Wilkinson, & Muller, 2010); reclassification and the effects of tenure in language programs on academic performance (Slama, 2014). In addition, there has been some research at the post-secondary level including students' access and persistence in college (Kanno & Harklau, 2012; Kanno & Cromley, 2013). Although there has been a growing body of research on ELLs, there has not been a lot of research conducted on ELL student outcomes beyond secondary or post-secondary education, such as investigating ELLs' career opportunities.

The lack of ELLs in the STEM fields is concerning, given the demand for more STEM professionals in the field. It is possible that this lack of representation may be due to a lack of self-efficacy in STEM subjects or a lack of positive attitudes toward STEM subjects. Given the increasing number of ELLs in the U.S., it is critical for educators and policy makers to be more informed about the academic development of this population. Thus it is important to study this population and gain a better understanding of how the patterns for ELLs might be different from native English speakers and how to strengthen the STEM pipeline for these populations. Although there has been some progress in research on ELLs, more research is needed on ELL student outcomes beyond college, such as investigating career opportunities among ELLs.

In this current study, we aim to contribute to the literature by using a diverse, national sample of students from Education Longitudinal Study of 2002 (ELS:2002) to examine the relationship between math attitudes and math self-efficacy beliefs with STEM career outcomes. More specifically, this study seeks to address the following research questions: (1) What are the different math attitudes and math self-efficacy beliefs among English Language Learners, linguistic minorities, and native English speakers? (2) How are the selected covariates related to students' math attitudinal class membership for each English proficiency group? (3) To what extent do the identified math attitudinal classes contribute to students STEM career attainment, and how does this differ among ELLs, linguistic minorities, and native English speakers?

Theoretical Framework

The theoretical framework that underlies this study comes from Lent, Brown, and Hackett's (1994) social cognitive career theory, which is derived from Bandura's (1986) general social cognitive theory. Social cognitive career theory provides a framework for understanding three aspects of career development including self-efficacy, expected outcome, and goals. This framework describes the dynamic processes and mechanisms that take place through which (a) career and academic interests develop, (b) career-relevant choices are created and enacted, and (c) performance outcomes are achieved (Lent et al., 1994). Through this model, the authors argue that one's self-efficacy strongly influences the choices people make, the amount of effort they expend, and how long they persevere when they encounter challenges.

Based on SCCT, learning experiences affect self-efficacy, and self-efficacy expectations affect career outcome expectations (Lent et al, 1994). The self-efficacy and career outcome expectations, in turn, have an effect on career interests, which motivates an individual to set goals and take actions to pursue a career, where both choice goals and actions are affected by contextual influences. To date, there has not been any literature that examines ELLs' STEM major and career outcomes using the SCCT framework. Thus this study has potential contributions to the theory by applying the framework to the ELL student population.

Much research has shown that math attitudes and math self-efficacy are related to students' career decisions (Betz & Hackett, 1983; Hackett & Betz, 1981, 1989; Ing & Nylund-Gibson, 2013; Lent & Hackett, 1987; Luzzo, Hasper, Albert, Bibby, & Martinelli, 1999; O'Brien, Martinez-Pons, & Kopala, 1999; Pajares & Miller, 1995; Wang, Eccles, & Kenny, 2013; Zeldin, Britner, & Pajares, 2008). Hackett and Betz (1981) proposed the utility of self-efficacy expectations to career-related behaviors. They hypothesized that having low or weak self-efficacy expectations of one's career pursuits may limit one's career options. Additionally, the authors claimed that the level and strength of self-efficacy expectations of individuals choosing a specific career is related to the individual's degree of persistence and success in that choice.

Other studies have confirmed the predictive power of math self-efficacy expectations on math-related career choices. Hackett & Betz (1989) reported that math self-efficacy expectations were stronger predictors of math-related career choices than actual math performance or past math achievement. Moreover, Luzzo et al., (1999) found statistically significant relationships between math self-efficacy measures of career choice and actions. They concluded that those who have a higher math self-efficacy were more likely to have a greater interest in math/science-related careers and select majors that were more math- or science-related. Thus, based on the findings from the reviewed literature, it has been demonstrated that math self-efficacy has a strong influence on students' career decisions.

Within the ELL populations, there are many different subpopulations that include recent immigrants, immigrants who came to the United States many years ago, immigrants who speak different native languages, and children of immigrants. Since ELLs are a diverse group of people, the Callahan et al. (2010) suggests that there may be different profiles for ELLs. There may be some characteristics that distinguish ELLs from their native English-speaking peers such as their math attitudes, math self-efficacy beliefs, gender, race, socioeconomic status (Fuligni, 1997; Thomas, 2000), math coursetaking patterns (Mosqueda, 2012) and track placement in school (Koelsch, 2011; Oakes, 2005). These characteristics are important to examine because research has shown that these factors contribute to students' career decisions.

Method

Study Design

The data for this study was drawn from the Education Longitudinal Study of 2002 (ELS:2002), which is a nationally representative data set. Over 750 schools were randomly selected across the U.S. and then 10th graders were randomly selected within the selected schools. The ELS:2002 began its base year data collection in 2002, with the first follow up in 2004, second follow up in 2006, and third follow up in 2012. In 2002, baseline surveys were administered to 10th grade students, their parents, teachers, school principals and librarians. In the first follow up in 2004, most of the students were 12th graders in high school. High school transcripts were collected from the high school last attended by students in 2005. By the second follow up in 2006, many sample members were in their second year of college, while others were employed in the labor force or may not have ever attended college. By the third follow up in 2012, most sample members graduated from college, while many others were pursuing their careers.

Analytic Sample

Participants. The ELS:2002 dataset consists of a total sample of over 16,100[1] students. At the base year data collection in 2002, there were 15,240 respondents; by the first follow up in 2004, there were 14,930 respondents; at the second follow up in 2006, there were 14,150 respondents; and at the third follow up in 2012, there were 13,250 respondents.

[1] Following the restricted data security policy of the National Center for Education Statistics (NCES), which collected the ELS:2002 data, unweighted sample sizes were rounded to the nearest 10.

This present study included a sub-sample of 10,780 students, who responded to the base year, first follow up, second follow up, and third follow up surveys. Using a similar classification system as described by Kanno and Cromley (2013), respondents were classified as *English Language Learner* if they met any one of the following criteria: (1) respondents indicated that English was not their first language and their complete high school transcripts indicated they took a course with the following labels: “English as a Second Language (ESL),” “English language (EL),” “English Language Learner (ELL),” “English language development (ELD),” “Limited English Proficiency (LEP),” “Sheltered (integration of native language and content instruction),” and “Specially Designed Academic Instruction in English (SDAIE)” (Callahan et al., 2010; Finkelstein, Huang, & Fong, 2009); (2) respondents indicated that English was not their first language and they reported they did not read, speak, write, and/or understand English very well; (3) respondents indicated that English was not their first language and their teacher reported the student was behind in math due to limited English proficiency (LEP).

Respondents were classified as *linguistic minority* if they reported that English was not their first language and they responded that they read, speak, write, and/or understand English well. Respondents were classified as *native English speakers* if they indicated they speak English as a first language and they read, speak, write, and understand English well. Using this criteria, among the total 10,780 students, 9,190 (85.3%) were classified as native English speakers, 1,220 (11.3%) were classified as linguistic minority students, and 370 (3.4%) were classified as ELLs.

Measures

Math attitude. On the base-year survey, students were asked a series of questions that aimed to assess their attitudes toward math. Regarding the math attitudes construct, the following variables will be analyzed: “Gets totally absorbed in mathematics” (BYS87A); “Thinks math is fun" (BYS87C); and "Mathematics is important" (BYS87F). These math attitude variables were recoded where 1 indicated endorsement on the item and 0 indicated not endorsing on the items. Table 1 displays the weighted means and standard deviation for the math attitude items.

Math self-efficacy. Students' math self-efficacy was measured by five items based on the base-year student survey. The variables that will be used to describe the math self-efficacy construct include the following: "Can do excellent job on math tests" (BYS89A); "Can understand difficult math texts" (BYS89B); "Can understand difficult math class" (BYS89L); "Can do excellent job on math assignments" (BYS89R); and "Can master math class skills" (BYS89U). These math attitude and self-efficacy variables were recoded where 1 indicated endorsement on the item and 0 indicated not endorsing on the items. Table 1 displays the weighted means and standard deviation for the math self-efficacy items.

Prior studies have utilized similar math attitudes and math self-efficacy scales from the ELS:2002 data and have confirmed the latent constructs of students' math attitudes and math self-efficacy (Wang, 2012, 2013; You, 2013). In addition, prior research has provided high item loadings and high internal consistency reliability coefficient (alpha) for the math attitude and math self-efficacy variables (Wang, 2012, 2013; You, 2013; You & Sharkey, 2012). Thus, based on the confirmatory factor analyses from these previous studies, this current study employs these items to describe math attitudes and math self-efficacy constructs. Since the items used in the study were dichotomously coded, the Kuder-Richardson Formula was used to test the reliability of the items instead of Cronbach's alpha. The Kuder-Richardson coefficient only applies to dichotomous items, whereas Cronbach's alpha applies to any set of items regardless of the scale (Cortina, 1993). Using the Kuder-Richardson Formula 20 (Kuder & Richardson, 1937), the internal consistency of the dichotomous math attitude items had a reliability coefficient of .69, and the dichotomous math self-efficacy items had a reliability coefficient of .90. The KR-20 for the math attitudes items was close to the acceptable range of .70 or higher, and the KR-20 for the math self-efficacy items was considered acceptable according to the guidelines from Cortina (1993).

Covariates

The covariates in the study included students' gender, race/ethnicity, socioeconomic status, track placement in high school, and the highest level of math taken in high school. Table 1 displays the weighted frequencies of the covariates included in the study. Descriptive statistics were weighted by a panel weight for sample members who completed Base Year through Third Follow Up and for whom high school transcript data has been collected (F3BYTSCWT).

Gender. Gender was represented by students' self-reported response (BYSEX) on the base year survey. Among the 10,780 students in the sample, there were 5,830 females (54.1%) and 4,950 males (45.9%). A dichotomous variable "Female" was created where 1 indicated female, 0 indicated male.

Race/ethnicity. Race/ethnicity was represented by students' self-reported response on the base year survey using the restricted data (BYRACE_R). There were 80 (.7%) American Indian/Alaska Native, non-Hispanic; 970 (9.0%) Asian, non-Hispanic; 1340 (12.4%) Black or African-American, non-Hispanic; 1390 (12.9%) Hispanic; 490 (4.5%) more than one race, non-Hispanic; 30 (.3%) Native Hawaii/Pacific Islander; and 6,480 (60.1%) White, non-Hispanic. Using the race/ethnicity variable, three dichotomous variables were created (i.e., "Latino," "African American," "Asian," and "Other Race"), where 1 indicates the respective race/ethnicity, and 0 otherwise. Due to the small sample size, the "Other Race" category was created to include American Indian/Alaska Native, Native Hawaii/Pacific Islander, and multi-race respondents.

Socioeconomic status. Students' socioeconomic status was measured using the variable, "BYSES2," which is a composite variable from the parent survey constructed from the following five equally weighted variables: mother's education, father's education, mother's occupation, father's occupation, and family income (Ingels, Pratt, Rogers, Siegel, & Stutts, 2004). To account for occupational prestige, the 1989 General Social Survey occupational prestige score were used (Nakao & Treas, 1992). Students' SES was calculated using the variable, "BYSES2QU," which is the quartile coding from the "BYSES2" variable, and was divided into four quartiles, where 1=*lowest quartile*, 2=*second lowest quartile*, 3=*second highest quartile*, 4=*highest quartile*. For this study, a dichotomous variable was created where 1 indicates the lowest quartile and 0 otherwise. In this sample, there were 2,270 (21.1%) respondents classified as coming from low socioeconomic backgrounds.

Track placement. Track placement was represented by students' self-reported measure of their high school program (BYS26). The different types of high school programs included "general," "college preparatory-academic," and "vocational-including technical/business." There were 3,300 (30.6%) of students who reported they were in the general high school program, while 5,920 (54.9%) reported being in the college preparatory-academic track, and 930 (8.6%) indicated there were in the vocational track. In addition, there were 630 (5.8%) of students who did not report their high school program (i.e., missing). A dichotomous variable was created to indicate whether or not a student was enrolled in the college preparatory-academic program, where 1 indicated a student was in the college preparatory track program, and 0 indicated a student was not in the college preparatory track program (i.e., general or vocational track).

Math coursetaking level. Students' mathematics course level was based on a math course taking pipeline variable (F1RMAPIP) that was available in the first follow up when most students were seniors in high school. This math coursetaking pipeline indicated students' highest level of mathematics completed in high school, in which the student received nonzero credit. The original math pipeline measure was developed by Burkam and Lee (2003) using the transcript data from the National Education Longitudinal Study 1988 (NELS:88). This pipeline variable was created based on the high school course titles and course descriptions using the Classification of Secondary School Courses (CSSC) codes. The math coursetaking variable took on the following values: "no math," "non-academic," "low academic," "middle academic," "middle academic II," "advanced I," "advanced II/Pre-calculus," and "advanced III/calculus." A complete list of the CSSC codes under each pipeline level is provided in Appendix A.

A dichotomous variable was created to indicate the highest math course taken at or above "advanced math I" which is equivalent to courses beyond Algebra II. A value of 1 indicates a student's highest math course taken was beyond Algebra II, while a value of 0 indicates a student's highest math course taken was Algebra II or below. This "advanced math I" level was selected as a high math course indicator based on Adelman's (1999) study, which found that taking math courses beyond algebra II (i.e., trigonometry, pre-calculus, calculus) is critical for African Americans and Hispanic American students in increasing their likelihood of attaining a bachelor's degree in college. In this study, there were 5,270 (48.9%) students whose highest math course was beyond Algebra II.

Distal outcome variable. The distal outcome used in this study was the respondents' current occupation at the time of the third follow up data collection. A dichotomous variable was created where 1 indicated whether the respondent had a STEM-related job, and 0 otherwise. This variable was coded from the two-digit Occupational Information Network (O*NET) variable (F3ONET2CURR). Respondents were asked to indicate a job title and describe job duties for each occupation. The coding experts at Research Triangle Institute (RTI) matched the text from the job title and description to the O*NET occupation descriptions and classified the job using the O*NET two-digit code (Ingels, Pratt, Alexander, Jewell, Lauff, Mattox, & Wilson, 2014). The complete list of occupations that were coded as STEM and non-STEM are provided in Appendix B. Among the 10,780 respondents, there were 770 (7.2%) respondents who pursued a career in STEM. Among the 770 STEM career seekers, 640 (83.1%) were native English speakers, 110 (14.3%) were linguistic minorities, and 20 (2.6%) were English Language Learners.

Latent Class Analysis of Three English Proficiency Groups

For each English proficiency group (i.e., English Language Learner, linguistic minority, and native English speaker), an independent latent class analysis (LCA) was conducted, for a total of three LCAs. LCA is a statistical model, a type of mixture modeling technique where it is a hypothesized that there is an underlying categorical latent variable that groups individuals. Traditionally in LCA the indicators of the latent variable are categorical (Collins & Lanza, 2010; Muthen, 2001). Implementing a separate LCA for each English proficiency group allowed for the number and structure of the emergent latent classes to be different.

Three-step LCA. The three-step LCA approach was implemented in this study, which is a relatively new method in modeling LCA with covariates (Vermunt, 2010) and distal outcomes (Asparouhov & Muthen, 2013). The goal of this three-step approach is to build a measurement model based on a set of categorical indicators and then relate the class membership to auxiliary variables (i.e., covariates and distal outcomes). The LCA with covariates uses the observed variable (i.e., covariate) as a predictor of the latent class variable and the distal outcomes is an outcome of the latent class variable. Both methods involve estimating logistic regression models for the latent classes. For more on the three-step model including sample syntax, see Nylund-Gibson, Grimm, Quirk, and Furlong (2014).

Class enumeration. When fitting a latent class model for each English proficiency group, the class enumeration process was conducted separately for each group. In LCA, determining the number of classes in a final model may be challenging, as there is no one specific method to do so (Muthen & Asparouhov, 2006; Nylund, Asparouhov, & Muthen, 2007). Masyn (2013) argues that class enumeration requires a lot of consideration in terms of examining a series of fit indices, applying the parsimony principle, and interpreting the theoretical meaning of the classes. In this study, we used a number of fit indices to assess absolute fit and relative fit since there is no perfect indicator of which model fits best (Nylund et al., 2007).

First, we used the likelihood ratio (LR) chi-square goodness-of-fit to assess how well a latent class model fitted the observed data (Collins & Lanza, 2010). Second, we included the Bayesian Information Criterion (BIC) (Schwartz, 1978) and adjusted BIC. The BIC is the most common and trusted fit indices used to compare values across a series of models, where lower values indicated better fit (Nylund et al, 2007). Third to compare models with different number of classes, we used the Bootstrap Likelihood Ratio Test (BLRT) and the Lo-Mendell-Rubin-Likelihood Ratio Test (LMR-LRT), which tested neighboring class models, where statistically significant *p*-value suggested the model fitted the data significantly better than the model with one less class (Masyn, 2013; Nylund et al., 2007). In addition to assessing these fit indices, it is important to employ the parsimony principle such that the model with the fewest number of classes that is statistically and substantively meaningful is selected (Masyn, 2013). Taking into account these considerations, there were different classes for each of the English proficiency groups, which will be presented in the following section.

Results

Research Question 1: What are the different math attitudes and math self-efficacy beliefs among English Language Learners, linguistic minorities, and native English speakers?

English Language Learners

Table 2 presents a summary of the latent class analysis fit indices with 1 to 5 classes. After examining the fit indices, the model with the lowest BIC value was the two-class model. In addition, applying the parsimony principle confirmed the decision to select a two-class model. The item probability plot presented in Figure 1 was used to identify two emerging classes for English Language Learners. The first class was labeled *Medium math attitude, Low self-efficacy (ML)*, which represented 57.1% of the sample; the second class was labeled *High math attitudes, High math self-efficacy (HH)*, which represented 42.9% of the sample.

Linguistic Minorities

Table 3 presents a summary of the LCA fit indices with 1 to 5 classes. Taking into consideration the fit indices and interpreting the theoretical meaning of the classes, a four-class model was identified for linguistic minorities. The non-significant *p*-value of the Lo-Mendell-Rubin Likelihood Ratio Test (LMRT) suggested that a five-class model does not significantly improve the model fit, and therefore a four-class model fits better. The item probability plot presented in Figure 2 illustrates the four emerging classes for linguistic minorities. The first class was labeled *High math attitudes, Low math self-efficacy (HL)*, which represented 23.4% of the sample; the second class was labeled *Low math attitude, High self-efficacy (LH)*, which represented 17.6% of the sample; the third class was labeled *Low math attitudes, Low math self-*

efficacy (LL), which represented 29.4% of the sample; and the fourth class was labeled *High math attitudes, High math self-efficacy (HH),* which represented 29.6% of the sample.

Native English Speakers

Table 4 presents a summary of the latent class analysis fit indices with 1 to 6 classes. The class enumeration process for identifying classes for native English speakers required more consideration. None of the *p*-values of the Bootstrap Likelihood Ratio Test (BLRT) or the Lo-Mendell-Rubin Likelihood Ratio Test (LMRT) were significant, which did not inform the decision of selecting the best fitting LCA model. To aid in identifying the number of classes, the BIC values were examined. The BIC never reached a minimum; however, an “elbow,” or the largest decrease in the BIC value (Nylund et al., 2007) occurred with the five-class model. Considering substantive reasons and the “elbow” in BIC value suggested that a five-class model was preferable.

The item probability plot presented in Figure 3 was displays the five emerging classes for native English speakers. The first class was labeled *High math attitudes, High math self-efficacy (HH),* which represented 25.6% of the sample; the second class was labeled *Low math attitude, High self-efficacy (LH),* which represented 11.2% of the sample; the third class was labeled *High math attitudes, Low math self-efficacy (HL),* which represented 11.8% of the sample; the fourth class was labeled *Medium math attitudes, Medium math self-efficacy (MM),* which represented 17.7% of the sample; and the fifth class was labeled *Low math attitudes, Low math self-efficacy (LL),* which represented 33.6% of the sample.

Research Question 2: How are the selected covariates related to students’ math attitudinal class membership for each English proficiency group?

The covariates included in this analysis were students' gender; race/ethnicity (i.e., whether or not the student is Latino, African American, Asian, or other); whether or not students came from low socioeconomic backgrounds; whether or not students were placed in a college preparatory track; and whether or the highest level of math course taken in high school was beyond Algebra II. When comparing the emergent latent classes with and without covariates, there were no large shifts in the emergent latent classes, which suggested that these latent classes were stable. In interpreting the logit coefficients, a *negative* logit indicates that individuals who are coded 1 on the covariate were more likely to be in the reference class than the comparison class, whereas a *positive* logit indicates that individuals who are coded 1 are more likely to be in the comparison class than the reference class. The following sections present the relationship of the covariates and students' class membership for each of the English proficiency groups.

English Language Learners

The positive logit coefficient presented in Table 5 suggest that females were more likely to be in the *Medium math attitude, Low math self-efficacy (ML)* class compared to the *High math attitude, High math self-efficacy (HH)* class relative to males, and this was statistically significant at the $p < .001$ level. When examining race/ethnicity covariates, the negative logit coefficients suggest that Latino and Asian ELLs were more likely to be in the HH class compared to the ML class, relative to their White counterparts.

Linguistic Minorities

Results from Table 6 suggest that there was a consistent gender effect, where female linguistic minorities were more likely to be in classes that were not the *High math attitude, High math self-efficacy (HH)* class relative to males (i.e., more likely to be in HL, LH, or LL), and this was statistically significant at the $p < .001$ level. Another significant comparison was linguistic minorities from low socioeconomic (SES) backgrounds were more likely to be in the HL class or the LL class when compared to the HH class, relative to linguistic minorities who come from higher SES backgrounds. This suggests that low SES linguistic minorities tend to have low self-efficacy compared to higher SES linguistic minorities. In addition, linguistic minorities on the college preparatory track were more likely to be in the HH class than the LL class, relative to their peers on the non-college preparatory track (i.e., general or vocational track). Similarly, linguistic minorities who have taken a math course beyond Algebra II were significantly more likely to be in the HH class compared to the HL or the LL class, relative to those who have not taken a math course beyond Algebra II.

Native English Speakers

Results from Table 7 suggest that when compared to male native English speakers, female native English speakers were more likely to be in the HL, MM, or LL class relative to the HH class. This suggests that females tend to have lower math self-efficacy beliefs than their male counterparts. In examining racial/ethnic comparisons, Latino native English speakers were more likely to be in the HH class compared to the LH or LL class, relative to their White counterparts. This suggests that Latino native English speakers tend to have high math attitudes. Similarly, the negative logit coefficient suggest that African Americans were more likely to have high math attitudes, where African Americans native English speakers were more likely to be in the HL class compared to the HH class, but were also more likely to be in the HH class compared to the LL, LH, or MM class, relative to White native English speakers. Lastly, native English speakers of "other" race were more likely to be in the HH class compared to the MM class, relative to their White native English speaking peers.

Similarly to linguistic minorities, native English speakers from low SES backgrounds were more likely to be in the HL class compared to the HH class, relative to those from high SES backgrounds. In terms of track program, there was a consistent effect of native English speakers on the college preparatory track being in the HH class compared to the other classes. In addition, there was a consistent effect of native English speakers who took math courses beyond Algebra II, were more likely to be in the HH class compared to the other classes (i.e., LH, HL, MM, or LL).

Research Question 3: To what extent do the identified math attitudinal classes contribute to students STEM career attainment, and how does this differ among ELLs, linguistic minorities, and native English speakers?

The distal outcome used in this analysis was a dichotomous variable indicating whether or not the respondents' current job or most recent job as of 2012 was STEM-related. The following sections present the relationship of the students' class membership and STEM career attainment for each of the English proficiency groups.

English Language Learners

The results presented in Table 8 suggest that across all classes, there was a higher proportion of individuals in the *High math attitudes, High math self-efficacy* who pursued a STEM career (13%), compared to 3% of individuals in the *Medium math attitudes, Low math self-efficacy* class, and this was statistically significant at the $p < .05$ level.

Linguistic Minorities

Table 9 displays the distal outcomes for the final four-class model for linguistic minorities. There were 16% of linguistic minorities in the HH who pursued a STEM career and this was statistically significant compared to the 6% of linguistic minorities in the HL class and the 7% of linguistic minorities in the LL class. There were 9% of linguistic minorities in the LH class who pursued a STEM career, but this was not significantly different from the other classes.

Native English Speakers

Table 10 presents the STEM outcomes for the five-class model for native English speakers. There was a significantly higher proportion of native English speakers in the HH class (12%) who pursued a STEM career compared to the other classes. In addition, compared to the LL class, where there were only 4% of students in a STEM career, the LH, HL, and MM have significantly higher proportions of students in a STEM career at 8%, 7%, and 7% respectively.

Discussion

The results from this study extend the social cognitive career theory to English language learners, linguistic minorities, and native English speakers, and also provide information on how math attitudes and math self-efficacy beliefs differ within each English proficiency group. The result of fitting independent LCAs on each of the English proficiency group revealed that there were different patterns of math attitudes and math self-efficacy for each group. Combining the English proficiency groups into one group masks these differences. Thus, had we not done the analysis by English proficiency subgroup, this interesting result would have been overlooked and we would not know that there were different heterogeneity in math attitudes and math self-efficacy beliefs among these English proficiency groups. The findings from this study stress the importance to not make the assumption that all linguistic minorities or all ELLs are the same, but that they have different profiles and experiences and should be treated differently instead of aggregated together.

In summary, across the English proficiency groups, there were common and unique themes. What was common among the ELLs, linguistic minorities, and native English speakers was that females tended to be in classes that were not *High math attitudes, High math self-efficacy (HH)*, suggesting they have less positive math attitudes and math self-efficacy compared to their male counterparts. This finding is consistent with research that suggest females perceive to have more negative attitudes and have lower math self-efficacy compared to males (Betz & Hackett, 1983; Hackett & Betz, 1981; Ing & Nylund-Gibson, 2013; Luzzo et al., 1999; O'Brien et al., 1999; Wang et al., 2013; Zeldin et al., 2008). Females having low math attitudes and math self-efficacy may be one of the reasons why there is an underrepresentation of females in STEM fields (NSF, 2010). Future research should examine interventions to improve females' math attitudes and self-efficacy beliefs and promote positive attitudes, while also encouraging females to study STEM fields and pursue STEM careers.

In terms of STEM career attainment, another commonality across all three English proficiency groups was students with high math attitudes and high math self-efficacy beliefs had a higher proportion of students in STEM careers compared to the other classes. This was not surprising since social cognitive theory suggests that self-efficacy strongly influences the choices people make, the amount of effort they expend, and how long they persevere when they encounter challenges (Bandura, 1977; Lent et al., 1994; Pajares & Miller, 1994, 1995).

Another commonality was native English speaking students and linguistic minority students on the college preparatory track and/or whose highest math course was beyond Algebra II were more likely to be in the HH class compared to the other classes. Both of these findings are consistent with the literature that suggest those on the college preparatory track are more likely to have positive math attitudes and positive math self-efficacy beliefs (Oakes, 2005). In addition, students who take more advanced math courses are more likely to have higher math attitudes and higher math self-efficacy (Ma, 2000; Wang, 2013; You, 2013). However, this pattern was not significant for ELLs, who may have not been afforded the opportunity to be on the college preparatory track or take math courses beyond Algebra II due to the tracking policies in place at the school (Oakes, 2005). This finding has implications for policymakers and administrators to review the tracking policies in schools to ensure that those on the general or vocational track have equitable opportunities as those on the college preparatory track.

Another common finding between the linguistic minority and native English speaking students was the relationship between students' socioeconomic backgrounds and math attitudes and math self-efficacy beliefs. Linguistic minority and native English speaking students with low SES backgrounds were more likely to be in the HL class compared to the HH class, which suggests that they share similar positive math attitudes, but have lower math self-efficacy beliefs compared to their peers with higher SES backgrounds. The low SES covariate was not significant for ELLs. The literature has provided mixed results on the relationship between one's SES background and their math attitudes and math self-efficacy beliefs (Fuligni, 1997; Muthen, 1994; Thomas, 2000). However, this finding provides reason to believe that there is a significant relationship between SES and math self-efficacy for linguistic minorities and native English speakers.

A unique finding among the English proficiency groups was how race/ethnicity functions differently, where Latino and Asians ELLs were more likely to be in the HH class compared to the ML class. This is interesting to note since it provides evidence against some literature that suggests Latino ELLs hold have low self-efficacy beliefs that may be due to the cognitive (Campbell, Adams, & Davis, 2007) and linguistic demands in math (Spanos, Rhodes, Dale, & Crandall, 1988; Wolf & Leon, 2009).

Another unique result was Latino native English speakers were more likely to be in the HH class compared to the LH or LL class, while African Americans were more likely to be in high attitudinal classes compared to their White counterparts. These results confirm findings from previous research that suggests Latinos and African Americans tend to have higher math attitudes and math self-efficacy compared to their White counterparts (Else-Quest, Mineo, & Higgins, 2013; Stevens, Olivarez, Lan, & Tallent-Runnels, 2004). Although the results from the study suggest that Latinos and African Americans have higher math attitudes and math self-efficacy beliefs, results from the 2013 Mathematics Assessment from the National Assessment of Educational Progress (NAEP, 2013) show that 12th grade Latino and African Americans performed significantly lower on the math assessments compared to their White counterparts. Future research is needed to investigate why Latinos and African American students express positive math attitudes and math self-efficacy beliefs, yet perform lower than their peers. Perhaps there are other factors that may impact Latinos' and African Americans' mathematical performance. Nevertheless, what is important is for parents and educators to continue to foster these positive attitudes and beliefs that will keep these underrepresented minorities interested in STEM and motivate them to pursue STEM fields.

Limitations

There are a few limitations that the reader should be aware when interpreting the results. First, this study only used data from respondents who participated in all four data collection waves (i.e., base year, first follow up, second follow up, and third follow up). Students who respond to multiple data collection waves and persist through a longitudinal study are likely to persist through their educational and career goals (Kanno & Cromley, 2013). Thus, limiting the sample to those who participated in all data collection waves may show a more optimistic perspective than if all the respondents in the base year completed all waves of data collection.

Second, the sample excludes students with extremely low English proficiency skills who were unable to read or respond to the base year survey. Thus, the ELLs in the sample may not be truly representative of the ELL population in the U.S. as a whole. Furthermore, those ELLs who persist in the longitudinal data collection are likely to persist in attaining their educational and career goals compared to those who did not respond to all four data collection waves. Nevertheless, this study is one of few studies to examine ELL outcomes beyond high school.

Third, the ELS:2002 data relies on students' self-reported measures, where fields can be blank or filled in with false information, include responses to critical items. For example, respondents' English proficiency status was classified on one critical question that asks students whether English is their native language. Students may choose "Yes" even if English was not their native language. This may underestimate the number of ELLs and linguistic minorities in the sample. Therefore, some underestimation should be assumed in the study.

Fourth, data examined in this study relied on a secondary data, thus, some critical variables for the analysis were unavailable. For example, self-efficacy beliefs are central to the SCCT, which serves as the guiding theoretical framework for this study. Although the ELS:2002 data contains items measuring math attitudes and math self-efficacy, it does not include any variables on science attitudes or science self-efficacy beliefs. This study assumes that math attitudes and math self-efficacy beliefs influence STEM outcomes. Having the combination of math and science attitudes and self-efficacy may provide a better profile of students' STEM attitudinal and self-efficacy beliefs and would help researchers understand the complex nature of STEM outcomes.

Despite these limitations, the results from this study are important due to the fast growing population of ELLs and the lack of research conducted on this population. Through this study, we aim to contribute to the field by bridging the gap in knowledge of ELLs' career opportunities beyond secondary and postsecondary education. Findings from this study will potentially contribute to the emerging body of literature of ELLs in STEM. The results from this study will serve to inform educators, administrators, policy makers, and educational researchers. For educators, this study suggests that ELLs have different educational needs and thus more research should focus on how to best support this at-risk population as well as improve their math self-efficacy. For administrators, this study may reveal the effects that school policies, such as tracking, have on students' STEM outcomes. In this study, students on the college preparatory track were more likely to pursue STEM jobs, however, the same may not be true for students on the general or vocational track. For policy makers, this study may have implications for developing interventions to help address the issues that may hinder STEM outcomes among the ELL population. For educational researchers, this study may be a stepping stone to one of many studies conducted in the future that examines ELLs' STEM outcomes beyond high school.

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Table 1

Descriptive Statistics of the Math Attitude and Math Self-Efficacy Items, Covariates, and Distal Outcome used in the Final Model (Weighted)

Variables	*M*	*SD*
Math Attitude Items		
Gets totally absorbed in math	.51	.50
Thinks math is fun	.33	.47
Math is important	.51	.50
Math Self-Efficacy Items		
Can do excellent job on math tests	.46	.50
Can understand difficult math texts	.41	.49
Can understand difficult math class	.46	.50
Can do excellent job on math assignments	.53	.50
Can master math class skills	.54	.50
Covariates		
Female	.53	.50
Latino	.14	.35
African American	.14	.34
Asian	.04	.19
White	.63	.48
Other Race	.05	.22
Low Socioeconomic Status	.24	.42
College Preparatory/Academic Track	.54	.50
Math Course Beyond Algebra II	.47	.50
Distal Outcome		
STEM Career	.07	.25

Table 2

Latent Class Analysis Fit Indices with 1-5 Classes (English Language Learners)

Number of classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of LMRT
1	-1189.25	2422.83	2397.472	-	-
2	-995.26	2084.73	2030.831	< .001	< .001
3	-971.82	2087.72	2005.289	< .001	0.005
4	-955.02	2103.98	1993.02	< .001	0.21
5	-944.33	2132.47	1992.979	.14	0.22

Note. BIC = Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT = Bootstrap Likelihood Ratio Test; LMRT = Lo-Mendell-Rubin Likelihood Ratio Test

Table 3

Latent Class Analysis Fit Indices with 1-5 Classes (Linguistic Minorities)

Number of classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of LMRT
1	-5258.43	10572.48	10547.07	-	-
2	-4155.17	8428.50	8374.503	< .001	< .001
3	-4050.71	8282.13	8199.552	< .001	0.0005
4	-3960.83	8164.93	8053.764	< .001	< .001
5	-3913.69	8133.22	7993.471	< .001	0.1089

Note. BIC = Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT = Bootstrap Likelihood Ratio Test; LMRT = Lo-Mendell-Rubin Likelihood Ratio Test

Table 4

Latent Class Analysis Fit Indices with 1-6 Classes (Native English Speakers)

Number of classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of LMRT
1	-38488.25	77047.86	77022.44	-	-
2	-29338.43	58828.53	58774.51	< .001	< .001
3	-28508.73	57249.43	57166.81	< .001	< .001
4	-27804.46	55921.18	55809.96	< .001	< .001
5	-27497.77	55388.10	55248.28	< .001	< .001
6	-27369.35	55211.56	55043.14	< .001	0.0001

Note. BIC = Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT = Bootstrap Likelihood Ratio Test; LMRT = Lo-Mendell-Rubin Likelihood Ratio Test

Table 5

Covariate Table for the Final Two-Class Model (English Language Learners)

Latent Classes	Effect	Logit	SE	Logit/SE	*p*-value	OR
Med MA, Low MSE	Female	1.09**	0.34	3.19	< .01	2.97
	Latino	-1.69*	0.86	-1.97	.05	0.19
	African American	-1.92	1.22	-1.58	.12	0.15
	Asian	-1.74*	0.87	-2.01	.05	0.18
	Other Race	0.65	2.09	0.31	.76	1.91
	Low SES	0.23	0.33	0.70	.49	1.26
	College Prep Track	-0.12	0.33	-0.38	.70	0.88
	Math Beyond Alg II	-0.79	0.41	-1.92	.06	0.45

Note. Reference class is *High Math Attitude, High Math Self-Efficacy*; Med MA, Low MSE = *Medium Math Attitudes, Low Math Self-Efficacy*; OR = odds ratio
* $p < .05$, ** $p < .01$

Table 6

Covariate Table for the Final Four-Class Model (Linguistic Minorities)

Latent Classes	Effect	Logit	SE	Logit/SE	*p*-value	OR
High MA, Low MSE	Female	0.63*	0.23	2.74	.01	1.87
	Latino	-0.60	0.42	-1.44	.15	0.55
	African American	-0.50	0.68	-0.73	.46	0.61
	Asian	-0.37	0.40	-0.93	.35	0.69
	Other Race	0.61	0.62	0.98	.33	1.85
	Low SES	0.66*	0.25	2.68	.01	1.94
	College Prep Track	-0.33	0.25	-1.35	.18	0.72
	Math Beyond Alg II	-1.09***	0.25	-4.37	< .001	0.34
Low MA, High MSE	Female	0.82**	0.26	3.12	< .01	2.26
	Latino	-0.05	0.47	-0.11	.91	0.95
	African American	-0.37	0.85	-0.43	.67	0.69
	Asian	0.01	0.46	0.03	.98	1.01
	Other Race	-0.75	1.10	-0.68	.50	0.47
	Low SES	-0.34	0.29	-1.17	.24	0.71
	College Prep Track	-0.36	0.27	-1.31	.19	0.70
	Math Beyond Alg II	-0.31	0.28	-1.12	.26	0.73
Low MA, Low MSE	Female	0.64**	0.20	3.25	< .01	1.90
	Latino	-0.17	0.39	-0.45	.65	0.84
	African American	-0.17	0.65	-0.25	.80	0.85
	Asian	-0.09	0.38	-0.23	.82	0.92
	Other Race	0.88	0.56	1.58	.12	2.41
	Low SES	0.43*	0.21	2.00	.05	1.53
	College Prep Track	-0.75***	0.21	-3.50	< .001	0.47
	Math Beyond Alg II	-1.22***	0.22	-5.49	< .001	0.30

Note. Reference class is *High Math Attitude, High Math Self-Efficacy*; Low MA, High MSE = *Low Math Attitudes, High Math Self-Efficacy;* High MA, Low MSE = *High Math Attitude, Low Math Self-Efficacy*; Low MA, Low MSE = *Low Math Attitude, Low Math Self-Efficacy*; OR = odds ratio

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

Table 7

Covariate Table for the Final Five-Class Model

Latent Classes	Effect	Logit	SE	Logit/SE	*p*-value	OR
Low MA, High MSE	Female	-0.12	0.11	-1.15	.25	0.88
	Latino	-0.46*	0.22	-2.08	.04	0.63
	African American	-0.62**	0.19	-3.19	< .01	0.54
	Asian	-0.30	0.28	-1.06	.29	0.74
	Other Race	-0.27	0.22	-1.23	.22	0.76
	Low SES	-0.17	0.17	-1.01	.31	0.84
	College Prep Track	-0.27*	0.12	-2.25	.02	0.76
	Math Course Beyond Alg II	-0.29*	0.12	-2.46	.01	0.75
High MA, Low MSE	Female	0.42***	0.11	3.80	< .001	1.53
	Latino	-0.08	0.22	-0.38	.70	0.92
	African American	0.58***	0.14	4.02	< .001	1.78
	Asian	0.20	0.28	0.71	.48	1.22
	Other Race	-0.24	0.24	-0.99	.32	0.79
	Low SES	0.28*	0.14	1.97	.05	1.33
	College Prep Track	-0.62***	0.12	-5.31	< .001	0.54
	Math Course Beyond Alg II	-0.95***	0.12	-8.00	< .001	0.39
Med MA, Med MSE	Female	0.40*	0.09	4.30	< .001	1.50
	Latino	-0.21	0.18	-1.20	.23	0.81
	African American	-0.30*	0.15	-1.99	.05	0.74
	Asian	0.02	0.23	0.07	.94	1.02
	Other Race	-0.50*	0.22	-2.29	.02	0.61
	Low SES	0.08	0.14	0.61	.54	1.09
	College Prep Track	-0.34**	0.10	-3.29	< .01	0.71
	Math Course Beyond Alg II	-0.72***	0.10	-7.16	< .001	0.49
Low MA, Low MSE	Female	0.87***	0.07	11.83	< .001	2.40
	Latino	-0.28*	0.14	-1.98	.05	0.76
	African American	-0.58*	0.12	-4.71	< .001	0.56
	Asian	-0.38	0.20	-1.84	.07	0.69
	Other Race	-0.28	0.15	-1.86	.06	0.76
	Low SES	-0.08	0.11	-0.78	.44	0.92
	College Prep Track	-0.60***	0.08	-7.58	< .001	0.55
	Math Course Beyond Alg II	-1.33***	0.08	-16.66	< .001	0.27

Note. Reference class is *High Math Attitude, High Math Self-Efficacy*; Low MA, High MSE = *Low Math Attitudes, High Math Self-Efficacy*; High MA, Low MSE = *High Math Attitude, Low Math Self-Efficacy*; Med MA, Med MSE = *Medium Math Attitudes, Medium Math Self-Efficacy*; Low MA, Low MSE = *Low Math Attitude, Low Math Self-Efficacy*; OR = odds ratio

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

Table 8

Distal Outcome Table for the Final Two-Class Model (ELLs)

Latent Classes	Mean
ML vs. HH (Class 1 vs. Class 2)	**.03 vs. .13**

Note. ML = *Medium Math Attitude, Low Math Self-Efficacy;* HH = *High Math Attitude, High Math Self-Efficacy.* Bolded values indicate significant differences at the *p* = .05 level.

Table 9

Distal Outcome Table for the Final Four-Class Model (Linguistic Minorities)

Latent Classes	Mean
HL vs. LH (Class 1 vs. Class 2)	.06 vs. .09
HL vs. LL (Class 1 vs. Class 3)	.06 vs. .07
HL vs. HH (Class 1 vs. Class 4)	**.06 vs. .16**
LH vs. LL (Class 2 vs. Class 3)	.09 vs. .07
LH vs. HH (Class 2 vs. Class 4)	.09 vs. .16
LL vs. HH (Class 3 vs. Class 4)	**.07 vs. .16**

Note. HH = *High Math Attitude, High Math Self-Efficacy*; Low MA, High MSE = *Low Math Attitudes, High Math Self-Efficacy;* High MA, Low MSE = *High Math Attitude, Low Math Self-Efficacy*; Low MA, Low MSE = *Low Math Attitude, Low Math Self-Efficacy*. Bolded values indicate significant differences at the *p* = .05 level.

Table 10

Distal Outcome Table for the Final Five-Class Model (Native English Speakers)

Latent Classes	Mean
HH vs. LH (Class 1 vs. Class 2)	**.12 vs. .08**
HH vs. HL (Class 1 vs. Class 3)	**.12 vs. .07**
HH vs. MM (Class 1 vs. Class 4)	**.12 vs. .07**
HH vs. LL (Class 1 vs. Class 5)	**.12 vs. .04**
LH vs. HL (Class 2 vs. Class 3)	.08 vs. .07
LH vs. MM (Class 2 vs. Class 4)	.08 vs. .07
LH vs. LL (Class 2 vs. Class 5)	**.08 vs. .04**
HL vs. MM (Class 3 vs. Class 4)	.07 vs. .07
HL vs. LL (Class 3 vs. Class 5)	**.07 vs. .04**
MM vs. LL (Class 4 vs. Class 5)	**.07 vs. .04**

Note. HH = *High Math Attitude, High Math Self-Efficacy*; Low MA, High MSE = *Low Math Attitudes, High Math Self-Efficacy*; High MA, Low MSE = *High Math Attitude, Low Math Self-Efficacy*; Med MA, Med MSE = *Medium Math Attitudes, Medium Math Self-Efficacy*; Low MA, Low MSE = *Low Math Attitude, Low Math Self-Efficacy*. Bolded values indicate significant differences at the $p = .05$ level.

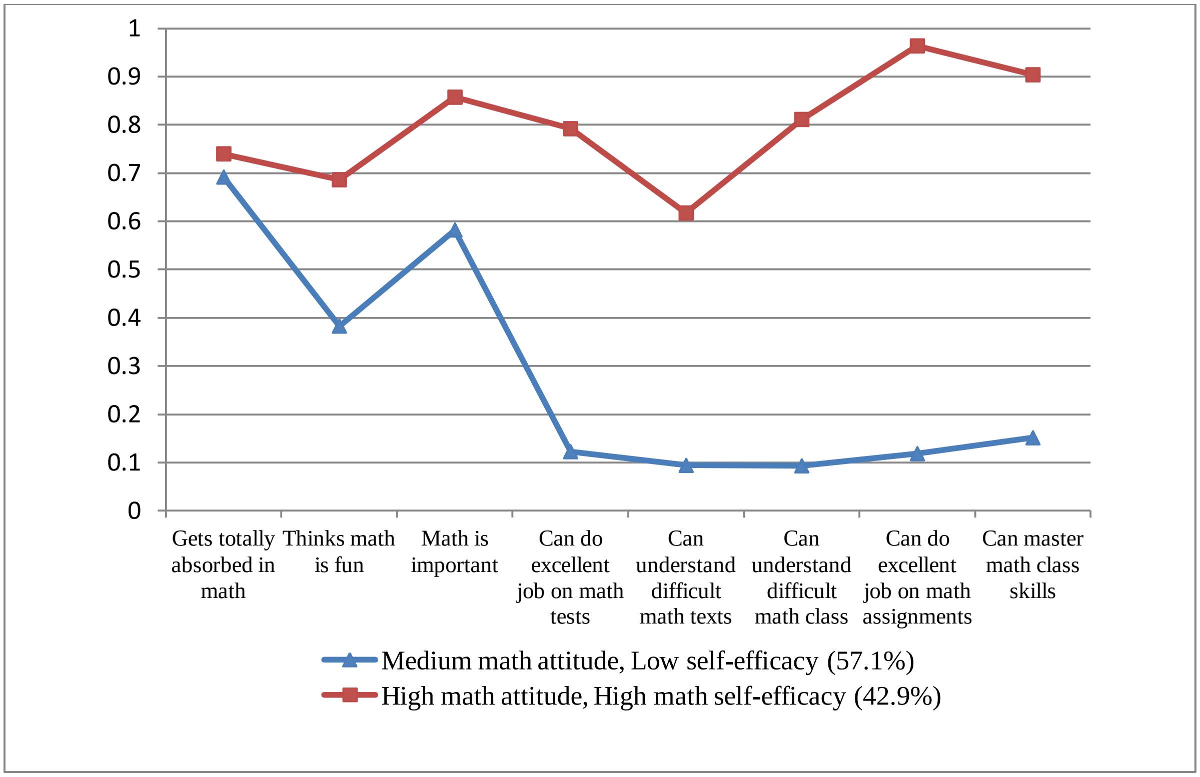

Figure 1. Item Probability Plot for English Language Learners

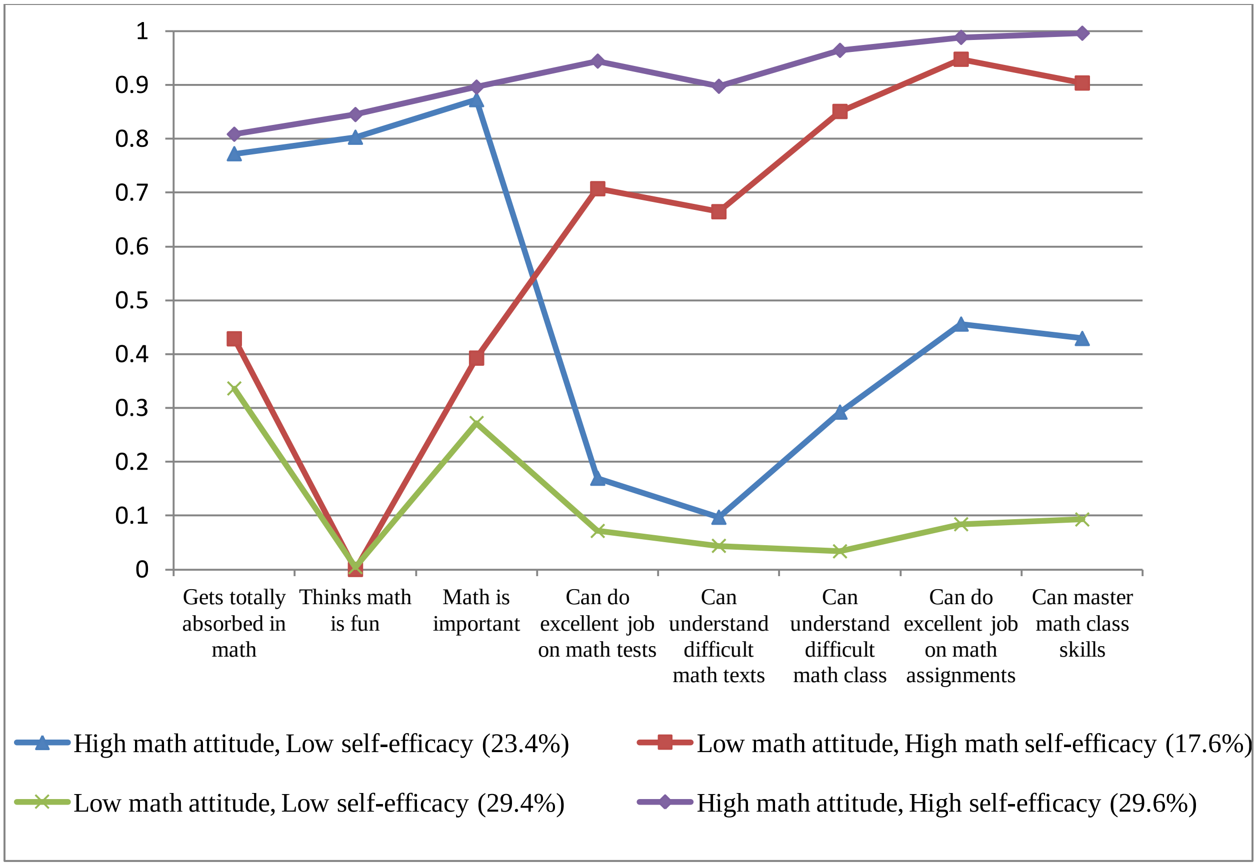

Figure 2. Item Probability Plot for Linguistic Minorities

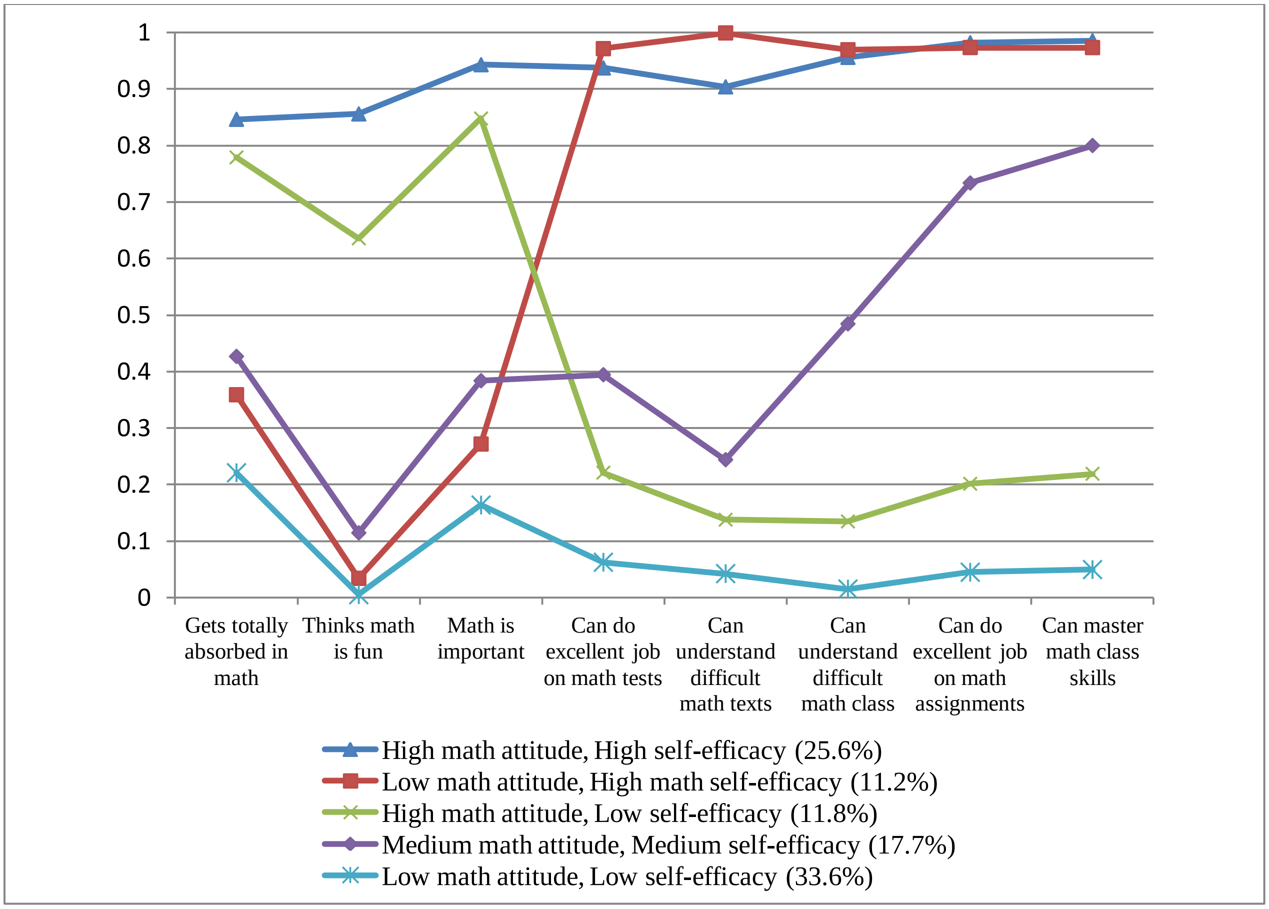

Figure 3. Item Probability Plot for Native English Speakers

Appendix A

Table A1

Course Lists for Math Coursetaking Pipeline Variable (F1RMAPIP)

Math Coursetaking Pipeline	Course Code	Course Name
No Math (F1RMAPIP=1)	N/A	N/A
Non-Academic Math (F1RMAPIP=2)	270100	Mathematics, Other General
	270101	Mathematics 7
	270102	Mathematics 7, Accelerate
	270103	Mathematics 8
	270104	Mathematics 8, Accelerated
	270106	Mathematics 1, General
	270107	Mathematics 2, General
	270108	Science Mathematics
	270109	Mathematics in the Arts
	270110	Mathematics, Vocational
	270111	Technical Mathematics
	270112	Mathematics Review
	270113	Mathematics Tutoring
	270114	Consumer Mathematics
	270200	Actuarial Sciences, Other
	270300	Applied Mathematics, Other
	270601	Basic Math 1
	270602	Basic Math 2
	270603	Basic Math 3
	270604	Basic Math 4
Low Academic Math (F1RMAPIP=3)	270401	Pre-Algebra
	270402	Algebra 1, Part 1
	270403	Algebra 1, Part 2
	270409	Geometry, Informal
Middle Academic Math I (F1RMAPIP=4)	270400	Pure Mathematics, Other
	270404	Algebra 1
	270406	Geometry, Plane
	270407	Geometry, Solid
	270408	Geometry
	270421	Mathematics 1, Unified
	270422	Mathematics 2, Unified
	270425	Geometry, Part 1
	270426	Geometry, Part 2
	270427	Unified Math 1, Part 1
	270428	Unified Math 1, Part 2

	270429	Pre-IB Geometry
	270431	IB Math Methods 1
	270432	IB Math Studies 1
	270436	Discrete Math
	270437	Finite Math
	270441	Algebra and Geometry
	279900	Mathematics, Other
Middle Academic Math II	270405	Algebra 2
(F1RMAPIP = 5)	270423	Mathematics 3, Unified
	270430	Pre-IB Algebra 2/Trigonometry
Advanced Math I	270410	Algebra 3
(F1RMAPIP = 6)	270411	Trigonometry
	270412	Analytic Geometry
	270413	Trigonometry and Solid Geometry
	270414	Algebra and Trigonometry
	270415	Algebra and Analytic Geometry
	270417	Linear Algebra
	270424	Mathematics, Independent Study
	270500	Statistics, Other
	270511	Statistics
	270521	Probability
	270531	Probability and Statistics
	270532	AP Statistics
Advanced Math II	270416	Analysis, Introductory
(F1RMAPIP = 7)	270433	IB Math Studies 2
Advanced Math III	270418	Calculus and Analytic Geometry
(F1RMAPIP = 8)	270419	Calculus
	270420	AP Calculus
	270434	IB Math Studies/Calculus
	270435	AP Calculus CD

Appendix B

Table B1

Classification of STEM Occupations in ELS:2002

O*NET Code	STEM Occupation Description
11	**Management Occupations**
113021	Computer and info systems managers
113051	Industrial production managers
119041	Engineering managers
119121	Natural sciences managers
15	**Computer and Mathematical Occupations**
151111	Computer and Information Research Scientists
151121	Computer Systems Analysts
151122	Information Security Analysts
151131	Computer Programmers
151132	Software Developers, Applications
151133	Software Developers, Systems Software
151134	Web Developers
151141	Database Administrators
151142	Network and Computer Systems Administrators
151143	Computer Network Architects
151151	Computer User Support Specialists
151152	Computer Network Support Specialists
151199	Computer Occupations, All Other
152011	Actuaries
152021	Mathematicians
152031	Operations research analysts
152041	Statisticians
152099	Mathematical Science Occupations, All Other
17	**Architecture and Engineering Occupations**
172011	Aerospace engineers
172021	Agricultural engineers
172031	Biomedical engineers
172041	Chemical engineers
172051	Civil engineers
172061	Computer hardware engineers
172071	Electrical engineers
172072	Electronics engineers, except computer
172081	Environmental engineers

	172111	Health/safety engineer, except mining
	172112	Industrial engineers
	172121	Marine engineers and naval architects
	172131	Materials engineers
	172141	Mechanical engineers
	172161	Nuclear engineers
	172171	Petroleum engineers
	172199	Engineers, all other
	173011	Architectural and civil drafters
	173012	Electrical and electronics drafters
	173013	Mechanical drafters
	173019	Drafters, all other
	173022	Civil engineering technicians
	173023	Electrical engineering technicians
	173025	Environmental engineering technicians
	173026	Industrial engineering technicians
	173027	Mechanical engineering technicians
	173029	Engineering tech, other (except drafter)
	173031	Surveying and mapping technicians
19		**Life, Physical, and Social Science Occupations**
	191012	Food Scientists and Technologists
	191013	Soil and plant scientists
	191021	Biochemists and biophysicists
	191022	Microbiologists
	191023	Zoologists and wildlife biologists
	191029	Biological scientists, all other
	191031	Conservation scientists
	191032	Foresters
	191041	Epidemiologists
	191042	Medical scientist, except epidemiologist
	191099	Life scientists, all other
	192011	Astronomers
	192012	Physicists
	192021	Atmospheric and space scientists
	192031	Chemists
	192032	Materials scientists
	192041	Environmental scientist, includes health
	192042	Geoscientist, except hydrologists
	192099	Physical scientists, all other
	194021	Biological technicians
	194031	Chemical technicians

	194041	Geological and petroleum technicians
	194051	Nuclear technicians
	194091	Environmental/protection science tech
	194092	Forensic science technicians
	194093	Forest and conservation technicians
	194099	Life/physical technician, other
25		**Education, Training, and Library Occupations**
	251022	Mathematical science, postsecondary
	251042	Biological science, postsecondary
	251051	Atmospheric science, postsecondary
	251052	Chemistry teachers, postsecondary
45		**Farming, Fishing, and Forestry Occupations**
	451011	First-line manager, farming/fishing/etc
	452041	Grader/sorter, agricultural products
	452091	Agricultural equipment operators
	452092	Farm worker/laborer: crop, nursery, etc
	452093	Farm workers, farm and ranch animals
	452099	Agricultural workers, all other
	453011	Fishers and related fishing workers
	454022	Logging equipment operators
	454023	Log Graders and Scalers
51		**Production Occupations**
	518011	Nuclear power reactor operators
	518091	Chemical plant and system operators
	519011	Chemical equipment operators and tenders

Note. O*NET = Occupational Information Network