Title
Examining the math attitudes, math self-efficacy, and STEM outcomes among native and non-native English speakers using a latent class analysis

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Publication Date
2015

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Santa Barbara

Examining the Math Attitudes, Math Self-Efficacy, and STEM Outcomes Among Native and Non-Native English Speakers Using a Latent Class Analysis

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Education

by

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September 2015

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ACKNOWLEDGEMENTS

This dissertation would not have been possible without my family, dissertation committee, mentors, friends and colleagues. I would like to thank my family for their support throughout my journey in attaining my doctorate degree.

I would like to thank my dissertation committee, Betsy Brenner, Karen Nylund-Gibson, Michael Gottfried, and Garrett Glasgow for their mentorship, guidance, feedback, and support throughout grad school.

I would like to thank John Yun, Patricia Marin, Edwin Hunt and the rest of the UCEC team. Thank you for giving me the opportunity to work at the UCEC. Thank you for opening my world to program evaluation!

I would like to thank my boyfriend, Matthew Laurent, who has always been very loving, supportive, and encouraging throughout graduate school.

I would like to thank my research group, the Latent Variable Group, for the stimulating discussions on latent variable modeling and for expanding my statistical knowledge. I have learned so much from this group! Thank you for welcoming me to the LVG community!

Lastly, but certainly not the least, I would like to thank my friends and colleagues: Jane Choi, Erika Baldwin, Ryan Grimm, Ann Kim, Diane Morovati, Lauren Taylor, Alma Boutin-Martinez, Ashley Mayworm, Shadi Roshandel, Mark Grimes, Meghan Corella, Hannah Grossman, Jay Plasman, Cameron Sublett, Yu Zhang, Wu Ti, Lois Harmon, Patrick Pieng, Yeana Lam, Wona Lee, Anne Emerson Leak, Melissa Bator, Lorna Gonzales, Michael Davenport, Joseph Nedy, Laura Urbisci, Carl Neufeld, Jennifer Smith, Michael Belt, Jacquie Dodd, Asma Mahdi, and Travis Mitchell. Thank you for being such wonderful friends and for all the fun times we shared these last five years!

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EDUCATION

2015	Ph.D.	University of California, Santa Barbara (UCSB) Education, Teaching and Learning in Mathematics Education Emphasis in Quantitative Methods in the Social Sciences *"Examining the Math Attitudes, Math Self-Efficacy, and STEM Outcomes Among Native and Non-Native English Speakers Using a Latent Class Analysis"*
2012	M.A.	University of California, Santa Barbara (UCSB) Education, Teaching and Learning in Mathematics Education *"Investigating the Effects of Teachers' Questioning on Students' Mathematical Reasoning and the Effects of the 2011 Algebra Readiness Academy on Students' Mathematical Achievement"*
2007	B.S.	University of California, Los Angeles (UCLA) Mathematics, Minor in Statistics

RESEARCH EXPERIENCE

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- Investigate the extent to which 10^{th} grade students' math attitudes and self-efficacy beliefs predict their outcomes in the Science, Technology, Engineering, and Mathematics (STEM) disciplines using the Education Longitudinal Study of 2002 (ELS:2002)
- Synthesize literature on factors that influence native and non-native English speaking students' math achievement, STEM degree attainment, and STEM career attainment
- Perform three independent latent class analyses on native and non-native English speaking graduates from high school, community college, and university

06/11-09/11 **Graduate Student Researcher**, Summer Algebra Academy, UCSB

- Conducted weekly observations on three secondary math teachers who implemented an algebra inquiry-based curriculum in classrooms of students with diverse English proficiencies
- Collected student pre- and post-tests and examined the effects of the inquiry-based curriculum on students' math test scores, mathematical reasoning and inquiry skills
- Administered interviews with teachers and coded interview data based on the types and quality of questions each teacher asked during warm up exercises

EVALUATION EXPERIENCE

01/13-12/14 **Graduate Student Evaluator**, Project ASCENSION at Oxnard College, UCSB

- Established research and evaluation plans and led the evaluation for 14 programs designed to increase the number of Hispanic high school and community college students in STEM disciplines
- Trained and supervised five graduate student evaluators on implementing study designs, data collection procedures, and preparing for interviews
- Directed the design and data collection of pre- and post-survey and interview data and applied mixed-method research skills to manage and analyze data
- Collected student and teacher surveys and interview data and applied mixed-method research skills to analyze data using Stata, SPSS, Excel, and Express Scribe
- Produced 14 technical program evaluation reports and presented findings and recommendations at professional development colloquiums

1/11-1/13, 8/13-9/13 **Graduate Student Researcher**, UC Educational Evaluation Center (UCEC), UCSB

- Assessed the effectiveness of the UC Online Instructional Pilot Project
- Worked with a team on the design, collection, and analyses of survey and interview data for 23 online courses across the UC campuses
- Performed parametric and non-parametric comparison of mean differences, and employed regression analyses on pre- and post-survey data using SPSS and Stata
- Coded, evaluated, and extracted themes from the interview data and open-ended comments from the student survey data
- Produced an evaluation report for the UC Office of the President

PROFESSIONAL EXPERIENCE

10/14-8/15 **Instructional Design Consultant**, Collaborate, UCSB

- Provide support in instructional technology tools and software for faculty and students using GauchoSpace, a campus-wide online learning management system

7/07-7/10 **Associate Economist**, Welch Consulting, Ltd., Los Angeles, CA

- Performed statistical analyses on wage and hour cases involving meal and rest break violations using Stata
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You, S., Lim, S., No, U. K., & Dang, M. (2015). Multidimensional aspects of parental involvement in Korean adolescents' Schooling: A mediating role of general and domain-specific self-efficacy. *Educational Psychology: An International Journal of Experimental Educational Psychology*. doi: 10.1080/01443410.2015.1025705

Yun, J. T., Grimes, M. S., Dang, M., Grimm, R., Wigginton, R., Espinosa, J. E., DiGuilio, L., Hunt, E., Baldwin, E. E., & Harmon, L. (2014, March). *Online Instruction Pilot Project (OIPP) Final Evaluation Report*. University of California, Santa Barbara: University of California Educational Evaluation Center.

Dang, M. (2012). *Investigating the effects of teachers' questioning on students' mathematical reasoning and the effects of the 2011 Algebra Readiness Academy on students' mathematical achievement* (Unpublished master's thesis). University of California, Santa Barbara.

CONFERENCE PRESENTATIONS

Dang, M., Brenner, M. E. & Nylund-Gibson, K. (2015, April). *Relating English Language Learners' mathematics attitudes to college STEM degree: A latent class analysis approach.* Roundtable discussion presented at the annual meeting of the American Educational Research Association, Chicago, IL.

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Dang, M., Brenner, M. E. (2013, April). *Understanding teachers' questioning style and its effects on student inquiry*, Paper presented at the annual meeting of the American Educational Research Association, San Francisco, CA.

Espinosa, J. E., Dang, M., Yun, J. T. (2012 November). *Towards a new engagement framework in higher education: Comparing students' course engagement to instructors' predicted engagement outcomes.* Roundtable discussion presented at the annual conference of the Association for the Study of Higher Education, Las Vegas, NV.

Dang, M., Brenner, M. E. (2012, January). *Understanding the development of students' mathematical thinking in an inquiry-based mathematics classroom*, Poster session presented at the annual meeting of the Hawaii International Conference on Education, Honolulu, HI.

PROFESSIONAL AFFILIATIONS

2012-present	American Educational Research Association (AERA) Division C: Learning and Instruction Division D: Measurement and Research Methodology Special Interest Groups (SIGs): Research on Mathematics Education; Research on Evaluation; Longitudinal Studies; Advanced Studies of National Databases
2012-present	Association for the Study of Higher Education (ASHE)

PROFESSIONAL DEVELOPMENT

05/15	Selected as one of the 23 participants to attend the American Educational Research Association (AERA) Institute on Statistical Analysis for Education Policy: Causal Analysis using International Data, Washington, D.C.
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04/15	Invited speaker to the Quantitative Methods in Social Sciences (QMSS) colloquia series to provide a workshop on *An Introduction to Stata, General Uses and Applications,* UCSB.
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07/13	Selected as one of the 20 graduate students and faculty members to attend the NAEP High School Transcript Study (HSTS) 2009 Database Training Seminar, sponsored by the National Center for Education Statistics (NCES), Institute of Education Sciences (IES), and U.S. Department of Education, Washington, D.C.
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Research Grants

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2014-2015	UCSB Humanities and Social Sciences Research Grant
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2012-2013	UCSB Graduate Division Central Fellowship Award, Graduate Opportunity Fellowship
2011-2012	UCSB Gevirtz Graduate School of Education Block Grant

ABSTRACT

Examining the Math Attitudes, Math Self-Efficacy, and STEM Outcomes

Among Native and Non-Native English Speakers

Using a Latent Class Analysis

by

Myley Dang

Our nation faces an exponentially high demand for science, technology, engineering, or mathematics (STEM) professionals and a scarce supply of individuals who pursue STEM careers, especially multilingual individuals. Particularly among students who are non-native English speakers (i.e., students whose native language is not English), there is little information on what role math attitudes and math self-efficacy play in understanding STEM outcomes. This information is critical to inform educators and policymakers on how to better prepare students and provide them the proper skills to be college and career-ready in STEM careers. To address this need, this dissertation explores the relationship between native and non-native English speakers' math attitudes and math self-efficacy with their 12th grade math achievement, STEM bachelor degree attainment, and STEM career attainment. More specifically, this study examines students' STEM outcomes at three levels of educational attainment including the graduation of high school, community college, and university.

Using the Education Longitudinal Study (ELS:2002), I performed a latent class analysis (LCA) to group a nationally representative sample of U.S. 10th grade students (N=9,270) based on their math attitudes and math self-efficacy. Fitting independent LCAs on the sample of non-native and native English speaking groups revealed that there were different patterns of math attitudes and math self-efficacy among these groups. Results from this study suggest that regardless of English proficiency level, female students were less likely to have high math attitudes and high math self-efficacy beliefs relative to their male peers. In regards to STEM outcomes, students with high math attitudes and high math self-efficacy had higher 12th math achievement scores and had higher proportions of individuals with a STEM degree and STEM career. In particular, results from this study suggest that math self-efficacy played a stronger role in predicting STEM outcomes regardless of math attitudes. In regards to non-native English speakers, those with at least a bachelor's degree were not far behind their native English speaking peers in terms of their STEM outcomes. Findings from this study will help educators and researchers understand ways to support positive math attitudes and math self-efficacy, particularly for non-native English speakers and female students so that they can persist in STEM and meet the high demand for STEM professionals. Additionally, findings from this study indicate the need for positive perceptions of non-native speakers and recognize the important roles they may play in creating a multilingual STEM workforce.

Keywords: Non-native English speaker, math attitudes, math self-efficacy, latent class analysis, STEM outcomes

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I. Introduction

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, which is about 34% annually more than current rates. This calls attention to the need to not only increase the number of STEM professionals, but also increase the number of STEM degree recipients and high school math achievement, both of which have been linked to STEM careers (Herrera & Hurtado, 2011; Maltese & Tai, 2011; Trusty, 2002; Ware & Lee, 1988). Based on the 2013 National Science Foundation report on Women, Minority, and Persons with Disability in STEM, among individuals who completed at least a bachelor's degree and attained a STEM career (*N*= 5,069,000), only 25% were female compared to 75% who were male, and only 2.4% were underrepresented minorities compared to 69.3% whites. These STEM careers include occupations in biological science, computer and information science, mathematics, physical science, and engineering.

There are even smaller percentages of non-native English speakers[1], that is, individuals whose native language is not English, who pursue a STEM degree, let alone attain a bachelor's degree. Klein, Bugarin, Beltranena, and McArthur (2004) found that 18 to 24 year old linguistic minorities, who they define as individuals who speak a language other than English at home and/or have varying English-speaking abilities, were less likely than their monolingual peers to be enrolled in college. Additionally, using the National Education Longitudinal Study of 1988 (NELS:88), Kanno and Cromley (2013) found that only one in

[1] The literature defines English Language Learners and Linguistic Minorities differently. The definitions will be based on how the authors define the term. For this dissertation, non-native English speakers will be used to indicate individuals who first language is not English and/or have different levels of English-speaking abilities (i.e., "very well," "well," "not well," or "not at all").

eight English Language Learners (ELLs) attained a bachelor's degree compared to one in four English-proficient linguistic minorities and one in three native English speakers who earned a bachelor's degree. From an educational equity perspective, such large gaps in bachelor's degree attainment are unacceptable and bring cause for concern.

Importance of Studying Non-Native English Speakers

Studying ELLs and linguistic minorities is an urgent matter because they have become one of the largest growing populations in the United States. In 2012-2013, there were approximately 4.4 million ELL students, or an estimated 9.2% of the total number of public school students in the United States (Kena et al., 2015). 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., 2015). The authors define ELL as

> "an individual who, due to any of the reasons listed below, has sufficient difficulty speaking, reading, writing, or understanding the English language to be denied the opportunity to learn successfully in classrooms where the language of instruction is English or to participate fully in the larger U.S. society. Such an individual (1) was not born in the United States or has a native language other than English; (2) comes from environments where a language other than English is dominant; or (3) is an American Indian or Alaska Native and comes from environments where a language other than English has had a significant impact on the individual's level of English language proficiency" (Kena et al., 2015, p. 273).

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 or linguistic minority (Thomas & Collier, 2002). Studying non-native English speakers is important because they are a large at-risk population who encounter multiple barriers throughout their education. For example, ELLs face unique challenges where they not only need to learn the academic content, but also develop English proficiency (Abedi & Herman, 2010; Callahan, Wilkinson, & Muller, 2010). Therefore to understand the factors involved in explaining the gap in STEM outcomes, it is necessary to understand the issues specifically for non-native English speakers, as these issues are different compared to their native English speaking peers.

Despite the increasing number of ELLs in the U.S., there has been very little research on this population, specifically in STEM outcomes. The lack of non-native English speakers in the STEM fields is concerning, given the demand for STEM professionals in the field. There are reasons to believe that academic and career trajectories for ELLs and linguistic minorities is different compared to native English speakers (Kanno & Cromley, 2013) and that these differences could be due to several individual and structural characteristics. In terms of individual characteristics, it is possible that this lack of representation is due low math self-efficacy or low math attitudes. Furthermore, the constructs of math attitude and math self-efficacy can look different for native and non-native English speakers. There may also be differences in terms of gender and race/ethnicity (Else-Quest, Mineo, & Higgins, 2013). In terms of structural characteristics, there are differences in schooling characteristics between native and non-native English speakers such as tracking (Oakes, 2005) and math coursetaking (Mosqueda, 2012). Thus it is important to study this population and gain a better understanding of how the patterns for non-native English speakers might be different from native English speakers and how to strengthen the STEM pipeline for these populations.

Although there has been a growing body of research on non-native English speakers, there has not been a lot of research conducted on factors that lead non-native English speakers into or dissuade them from STEM fields. There has been some research that distinguish groups who pursue STEM fields compared to groups who do not pursue STEM fields by individual characteristics such as students' math attitudes, math self-efficacy, gender, race/ethnicity, and structural characteristics including socioeconomic status, immigrant generation status, prior math achievement, tracking, coursetaking patterns, and extracurricular involvement. However, there has been no research to date that differentiates groups by language proficiency (i.e., native English speakers and non-native English speakers) or by educational attainment (i.e., completion of high school, community college, or university). Therefore, this gap in the literature provides the motivation behind this study.

Purpose of This Study

The purpose of this study is to examine individual and structural characteristics that relate to STEM outcomes at different time points in students' educational and career trajectories. The STEM outcomes that are examined in this study include students' 12th grade math achievement, degree major in college, and occupation after high school or college. This study investigated the effects of these individual and structural variables on native English speakers and non-native English speakers for three different levels of educational attainment: high school, community college, and university and beyond. Using a diverse, nationally representative sample of 10th grade students from Education Longitudinal Study of 2002 (ELS:2002), this proposed study includes a sample of 9,270[2] students, where 7,900 (85.2%) were classified as native English speakers and 1,370 (14.8%) were classified as non-native English speakers, which include English Language Learners and linguistic minority students. This study examines the extent to which students' 10th grade math attitudes and math self-

[2] Following the restricted data security policy of the National Center for Education Statistics (NCES), which collected the ELS:2002 data, I rounded numbers to the nearest 10 when reporting unweighted sub-sample sizes in order to avoid the identification of individual students

efficacy relate to their 12^{th} grade math achievement, degree major in college, and occupation after school. More specifically, the following research questions were examined in this study:

1. How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?
2. What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?
3. To what extent do students' math attitudes and math self-efficacy contribute to their 12^{th} grade math achievement, and how does this differ between non-native English speakers and native English speakers?
4. To what extent do students' math attitudes and math self-efficacy contribute to their STEM degree, and how does this differ between non-native English speakers and native English speakers?
5. To what extent do students' math attitudes and math self-efficacy contribute to their STEM career, and how does this differ between non-native English speakers and native English speakers?

Each of these research questions were investigated for group of high school graduates, community college graduates, and university graduates. Additional questions were explored for university graduates, which include the following:

1. Are there differential effects in the relationship between 12^{th} grade math achievement and STEM degree for students holding at least a bachelor's degree? Does this differ between native and non-native English speakers?

2. Are there differential effects in the relationship between STEM degree and STEM career for students holding at least a bachelor's degree? Does this differ between native and non-native English speakers?

Profiles of Math Attitudes and Math Self-Efficacy

To address these research questions, it is important to examine profiles of math attitudes and math self-efficacy and understand how they differ between native and non-native English speakers. Non-native English speakers are a diverse group of students whose varied linguistic, economic, and cultural backgrounds present unique needs and assets for the school community (Kanno & Harklau, 2012). Since non-native English speakers are a diverse group of people, Callahan et al. (2010) suggests there are different profiles for ELLs. Within the population of non-native English speakers, there are many different subpopulations that vary by gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking, math coursetaking, and extracurricular involvement. Therefore because of the heterogeneity within each English proficiency group, the application of a clustering technique such as latent class analysis (LCA) is useful to identify groups or classes of individuals who respond similarly to a set of indicators. Furthermore, different profiles can lead to different outcomes. For example, a latent class of students with low math attitude and low math self-efficacy could have different math achievement scores compared to a latent class of students with high math attitude and high math self-efficacy. Thus, there is a need to understand profiles for each language proficiency group so that educators and researchers can address specific issues to each subgroup and develop interventions for each language proficiency group. Classifying students into distinct classes based on a set of math attitude and math self-efficacy indicators, while taking into account differences in gender, race/ethnicity, SES, track program, math coursetaking, prior math achievement, and extracurricular involvement, is important for understanding individual and structural differences in students' STEM outcomes.

Using latent class analysis, which is considered a "person-centered" approach, this study aims to identify latent classes of math attitudes and math self-efficacy beliefs and the extent to which these classes' attitudes and beliefs influences 12^{th} grade math achievement, STEM degree attainment, and STEM occupation attainment, while taking into consideration several individual and structural variables. To my knowledge, there has been no research to date that uses a nationally representative dataset to analyze STEM outcomes from high school to postsecondary education for native and non-native English speakers using a latent class analysis. This study has potential to uncover groups of non-native English speakers and native English speakers who share similar characteristics and study how they differ with respect to STEM outcomes. This study could also provide insight on the various factors that explain the underrepresentation of non-native English speakers in STEM fields.

The Role of Math Attitudes and Math Self-Efficacy on STEM Outcomes

Much research has suggested that math attitudes and math self-efficacy play an important role in the following STEM outcomes: math achievement, degree, and occupation. Specifically, many studies suggest that math attitudes and math self-efficacy positively influence student's math performance (Dumais, 2009; Else-Quest et al., 2013; Pajares & Kranzler, 1995; Pajares & Miller, 1994, 1995; Schunk, 1989; Stevens, Olivarez, Lan, & Tallent-Runnels, 2004), decision to major in a STEM field (Byars-Winston, Estrada, Howard, Davis, & Zalapa, 2010; Lent & Hackett, 1987; Lent, Sheu, Singley, Schmidt, & Gloster, 2008; Luzzo, Hasper, Albert, Bibby, & Martinelli, 1999; Pajares & Miller, 1995) as well as student's decision to pursue a STEM occupation (Betz & Hackett, 1983; Hackett & Betz, 1981, 1989; Ing & Nylund-Gibson, 2013; Lent & Hackett, 1987; Luzzo et al., 1999;

O'Brien, Martinez-Pons, & Kopal, 1999; Pajares & Miller, 1995; Wang, Eccles, & Kenny, 2013; Zeldin, Britner, & Pajares, 2008). There has also been some research suggesting the relationship between the three outcomes, where math achievement influences STEM degree attainment (Maltese & Tai; Trusty, 2002; Ware & Lee, 1988), which influences STEM occupation (Herrera & Hurtado, 2011). However, there has been little research to date that examines profiles of math attitudes and math self-efficacy together and how this differs among language proficiency groups, while taking into consideration various individual and structural characteristics.

Research thus far has focused on secondary and post-secondary outcomes. For example, several studies focus on non-native English speakers' opportunities to learn mathematics in high school (Abedi & Herman, 2010; Mosqueda, 2012); or their achievement and coursetaking patterns (Callahan et al., 2010); or their reclassification and the effects of tenure in language programs on academic performance (Slama, 2014). In addition, there has been some research on students' access and persistence in college (Kanno & Harklau, 2012; Kanno & Cromley, 2013; Rodriguez & Cruz, 2009). These studies have shown that non-native English speakers face challenges in not only acquiring English proficiency, but also learning content in a language in which they are not proficient. This results in fewer opportunities to learn, which may play a role in the achievement gap between native and non-native English speakers in high school, as well as lower levels of access and attainment in postsecondary education.

Although there has been some progress in research on non-native English speakers at the secondary level, there are very few studies that examine non-native English speakers beyond the secondary level. More specifically, there has been little research on analyzing the pipeline from high school to postsecondary education. In addition, there has been limited research on factors contributing to non-native English speakers' decision to pursue a STEM field. Very little research has been conducted on non-native English speakers' math attitudes and math self-efficacy as it relates to math performance and STEM outcomes. Schunk (1989) argued that within the context of self-efficacy, research is needed among racial and ethnic minorities to reflect the changing cultural demographics of our society. Thus, it is important to understand how self-efficacy operates among non-native English speakers, and how their math attitudes and self-efficacy influences their academic achievement. Although there is currently limited research on non-native English speakers in STEM, this can change in the future as the population of ELLs continues to grow and the need to produce one million STEM professionals (PCAST, 2012) becomes more imminent.

Motivation for This Study

Due to the lack of research in understanding the relationship and heterogeneity of math attitudes and math self-efficacy beliefs as it relates to STEM outcomes for native and non-native English speakers, the motivation for this study is to address this gap in the literature by using latent class analysis to identify groups who share similarities based on selected individual and structural characteristics but differ on academic and career outcomes. More specifically, using a diverse, nationally representative sample of 10^{th} grade students from the ELS:2002, this study examined key variables related to math achievement and interest in STEM and investigated the effects of these variables on native and non-native English speakers. This study classifies students into distinct latent classes based on a set of math attitude and math self-efficacy indicators while taking into account differences in gender, race/ethnicity, SES, track program, math coursetaking, prior math achievement, and involvement extracurricular activities, which are important factors in understanding differences in math achievement, STEM degree attainment, and STEM career attainment.

Furthermore, this study implemented regression mixture modeling to test the differential effects of these STEM outcomes by latent class and to better understand the STEM pipeline from high school to postsecondary education to the work force.

II. Literature Review

Challenges Faced by Non-Native English Speakers

There is a commonly held belief that mathematics should be simple for non-native English speakers because it is the "universal language". The assumption is that mathematics utilizes numbers, which are recognized internationally and that mathematics relies less on language, hence it should theoretically be an easy subject for non-native English speakers to grasp. However, due to the linguistic demands (Solano-Flores, 2014; Spanos, Rhodes, Dale, & Crandall, 1988; Wolf & Leon, 2009) and cognitive demands (Campbell, Adams, & Davis, 2007) in high stakes testing (Abedi & Herman, 2010; Abedi & Lord, 2001; Abedi, Lord, & Hofstetter, 1998; Abedi, Lord, & Plummer, 1997; Martiniello, 2008; Shaftel, Belton-Kocher, Glasnapp, & Poggio, 2006), mathematics has become heavily reliant on language. It then becomes a challenge for non-native English speakers to not only learn English as their second language, but also struggle with other issues such as understanding the language incorporated into mathematics (Abedi & Lord, 2001), comprehending the instruction that is conducted mainly in English (Abedi & Herman, 2010), and writing out explanations of solutions (Bailey & Heritage, 2014).

Linguistic demands of mathematics. Research has shown that linguistic features of mathematics create comprehension difficulties for non-native English speakers (Abedi & Lord, 2001; Abedi et al., 1998; Abedi et al., 1997; Campbell et al., 2007; Martiniello, 2008; Spanos et al., 1988). There is a common consensus among the literature that shows the greater the linguistic complexity in mathematics word problems, the greater the challenge for non-native English speakers as compared to native English speakers. Martiniello (2008) describes the linguistic challenges presented in mathematics word problems are due to syntax and vocabulary, where the syntax could incorporate multiple clauses, long noun phrases, and relationships between syntactic units. In addition, the vocabulary words that have multiple meanings and words that are specific to American culture are unfamiliar to non-native English speakers (Martiniello, 2008).

Abedi and Lord (2001) argue that language proficiency is a predictor of high mathematics performance. In their study, the authors analyzed the extent to which language complexity in math word problems affects students' math test performance, where students were given sample items released from the National Assessment of Educational Progress (NAEP) math assessment and another set of items with reduced linguistic complexity. The authors argued that the high performing students did not benefit from the linguistically modified version as much as the low performing students because they already had strong language ability, whereas the low performing students benefited more because they had weaker language ability than their native English speaking peers. Although the authors controlled for class, teacher, and school effects, they did not take into account other factors that might have contributed to students' performance including students' previous educational experience, students' exposure to English, students' social and cognitive abilities, and students' motivation to learn.

Cognitive demands of mathematics. In addition to the linguistic demands of math, there are also cognitive demands of math. Campbell et al. (2007) discussed elements of mathematics word problems that contribute to the cognitive demands of mathematics for ELLs. Campbell et al. (2007) argue that the language used in math word problems is difficult for ELLs to understand even though they comprehend the context of the problem and know the relevant mathematics to solve the problem. The authors provide two examples in their article that makes implicit assumptions about a typical student in a particular grade level doing laundry and playing in a soccer league. These example word problems make assumptions about students' prior experiences and can increase what Paas, Renkl, and Sweller (2003) calls "extraneous cognitive load."

Campbell et al. (2007) incorporate the idea of working memory and long-term memory from Paas et al.'s (2003) study and illustrated how it affects cognitive load. Paas et al. (2003) describe working memory to be where "all conscious cognitive processing occurs" and that working memory can only handle a limited number of processes at a time (p. 2). Campbell et al. (2007) suggest that since a limited amount of information can be stored and processed in working memory, students must be able to efficiently recall knowledge stored in long-term memory, hold it in working memory, and be able to work on the problem simultaneously. This suggests that if the amount of information is more than the capacity of working memory, then cognitive overload results, where the demands of the task exceed the cognitive capacity. Campbell et al. (2007) argue that when mathematics problems increase the cognitive load, the cognitive challenges for ELLs also increase.

Achievement gap among native and non-native English speakers. Given that there are linguistic and cognitive demands that non-native English speakers face, it is no surprise that there are few non-native English speakers that pursue a STEM field that requires high linguistic competency and cognitive knowledge base. Based on the limited research on non-native English speakers (Kanno & Harklau, 2012), it is known that non-native English speakers have lagged behind their English proficient peers in all content areas, specifically academic subjects that require a high demand of the English language (Abedi & Gándara, 2006). This not only includes reading and writing in language arts, but also in mathematics and science where students must be able to read and understand complex problems before attempting to solve them (Abedi & Lord, 2001).

Particularly in mathematics, the U.S. Department of Education, Institution of Educational Sciences, National Center for Education Statistics, and National Assessment of Educational Progress (NAEP) tracked achievement levels for public schools across the nation for grades 4, 8, and 12. In 2013, ELLs scored significantly lower on the math assessments compared to non-ELLs, where the gap was 25 points for 4th graders, 41 points for 8th graders, and 46 points for 12th graders. Similarly in 2009, ELLs scored significantly lower on the science assessments compared to non-ELLs, where the gap was 39 points for 4th graders, 48 points for 8th graders, and 47 points for 12th graders (NCES, 2014). The literature suggests that this performance gap could be explained by many different individual and structural factors such as gender, race/ethnicity (Else-Quest et al., 2013), socioeconomic status (Krashen & Brown, 2005), immigrant generation status (Drake, 2014; Rodriguez & Cruz, 2009; Rumbaut, 2005), and a host of inequitable schooling conditions (Gándara, Rumberger, Maxwell-Jolly, & Callahan, 2003). Given these unique challenges and circumstances that non-native English speakers face, it is important to study this population and understand the factors involved in their underachievement in math and underrepresentation in STEM fields. One perspective that can be used to understand these issues is through the social cognitive career theory (SCCT) framework.

Theoretical Framework

The theoretical model displayed in Figure 1 integrates Lent, Brown, and Hackett's (1994) social cognitive career theory (SCCT) and prior literature on factors related to STEM outcomes. Lent et al. (1994) developed this SCCT framework based on Bandura's (1986) social cognitive theory to describe three interlocking mechanisms related to career development, which include self-efficacy, outcome expectations, and goals. Social cognitive career theory suggests that there are dynamic processes and mechanisms that take place where (a) career and academic interests develop, (b) career-relevant choices are created and enacted, and (c) performance outcomes are achieved (Lent et al., 1994). Based on SCCT, learning experiences affect self-efficacy, and self-efficacy expectations affect career outcome expectations (Lent et al., 1994). In addition, the SCCT model 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 (Lent et al., 1994). In this sense, people form interests in activities in which they view themselves to be efficacious and in which they anticipate positive outcomes (Bandura, 1986; Lent et al., 1994). Moreover, Bandura (1986) theorized that people's behavior can be better predicted by their beliefs rather than their actual capabilities of accomplishing tasks, and that it is these beliefs that help determine what people do with the knowledge and skills that they have.

The theoretical framework used in this dissertation builds from the social cognitive career theory by focusing specifically on math self-efficacy and including math attitudes. Hackett and Betz (1989) defined math self-efficacy as "a situational or problem-specific assessment of an individual's confidence in his or her ability to successfully perform or accomplish a particular [mathematics] task or problem" (p. 262). This study extends SCCT and contributes to the literature by including students' attitudes toward math, which is generally defined as positive or negative emotional dispositions toward mathematics (McLeod, 1992). Math attitudes and math self-efficacy were included in this model because prior literature suggests they are related to STEM outcomes (Dumais, 2009; Else-Quest et al., 2013; Hackett & Betz, 1981, 1989; Ing & Nylund-Gibson, 2013; Maltese & Tai, 2011).

Some studies have examined the relationship of one construct (either math attitude or math self-efficacy) on STEM outcomes (Fast et al., 2010; Ing & Nylund-Gibson, 2013; Lent et al., 2008; Pajares & Miller, 1995), while other studies have examined the relationship of both constructs (math attitude and math self-efficacy) on STEM outcomes (Byars et al., 2010; Else-Quest et al., 2013; Pajares & Kranzler, 1995; Pajares & Miller, 1994; Stevens et al., 2004). Therefore, this theoretical framework includes both constructs to determine the effects on STEM outcomes. The model includes a dashed line between math attitude and math self-efficacy to illustrate that both constructs are important, but are conceptually distinct from one another. In this study, this theoretical framework was applied on to a large, nationally representative sample of a cohort of 10th graders. This is a contribution to the literature since there has been no study to date that examines the effects of the combination of math attitudes and math self-efficacy on STEM outcomes among native and non-native English speakers using a nationally representative sample.

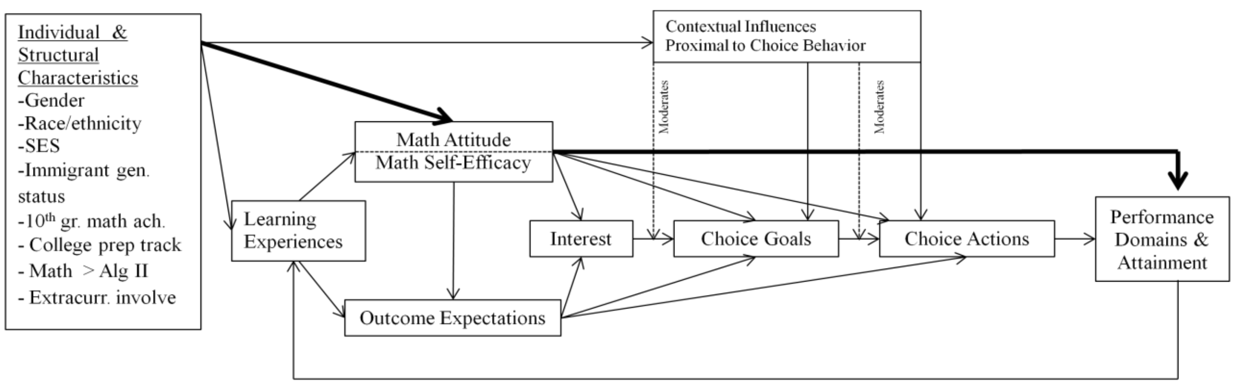

Figure 1. Theoretical model.

As seen in Figure 1, individual and structural characteristics influence an individual's learning experience, which influences an individual's math attitudes and math self-efficacy and outcome expectations. These individual and structural variables were included in the model based on prior literature that suggests the significant influence of these variables on math attitudes and math self-efficacy and STEM outcomes. Figure 1 illustrates how math attitudes, math 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. These choice actions then lead an individual to pursue particular performance domains and attainment. This becomes a feedback loop, where an individual's performance influences his/her learning experiences, which influence his/her self-efficacy and outcome expectations, interests, choice goals, actions, and performance.

This theoretical model includes an *indirect* path from math attitudes and self-efficacy to interest, to choice goals, to choice actions, and to performance attainment. There is also a *direct* path from math attitudes and self-efficacy to performance attainment. When focusing on this direct path, it is assumed that the indirect path that include the mediating factors of interest, choice goals, and choice actions are processes that take place in an individual's performance attainment. Although this indirect path is an important process, it was not the focus of this dissertation. Instead, this dissertation focused specifically on the direct path. More specifically, this dissertation focused on the path of individual and structural characteristics to math attitude and math self-efficacy, as well as the direct path from math attitude and self-efficacy to performance attainment (bolded paths in Figure 1). This is a contribution to the literature since not many studies have included the combination of math attitudes and math self-efficacy in predicting students' STEM outcomes.

To gain a better understanding of how math attitudes and self-efficacy influence STEM outcomes, I developed a statistical model that maps the direct path of the theoretical model, which is depicted in Figure 2. The latent, or unobserved, variable, 10^{th} grade math attitudes and math self-efficacy, is measured using three math attitude and five math self-efficacy indicators. Different latent classes will be identified by these two constructs of math attitudes and math self-efficacy. The theoretical framework in Figure 1 was used to guide the statistical model in Figure 2, which illustrates how the latent classes of math attitudes and math self-efficacy influence STEM outcomes of 12th grade math achievement, STEM degree and STEM career attainment, controlling for gender, race/ethnicity, immigrant generation status, socioeconomic status, 10th grade math achievement, tracking program, math coursetaking, and extracurricular involvement. This model includes math attitudes, which is a contribution to the SCCT theoretical model that only examines self-efficacy.

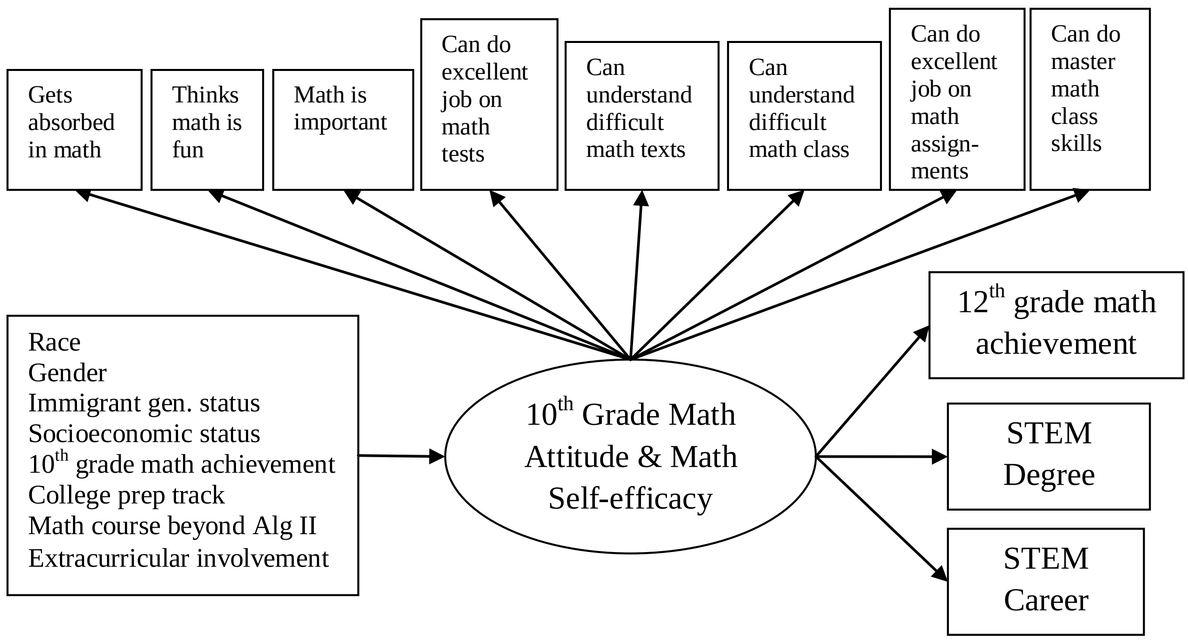

Figure 2. Statistical model.

This statistical model is used to address the research questions for all three levels of educational attainment (i.e., high school, community college, university) for both native and non-native English speakers. Focusing on these three levels of educational attainments gives a glimpse of the STEM pipeline by analyzing how different math attitude and self-efficacy beliefs can predict different STEM outcomes for each native and non-native English speaking group. To date, there has not been any literature that examines non-native English speakers' STEM outcomes using an SCCT framework. Thus this study has potential contributions to the theory by incorporating math attitudes with math self-efficacy and applying the framework to non-native English speakers.

Math Attitudes and Math Self-Efficacy in Relation to STEM Outcomes

There are multiple variables that explain the underachievement of non-native English speaking students compared to their native English speaking peers, which include individual and structural characteristics that prohibit them from pursuing STEM fields. Increasingly, researchers have been examining other characteristics that are associated with the lack of non-native English speakers in STEM fields. There has been research in examining differences in individual characteristics including differences in math attitudes and math self-efficacy beliefs for native English speakers, however not much research have investigated these differences for non-native English speakers. There also has not been much research on examining the combination of math attitudes and math self-efficacy in predicting STEM outcomes. This dissertation will contribute to the literature by studying how math attitude and math self-efficacy jointly influence STEM outcomes for native and non-native English speakers. The following section describes how math attitudes and math self-efficacy have been measured in the reviewed literature.

Measures of math attitudes. A review of the math attitude literature reveals that there is not a clear definition of math attitudes. Generally speaking, math attitudes are an individual's positive or negative emotional dispositions toward math (McLeod, 1992). Most researchers have linked the definition of math attitudes based on the choice of the measuring instruments. Some studies have measured math attitudes using the Fennema-Sherman Math Attitude Scales that includes five 10-item scale using a 5-point scale from 1 (strongly disagree) to 5 (strongly agree) (Betz & Hackett, 1983; Hackett & Betz, 1989). This scale includes items pertaining to math anxiety, math confidence, perceptions of math as a male domain, perceptions of the usefulness of math, and effectance of motivation in mathematics. Higher scores on this scale indicate a more positive attitude toward math (i.e., lower math anxiety, less tendency to view math as a male domain, and greater tendency to view math as useful). Although the math attitude scale includes items related to math confidence, the authors considered this distinct from math self-efficacy, which was measured using the Math Self-Efficacy Scale (MSES).

More recently, Riegle-Crumb and King (2010) used the ELS:2002 data in their study and measured math attitudes using three items related to math affect. These items were related to the extent to which a student "gets totally absorbed in math", "think math is fun", and "thinks math is important." Students were asked to self-report on the extent to which they strongly agree (1), agree (2), disagree (3), or strong disagree (4) to the items. The authors reverse coded these responses such that higher values indicate positive math attitudes. Given that this dissertation uses the ELS:2002 data, I measured math attitudes in a similar fashion to how Riegle-Crumb and King (2010) measured math attitudes using these three items related to math affect.

Measures of math self-efficacy. There has been a general definition of math self-efficacy, which Hackett and Betz (1989) defined as "a situational or problem-specific assessment of an individual's confidence in his or her ability to successfully perform or accomplish a particular [mathematics] task or problem" (p. 262). This definition is consistent with Bandura's (1977) notion of self-efficacy and performance assessment, but is specific to math. It is theorized that people generally attempt tasks that they believe they will succeed, where someone with low self-efficacy will put little effort and stop a task because they believe they will not succeed; however, someone with high self-efficacy will put forth a large amount of effort and will keep trying to succeed because they have the belief that they will succeed (Bandura, 1997). Thus, framed in a mathematical domain, those who have high math self-efficacy are more likely to succeed in math-related tasks compared to those who have low math self-efficacy.

Similarly to math attitudes, math self-efficacy has been defined based on the measuring instruments. Some researchers have measured math self-efficacy using the 52-item Math Self-Efficacy Scale (MSES) (Betz & Hackett, 1983; Hackett & Betz, 1989), which includes assessment of one's level of confidence in his/her ability to solve specific math problems, to perform math-related tasks, and to succeed in subsequent math courses. Another scale used to measure math self-efficacy is the Math Confidence Scale (MCS), which contains three components of math including arithmetic, algebra and geometry, and three levels of cognitive demand including computation, comprehension, and application. Similar to MSES, respondents were asked to rate their level of confidence in solving math problems and subsequently were asked to solve the same or similar math problems on which their confidence was assessed (Pajares & Miller, 1994, 1995).

Other researchers have measured math self-efficacy using items related to math confidence. Riegle-Crumb and King (2010) used the ELS:2002 data and measured students' confidence using items related to the extent to which a student "can do an excellent job on math tests," "can understand difficult math texts," "can understand difficult math classes," "can do well on math assignments," and "can master math classes." Students were asked to respond to these items with almost never (1), sometimes (2), often (3), and almost always (4). This dissertation measured math self-efficacy in a similar fashion using these five items related to math self-efficacy.

It is important to point out that self-efficacy has often been confused with self-concept or self-esteem in the literature, but Pajares and Miller (1994) makes this distinction clear by describing how self-efficacy is more context-specific in assessing one's competence to perform a specific task, whereas self-concept is more broad in assessing one's general competence. Self-esteem is different from self-efficacy, where self-esteem is concerned about beliefs of self-worth; whereas self-efficacy is concerned with judgments of personal capability (Bandura, 1997).

Previous research on self-efficacy has mainly focused on two major areas. The first area examines the relationship among self-efficacy and related psychological constructs (i.e., academic motivation) with achievement (Multon, Brown, & Lent, 1991; Schunk, 1989). The second area explores the relationship between self-efficacy and college major and career choices (Betz & Hackett, 1983; Hackett & Betz, 1989; Lent & Hackett, 1987; O'Brien, et al., 1999; Pajares & Miller, 1995). This study focused on both areas as it relates to math self-efficacy; that is, this study investigates the relationship of students' math self-efficacy with their achievement, college major, and career choices. This dissertation includes math attitudes in addition to math self-efficacy and investigates how these two constructs relate to STEM outcomes. The following sections describe the relationships between math attitudes and math self-efficacy with STEM outcomes in math achievement, college major choice, and career choice. Before discussing this relationship, it is important to note the endogeneity of math attitudes and self-efficacy with STEM outcomes.

Addressing the Endogeneity of Math Attitudes and Self-Efficacy with STEM Outcomes

There has been much debate in the literature regarding the directionality of math attitudes and self-efficacy on STEM outcomes, where some researchers have found that math self-efficacy is predictive of math performance (Fast et al., 2010; Multon et al., 1991; Pajares & Kranzler, 1995; Pajares & Miller, 1994, 1995; Schunk, 1989; Stevens et al., 2004), while other researchers suggest math performance predicts math self-efficacy (Campbell &

Hackett, 1986; Hackett & Campbell, 1985). There is also some research that examines this relationship beyond high school, where prior math achievement influences math self-efficacy, which in turn, significantly predicts STEM major (Hackett, 1985). Others argue that the relationship between math attitudes and math self-efficacy with STEM outcomes is not as unidirectional. Li and Moschkovich (2013) suggest there is a bidirectional effect, where math self-efficacy not only influences math performance, but also math performance influences math self-efficacy, where successes raises self-efficacy and failures lower self-efficacy.

Due to the ambiguity of the direction of influence, there have been some experimental studies conducted that offer stronger inferences about the direction or cause-effect relationship (Betz & Schifano, 2000; Luzzo et al., 1999; Silvia, 2003). There have been some experimental studies in the literature that suggest self-efficacy is not a product of success in STEM outcomes. Betz and Schifano (2000) developed and evaluated a self-efficacy based intervention for college women to determine if the intervention increased their confidence and interests in specific activities such as assembling, building, and operating machinery. There were 54 college women participants who were randomly selected to be in the treatment group (24 participants received the intervention) and compared against the control group (30 participants did not receive the intervention). Results from pre- and post-test comparisons suggest that participants in the treatment group showed a significant increase in self-efficacy and interest compared to those in the control group. For example, participants in the treatment group had significantly higher self-efficacy and interest in repairing a clock, learning to repair electrical wiring, and building a doll house compared to the control group. These results are important in increasing self-efficacy facilitating female students' pursuit of STEM fields.

Another experimental study was conducted by Luzzo et al. (1999), who investigated the effects that different sources of self-efficacy have on STEM career interests, vocational aspirations, college major choices, and course selection among 94 undergraduates with undecided careers. The authors conducted an experiment and randomly assigned students into a control group or different treatment conditions of performance accomplishment only, vicarious learning only, and combined treatment (i.e., both performance accomplishment and vicarious learning). Results from this study revealed that interventions involving exposure to two of the self-efficacy sources (i.e., personal performance accomplishments, vicarious learning) produced significant increases in math/science interests between pre- and post-treatment and participants were more likely to enroll in STEM courses, declare STEM majors, and express interest in STEM careers. Participants in the combined treatment group had significantly higher interests in STEM careers compared to participants in other groups. Findings from this study suggest that there are strategies to enhance math self-efficacy to increase math and science-related careers interests among undecided undergraduate students.

Using the results from these experimental studies cited in the literature, there is evidence to believe that math attitudes and math self-efficacy beliefs are not simply a result of successful STEM outcomes. Due to the experimental design of these interventions, endogeneity is eliminated (Antonakis, Bendahan, Jacquart, & Lalive, 2014), and thus building from these results, I believe that the same process holds true in this dissertation, where math attitudes and math self-efficacy influence STEM outcomes, and not the reciprocal effect, even though this is not an experimental study. The following section provides evidence from the literature that examines the extent to which math attitudes and math self-efficacy influence STEM outcomes.

Combining Math Attitudes and Math Self-Efficacy to Predict STEM Outcomes

Some research has shown there is a positive and significant relationship between math self-efficacy and math attitudes, where individuals with stronger math self-efficacy beliefs tend to report lower levels of math anxiety, higher levels of overall confidence and motivation, and a greater tendency to perceive math as useful (Betz & Hackett, 1983; Hackett & Betz, 1989; Pajares & Miller, 1994). These studies suggest that it is important to study these two constructs together as they are correlated with one another and are worth studying the relationship with STEM outcomes. Although these two constructs of math attitudes and math self-efficacy are related, they may not be perfectly correlated, where having high math attitude does not necessarily relate to having high math self-efficacy. For instance a student may have high math attitudes and low math self-efficacy, or vice versa, and their outcomes may look different based on their patterns of math attitude and math self-efficacy. This dissertation aims to study these patterns of math attitude and self-efficacy using a latent class analysis technique, which groups students based on their responses to items related to math attitudes and math self-efficacy. This dissertation further examined how these different patterns of math attitudes and math self-efficacy can be used to predict 12th grade math achievement, STEM degree, and STEM careers. Knowing and understanding what these patterns look like may be useful in developing interventions for specific groups.

The following section describes the relationship of students' math attitudes and math self-efficacy with their STEM outcomes in 12th grade math achievement, STEM degree attainment, and STEM career attainment.

Relations of math attitudes and math self-efficacy on math achievement. There has been much research showing a positively significant relationship between math attitudes on math performance (Betz & Hackett, 1983; Dumais, 2009; Else-Quest et al., 2013) as well as self-efficacy beliefs on performance (Fast et al., 2010; Hackett & Betz, 1989; Li & Moschkovich, 2013; Multon et al., 1991; Pajares & Kranzler, 1995; Pajares & Miller, 1994, 1995; Schunk, 1989; Stevens et al., 2004). In one study, Hackett and Betz (1989) explored the relationship between math performance and math self-efficacy, math attitudes, and the choice of mathematics-related majors among 262 college students attending a Midwestern university. Math self-efficacy and math attitude measures were measured on separate scales and were both included in the study. Math performance was assessed using an 18-item Math Problems Performance Scale (MPPS) that contained items on three subscales including the type of problem solved, type of operation necessary to solve the problem, and the level of abstraction of the problems. Results from Hackett and Betz's (1989) study showed that both math self-efficacy and math performance were significantly and positively correlated with students' math attitudes, masculine sex-role orientation, and a math-related major. Results also indicated that students with high scores on math self-efficacy scales and math performance and achievement scales tended to report lower levels of math anxiety, higher levels of confidence and motivation, and had a greater tendency to see math as useful when compared with students who had low scores of math self-efficacy and low math performance.

In a similar study, Pajares and Miller (1994) conducted a study to investigate the role of self-efficacy and self-concept beliefs on math problem solving. The authors performed a path analysis involving 350 undergraduate students at a large public university in the South to examine whether students' confidence in their approach to solving math problems had a stronger effect on their problem-solving performance when compared to other factors including math self-concept, math anxiety, perceived usefulness of math, previous experience with math, and gender. The findings from this study revealed that math self-efficacy was a stronger predictor of math problem solving than math self-concept, perceived usefulness of math, prior math experience, or gender. These two results are consistent with what other researchers have concluded with regards to math attitudes, math self-efficacy, and math performance (Pajares & Kranzler, 1995; Pajares & Miller, 1994, 1995; Stevens, et al., 2004). In addition, the findings are consistent with what Bandura (1977) hypothesized, that is, self-efficacy is a central mediator of past experience and performance and the main predictor of future performance. In other words, those who have the confidence to succeed will continue to persist regardless of any challenges they may face.

The results from these two studies suggest that both math attitudes and math self-efficacy are important predictors of math achievement. Since these studies were conducted on a small sample of college students, it is not known how math attitudes and self-efficacy influence a larger population of students. Therefore, my dissertation investigated these constructs of math attitudes and self-efficacy beliefs and applied them to a larger, more nationally representative sample using the ELS:2002 data. In addition to math attitudes and math self-efficacy predicting math performance, the literature suggests that there may be gender and racial/ethnic differences in math achievement. This will be discussed in the following section.

Gender differences. Throughout the reviewed literature, there has been mixed results on whether gender differences exist in math attitudes, math self-efficacy, and math achievement. On one hand, some researchers argue there are gender differences in math attitudes and math performance (Dumais, 2009; Else-Quest et al., 2013; Pajares & Miller, 1994; Pajares & Kranzler, 1995), and on the other hand, other researchers argue there are little to no gender differences (Hyde, Fennema, & Lamon, 1990; Hyde, Lindberg, Linn, Ellis, & Williams, 2008). Pajares and Miller (1994) found that gender had a direct effect on self-efficacy, and concluded that male students had higher performance, self-efficacy, and self-concept, and lower anxiety compared to female students.

However, there are other studies that suggest there are no gender differences in math performance. For instance, Hyde et al. (1990) performed a meta-analysis on 100 studies to assess gender differences in math performance at the elementary, middle, and high school levels. The authors found that although gender differences in math performance were small, female students in high school had lower performance in problem solving. More recently, in Hyde et al.'s (2008) study, the authors found that based on standardized tests in the U.S. for grades 2 through 11, there was no gender difference in students' math skills. Although these studies suggest there were no gender differences in high school math achievement, and female students take and pass as many high school advanced math and science courses as their male counterparts, female students still fall short of equal representation in STEM fields (Lindberg, Hyde, Peterson, & Linn, 2010). Differences in these mixed findings from the literature were investigated in this dissertation, where I examined how gender relates to math attitude and math self-efficacy beliefs.

Racial/ethnic differences. There is also evidence demonstrating racial/ethnic differences in math achievement (Else-Quest et al., 2013; Pajares & Kranzler, 1995; Stevens et al., 2004). Else-Quest et al. (2013) found no significant racial/ethnic differences in math attitudes; however, there were significant racial/ethnic group differences in math achievement, even after controlling for socioeconomic status. The authors concluded that White and Asian students tended to outperform their peers from other ethnic groups in terms of their math and science achievement. Asians were the highest achieving group, while Latino and African American males were among the lowest achieving group. Interestingly, the authors found that African Americans reported significantly higher math value compared to their White and Asian peers, but that was not enough to significantly close the achievement gap. The underachievement of minority students is a persistent trend and needs more attention.

Findings from these aforementioned studies suggest that math attitudes and math self-efficacy are important predictors of math achievement, and that gender and race/ethnicity is worth investigating in studying this relationship. However, there has been no literature to date that examines the combination of both math attitudes and math self-efficacy and the different levels within each construct. More specifically, there has been no literature that uses a latent class analysis to identify varying groups, or profiles, of math attitudes and math self-efficacy and study how these two combined constructs can be used to predict STEM outcomes. There also has not been much research that studies STEM outcomes for non-native English speakers. Previous research has focused on the native English student population. There has been little research that particularly analyzes the predictive power of non-native English speakers' math attitudes and self-efficacy beliefs on math achievement. There have been several authors who have examined the relationship between self-perceptions, self-esteem, and/or self-concept (Guglielmi, 2012; Marsh & Martin, 2011; Marsh & Yeung, 1997) with academic achievement among ELLs, but none to my knowledge, that have examined the effects of the combination of math attitudes and math self-efficacy on math achievement, college major choice, and career decisions. Thus, this current study will contribute to the literature by analyzing a longitudinal, nationally representative sample of native and non-native English speakers and study the combined effects of math attitudes and math self-efficacy on STEM outcomes at the secondary level and beyond.

In addition, another reason to study math achievement is because it has been shown to be one of the strongest predictors of success in college (Adelman, 1999, 2006; Trusty & Niles, 2003). It is subsequently connected to employment opportunities and income, where many of the high-paying jobs (e.g., business, computer science, science and medical careers, engineering) require a solid foundation in mathematics (Adelman, 2006). Studying math attitudes and math self-efficacy as it relates to math achievement can help us understand the pipeline issues in STEM from high school, to postsecondary education, to the work force. Studying this relationship can help us understand how to increase the number of STEM professional workers to meet the demands of the growing STEM work force. Although the demand for STEM careers is high, there are not many people, especially non-native English speakers who complete a STEM degree and further pursue a career in a STEM field. This is worth investigating and can help researchers understand the gap between native and non-native English speakers in STEM outcomes.

The following two sections discuss the relationship between math attitudes and math self-efficacy on college major choice and career choice.

Relations of math attitudes and math self-efficacy on college major choice. There has been much research that shows how math attitudes and math self-efficacy are not only related to math performance but also to college major choice (Betz & Hackett, 1983; Byars-Winston, et al., 2010; Hackett & Betz, 1989; Lent & Hackett, 1987; Lent, et al., 2008; Luzzo et al., 1999; Ma, 2009; Maltese & Tai, 2011; Pajares & Miller, 1995). In one study, Pajares and Miller (1995) examined the relationship of math self-efficacy, math performance and college major choice among 391 undergraduates. The authors created three math self-efficacy scales that were derived from items on the revised math self-efficacy scale (MSES-R) and math confidence scale (MCS). These three math self-efficacy subscales involved items that were related to an individual's self-efficacy to solve math problems, perform math-related tasks, and succeed in math-related courses. The results from this study indicated that students' confidence to succeed in math-related courses was a stronger predictor of math-related major choice than was students' reported confidence to solve problem or perform mathematics-related tasks.

In another study, Ma (2009) examined three pre-college influences of achievement, attitude, and coursetaking on college major choice among 14,681 students from the NELS:88 data. Ma (2009) found that students' math attitudes were more important to predicting college major choice than math achievement or highest math course taken. Ma (2009) also investigated these pre-college influences on STEM major by gender and race, where female students were less likely than male students to pursue STEM degrees. In terms of race, after taking into account pre-college influences, Latino students were significantly more likely to pursue a technical degree compared to their White peers.

Results from both of these studies suggest that both math attitudes and math self-efficacy are significant predictors to pursuing a STEM major. Pajares and Miller (1995) studied only math self-efficacy predicting a math-related major, while Ma (2009) studied only math attitudes and its relation to STEM major choice. Given the results of both studies, I included both math attitudes and math self-efficacy to predict STEM major and explored this relationship using a large nationally representative sample of a cohort of 10^{th} graders.

Gender differences. There have been some studies showing that math attitudes and math self-efficacy differs by gender (Betz & Hackett, 1983; Perez-Felkner, McDonald, Schneider, & Grogan, 2012; Wang, 2013; Ware & Lee, 1988). In general, these studies found that female students had lower or weaker math attitudes and math self-efficacy beliefs compared to male students. However for female students who had positive math attitudes were significantly more likely to pursue a degree in STEM compared to female students with lower math attitudes (Wang 2013; Ware & Lee, 1988).

Racial/ethnic differences. There has also been literature examining racial differences in math attitudes and math self-efficacy (Riegle-Crumb & King, 2010; Wang, 2013). The general trend for racial differences is that once academic preparation and achievement was taken into account, African American and Latino students tended to report high math attitudes compared to other racial/ethnic groups. This finding has been consistent with other studies that have found racial/ethnic minority groups having more positive math attitudes compared to Whites and Asians (Pajares & Kranzler, 1995; Stevens et al., 2004).

The results from these aforementioned studies suggest that math attitudes and math self-efficacy are important to consider since these two constructs not only have predictive power on math performance, but also on STEM-related major choice. In addition, individual characteristics such as gender and race/ethnicity are important to take into account when examining STEM degrees. The next section details the relationship between math attitudes and self-efficacy on an individual's career choice.

Relations of math attitudes and math self-efficacy on career choice. Some research has shown that math attitudes and math self-efficacy are related to students' career decisions (Hackett & Betz, 1981, 1989; Lent & Hackett, 1987; Luzzo et al., 1999; Pajares & Miller, 1995) and that it differs by gender (Hackett & Betz, 1981; Ing & Nylund-Gibson, 2013; O'Brien et al., 1999; Wang et al., 2013; Zeldin et al., 2008) and race/ethnicity (Ing & Nylund-Gibson, 2013; O'Brien et al., 1999). In general, these studies suggest that positive math attitudes and math self-efficacy beliefs significantly predicts STEM career attainment. This relationship is demonstrated in a study conducted by Hackett and Betz (1981), where the authors 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 limits 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. For example, students with low math self-efficacy expectations were more likely switch majors than students with high math self-efficacy expectations. In a similar study, 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.

Other studies have confirmed the predictive power of math self-efficacy expectations on math-related career choices. Lent and Hackett (1987) conducted a review of the literature on applying the theory of self-efficacy to career entry behaviors (i.e., college major choice and career decisions) and found there are a substantial number of studies that provide support linking self-efficacy to career entry behaviors. Moreover, Luzzo et al., (1999) found statistically significant relationships between math self-efficacy measures of career choice and actions. They concluded that students with higher math self-efficacy were more likely to have a greater interest in math/science-related careers and select majors that were more math/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.

Gender differences. Several studies have researched the extent to which gender differences in math attitudes and math self-efficacy influence one's career decisions (Hackett & Betz, 1981; Ing & Nylund-Gibson, 2013; O'Brien et al., 1999; Wang et al., 2013; Zeldin et al., 2008). In terms of gender, the general trend from the literature suggests that female students tend to have lower math attitudes and self-efficacy beliefs compared to their male peers. In one study, O'Brien et al. (1999) examined the relationship between math self-efficacy, ethnic identity, gender and career interests in math and science using a path analysis of 415 11th grade students. O'Brien et al. (1999) found that students' math self-efficacy significantly predicted career interest in math or science. This finding support results from previous studies (Betz & Hackett, 1983; Hackett & Betz, 1981; Lent & Hackett, 1987). O'Brien et al. (1999) also concluded that gender directly predicted students' career interest in STEM, where females had a weaker career interest in STEM compared to males.

Racial/ethnic differences. There is also research from the literature that suggests there are racial/ethnic differences in STEM career attainment (Ing & Nylund-Gibson, 2013; O'Brien et al., 1999). Ing and Nylund-Gibson (2013) examined students' early attitudes toward math and science and its effect on long-term persistence in STEM careers. Applying a the Longitudinal Study of American Youth (LSAY) data, the authors studied the attitudinal profiles of 2,861 seventh graders with respect to proximal (i.e., math and science achievement) and distal outcomes (i.e., STEM career attainment). Using latent class analysis, Ing and Nylund-Gibson (2013) identified a four-class model with labels, "positive," "qualified positive," "indifferent," and "dim," with regards to low, medium, and high math and science attitudes. The authors assessed group differences and found that underrepresented minorities had similar math and science attitudes compared to their White and Asian peers and were more likely to be in the "positive" group. This finding has been consistent with other studies that have found racial/ethnic minority groups tend to have more positive math attitudes compared to Whites and Asians (Pajares & Kranzler, 1995; Stevens et al., 2004). Yet despite these early positive attitudes toward math, when regressing on STEM career choice 20 years later, the authors concluded that female and underrepresented minority students were less likely to be employed in a STEM career. This finding is alarming since students who were highly interested and had positive attitudes early in seventh grade end up falling through the cracks of the STEM pipeline, where many female and underrepresented minority students lost interest and consequently pursued non-STEM fields.

Much research thus far has focused on the predictive power of math attitudes and math self-efficacy on postsecondary outcomes for the general population. However there have been very few studies thus far that have examined non-native English speakers' postsecondary outcomes (Kanno & Harklau, 2012). Furthermore, these previous studies have focused on a sample of college students, which may not be representative of all students. Therefore this dissertation applied the combination of math attitude and math self-efficacy constructs to a larger, more nationally representative sample using the ELS:2002 data. In addition, there have been few studies aside from the study conducted by Ing and Nylund-Gibson (2013) that implements a latent class analysis to understand different profiles of math attitudes and self-efficacy beliefs. Thus, this current study will potentially contribute to the literature by analyzing the relationship of the combination of math attitudes and math self-efficacy on STEM outcomes among native and non-native English speakers while considering individual and structural characteristics. The following section presents the structural characteristics of coursetaking, socioeconomic status, prior math achievement, immigrant generation status, tracking, and extracurricular involvement as it relates to STEM outcomes.

Structural Characteristics in Relation to Attitudes, Self-Efficacy, and STEM Outcomes

There has been an extensive amount of research showing the effects of various structural characteristics related to students' math attitudes, math self-efficacy, and STEM outcomes. Some of these characteristics include coursetaking (Bozick & Ingels, 2008; Callahan, 2005; Cunningham, Hoyer, & Sparks, 2015; Finkelstein, Huang, & Fong, 2009; Gottfried, Bozick, & Srinivasan, 2014; Ma, 2000; Ma, 2009; Ma, 2011; Mosqueda, 2012;

Riegle-Crumb, 2006; Riegle-Crumb & Grodsky, 2010; You, 2013; You & Sharkey, 2012); socioeconomic status (Flores, Batalova, & Fix, 2012; Krashen & Brown, 2005; O'Brien et al., 1999); prior math achievement (Trusty, 2002); immigrant generation status (Drake, 2014; Fuligni, 1997); tracking (Callahan, 2005; Callahan et al., 2010; Finn, Gerber, & Wang, 2002; Gamoran, 2009; Kalogrides & Loeb, 2012; Mosqueda, 2010; Oakes, 2005); and participation in extracurricular activities and programs (Contreras, 2011; Dumais, 2008; Fredricks, 2012; Gottfried & Williams, 2013; Lipscomb, 2007). In terms of STEM outcomes, there has been some research demonstrating that coursetaking (Crisp, Nora, & Taggart, 2009; George, Neale, Van Horne, & Malcom, 2001; Ma, 2009; Ma, 2011; Simpson, 2001; Tyson, Lee, Borman, & Hanson, 2007; Trusty, 2002; You, 2013) and participation in extracurricular activities (Broh, 2002; Dumais, 2008; Ware & Lee, 1988) are associated with students' intent to major in STEM. These studies will be discussed in more detail in the following sections.

Math coursetaking. Research has shown that math coursetaking is associated with math attitudes and math self-efficacy beliefs. In one study, Else-Quest et al. (2013) applied Eccles (1994) expectancy value theory and found that students take advanced math courses because of their individual expectations for success and perceived value or importance. For instance, if a student believes that he/she can succeed in a math course and believes the course is valuable, he/she will choose to enroll in the course. Ma (2009) applied a similar framework and found that students' positive math attitudes were linked to more coursetaking in math, higher math achievement, and higher likelihood of pursing a math-related major.

There is also some research showing that the number of advanced math courses and the type of math course (applied vs. non-applied) students take have an effect on students' STEM achievement (Cunningham et al., 2015; Gottfried & Bozick, in press; Gottfried et al., 2014; Riegle-Crumb & Grodsky, 2010). In general, research has shown that students who take more advanced classes in high school have higher math scores on standardized tests (Bozick & Ingels, 2008; Cunningham et al., 2015; Mosqueda, 2012; Mosqueda & Maldonado, 2013); Riegle-Crumb & Grodsky, 2010). Specifically in mathematics, Mosqueda (2012) examined whether English proficiency status and access to rigorous math courses differentially influenced the math assessment scores of Asian and Latino students at the end of high school. Results from this study showed linguistic minority students significantly underperformed in math when compared to their native English speaking peers. Furthermore, Mosqueda (2012) found that advanced math coursetaking and English proficiency level were significant predictors of students' 12th grade math achievement test scores, where Asian and Latino linguistic minorities had lower math achievement scores compared to native English speakers. In addition with every additional higher level math course taken, there was an increase in math achievement score for both native and non-native English speakers. In particular, this effect was larger for linguistic minority students. The findings from this study suggest that if linguistic minority students are given access to advanced math coursetaking, then there is a potential opportunity to increase their math achievement test scores.

The relationship of coursetaking and STEM outcomes can be extended to postsecondary education, where several studies have examined the relationship between students' high school coursework with their intended major and bachelor's degree attainment (Crisp et al., 2009; George, et al., 2001; Gottfried & Bozick, 2014; Ma, 2009; Ma, 2011; Riegle-Crumb, King, Grodsky & Muller, 2012; Simpson, 2001; Tyson et al., 2007; Trusty, 2002; You, 2013). Simpson (2001) suggested that in general, the more math and science courses a student takes in high school, the more likely the student is to choose a technical degree program over a non-technical degree, and that these effects are slightly stronger for White students compared to Asian, African, Hispanic, and Native Americans. However, Callahan (2005) argues that ELL students lack access to college preparatory courses, which limits their ability to prepare for study beyond high school.

Results from these studies suggest that math coursetaking is related to math attitudes and math self-efficacy, and it significantly predicts STEM outcomes. Findings from the literature also suggest that coursetaking patterns may be different for native and non-native English speakers. Therefore, math coursetaking was included in this dissertation to study these relationships using a nationally representative sample.

Immigration generation status. Another variable that has been related to math attitudes, self-efficacy, and STEM outcomes is students' immigrant generation status. Some research suggests that math attitudes and math self-efficacy beliefs differ by immigrant generation status (Ma, 2009). Using the NELS:88 data, Ma (2009) measured math attitudes using the following two items: "Math is one of the best subjects," and "I always do well in math." In general, the author found that positive math attitudes were related to more coursetaking in math. In regards to immigrant generation status, the author found that immigrant students tended to report more positive math attitudes compared to their native born counterparts. In addition, once the author included math attitude and math coursework into the probit model, these two factors significantly predicted students' degree in a technical, life/health, and business field. The results from this study suggest that math attitudes and math coursework are related, and are both significant predictors of a STEM degree.

There is also evidence to believe that students' immigrant generation status has an effect on student math achievement (Drake, 2014; Fuligni, 1997; Halle, Hair, Wandner, McNamara, & Chien, 2012; Rodriguez & Cruz, Rumbaut, 2005; Tseng, 2006) and STEM major choice (Ma, 2009). Findings from the literature suggest that students who are first generation immigrants, that is, students whose parents were born outside of the U.S., have higher educational values compared to second- or third-generation students (Goldenberg, Rueda, & August, 2006; Tseng, 2006). In addition, there is some evidence suggesting that parents of ELL children have high academic expectations for their children, although this research has been limited to elementary school samples (Halle et al., 2012). Furthermore, Fuligni (1997) argues that first and second generation students have higher math achievement scores compared to students coming from U.S.-native born families. In terms of recent immigrants, Callahan et al. (2010) found that students participating in English as a Second Language (ESL) course were associated with positive math outcomes for recent immigrants with low English proficiency. However this was not the case for students who were not recent immigrants or students with a greater English proficiency. Immigrant generation status can have different impacts for native and non-native English speakers and at different educational attainments. Thus it is important to consider the effects of students' immigration status on student STEM outcomes.

Socioeconomic status (SES). Another variable that is related to math attitudes, self-efficacy, and STEM outcomes is a student's socioeconomic status (SES). The extant literature provides mixed results on the effects of SES on students' math attitudes and math self-efficacy. Thomas (2000) suggests that a school's SES status is inversely related to math attitudes, where schools with higher proportions of students receiving free or reduced-price lunch tend to have more negative attitudes toward mathematics. Additionally, Muthén (1994) implemented a latent growth model and found that students from high SES homes tend to have stronger math attitudes, but it became less positive later. On the other hand, Fuligni (1997) found that socioeconomic status had no effect on students' math attitudes.

Regardless of these mixed results, it has been established in the literature that SES influences math achievement outcomes, where students from high SES backgrounds perform better on standardized test compared to their low SES counterparts (Abedi & Lord, 2001; Maltese & Tai, 2011; MacSwan, 2000; Ware & Lee). However, particularly for ELLs, Krashen and Brown (2005) found that high SES ELLs performed as well or better on standardized math and reading test scores compared to their low SES native English speakers. Thus this variable was included in my dissertation because it is worth studying the extent to which students' SES backgrounds relate to their STEM outcomes.

Prior math achievement. Some research suggests that students' prior math achievement influences their math attitudes and self-efficacy (Ma, 2000; Wang, 2013), as well as future STEM outcomes (Maltese & Tai, 2011; Trusty, 2002; Wang, 2013). In general, these studies found that students' high prior math achievement was significantly and positively related to their math attitudes and future math achievement scores. Applying the social cognitive career theory framework, Wang (2013) theorized that students' 10th grade math attitudes and math achievement scores influenced their 12th grade math self-efficacy beliefs, exposure to math and science, and 12th grade math achievement, all of which influences a student's intent and entrance into a STEM field of study. Wang (2013) used the ELS:2002 data and found that students' 12th grade variables (i.e., math self-efficacy, exposure to math and science, and math achievement) were significantly and positively influenced by students' 10th grade variables (i.e., math attitudes and math achievement). This finding suggests there is a significant effect of prior math achievement on math self-efficacy and STEM outcomes.

In another study, Maltese & Tai (2011) analyzed factors associated with completing a STEM degree and found that race, prior math test scores, math grades, math and science interests and attitudes, and expectations of having a STEM career at age 30 were significant predictors in completing a STEM degree. Similarly, Trusty (2002) used a nationally representative dataset to examine factors that influenced students' math and science college majors. Results from this study suggest that early math test scores positively influenced female students' choice of science and math major and early science test scores positively influence male students' choice of science and math major. Based on the literature, 10th grade math achievement was included in this study to serve as a proxy for prior math achievement.

Tracking. Another characteristic that influences math attitudes, self-efficacy, and STEM outcomes is tracking. Callahan (2005) defined tracking as "the assignment of students to differentiated coursework with varying levels of academic content" (p. 307). Callahan (2005) argued that track placement is a more influential characteristic than English proficiency in students' ability to prepare for postsecondary education. In terms of track placement, Callahan (2005) argues that schools often fail to differentiate students with limited English proficiency and students with limited ability to master academic content, and consequently, ELLs are tracked into classes that have less rigorous content compared to the mainstream classes. It has also been theorized that self-efficacy is related to tracking, where track placement diminishes students' self-efficacy since they are placed into lower level classes, where little is expected of them, and thereby students continue to fall further behind in their academics (Bandura, 1997). Since students need to be reassessed to advance to the next ELL proficiency, being placed in a lower level track could prevent these students from gaining access to the more advanced math classes.

There have been very few studies linking math attitudes and math self-efficacy with tracking, but there have been extensive studies connecting tracking with STEM outcomes. In general, students on the higher track tend to have more positive attitudes and greater confidence compared to students on the lower track (Oakes, 1992). The author only examined attitudes in general, and not specifically in math. Therefore, this dissertation is a contribution to the literature as it includes tracking and explores the relationship of tracking with math attitudes and math self-efficacy.

In addition, there has been some research suggesting that tracking is related to STEM outcomes. In particular, several researchers argue that tracking contributes to the inequalities in STEM outcomes (Finn et al., 2002; Kanno & Kangas, 2014; Mosqueda, 2010; Oakes, 2005). Mosqueda (2010) found tracking had a negative effect on math achievement for both native and non-native Latino English speakers, where students placed on the general track had lower math achievement scores than students placed on the academic track. This suggests that exposure and access to advanced math classes plays an important role in predicting math achievement for all Latino students and confirms previous research that suggests advanced math coursetaking is associated with greater gains in math achievement (Bozick & Ingels, 2008; Gottfried et al., 2014; Ma, 2000; Riegle-Crumb & Grodsky, 2010). Furthermore, Mosqueda (2010) found that when non-native English speakers obtained a high level of English proficiency, they outperformed their native English speaking peers in the general track, and scored as high as native English speakers in the college preparatory track. This raises concerns about the long-term effects of track placement for ELLs after they reach a high level of proficiency. As Callahan (2005) suggested, frequent assessments of ELLs is necessary to ensure that students are in classes that are challenging and promote students to succeed in STEM.

Finn et al. (2002) observed that minority students and students from low SES family backgrounds were placed in advanced tracks far less frequently than their White counterparts. Additionally, Finn et al. (2002) noted that students in vocational tracks took fewer and less challenging math courses than students in general and academic tracks. Oakes (2005) argued that since advanced courses are not equally available at all schools to all groups of students, it limits students' coursetaking options, and thus hinders students' opportunities to take more advanced classes compared to students on the college preparatory/academic track. As a result, students on the general track can fall behind in high school and end up taking remedial classes once they are in college (Crisp et al., 2009).

In examining the effect of tracking on STEM outcomes, Oakes (2005) found that high-track placement showed positive achievement effects, whereas low-track placement had negative achievement effects. Moreover, Oakes (2005) found that regardless of prior achievement levels, students placed in higher tracks outperformed their lower track peers in math achievement. Based on the research discussed thus far, it is evident that students in lower tracks are not afforded the opportunities to take advanced level courses that are necessary to be eligible for college. Research shows that students in the low tracks are usually not well informed about the content or discourse necessary to enter into higher education including the different courses required necessary to be eligible for college (Callahan, 2005; Callahan et al., 2010; Kanno & Kangas, 2014; Oakes, 2005).

Oakes (2005) adds that many low-income, minority and immigrant students do not know much information regarding coursetaking and college requirements, and are therefore, unaware of the consequences of the course choices and its effect on college entrance. In fact, in Callahan's (2005) study, barely 15% of the students in the sample had taken one or more college preparatory STEM course during high school, while the remaining ELLs took courses there were not college preparatory. This is alarming since it suggests that even a smaller percentage will be eligible for college, and it is questionable whether they will be academically prepared to participate in rigorous college courses.

Extracurricular involvement. Another characteristic that has been associated with students' math attitudes, math self-efficacy, and STEM outcomes is students' participation in extracurricular activities and programs. Very few studies have examined the relationship between extracurricular involvement specifically with math attitudes and math self-efficacy. In general, extracurricular activities are aimed to foster positive attitudes and learning (Cooper, Charlton, Valentine, & Muhlenbruck, 2000). Due to the lack of research of the relationship of math attitudes, self-efficacy, and extracurricular activities, this dissertation contributes to the field by including this variable as a structural characteristic influencing math attitudes and math self-efficacy and STEM outcomes.

There has been research that suggests involvement in extracurricular activities is significantly related to STEM outcomes. (Broh, 2002; Contreras, 2011; Dumais, 2008; Gottfried & Williams, 2013; Lipscomb, 2007; Ware & Lee, 1988). Participating in extracurricular activities has been shown to not only affect academic outcomes but also develop students' morals, leadership skills, and social networks, as well as improve students' self-esteem, and academic orientation (Broh, 2002; Lipscomb, 2007). In terms of academic outcomes, Broh (2002) analyzed 12,578 students from the NELS:88 data to study the effect of extracurricular activities on high school achievement. The regression results from this study revealed that participation in some activities including interscholastic sports and school music groups, significantly improved achievement, while participation in intramural sports and vocational clubs decreased achievement. The authors suggested that participation in intramural sports is different than participation in interscholastic sports, which are more selective and require greater commitment to participate than intramural sports. Their findings suggest that participation in intramural sports is no different than not participating in sports at all in terms of their self-esteem, time on homework, friendship groups, and relationships with teachers and peers. This research has demonstrated that there are differences in the types of extracurricular involvement and its effect on academic outcomes. However few studies have focused on extracurricular involvement among native and non-native English speakers.

There has been one study to date that examined an after-school program designed to help students with homework. Cosden, Morrison, Gutierrez, and Brown (2004) designed a three year program to provide students with homework help and learn study skills and randomly assigned students to treatment and non-treatment groups. The authors found that although there were no overall differences between the treatment and control group, ELLs in the treatment group received higher ratings from teachers in regards to academic effort and study skills compared to the ELLs in the control group. This is important to note since ELLs might not have the resources available to help them with their homework. Cosden et al. (2004) pointed out that families who do not speak English were not as likely to help their child with their homework and had fewer resources available to them. The authors concluded that the program helped promote students' confidence, improve study skills, and increase students' academic outcomes. Other benefits of participating in after school programs and activities include providing opportunities for parents to become involved, offering support to students in nonacademic arenas, connecting students to positive peer groups, maintaining a certain academic requirement to participate, and provide supervision while parents are working (Cosden et al., 2004). Thus, having after school programs, especially in providing homework help, can help ELLs whose parents are unable to provide help to their child.

Although involvement in some extracurricular activities has been linked to improvement in STEM achievement, there is some research showing the negative effects of extracurricular involvement (Cosden et al., 2004; Fredricks, 2012). Fredricks (2012) used the ELS:2002 data to study the extent to which the breadth (i.e., number of extracurricular activities) and intensity (i.e., time in extracurricular activities) of participation among 13,130 10th grade students influenced their 12th grade math achievement test scores, grades, and educational expectations. Fredricks (2012) performed a multivariate regression and found that after controlling for prior achievement, demographic factors, and school size, the breadth and intensity of 10th grade extracurricular participation was significant and positively related to math achievement test scores, GPA, and educational expectations at 12th grade. However, at higher breadth and intensity, there was a negative effect on academic outcomes, which suggests that over-scheduling in extracurricular participation can be detrimental to students' STEM outcomes.

The reviewed literature thus far has demonstrated a positive relationship between extracurricular participation and educational outcomes (Broh, 2002; Dumais, 2008; Fredrick's, 2012; Lipscomb, 2007; Ware & Lee, 1988), but very few studies have examined the relationship between extracurricular participation and choosing a STEM major in college. The only study to date that examined this relationship is a study by Gottfried and Williams (2013). The authors found that students' participation in a math club had a significantly positive relationship with choosing a STEM major in college, where the students who participated in a math club in high school were three times as likely to select a STEM major in college compared to a student who did not participate in a math club. The results were still positive, but slightly reduced with the inclusion of covariates, where students who participated in a math club was twice as likely to select a STEM major in college compared to a student who did not participate in a math club. In addition, when students were matched based on their propensities to select into a math club, there was a significant likelihood that students selected a STEM major. Although this study provided evidence of a positive relationship between extracurricular activities and STEM major selection, more studies are needed to examine this relationship by English proficiency group (i.e., native and non-native English speaking students).

Thus far, the literature has examined the differences in individual and structural characteristics that explain the lack of individuals pursuing STEM fields. Much of this research has focused on native English speakers, and very few studies have examined these differences for non-native English speakers. Given the growing population of non-native English speakers and the demand to increase the number of STEM professionals (PCAST, 2012), it is important to examine differences in individual and structural characteristics of non-native English speakers and understand which factors lead them into STEM fields. Understanding the individual characteristics (i.e., students' math attitudes, math self-efficacy, gender, and race/ethnicity) and structural characteristics (i.e., socioeconomic status, immigrant generation status, prior math achievement, tracking, coursetaking patterns, and extracurricular involvement) has potential to shed light on why there is a lack of individuals pursuing STEM fields.

Current Study

Using the Education Longitudinal Study of 2002 (ELS:2002) data, this study examines the math achievement and postsecondary outcomes of native and non-native English speakers, the latter group including English Language Learners (ELLs) and linguistic minorities. Using knowledge from the reviewed literature, this study investigated several explanatory variables related to mathematics achievement, STEM degree attainment, and STEM career attainment including students' math attitudes, math self-efficacy, gender, race/ethnicity, generation immigration status, socioeconomic status, prior math achievement, track placement, highest math course taken, and participation in extracurricular activities.

This study employed a latent class analysis to identify groups of native English speakers and non-native English speakers who responded similarly to a set of math attitude and math self-efficacy indicators. In addition, this study investigated the extent to which individual level and structural characteristics relate to students' math attitudes and math self-efficacy. Furthermore, this study considered how the identified groups' math attitudes and math self-efficacy influenced their math achievement, decision to obtain a degree in STEM, as well as pursue a career in STEM and examine this relationship for high school, community college, and university graduates. This study addresses the following:

Research Questions

For high school graduates:

1. How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?
2. What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?
3. To what extent do students' math attitudes and math self-efficacy contribute to their 12^{th} grade math achievement, and how does this differ between non-native English speakers and native English speakers?
4. To what extent do students' math attitudes and math self-efficacy contribute to their STEM career, and how does this differ between non-native English speakers and native English speakers?

For community college graduates:

1. How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?
2. What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?
3. To what extent do students' math attitudes and math self-efficacy contribute to their 12th grade math achievement, and how does this differ between non-native English speakers and native English speakers?
4. To what extent do students' math attitudes and math self-efficacy contribute to their STEM degree, and how does this differ between non-native English speakers and native English speakers?
5. To what extent do students' math attitudes and math self-efficacy contribute to their STEM career, and how does this differ between non-native English speakers and native English speakers?

For university graduates who attained a bachelor's degree or higher:

1. How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?
2. What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement,

tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?

3. To what extent do students' math attitudes and math self-efficacy contribute to their 12th grade math achievement, and how does this differ between non-native English speakers and native English speakers?
4. To what extent do students' math attitudes and math self-efficacy contribute to their STEM degree, and how does this differ between non-native English speakers and native English speakers?
5. To what extent do students' math attitudes and math self-efficacy contribute to their STEM career, and how does this differ between non-native English speakers and native English speakers?
6. Are there differential effects in the relationship between 12th grade math achievement and STEM degree for students holding at least a bachelor's degree? Does this differ between native and non-native English speakers?
7. Are there differential effects in the relationship between STEM degree and STEM career for students holding at least a bachelor's degree? Does this differ between native and non-native English speakers?

A summary of research questions and variables included in the study can be found in Appendix A, Table A1.

To address these research questions, a latent class analysis was implemented with covariates, proximal and distal outcomes. The covariates included in this analysis were the following: gender, race/ethnicity, immigration generation status, socioeconomic status, 10th math grade achievement, track placement, highest level of math taken, and extracurricular involvement. The proximal outcome is 12th grade math achievement and the distal outcomes are STEM degree and STEM occupation. To my knowledge, there has not been any research conducted using an LCA to study non-native English speakers in STEM using nationally representative data of high school students. Thus, this study aims to use the ELS:2002 data to gain a better understanding of why there is a lack of these underrepresented groups in the STEM fields.

Employing an LCA is useful for this study because it is a person-centered and exploratory method that is capable of capturing the rich patterns of important indicators that contribute to student success. This technique enabled me to examine the differences in math attitudes and math self-efficacy and how that relates to students' math achievement and decision to pursue a STEM degree and STEM career, rather than provide descriptive statistics techniques alone. Furthermore, using an LCA allowed me to investigate how the combination of math attitudes and self-efficacy can be related to how students move through the STEM pipeline. For example, a student with low math attitudes and low math self-efficacy may not have aspirations to pursue a career in STEM and therefore may not want to attend college. Given the high demand for STEM professionals, it is important to increase the number of students pursuing STEM. Thus, understanding and acknowledging that there are different latent classes of math attitudes and math self-efficacy has implications for educators and researchers to develop interventions aimed to improve attitudes and self-efficacy, both of which have been related to STEM outcomes. In addition, the use of LCA aims to advance the field's understanding of profiles associated with student STEM outcomes because it takes into account individual and structural characteristics that influence STEM achievement at the secondary and postsecondary levels. The following chapter will discuss the method of latent class analysis in more detail.

III. Methods

Dataset

The data for this study were drawn from the Education Longitudinal Study of 2002 (ELS:2002), which is a nationally representative dataset provided by the National Center of Education Statistics (NCES). There were 750 schools that were first randomly selected across the U.S. and then 10^{th} 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 10^{th} grade students, their parents, teachers, school principals and librarians. In the first follow up in 2004, most of the students were 12^{th} 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 did not ever attend college. By the third follow up in 2012, most sample members had graduated from college, while many others were pursuing their careers.

Studying the ELS:2002 enables researchers to see students' trajectory from 10^{th} grade in high school into postsecondary education, the workforce, and beyond. Using longitudinal data is important because it allows researchers to analyze changes within the institutional, cultural and social environments that shape an individuals' life (Ruspini, 2002). The ELS:2002 is an appropriate dataset to use for my dissertation since my research questions focus on students' math attitudes and self-efficacy in 10^{th} grade and investigates how these patterns influence students' STEM outcomes (i.e., 12^{th} grade math achievement, STEM major in college, and STEM career).

Participants

The ELS:2002 dataset consists of students that were 10th graders in 2002 and 12th graders in 2004. The complete sample contains over 16,100 students from a random sample of 750 public, Catholic, and other private schools (Ingels, Pratt, Rogers, Siegel, & Stutts, 2004). This present study analyzed three sub-samples of the ELS:2002 data, which include the following: (1) *high school graduates* were students who graduated from high school and had no post-secondary degree as of the third follow up; (2) *community college graduates* were students whose highest earned degree as of the third follow up was an associate's degree or undergraduate certificate; and (3) *university graduates* were students who earned at least a bachelor's degree or higher as of the third follow up.

These three levels of educational attainment were selected because it is important to disentangle the complex patterns at each point and understand the process of math attitudes and math self-efficacy on STEM outcomes. Within each of the levels of educational attainment (i.e., high school graduate, community college graduate, university graduate), the population was further disaggregated by native English speakers and non-native English speakers. The sample was disaggregated by English proficiency and level of educational attainment because it provides researchers and policymakers a better understanding of where and when, and for whom to target interventions.

Using a similar classification system as described by Kanno and Cromley (2013), respondents in the ELS:2002 were categorized into native and non-native English speakers. Students were asked whether or not English was their first language (BYSTLANG) and had the option to respond "yes" or "no". Respondents were classified as *non-native English speaker* if they indicated that English was not their first language (i.e., responded "no"). Respondents were classified as *native English speakers* if they indicated English was their first language (i.e., responded “yes”). It should be noted that students with severely limited English proficiency (i.e., not able to read or respond to the surveys) and students with severe disabilities were excluded from the ELS:2002 sample (Ingels et al., 2004). Table 1 displays the analytic sample for native and non-native English speakers for each of the three sub-samples in this study.

Table 1

Analytic Sample of Non-Native English Speakers and Native English Speakers

	Non-Native English Speakers		Native English Speakers		Total	
	Count	Percent	Count	Percent	Count	Percent
High School Graduates	560	15.4%	3,070	84.6%	3,630	100.0%
Community College Graduates	250	15.5%	1,360	84.5%	1,610	100.0%
Bachelor’s Degree or Higher	560	13.9%	3,470	86.1%	4,030	100.0%
Total	1,370	14.8%	7,900	85.2%	9,270	100.0%

Measures

A complete list of variables used in this study with recoded values is presented in Appendix A, Table A2.

Math attitude. On the base-year survey, students were asked three questions that aimed to assess their attitudes toward math, which included the following: “When I do mathematics, I sometimes get totally absorbed” (BYS87A); “Because doing mathematics is fun, I wouldn’t want to give it up” (BYS87C); and “Mathematics is important to me personally” (BYS87F). Students had the option to respond “Strongly Agree (1),” “Agree (2),” “Disagree (3),” and “Strongly Disagree (4).” In this study, these math attitude variables were reverse coded and then dichotomously recoded where a value of 1 indicated more positive math attitude and 0 indicated more negative math attitude.

Math self-efficacy. There were five questions on the student base-year survey that aimed to assess how confident or certain students felt in doing specific math tasks. The variables that were used to measure the math self-efficacy construct include the following: “I’m confident that I can do an excellent job on my math tests” (BYS89A); “I’m certain I can understand the most difficult material presented in math texts” (BYS89B); “I’m confident I can understand the most complex material presented by my math teacher” (BYS89L); “I’m confident I can do an excellent job on my math assignments” (BYS89R); and “I’m certain I can master the skills being taught in my math class” (BYS89U). Students had the option to respond “Almost Never (1),” “Sometimes (2),” “Often (3),” or “Almost Always (4).” These math self-efficacy variables were dichotomously recoded where 1 indicated more positive self-efficacy and 0 indicated more negative self-efficacy. The descriptive statistics of the math attitude items, math self-efficacy items, covariates and distal outcomes are displayed in Table 2. Data were cleaned and managed using Stata 11 (StataCorp, 2009).

Prior studies have utilized similar math attitudes and math self-efficacy scales from the ELS:2002 data and have confirmed the presence of latent constructs of students’ math attitudes and math self-efficacy (Lent, Lopez, Brown, & Gore, 1996; 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 uses these same items to explore heterogeneity in 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 is used with dichotomous items, whereas Cronbach’s alpha applies to any set of items regardless of the scale (Cortina, 1993). Using the Kuder-Richardson Formula 20 (KR-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 that were used in the study include the following: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking, math coursework, and extracurricular involvement. These covariates were included to increase the accuracy of classifying individuals into latent classes.

Gender. Gender is represented by students' self-reported response (BYSEX) on the base year survey. In this study, a dichotomous variable "female" was created, where 1 indicates female and 0 indicates male.

Race/ethnicity. Race/ethnicity is represented by students' self-reported response on the base year survey using the restricted data (BYRACE_R). Using the race/ethnicity variable, a few dichotomous variables were created (i.e., "Latino," "African American," "Asian," and "Other Race"), where 1 indicates the respective race/ethnicity and 0 otherwise. Other race includes students who reported "American Indian/Alaska Native," "More than one race, non-Hispanic," or "Native Hawaiian/Pacific Islander."

Table 2

Descriptive Statistics of Math Attitude and Self-Efficacy Items, Covariates, and Distal Outcomes (Unweighted)

	HS Non-Native English Speakers (*n*=560)		HS Native English Speakers (*n*=3,070)		CC Non-Native English Speakers (*n*=250)		CC Native English Speakers (*n* =1,360)		Univ Non-Native English Speakers (*n*=560)		Univ Native English Speakers (*n*=3,470)	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
1. Absorb in math	0.61	0.49	0.47	0.50	0.62	0.49	0.48	0.50	0.62	0.49	0.53	0.50
2. Math is fun	0.43	0.50	0.30	0.46	0.44	0.50	0.28	0.45	0.49	0.50	0.36	0.48
3. Math important	0.60	0.49	0.47	0.50	0.62	0.49	0.47	0.50	0.67	0.47	0.53	0.50
4. Excellent job on math tests	0.42	0.49	0.40	0.49	0.32	0.47	0.38	0.49	0.56	0.50	0.56	0.50
5. Can understand difficult math texts	0.38	0.49	0.37	0.48	0.24	0.43	0.34	0.47	0.50	0.50	0.49	0.50
6. Can understand difficult math class	0.44	0.50	0.40	0.49	0.40	0.49	0.38	0.48	0.58	0.49	0.54	0.50
7. Excellent job on math assignment	0.53	0.50	0.46	0.50	0.47	0.50	0.43	0.50	0.66	0.47	0.62	0.48
8. Can master math class skills	0.52	0.50	0.47	0.50	0.45	0.50	0.46	0.50	0.66	0.48	0.65	0.48
9. Female	0.47	0.50	0.49	0.50	0.61	0.49	0.60	0.49	0.62	0.49	0.57	0.49
10. Latino	0.49	0.50	0.10	0.30	0.49	0.50	0.09	0.28	0.25	0.43	0.05	0.22
11. African American	0.04	0.21	0.15	0.36	0.05	0.22	0.14	0.35	0.03	0.17	0.08	0.27
12. Asian	0.33	0.47	0.03	0.16	0.30	0.46	0.02	0.15	0.57	0.50	0.05	0.22
13. Other Race	0.05	0.22	0.07	0.25	0.05	0.22	0.06	0.24	0.04	0.19	0.05	0.21
14. First generation immigrant	0.44	0.50	0.02	0.13	0.43	0.50	0.01	0.11	0.45	0.50	0.02	0.14
15. Low SES	0.50	0.50	0.23	0.42	0.46	0.50	0.21	0.41	0.28	0.45	0.07	0.25
16. 10th grade math achievement	47.27	10.41	49.40	9.02	45.85	8.20	49.63	8.86	56.71	9.64	57.40	7.94
17. College prep track	0.47	0.50	0.49	0.50	0.43	0.50	0.49	0.50	0.68	0.47	0.75	0.43
18. Math course beyond Algebra II	0.33	0.47	0.31	0.46	0.29	0.45	0.35	0.48	0.76	0.43	0.75	0.43
19. Extracurricular involvement	0.50	0.50	0.56	0.50	0.53	0.50	0.61	0.49	0.69	0.46	0.82	0.38
20. 12th grade math achievement	46.86	10.40	48.45	9.14	45.08	8.15	48.48	8.56	56.95	9.09	57.12	7.96
21. STEM Degree	N/A	N/A	N/A	N/A	0.10	0.30	0.10	0.29	0.25	0.43	0.17	0.37
22. STEM Job	0.05	0.22	0.04	0.20	0.03	0.18	0.04	0.20	0.15	0.36	0.11	0.31

Immigration generation status. The classification of immigration generation status was adopted from Callahan et al. (2010) and was created based on responses from the parent survey that included the student's birth place (BYP23), mother's birth place (BYP17), and father's birthplace (BYP20). Students were classified as *first generation* if both student and parents were foreign born (i.e., outside the United States). In this study, a dichotomous variable was created to indicate whether or not a student is a first generation immigrant, where 1 indicated yes and 0 otherwise.

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 et al., 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 is 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, "low SES," was created where 1 indicates the lowest quartile and 0 otherwise.

10th grade math achievement. Students' tenth grade math achievement score was measured using the math item-response theory (IRT) estimated number right (BYTXMIRR). This score is an estimated number of items the student would have answered correctly had they responded to all of the 73 questions in the math item pool (Ingels et al., 2004). The ability estimates and the parameters derived from the IRT calibration can be used to calculate a student's probability of a correct answer for each of the math items in the pool (Ingels et al., 2004). It is important to note that these scores are probabilities and not counts of the actual right and wrong answers. The sum of these probabilities produces the IRT-estimated number right score (Ingels et al., 2004).

Tracking. Tracking 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." 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 indicates 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 B.

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. The same could be true for non-native English speakers.

Extracurricular involvement. Students' extracurricular involvement was based on students' self-reported measure on the number of hours per week spent on extracurricular activities in a typical week (BYS42) and ranged from 0 to 21 or more hours. A dichotomous variable was created to indicate whether the respondent participated in extracurricular activities or not, where 1 indicated that a student was involved in at least 1 hour per week on extracurricular activities, and 0 indicated a student was not involved in any extracurricular activities (i.e., 0 hours).

Proximal Outcome Variable

This proximal outcome used in this study is students' 12^{th} grade mathematics achievement test scores (F1TXMSTD), which is represented by an Item Response Theory (IRT) scaled score. These scores were created based on patterns of correct, incorrect, and omitted answers, and it accounts for each question's difficulty, discriminating ability, and guessing factor. This score is used as ability estimates that are comparable across different test forms and provides a norm-referenced measurement of achievement that is relative to the population of high school seniors in 2004 (Ingels, et al., 2004).

Distal Outcome Variables

This study investigated two distal outcome variables, which include whether or not a student attained a STEM degree and whether or not a student attained a STEM career as of 2012.

STEM degree. The first distal outcome that was analyzed in this study is students' degree major. A dichotomous variable was created where 1 indicated whether the respondent had a STEM-related degree, and 0 otherwise. This variable was created using the following variables: Credential #1: highest/only credential from the institution: 1st major field-of-study (F3ICREDGEN_1); Credential #1: highest/only credential from the institution: 2nd major field of study (F3ICREDGEN2_1); Credential #2: additional credential from the institution: 1st major field-of-study (F3ICREDGEN_2); Credential #2: additional credential from the institution: 2nd major field of study (F3ICREDGEN2_2). Respondents reported their primary and secondary (if applicable) fields of study for each credential. Coding experts at Research Triangle Institute (RTI) coded these fields of study based on the classification system of major field of study from the National Center of Education Statistics (NCES) (2010) Classification of Instructional Programs (CIP) (Ingels et al., 2014).

In this current study, the major field of study was classified as STEM and non-STEM based on the 2013 NCES report on STEM in postsecondary education using the Beginning Postsecondary Students Longitudinal Study (BPS:04/09) data (Chen & Ho, 2013). This report classified STEM majors to include the following fields: agriculture and related sciences; natural resources and conservation; computer and information sciences; engineering and engineering technologies; biological and biomedical sciences; mathematics and statistics; military technologies; physical sciences, other natural sciences; and science technologies. The complete list of STEM and non-STEM majors and codes are provided in Appendix C.

STEM occupation. The second distal outcome that was analyzed in this study is the respondents' current occupation as of the third follow up data collection. A dichotomous variable was created where 1 indicated the respondent had a STEM-related occupation, 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. Coding experts at 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 et al., 2014). The complete list of occupations that were coded as STEM and non-STEM are provided in Appendix D.

The next section will discuss the method of analysis that I used for my dissertation, which is a latent class analysis and the practical importance of using this method.

An Overview of Latent Class Analysis (LCA)

Latent class analysis (LCA) has become a popular statistical technique used in the social sciences. LCA is a type of a larger class of models called mixture models that allows one to identify subgroups of students in a population, thus a mixture, rather than assuming there is a single population. LCA is often referred to as a "person-centered" approach because it studies individuals based on the patterns of their individual characteristics. This is different from a "variable-centered" approach, as in factor analysis, that focuses on identifying relationships between variables and assumes the relationships apply across all people (Collins & Lanza, 2010). As opposed to factor analysis, which uses continuous latent variables and clusters items, LCA uses categorical latent variables and clusters individuals based on categorical measures of shared observable characteristics (Magidson & Vermunt, 2004; Muthén, 2001).

Furthermore, LCA has the ability to uncover heterogeneous groups of individuals and capture underlining differences within a population by identifying the number of different latent classes based on their responses to a set of indicators (Collins & Lanza, 2010; Muthén, 2001). This statistical technique has many applications in the social sciences. For example, LCA can be used to help identify and assess the different subgroups of peer victimization (Nylund, Bellmore, Nishina, & Graham, 2007), tobacco and alcohol dependence (Muthén & Asparouhov, 2006), and smoking typologies (Henry & Muthén, 2010). For my dissertation, LCA was used to identify subpopulations of individuals' math attitudes and math self-efficacy.

Latent class analysis is a mixture modeling technique that is used when the latent variables and its indicators are categorical. A latent class variable is an unobserved construct that is measured by multiple observed indicators. LCA describes commonalities among individuals instead of variables, and creates classes based on a set of response patterns. For my dissertation, LCA is used to group students into latent classes of math attitudes and math self-efficacy based on their responses to categorical items used to measure math attitudes and math self-efficacy.

The primary goals of LCA is to identify items that define classes well, estimate the class probabilities, relate class probabilities to covariates, and classify individuals into classes (Muthén, 2001). For my dissertation, this involves determining the number of latent classes of math attitude and math self-efficacy, including individual and structural variables as covariates, and including distal outcomes related to STEM. One important assumption in LCA is that a latent variable accounts for the association between the outcomes, which is often referred to as the “conditional independence assumption” (Muthén, 2001). In other words, this assumes that conditional on latent class, the observed variables and their error components are independent, which implies that the observed variables are only related through the latent variable.

Social science researchers are interested in conducting LCA for several reasons including the ability to identify distinct latent classes; the ability to test whether outcomes differ across the identified latent classes; the ability to include covariates to help describe individuals who are likely to be in the latent classes; and the ability to include distal outcomes to see how latent class membership predicts outcomes. For these reasons, I implemented LCA in my dissertation to identify different latent classes of math attitudes and math self-efficacy for high school graduates, community college graduates, and university graduates for both native and non-native English speaking groups. I also include covariates (i.e., gender, race/ethnicity immigrant generation status, SES, prior math achievement, tracking, math coursetaking, and extracurricular involvement) and distal outcomes (i.e., 12^{th}, grade math achievement, STEM degree, and STEM career attainment).

In latent class analysis, there are two components to a latent class model, which include the measurement model (i.e., the number of classes and the class-specific distributions of the items) and the structural model (i.e., latent class proportion) (Masyn, 2013). As in factor analysis, the model building process involves establishing and confirming the measurement model for each of the latent variables (Masyn, 2013). Similar to factor analysis, one advantage of latent variable modeling is that it not only estimates the amount of measurement error, but also adjusts for measurement error (Collins & Lanza, 2010). In LCA, this implies that the estimates of the latent classes are adjusted for measurement error.

Item-Response Probabilities

To build the measurement model of a latent class model, it is necessary to determine the number of classes. This involves examining fit statistics and item-response probabilities, which refers to the probability of an individual in a specific class endorsing an item (Collins & Lanza, 2010). Evaluating the overall pattern of item-response probabilities involves high homogeneity and separation. Homogeneity is the extent to which individuals within a latent class are likely to provide the same observed responses (Collins & Lanza, 2010), and is considered to be high if the class-specific item response probabilities are greater than .70 or less than .30 (Masyn, 2013). Class separation is the extent to which the overall pattern of the item-response probabilities clearly distinguishes the latent classes (Collins & Lanza, 2010), and is considered high if the odds ratio of the item endorsement is greater than 5 (Masyn, 2013). Item probabilities are displayed in plots and are used to interpret the latent classes. These item probability plots will be presented throughout this dissertation to visually display the model parameters.

Model Estimation

The most common estimation methods for mixture models is the full information maximum likelihood (FIML) method, which is a model-based missing data procedure, where individuals with complete and partially complete data are examined together (Collins & Lanza, 2010). The FIML method assumes that the data are either missing completely at random (MCAR) or missing at random (MAR). Because of missing values in the variables used in this study, FIML estimation procedures were employed in the analyses. This method is superior to listwise deletion because it minimizes the biases due to nonrandom missing data that would result from methods such as listwise deletion of missing values (Arbuckle, 1996) and enables researchers to have a larger sample size and obtain more power.

The Practical Importance of using Latent Class Analysis (LCA)

For my dissertation, I used a latent class analysis to uncover subgroups of students' math attitudes and math self-efficacy beliefs. Based on students' response to a set of math attitude and math self-efficacy items, I identified patterns of different math attitudes and math self-efficacy. It is important to note that math attitude and math self-efficacy were not perfectly correlated with one another, where having positive math attitudes does not necessarily correspond with having positive math self-efficacy, and vice-versa. For instance, a student may report having high math attitudes and low math self-efficacy, while another student may report having low math attitudes and high math self-efficacy. Using a LCA allows one to see these distinct patterns and understand the different subpopulations of math attitudes and math self-efficacy. Latent class analysis allows researchers to group students based on multiple constructs. Rather than using a single variable to create groups (e.g., mean split or other methods), I am creating groups based on students' responses to both their math attitude and math self-efficacy. This is useful and is a contribution to the literature because previous studies have used one or the other, but this dissertation uses both constructs of math attitude and math self-efficacy. The combination of both constructs may be a more powerful predictor than of only one or the other.

In addition, LCA is a useful technique because I can include covariate and distal outcomes. Including covariates allowed me to see how different individual and structural characteristics influence these different subgroups, or latent classes, of math attitudes and math self-efficacy. For example, when I include gender as a covariate, I can see how likely it is for a female student to be in a specific latent class such as the high math attitude and high math self-efficacy class. Including distal outcomes allowed me to see how different latent classes can be used to predict STEM outcomes in 12^{th} grade math achievement, STEM degree attainment, and STEM career attainment. For instance, I can predict how students with low math attitudes and low math self-efficacy end up in terms of their STEM outcomes compared to students with high math attitudes and high math self-efficacy. Knowing which latent classes are more likely to pursue a STEM field is practical because it would give researchers and policymakers a sense of the types of interventions to develop in order to increase the number of students interested in STEM and who want to pursue a career in STEM. In addition, understanding which latent classes are less likely to pursue a STEM field is important to know because these interventions can target specific groups to improve their math attitudes and/or math self-efficacy beliefs.

The LCA Modeling Process

The LCA modeling process may take a considerable amount of time as there are many things to consider such as assessing fit statistics and using substantive theory to guide the decision on determining the number of latent classes in a model. There are three tools used to evaluate latent class models, which include evaluations of absolute fit, evaluations of relative fit, and evaluations of classification (Masyn, 2013). These tools will be discussed in the following sections.

Absolute fit. Evaluating the absolute fit involves comparing the models representation of the data to the actual data (Masyn, 2013). Absolute fit is the extent a latent class model provides an adequate representation of the data without referring to other models (Collins & Lanza, 2010). The most commonly used test of absolute fit of a model is the likelihood ratio (LR) chi-square goodness-of-fit, which is used to assess how well a latent class model fits the observed data (Collins & Lanza, 2010). The null hypothesis states that the data are generated by the assumed distribution of the model. Failure to reject the null hypothesis suggests an adequate model-data consistency, whereas rejection of the null hypothesis suggests the model does not adequately fit the data (Masyn, 2013). Masyn (2013) adds that the larger the test statistic, the bigger the discrepancy and poorer the fit between the model representation and the actual data.

It is important to note, however, that the LR chi-square goodness of fit is sensitive to sample size, where the null hypothesis could be rejected even though there was a "close" fit (Masyn, 2013). Further, in models with many categorical outcomes there can be problems with sparse cells, i.e., many 0 or near-0 cell frequencies, which results in major distributional disturbances for chi-square statistics since they are derived from asymptotic properties that are associated with contingency tables (Dayton, 2008). In other words, for models with sparse cells, as the number of observed items increases, models are rarely rejected (Nylund et al., 2007). Thus, educational researchers rarely rely on this fit statistic in applied work. For the sake of completeness, I included the chi-square statistics in my dissertation, but I did not rely on this statistic in evaluating absolute fit.

Relative fit. Another tool used to evaluate the latent class model is relative fit, which involves comparing the model's representation of the data to another model's representation using the following two criteria: inferential and information criteria (Masyn, 2013). There are two commonly used inferential comparison tests for nested models, which include the Lo-Mendell-Rubin Adjusted Likelihood Ratio Test (LMR-LRT) and the parameter Bootstrap Likelihood Ratio Test (BLRT). These tests are used to compare neighboring class models (i.e., tests the null model to the more parsimonious model). A statistically significant *p*-value suggests the model fits the data significantly better than the model with one less class (Masyn, 2013; Nylund, Asparouhov, & Muthén, 2007). With parsimony in mind, however, if the model with one less class has adequate absolute fit, it would be favored over the more complicated model. Thus it is important to consider both relative and absolute fit in deciding which model fits better.

The second category used to compare relative fit is the information criteria (IC), which compares values across a series of model specifications. The most commonly used IC is the Bayesian Information Criterion (BIC). Nylund et al. (2007) conducted a simulation study that investigated the performance of fit statistics in correctly identifying the number of classes across models using the Akaike's Information Criterion (AIC), Consistent Akaike's Information Criterion (CAIC), BIC, and adjusted BIC. The results from the study provided evidence that the BIC was superior among all ICs in correctly identifying the number of classes. For this reason, I relied heavily on the BIC statistic in determining the number of latent classes in my model. When evaluating information criteria, the model with the lowest value relative fit to the model suggests the best fitting model (Nylund et al., 2007). In addition, 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).

There are also other criteria used to assess model fit relative to other models, which include the Bayes Factor (BF) and the correct model probability (cmP). The $BF_{A,B}$ represents the ratio of the probability of Model A being the correct model compared to Model B, where higher BF values suggest a better the model (Masyn, 2013). More specifically, $1 < BF_{A,B} < 3$ is considered weak evidence for Model A, while $3 < BF_{A,B} < 10$ is considered moderate evidence for Model A, and $BF_{A,B} > 10$ is considered strong evidence for Model A. In addition, the cmP compares a set of more than two models, where the sum of cmP values across the set of models sums to 1.00, and it is assumed that the "true" model is included in the set (Masyn, 2013). In addition, Masyn (2013) suggests that any model with cmP > .10 is worth considering.

Classification diagnostics. The final tool that is used in evaluating latent class models is classification diagnostics, which uses posterior class probabilities to assess the degree of class separation. The classification diagnostic that was used in this study is relative entropy, which is an index that examines the accuracy of classification for the entire sample across the latent classes and is bounded between 0 and 1, where higher values of entropy indicates better classification of individuals (Clark & Muthén, 2009). Values that are 0.80 or higher are considered high entropy (Ram & Grimm, 2013).

Class Enumeration Process

After evaluating the LCA models in terms of absolute fit, relative fit, and classification diagnostics, the next step is to apply these tools in deciding the number of classes. Traditionally, latent class models are fitted through a number of steps. As described by Masyn (2013), the first step begins with fitting a one-class model. Next, a two-class model is considered, and the number of classes is increased one at a time until there is an unidentifiable model, which does not have a proper solution. The next step is to compute the approximate correct model probability (cmP) for all classes, and then choose a subset of models based on some fit statistics. To assess model fit, typically the AIC and BIC are used, where lower values indicate a better model (Dayton, 2008; Masyn, 2013; Muthén, 2001).

Next, Masyn (2013) suggests comparing the standardized residuals and classification diagnostics for the subset of models that were selected in the previous step. Determining the number of classes in a final model is challenging, as there is no one specific method to do so (Muthén & Asparouhov, 2006; Nylund et al., 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. The final step is to select the model from the previous two steps.

Three-Step Approach Overview

Once an unconditional model (i.e., a model without covariate or distal outcomes) is identified, the focus then shifts to understanding which groups of individuals are in each of the latent classes. This is often achieved by including auxiliary variables (i.e., covariates and distal outcomes) into the model. One issue that arises when this is done is that the classes that emerge in the unconditional model may change with the presence of the auxiliary variables. This is unintended and unwanted. To avoid this problem, I used the three-step method for including covariates and distal outcomes into mixture models (Asparouhov & Muthén, 2013; Vermunt, 2010).

The three-step approach is a relatively new method for estimating LCA models with covariates (Vermunt, 2010) and distal outcomes (Asparouhov & Muthén, 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. The LCA with covariates uses the observed variable (i.e., covariate) as a predictor of the latent class variable. On the other hand, the LCA with distal outcomes uses the latent class variable as a predictor of an observed variable (i.e., distal outcome). Both methods involve estimating logistic regression models for the latent classes. For my study, this involves building a measurement model based on students' math attitudes and math self-efficacy and then relating students' class membership to individual and structural variables as covariates and STEM outcomes and distal outcome variables.

As the name implies, the three-step approach involves three steps, where in the first step, the latent class model is estimated without auxiliary variables. In the second step, students are assigned to latent classes using modal class assignment and a measurement error is determined for the most likely class variable. This measurement error in class assignment was used in the third step. The final step involves estimating a model with auxiliary variables, where the latent class variable is measured by the most likely class, and the measurement error in the class assignment is fixed to a specific value found in the second step. Sample Mplus input files for the three-step approach are provided in Appendix E.

This three-step procedure is superior to other alternative approaches including the one-step and two-step approaches for a number of reasons. First, as Nylund-Gibson, Grimm, Quirk, and Furlong (2014) point out, the advantage of implementing this three-step approach is that class enumeration is decided before any covariate or distal variables are included. This process ensures that the measurement of the latent class variable is not affected with the inclusion of auxiliary variables. That is because the measurement parameters of the latent class variable of the model with covariates are fixed at values from the unconditional model. Second, based on a simulation study by Asparouhov and Muthén (2013), the three-step approach outperforms the pseudo-class approach for analyzing the relationship between a latent class variable and an auxiliary variable in terms of bias, mean squared error, and confidence interval coverage (Asparouhov & Muthén, 2013).

Third, the results from the simulation study demonstrated that if the entropy level is at least .60 or if there is sufficiently good class separation, this three-step approach was just as efficient as the one-step approach (Asparouhov & Muthén, 2013). Fourth, unlike the Lanza, Tan, & Bray (2013) method, the three-step procedure can be used with any arbitrary auxiliary model and can be used with any latent class model as the measurement model (i.e., latent transition analysis (LTA); growth analysis) and include any type of dependent variables. The Lanza et al. (2013) method, on the other hand, is limited in the scope of models it can accommodate. Lastly, this three-step approach is more superior to other approaches because it allows for the auxiliary variable to be either categorical or continuous.

Given all these advantages, there are, however, some disadvantages to using the three-step method. First, when entropy is low, the latent class variable is poorly measured, and this three-step approach could potentially fail. A second disadvantage is the three-step approach can fail when entropy is relatively high, but the latent class variable changes when the auxiliary variable is included (Asparouhov & Muthén, 2013). Another disadvantage is when there are direct effects in LCA, the three-step approach performs poorly when the number of direct effects is substantial, but it performs well when the number of direct effects is small and the entropy is large. Yet despite these disadvantages, the advantages of using this three-step outweigh the disadvantages, and thus, I implemented this three-step approach to test the hypotheses in my research.

Regression Mixture Modeling

Once latent classes are identified using the three-step approach, I examined whether or not differential effects exists when the relationship of a predictor and outcome differ across latent classes using regression mixture modeling. That is, for the different subgroups of math attitudes and self-efficacy, I used regression mixture models to examine the differential effects of the predictor, 12th grade math achievement, to the outcome, STEM degree, as well as the differential effects of the predictor, STEM degree, to the outcome, STEM career by class. As seen in Figure 3, the latent class variable, "10th grade math attitude and math self-efficacy" influences the regression parameter estimates for two regressions: (1) regressing STEM degree on 12th grade math achievement, and (2) regressing STEM career on STEM degree. This regression mixture add-on is only used for university graduates (i.e., students holding at least a bachelor’s degree or higher). Sample Mplus input files for regression mixture modeling are included in Appendix E.

Regression mixture modeling is a type of finite mixture model where the effects of a predictor variable on the outcome variable are allowed to vary for each latent class without the need for a moderator (Van Horn et al., 2012). Since regression mixture models do not include moderators, this method offers the potential to contribute to a better understanding of individual differences. Regression mixture modeling can be described as a combination of a latent class model with a conventional regression model (Ding, 2006), where this approach can be used to understand the differences in the relationship between predictor(s) and outcome(s) (i.e., regression part) by latent class (i.e., finite mixture modeling part).

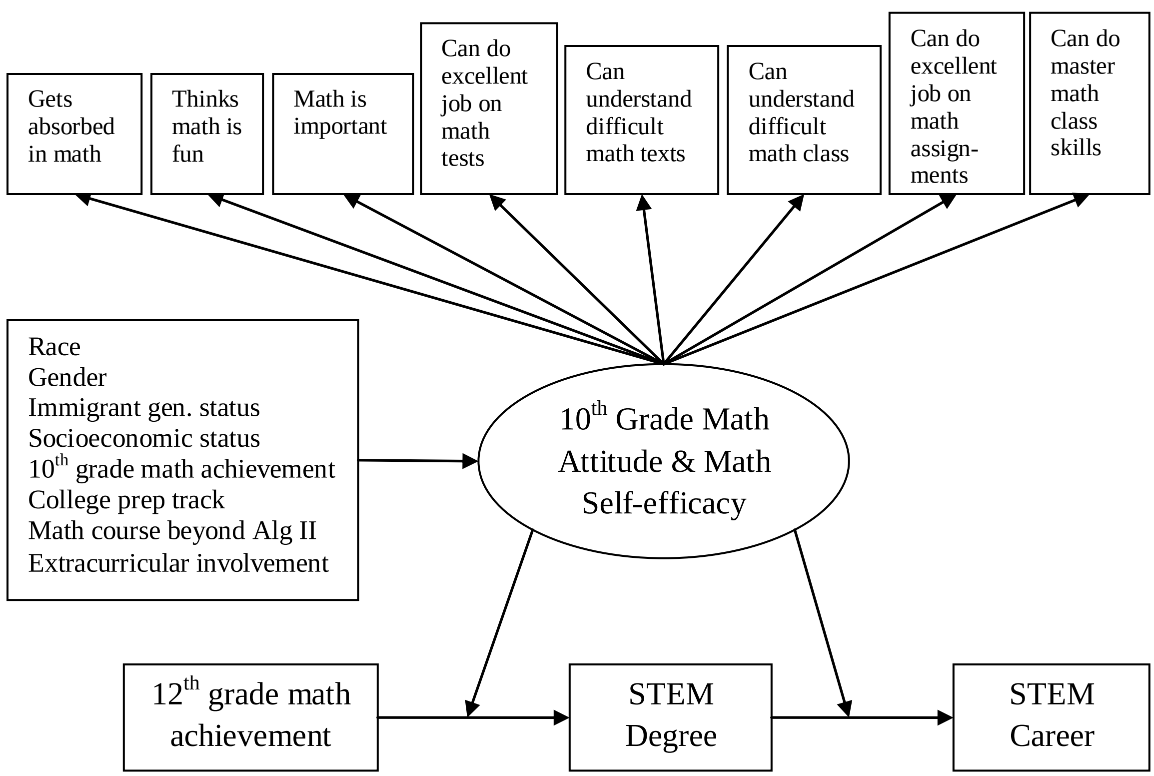

Figure 3. Theoretical regression mixture model using University graduates only, where the relationship between achievement, STEM degree, and STEM career differed by the latent classes of math attitude and self-efficacy.

In a conventional regression model, it is assumed that all individuals belong to a single population, and independent variables have the same influence on dependent variables for all individuals. However, in regression mixture modeling, there could be distinct subgroups of individuals where the independent variables have different effects on the dependent variables. If such heterogeneity is not considered, the traditional regression model could produce biased estimates (Ding, 2006). Using a regression mixture model incorporates the heterogeneity of the population in the model. In this sense, regression mixture modeling is used to understand the relationship between the predictor variable and the outcome variable among subpopulations of individuals, taking into account unobserved population heterogeneity. Applying this method is useful for understanding the heterogeneity across individuals and allows researchers to target these latent classes of individuals and tailor specific interventions for particular classes.

Model assumptions. Regression mixture modeling assumes the following for a continuous outcome: (1) the effect of x on y is linear in the parameters; (2) observations are independent; (3) x is measured without error; (4) and error terms are normal with each latent class (Van Horn et al., 2015). There have been some studies demonstrating the detrimental effect of violating these assumptions, particularly violating the strong assumption of normality of within-class distribution (George et al., 2013; Van Horn et al., 2012). Since the regression outcomes used in the study are dichotomous, there are more relaxed assumptions (George et al., 2013). Thus this study uses a logistic regression mixture analysis, which has more relaxed assumptions and does not require error terms to be normal within each latent class (Van Horn, et al., 2012). It is important to note that conducting a regression mixture analysis requires large sample sizes (Van Horn et al., 2015). Thus, a regression mixture analysis was conducted only on the largest subgroup, which is the university graduate group that contains 3,470 native English speakers and 560 for non-native English speakers.

Analysis Plan

Missing data. The analytic sample in this study includes students who had non-missing responses to items related to math attitudes and math self-efficacy. In addition, students with missing values on the covariates and distal outcomes were excluded from the analysis using listwise deletion. For high school graduates, this resulted in a drop from 560 participants to 420 participants for non-native English speakers and a drop from 3,070 to 2,490 participants for non-native English speakers. For community college graduates there was a decrease from 250 to 190 for non-native English speakers and a decrease from 1,360 to 1,160 for native English speakers. For university graduates, there was a drop from 560 to 450 for non-native English speakers and a drop from 3,470 to 3,110 for native English speakers. This decrease in sample size due to missing data still provides a large sample size to conduct my analysis.

LCA of two English proficiency groups and three educational attainment levels. For each English proficiency group (i.e., native English speakers and non-native English speakers), an independent LCA was conducted in Mplus version 7.11 (Muthén & Muthén, 1998-2013) for each educational attainment level (i.e., high school graduates, community college graduates, and university graduates attaining at least a bachelor's degree) for a total of six separate latent class analyses. Implementing a separate LCA for each English proficiency group and educational attainment level allowed for the number and structure of the emergent latent classes to be different.

Step 1: Class enumeration. Since there were six different LCAs implemented in this study, the class enumeration process was conducted separately for each of the six groups.

The first step in the three-step approach is to estimate an unconditional model. Using the seven steps provided by Masyn (2013), a one-class model was fitted and the number of parameter estimates, likelihood ratio chi-square, likelihood value, relative entropy, BIC, AIC, and adjusted BIC values were collected. Next, the class size increased one at a time, keeping track of the aforementioned statistics, as well as the LMR-LRT *p*-values, BLRT *p*-values, and the approximate Bayes Factor. These steps were repeated until the model did not have a proper solution. Next the correct model probability (cmP) was computed across all classes, and then a subset of models based on the absolute and relative fit statistics was selected for comparison. The standardized residuals and classification diagnostics for the subset of models were compared. Each fit statistic for each model was noted in a table and values were bolded to indicate the best fitting model given the fit index. Taking into account the theoretical meaning of each class and the parsimony principle, a final model was selected. Next, the classes were interpreted and labeled, while considering the probability of the students in the latent class endorsing the item, and how well the items differentiate the classes.

Step 2: Fixing classification error. The second step in the three-step approach is to assign individuals to latent classes using modal class assignment and a measurement error is calculated for the most likely class variable. In Mplus, the covariates and distal outcomes were designated as "auxiliary variables" and a "savedata" command was included to request the "cprobabilities," which produced the posterior class probabilities for each observation and the most likely class variable that is used in the final stage. The second step produced logit coefficients illustrating the likelihood the selected covariates are related to the identified classes in comparison to the reference class. In interpreting the logit coefficients[3], a *negative* logit indicates that individuals who are coded 1 on the covariate are 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.

Step 3: Adding auxiliary variables. In the third and final step, covariates and distal outcome variables were included. The threshold values for the latent class variables were fixed as specific values found in the previous step, and a final model was specified. It should be noted that throughout this three-step process, the results for each model were compared to ensure that the class sizes matched from the first and third step (Nylund-Gibson et al., 2014).

Regression Mixture Modeling. To capture differential effects, I implemented a regression mixture model on the sample containing university graduates holding at least a bachelor's degree for both native and non-native English speaking students. Because regression mixture models require a large sample size (Van Horn et al., 2015), this analysis was only conducted on the university group, which had the largest samples relative to the high school or community college level groups. The statement "ALGORITHM = INTEGRATION," which is a numerical integration method that uses a maximum likelihood estimator with robust standard errors, was included in the input file to address the latent variable corresponding to missing data on the outcome variable (Muthén & Muthén, 1998-2013). Two logistic regression models were specified within each class, where the first regressed STEM degree on 12^{th} grade math achievement and the second regressed STEM career on STEM degree. Regression coefficients were freely estimated without any

[3] Typically a negative logit suggests that individuals who are coded 1 on the covariate are less likely to be in the reference class than the comparison class. However for the consistency of interpreting positive likelihoods, I interpreted a negative logit to indicate that individuals who are coded 1 on the covariate are more likely to be in the reference class than the comparison class, and a positive logit to indicate that individuals coded 1 on the covariate are more likely to be in the comparison class than the reference class. This interpretation will be done throughout the dissertation.

constraints. Point estimates from each regression were calculated to test if there were differences in point estimates between classes.

The following section presents the modeling results for each of the research questions for both native and non-native English speakers at the different educational attainment levels. The first research question relates to the number of latent classes in each group (e.g., the class enumeration process for each native and non-native English speaker at each educational attainment level). The second research question relates to the inclusion of covariates (i.e., gender, race/ethnicity, immigrant generation status, SES, 10^{th} grade math achievement, tracking, highest level of math course taken, and extracurricular involvement) to increase the accuracy of classifying individuals into latent classes. The third research question relates to how the emergent classes differentiate in terms of the distal outcomes (i.e., 12^{th} grade math achievement, STEM degree or not, and STEM career or not). Finally, only for the university graduates, results from the regression mixture modeling will be discussed. These results will be presented by research question, rather than proficiency group, to highlight differences that emerged across groups.

IV. Results

High School Graduates

Native English speakers. From the first step of the three-step LCA, an unconditional model was estimated and the number of classes was decided based on the fit statistics and substantive theory. Table 3 displays the fit statistics for native English speaking high school graduates. Bolded values indicate the best model given the fit index. Several fit indices suggest a six-class model, including the smallest BIC value, smallest ABIC, and largest cmP value. The BIC never reached a minimum value, however there was an “elbow” in the graph, which shows the last relatively large decrease in the BIC value (Nylund et al., 2007), which occurred with the four-class model. In addition, there was a non-significant *p*-value of the LMR, which suggest that a four class model was not significantly improved by the addition of another class (i.e., five-class model). Thus, a four-class model was selected as the final model for native English speaking high school graduates.

Table 3

Latent Class Analysis Fit Indices for Native English Speaking High School Graduates

Number of classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of LMRT	BF	cmP
1	-15421.25	30906.73	30881.31	-	-	0	0
2	-12036.77	24210.03	24156.02	< .001	< .001	0.00	0.00
3	-11693.38	23595.51	23512.90	< .001	< .001	0.00	0.00
4	-11353.67	22988.37	22877.16	< .001	**< .001**	0.00	0.00
5	-11244.49	22842.26	22702.45	< .001	.597	0.00	0.00
6	-11183.72	**22792.98**	**22624.57**	< .001	.001	N/A	**1.00**

Note. N = 3,070. BIC=Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT=Bootstrap Likelihood Ratio Test; LMRT=Lo-Mendell-Rubin Adjusted Likelihood Ratio Test; BF=Bayes Factor; cmP=Correct Model Probability. Bolded values indicate the preferred model by the given fit index.

Non-native English speakers. Table 4 displays the fit statistics for non-native English speaking high school graduates. A few fit indices suggest a six-class model, however a three-class solution was selected based on the smallest BIC value and the largest correct model probability (cmP). In addition, a three-class model was selected over a six-class model due to the parsimony principle, which suggests that the model with the fewest number of classes that is statistically and substantively meaningful is selected. Based on the results from Tables 3 and 4, it is evident there are differences in the number of classes of math attitudes and math self-efficacy beliefs among native and non-native English speakers.

Table 4

Latent Class Analysis Fit Indices for Non-Native English Speaking High School Graduates

Number of classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of LMRT	BF	cmP
1	-2803.22	5657.08	5631.68	-	-	0.00	0.00
2	-2285.36	4678.32	4624.35	< .001	< .001	0.00	0.00
3	-2230.17	**4624.90**	4542.37	< .001	< .001	1.50	**0.59**
4	-2202.09	4625.72	4514.61	< .001	.028	26.34	0.39
5	-2176.87	4632.26	4492.58	< .001	.028	48.50	0.01
6	-2152.27	4640.02	**4471.77**	< .001	**.017**	9.58 e7	0.00
7	-2142.17	4676.78	4479.96	.113	.192	N/A	0.00

Note. N = 560. BIC=Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT=Bootstrap Likelihood Ratio Test; LMRT=Lo-Mendell-Rubin Adjusted Likelihood Ratio Test; BF=Bayes Factor; cmP=Correct Model Probability. Bolded values indicate the preferred model by the given fit index.

Research Question 1 (High School): How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?

Native English speakers. After examining a series of fit indices, applying the parsimony principle, and interpreting the theoretical meaning of the classes, a four-class model was selected. The item probability plot presented in Figure 4 was used to identify four emerging classes of (1) *High math attitudes, Low math self-efficacy (HL)*; (2) *Low math attitudes, High math self-efficacy (LH)*; (3) *Low math attitudes, Low math self-efficacy (LL)*; and (4) *High math attitudes, High math self-efficacy (HH)*. Figure 4 also displays the composition of the sample in each class, where the *HL* class comprised of 17.7% of the sample, the *LH* class included 21.1%, the *LL* class included 39.7%, and the *HH* class comprised of 21.5% of the sample.

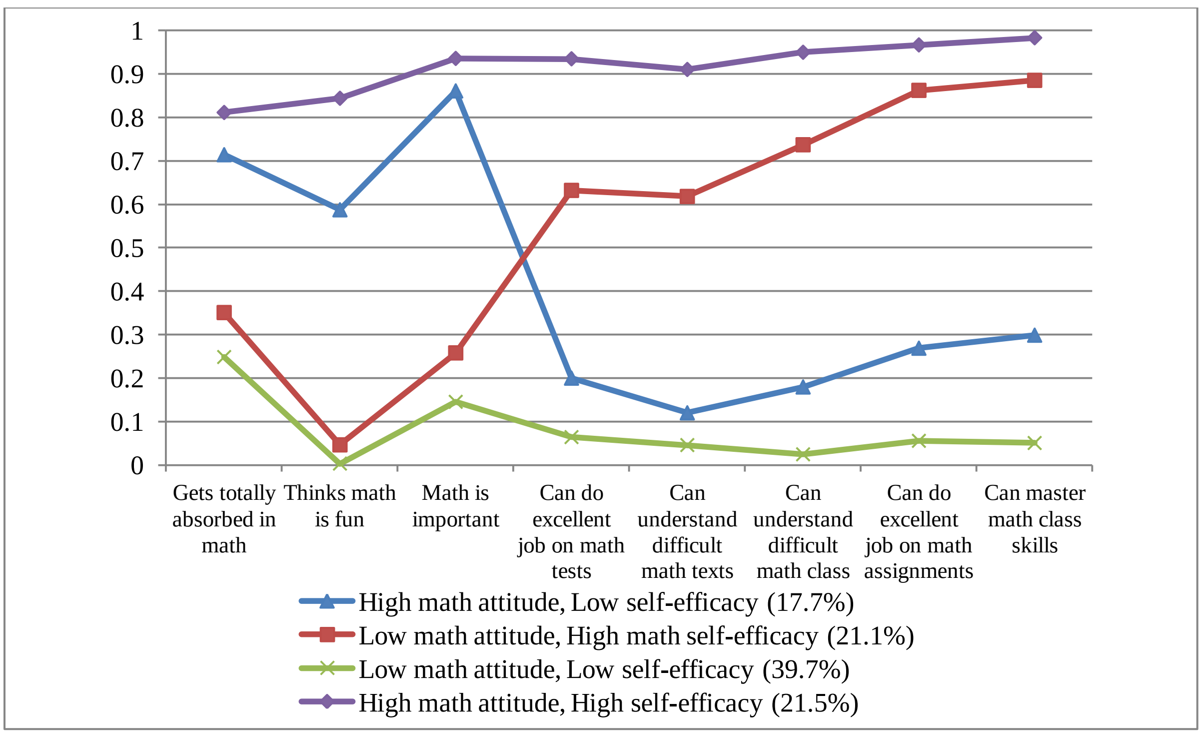

Figure 4. Item probability plot for native English speaking high school graduates

Non-native English speakers. The item probability plot presented in Figure 5 was used to identify three emerging classes of (1) *High math attitudes*, *Low math self-efficacy (HL)* (24.3%); (2) *Low math attitudes, Low math self-efficacy (LL)* (31.1%); (3) *High math attitudes, High math self-efficacy (HH)* (44.6%).

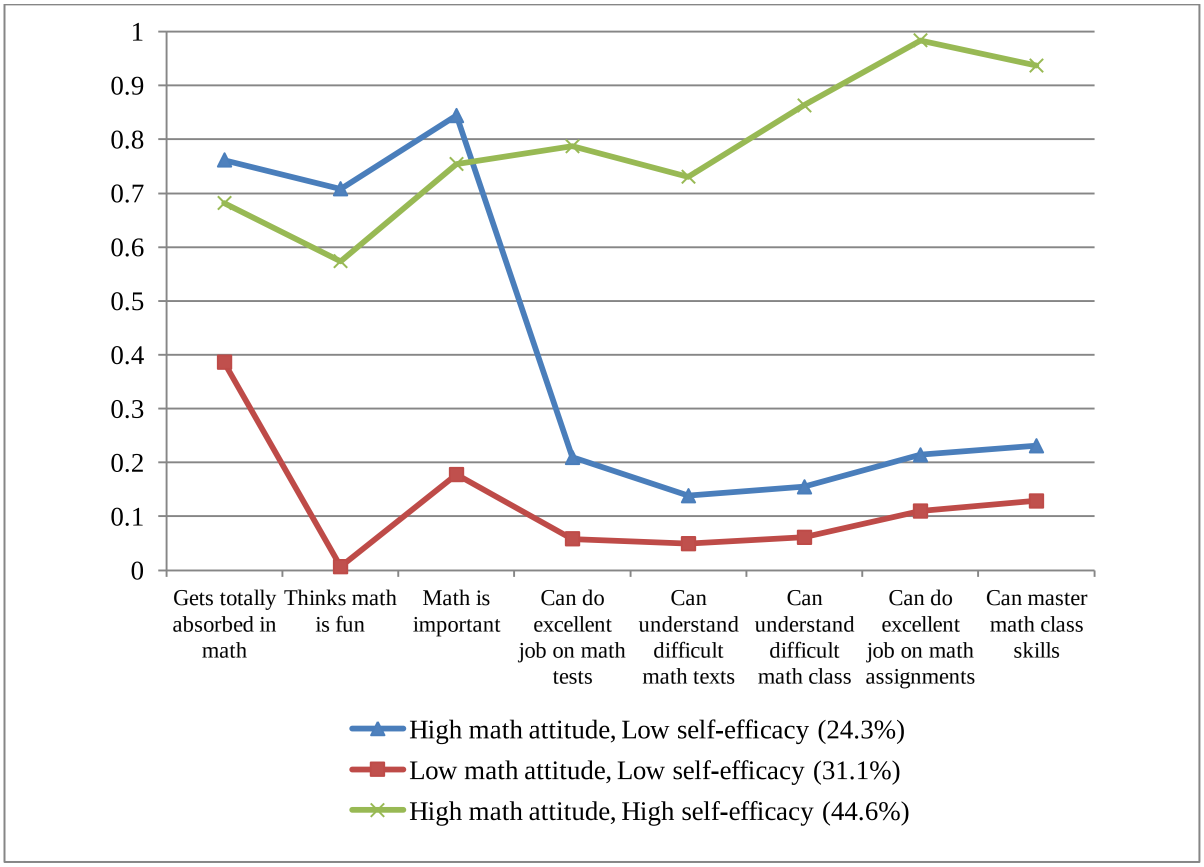

Figure 5. Item probability plot for non-native English speaking high school graduates

Comparison between native and non-native English speakers. It is apparent from these two figures that there are differences in math attitude and self-efficacy beliefs between native and non-native English speakers. For instance, there was a three-class solution for non-native English speakers compared to a four-class solution for native English speakers. In looking at these item probability plots, one interesting comparison is how the students in the *LL* students responded similarly to items for both native and non-native English speaking populations. However, it is important to note that this comparison is purely descriptive and not statistically compared since the latent classes were from two different populations.

Research Question 2 (High School): What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?

Native English speakers. When comparing the emergent latent classes with and without covariates, there were no large shifts in the emergent latent classes, which suggest that these latent classes were stable. The covariate results in Table 5 provide evidence that the covariates differentiate the classes well. It is important to note that the reference class is *HH*; thus a *negative* logit indicates that individuals who are coded 1 on the covariate are 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.

From Table 5, it is evident that the logit coefficient for female native English speakers was positive and significant for the *LL* class and the odds ratio was 2.20, which suggests that female students were more than twice as likely to be in the *LL* class compared to the *HH* class, relative to their male counterparts.

Table 5

Covariate Table for the Four-Class Model (Native English Speaking HS Graduates)

Latent Classes	Effect	Logit		SE	OR
High MA, Low MSE (17.7%)	Female	0.31		0.18	1.37
	Latino	-0.07		0.32	0.94
	African American	-0.11		0.25	0.89
	Asian	-0.55		0.83	0.58
	Other Race	-0.02		0.35	0.98
	First Generation	-0.56		1.08	0.57
	Low SES	0.29		0.21	1.33
	10th Grade Math Achievement	-0.10	***	0.01	0.91
	College Preparatory Track	-0.18		0.19	0.83
	Math Course Beyond Alg II	-0.46	*	0.20	0.63
	Extracurricular Involvement	0.30		0.20	1.35
Low MA, High MSE (21.1%)	Female	-0.03		0.16	0.97
	Latino	0.08		0.26	1.09
	African American	-0.81	**	0.25	0.45
	Asian	-0.05		0.47	0.95
	Other Race	-0.12		0.30	0.89
	First Generation	0.04		0.65	1.04
	Low SES	0.25		0.20	1.29
	10th Grade Math Achievement	-0.04	*	0.01	0.96
	College Preparatory Track	-0.01		0.17	0.99
	Math Course Beyond Alg II	-0.31		0.17	0.74
	Extracurricular Involvement	-0.23		0.16	0.79
Low MA, Low MSE (39.7%)	Female	0.79	***	0.13	2.20
	Latino	-0.19		0.24	0.83
	African American	-1.07	***	0.20	0.34
	Asian	-1.02		0.58	0.36
	Other Race	-0.40		0.26	0.67
	First Generation	-0.23		0.62	0.79
	Low SES	-0.24		0.18	0.79
	10th Grade Math Achievement	-0.07	***	0.01	0.93
	College Preparatory Track	-0.44	**	0.14	0.64
	Math Course Beyond Alg II	-0.82	***	0.15	0.44
	Extracurricular Involvement	-0.33	*	0.14	0.72

Note. N = 2,490. Class percentages are noted in parentheses. Reference class is High Math Attitude, High Math Self-Efficacy (21.5%); High MA, Low MSE = High Math Attitude, Low Math Self-Efficacy; Low MA, High MSE = Low Math Attitude, High Math Self-Efficacy; Low MA, Low MSE = Low Math Attitude, Low Math Self-Efficacy; OR = odds ratio. * $p < .05$. ** $p < .01$. *** $p < .001$.

In terms of racial/ethnic differences, African American students were more likely to be in the *HH* class compared to the *LL* or *LH* classes, relative to their white counterparts. Students with higher 10^{th} grade math achievement scores were significantly more likely to be in the *HH* class compared to the other classes. In addition, native English speakers on the college preparatory track were more likely to be in the *HH* class compared to the *LL* class. Similarly, those who took a math course beyond Algebra II were significantly more likely to be in the *HH* class compared to the *HL* or *LL* classes. Lastly, those involved in extracurricular activities were significantly more likely to be in the *HH* class compared to the *LL* class.

Non-native English speakers. The results presented in Table 6 suggest that the covariates differentiate the classes well for non-native English speaking high school graduates. Similar to the native English speaking female students, the positive coefficient of 0.79 ($p < .001$) for female students in the *LL* class suggests that female non-native English speaking high school graduates were more likely to be in the *LL* class compared to the reference class, *HH*, relative to their male peers. This finding is interesting to note since female students are more likely to be in the *LL* class regardless of their English proficiency. In terms of racial/ethnic differences, Latino non-native English speaking high school graduates were more likely to be in the *HH* class compared to the *LL* or *HL* classes, relative to white non-native English speaking high school graduates. In terms of math achievement scores, high school graduates with higher 10^{th} grade math achievement scores were significantly more likely to be in the *HH* class compared to the other classes.

Table 6

Covariate Table for the Three-Class Model (Non-native English Speaking HS Graduates)

Latent Classes	Effect	Logit		SE	OR
High MA, Low MSE (24.3%)	Female	0.48		0.37	1.62
	Latino	-1.76	**	0.62	0.17
	African American	-1.47		0.89	0.23
	Asian	-1.11		0.60	0.33
	Other Race	-0.78		1.58	0.46
	First Generation	0.69		0.39	1.98
	Low SES	0.55		0.37	1.73
	10th Grade Math Achievemt	-0.07	**	0.02	0.94
	College Preparatory Track	-0.43		0.41	0.65
	Math Course Beyond Alg II	-0.43		0.50	0.65
	Extracurricular Involvement	0.49		0.46	1.63
Low MA, Low MSE (31.1%)	Female	0.68	*	0.30	1.97
	Latino	-1.57	*	0.63	0.21
	African American	-2.50		1.39	0.08
	Asian	-0.89		0.64	0.41
	Other Race	0.59		0.89	1.81
	First Generation	-0.02		0.30	0.99
	Low SES	0.37		0.32	1.45
	10th Grade Math Achievemt	-0.08	***	0.02	0.93
	College Preparatory Track	-0.14		0.31	0.87
	Math Course Beyond Alg II	-0.46		0.38	0.63
	Extracurricular Involvement	-0.36		0.31	0.70

Note. N = 420. Class percentages are noted in parentheses. Reference class is High Math Attitude, High Math Self-Efficacy (44.6%); 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
* $p < .05$. ** $p < .01$. *** $p < .001$.

Comparison between native and non-native English speakers. The results from Tables 5 and 6 for native and non-native English speakers revealed both similarities and differences in the relationships between the math attitude and math self-efficacy latent classes and the selected covariates. In terms of similarities, both native and non-native English speaking female students tended to be in the *LL* class compared to male students. In addition, students with higher 10th grade math achievement were more likely to be in the *HH* class and this was significant for both native and non-native English speakers. The only difference between these two groups was the racial/ethnic groups. For non-native English speakers, Latino students were more likely to be in the *HH* class, whereas for native English speakers, African American students were more likely to be in the *HH* class compared to their white counterparts.

Research Question 3 (High School): To what extent do students' math attitudes and math self-efficacy contribute to their 12th grade math achievement, and how does this differ between non-native English speakers and native English speakers?

Native English speakers. The proximal outcome in this analysis was students' 12th grade math standardized test score. As seen in Table 7, individuals in the *HH* class had the highest 12th grade math standardized test score, with a mean of 53.64 and standard error of 0.44 , and this was statistically significant at the p = .05 level compared to the other three latent classes. It is interesting to point out that the mean score of 45.43 and standard error of 0.51 for those in the *HL* class was significantly different from the mean score of 47.24 and standard error of 0.28 for those in the *LL* class. However native English speakers in the *LH* class had a mean score of 50.70 and standard error of 0.48, which was the second highest average 12th grade math achievement score, and that was not too far behind the *HH* class. This suggests that having high math self-efficacy is important for predicting positive 12th grade math achievement.

Table 7

12th Grade Math Achievement for Native English Speaking High School Graduates

Latent Classes	Mean (SE)
HL vs. LH (Class 1 vs. Class 2)	**45.43 (0.51) vs. 50.70 (0.48)**
HL vs. LL (Class 1 vs. Class 3)	**45.43 (0.51) vs. 47.24 (0.28)**
HL vs. HH (Class 1 vs. Class 4)	**45.43 (0.51) vs. 53.64 (0.44)**
LH vs. LL (Class 2 vs. Class 3)	**50.70 (0.48) vs. 47.24 (0.28)**
LH vs. HH (Class 2 vs. Class 4)	**50.70 (0.48) vs. 53.64 (0.44)**
LL vs. HH (Class 3 vs. Class 4)	**47.24 (0.28) vs. 53.64 (0.44)**

Note. $N = 2{,}490$. HL = *High Math Attitude, Low Math Self-Efficacy*; LH = *Low Math Attitudes, High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*. Bolded values indicate significant differences at the $p = .05$ level.

Non-native English speakers. As seen in Table 8, non-native English speaking students who have high math attitudes and high math self-efficacy (*HH*) had the highest math achievement scores among the other classes, with a mean of 51.40 and standard error of 0.83. Only classes that had varying math self-efficacy, i.e., *HL* vs. *HH* or *LL* vs. *HH*, were significantly different from each other. Students in the *HL* class had a mean score of 44.83 and standard error of 1.13 and students in the *LL* class had a mean score of 44.35 and standard error of 0.94. This comparison was not significant, which suggest that students in the *HL* class do not different from students in the *LL* class in terms of 12th grade math achievement.

Table 8

12th Grade Math Achievement for Non-Native English Speaking High School Graduates

Latent Classes	Mean (SE)
HL vs. LL (Class 1 vs. Class 2)	44.83 (1.13) vs. 44.35 (0.94)
HL vs. HH (Class 1 vs. Class 3)	**44.83 (1.13) vs. 51.40 (0.83)**
LL vs. HH (Class 2 vs. Class 3)	**44.35 (0.94) vs. 51.40 (0.83)**

Note. N = 420. HL = *High Math Attitude, Low Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*. Bolded values indicate significant differences at the p = .05 level.

Comparison between native and non-native English speakers. The two bar charts in Figure 6 display students' 12th grade math achievement with standard error bars for native and non-native English speakers. This figure provides evidence that there are differences in native and non-native English speakers' 12th grade math achievement. It is important to note that these comparisons are strictly descriptive and not statistically compared since there are different latent classes from two different populations (even though they share the same labels). There are a few points worth mentioning. First, in terms of highest average math achievement, Native English speakers in the *HH* class had the highest math achievement score of 53.64 and this was higher than the non-native English speakers in the *HH* class (51.40). In terms of lowest math achievement score, non-native English speakers in the *LL* class had the lowest score of 44.35 and this was lower than the native English speakers' score of 47.24. These results suggest there is an achievement gap between native and non-native English speakers. Furthermore, these results point to the fact that within the same English proficiency group, there is a disparity in 12th grade math achievement scores between the *LL* and *HH* classes.

Second, for non-native English speakers, as students' math attitudes and math self-efficacy increase from low to high, there is an increase in average 12th grade math achievement. This is in congruence with the SCCT theory that suggests positive math attitudes and self-efficacy beliefs relate to positive math performance. This relationship was not apparent for native English speakers. Third, regardless of English proficiency, high school graduates with high math self-efficacy (i.e., *LH* or *HH*) had significantly higher math achievement compared to those with low math self-efficacy (i.e., *LL* or *HL*). This suggests that math self-efficacy has a stronger effect than math attitudes in predicting students' 12th grade math achievement.

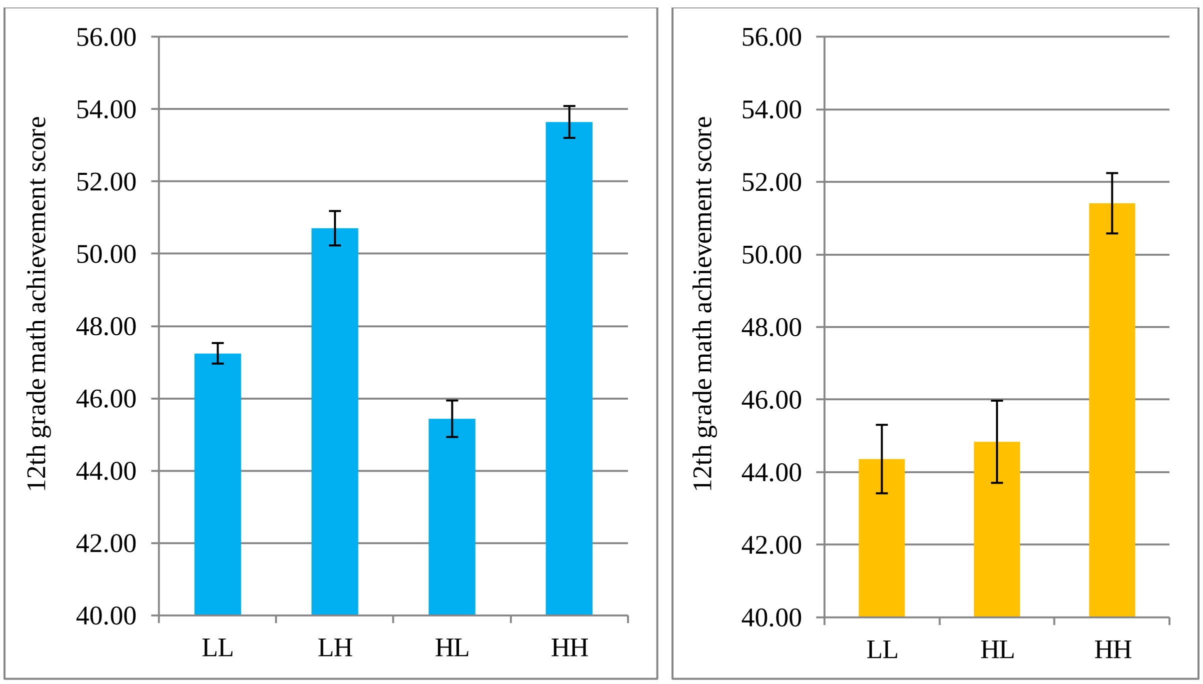

Figure 6. High School: 12th grade math achievement by class for native English speakers (left) and non-native English speakers (right). Error bars represent standard error of the mean.

Research Question 4 (High School): To what extent do students' math attitudes and math self-efficacy contribute to their STEM career? How does this differ between non-native English speakers and native English speakers?

Native English speakers. The distal outcome used in this study was whether or not students attained a career in STEM. As illustrated in Table 9, across all classes, there was a higher proportion of native English speakers in the *HH* class, who pursued a STEM occupation (7%), compared to 5% in the *LH* class, 5% in the *HL* class, and 3% in the *LL* class. In particular, students in the *HH* class were significantly different compared to students in the *LL* class and this was statistically different from the 3% in the *LL* class.

Table 9

Proportion of Native English Speaking High School Graduates with a STEM Occupation

Latent Classes	Mean (SE)
HL vs. LH (Class 1 vs. Class 2)	.05 (0.01) vs. .05 (0.01)
HL vs. LL (Class 1 vs. Class 3)	.05 (0.01) vs. .03 (0.01)
HL vs. HH (Class 1 vs. Class 4)	.05 (0.01) vs. .07 (0.01)
LH vs. LL (Class 2 vs. Class 3)	.05 (0.01) vs. .03 (0.01)
LH vs. HH (Class 2 vs. Class 4)	.05 (0.01) vs. .07 (0.01)
LL vs. HH (Class 3 vs. Class 4)	**.03 (0.01) vs. .07 (0.01)**

Note. N = 2,490. HL = *High Math Attitude, Low Math Self-Efficacy*; LH = *Low Math Attitudes, High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*. Bolded values indicate significant differences at the p = .05 level.

Non-native English speakers. For non-native English speaking high school graduates, as seen in Table 10, there were a higher proportion of individuals in the *HH* class who pursued a STEM occupation (8%), compared to 3% in the *HL* class, and 4% in the *LL* class. However none of these comparisons were significant at the .05 level.

Table 10

Proportion of Non-Native English Speaking High School Graduates with a STEM Occupation

Latent Classes	Mean (SE)
HL vs. LL (Class 1 vs. Class 2)	.03 (0.02) vs. .04 (0.02)
HL vs. HH (Class 1 vs. Class 3)	.03 (0.02) vs. .08 (0.02)
LL vs. HH (Class 2 vs. Class 3)	.04 (0.02) vs. .08 (0.02)

Note. N = 420. HL = *High Math Attitude, Low Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*.

Comparison between native and non-native English speakers. Figure 7 displays the proportion of native and non-native English speaking high school graduates with a STEM career. For native English speakers, individuals in the *LL* class had the lowest proportion of individuals with a STEM occupation (.03) and individuals in the *HH* class had the highest proportion of individuals with a STEM occupation (.07). Nevertheless, for native English speakers, there is an increasing trend of more positive math attitudes and math self-efficacy that corresponds to an increase in the proportion of students with a STEM career. However this trend was not the same for non-native English speakers, where individuals in the *HL* class had the lowest proportion of STEM occupation holders (.04) and those in the *HH* had the highest proportion of individuals with a STEM occupation (.08). Overall, the combined results suggest the importance of high math attitudes and self-efficacy beliefs with a high proportion of individuals with a STEM career.

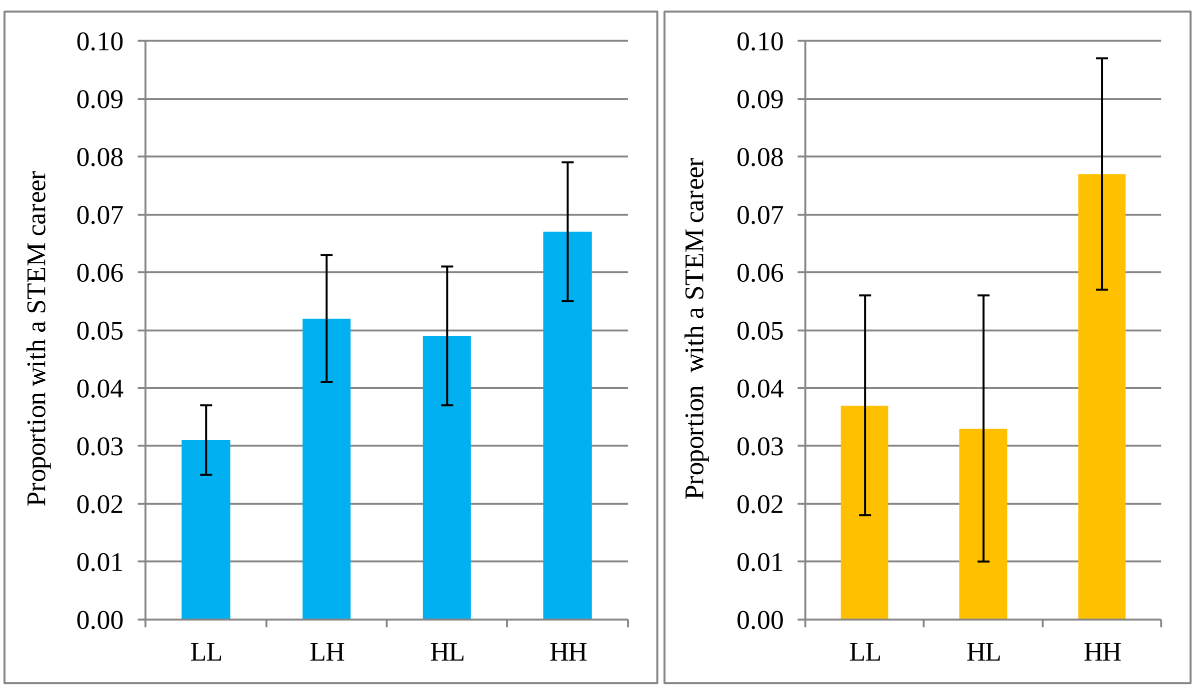

Figure 7. High School: Proportion of students with a STEM career by class for native English speakers (left) and non-native English speakers (right). Error bars represent standard error of the mean.

Community College Graduates

A similar latent class analysis was performed on students who graduated from community college with an associate's degree or undergraduate certificate. The results presented address the research questions for native and non-native English speaking community college graduates accordingly.

Native English speakers. Table 11 displays the fit statistics for native English speaking community college graduates. A five-class solution is selected based on the smallest BIC value and large cmP value. The significant *p*-value of the LMRT and the BF value suggest a six-class solution, but based on the parsimony principle, a five class solution was selected as the final model for native English speaking community college graduates.

Table 11

Latent Class Analysis Fit Indices for Native English Speaking Community College Graduates

Number of classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of LMRT	BF	cmP
1	-6821.69	13701.11	13675.70	-	-	0	0
2	-5377.18	10877.05	10823.05	< .001	< .001	0.00	0.00
3	-5237.29	10662.23	10579.64	< .001	< .001	0.00	0.00
4	-5106.94	10466.50	10355.32	< .001	< .001	0.00	0.00
5	-5056.72	**10431.01**	10291.24	< .001	.027	20.34	**0.95**
6	-5027.26	10437.03	10268.68	< .001	**.027**	**2.43 e5**	0.05
7	-5007.18	10461.84	**10264.89**	< .001	.147	N/A	0.00

Note. N = 1,360. BIC=Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT=Bootstrap Likelihood Ratio Test; LMRT=Lo-Mendell-Rubin Adjusted Likelihood Ratio Test; BF=Bayes Factor; cmP=Correct Model Probability. Bolded values indicate the preferred model by the given fit index.

Non-native English speakers. Table 12 displays the fit statistics for non-native English speaking community college graduates. Some of the fit statistics suggest a five-class model such as the non-significant *p*-value of the LMRT for the six-class model and a large Bayes Factor value. However, based on the smallest BIC value and large cmP values and applying the parsimony principle, a three-class solution was selected as the final model. Results from Tables 11 and 12, reveal differences in the number of classes of math attitudes and math self-efficacy beliefs among native and non-native English speaking community college graduates, where there were five latent classes for native English speakers and three latent classes for non-native English speakers.

Table 12

LCA Fit Indices for Non-Native English Speaking Community College Graduates

Number of classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of LMRT	BF	cmP
1	-1187.50	2419.10	2393.74	-	-	0.00	0.00
2	-989.62	2072.97	2019.08	< .001	< .001	0.00	0.00
3	-955.68	**2054.72**	1972.30	< .001	.007	61.56	**0.98**
4	-934.99	2062.96	1952.01	< .001	.015	4.97 e3	0.02
5	-918.70	2079.98	1940.50	< .001	**.003**	2.19 e5	0.00
6	-906.18	2104.58	**1936.56**	.03	.070	N/A	0.00

Note. N = 250. BIC=Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT=Bootstrap Likelihood Ratio Test; LMRT=Lo-Mendell-Rubin Adjusted Likelihood Ratio Test; BF=Bayes Factor; cmP=Correct Model Probability. Bolded values indicate the preferred model by the given fit index.

Research Question 1 (Community College): How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?

Native English speakers. The item probability plot presented in Figure 8 was used to identify a five-class model for native English speakers, which include the following labeled classes: (1) *Low math attitudes, High math self-efficacy (LH)* (13.0%); (2) *Medium math attitudes, Low-High math self-efficacy (MLH)* (14.3%); (3) *Low math attitudes, Low math self-efficacy (LL)* (40.2%); (4) *High math attitudes, Low math self-efficacy (HL)* (13.9%); and (5) *High math attitudes, High math self-efficacy (HH)* (18.5%).

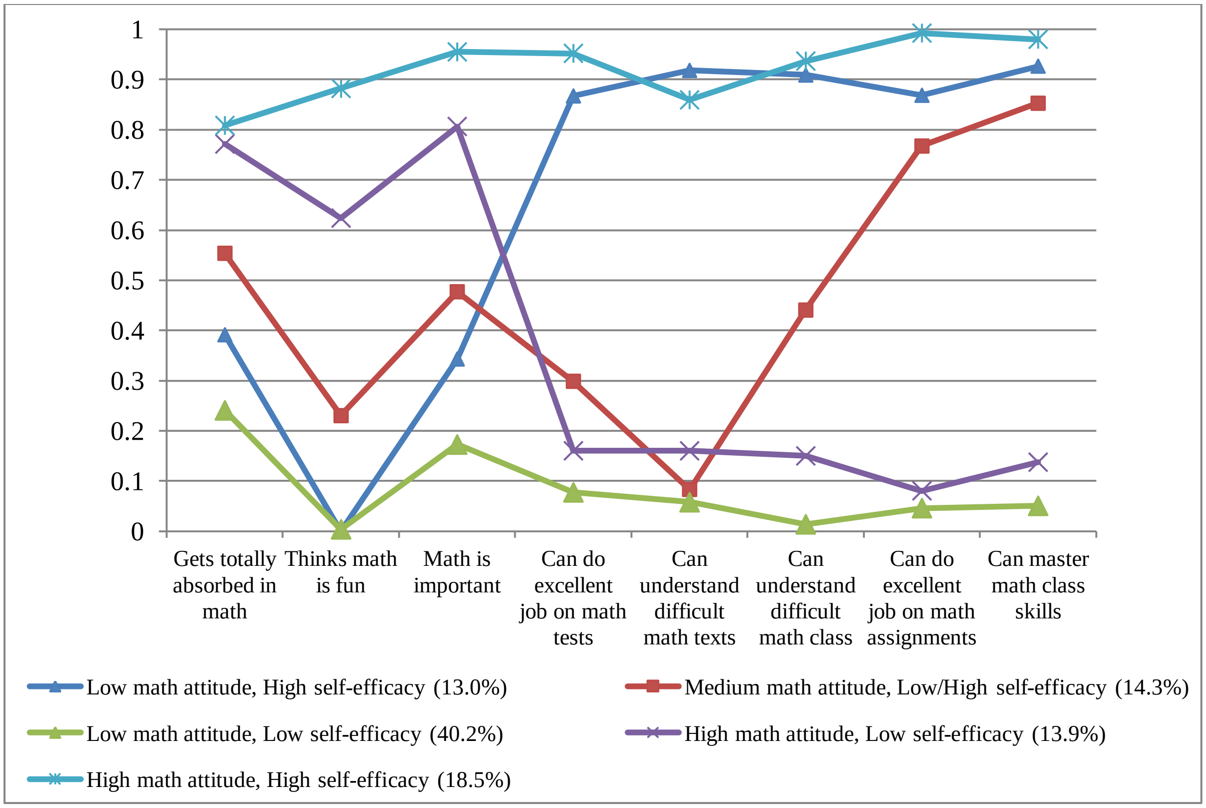

Figure 8. Item probability plot for native English speaking community college graduates

Non-native English speakers. Figure 9 presents the item probability plot for non-native English speaking community college graduates. A three-class model was identified and labeled as follows: (1) *High math attitudes*, *Low math self-efficacy (HL)* (21.0%); (2) *High math attitudes*, *Medium-High math self-efficacy (HMH)* (42.9%); and (3) *Low math attitudes*, *Low math self-efficacy (LL)* (36.1%).

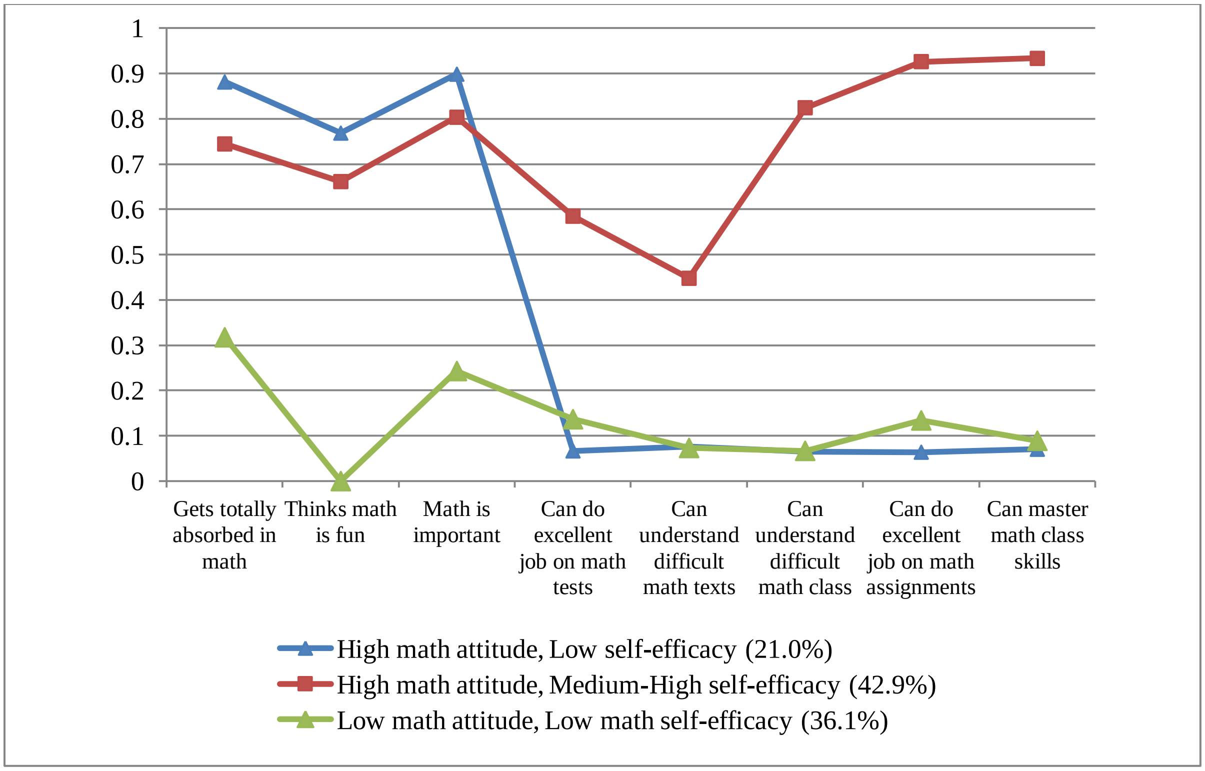

Figure 9. Item probability plot for non-native English speaking community college graduates

Comparison between native and non-native English speakers. Comparing Figures 8 and 9, it is evident that there are different math attitude and self-efficacy classes, where there are five latent classes for native English speakers, and three latent classes for non-native English speakers. For the native English speakers, there is more heterogeneity in math attitudes and math self-efficacy compared to non-native English speakers, hence the increase in the number of latent classes. It is interesting to note the *LL* in both populations look similar in terms of the pattern of response to math attitude and math self-efficacy items. Another interesting point is that the largest latent class for native English speakers was the *LL* class (40.2%), whereas the largest class for non-native English speakers was the *HMH* class (42.9%). This point is worth nothing because we can see the differences in the majority of attitudinal and self-efficacy beliefs between the two groups. The majority of the non-native

English speakers tended to report high math attitudes and medium to high math self-efficacy, whereas the native English speakers tended to report low math attitudes and self-efficacy.

Research Question 2 (Community College): What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?

Native English speakers. The relationships of the attitudinal classes with the covariates are presented in Table 13, where the reference class is *HH*. It is important to note that there is a large negative logit for first generation covariate for the *LH* class, which indicates that there were not many first generation, native English speaking community college graduates in this subsample. In terms of gender, female native English speakers were more likely to be in the *LL* class than the *HH* class, relative to male native English speakers. In terms of racial/ethnic differences, African American students were more likely to be in the *HH* class compared to the *MLH* or *LL* class. Similarly, Latino students were more likely to be in the *HH* class compared to the *LL* class. Regarding SES, students from low SES backgrounds were more likely to be in the *HH* class than the *LL* class. In addition, students with higher 10th grade math achievement scores were significantly more likely to be in the *HH* class than the *MLH*, *HL* or *LL* class. Native English speakers whose highest math course taken was above Algebra II were more likely to be in the *HH* class than the *LH* or *LL* classes.

Table 13

Covariate Table for 5-Class Model (Native-English Speaking Community College Graduates)

Latent Classes	Effect	Logit		SE	OR
Low MA, High MSE (13.0%)	Female	-0.20		0.27	0.82
	Latino	-0.66		0.51	0.52
	African American	-0.25		0.43	0.78
	Asian	-0.70		1.00	0.49
	Other Race	-0.45		0.59	0.64
	First Generation	-22.71		0.00	0.00
	Low SES	-0.17		0.34	0.84
	10th Grade Math Achievement	0.00		0.02	1.00
	College Preparatory Track	0.02		0.28	1.02
	Math Course Beyond Alg II	-0.67	*	0.29	0.51
	Extracurricular Involvement	0.06		0.28	1.06
Med MA, Low/High MSE (14.3%)	Female	0.56		0.32	1.75
	Latino	-0.41		0.51	0.66
	African American	-1.02	*	0.52	0.36
	Asian	-1.55		1.50	0.21
	Other Race	-1.63		1.28	0.20
	First Generation	1.03		0.88	2.80
	Low SES	-0.56		0.40	0.57
	10th Grade Math Achievement	-0.05	*	0.02	0.96
	College Preparatory Track	-0.40		0.31	0.67
	Math Course Beyond Alg II	-0.36		0.33	0.70
	Extracurricular Involvement	0.00		0.32	1.00
Low MA, Low MSE (40.2%)	Female	0.71	**	0.21	2.04
	Latino	-0.75	*	0.36	0.47
	African American	-1.11	**	0.34	0.33
	Asian	-0.55		0.68	0.58
	Other Race	-0.41		0.39	0.66
	First Generation	-0.32		0.94	0.72
	Low SES	-0.67	**	0.26	0.51
	10th Grade Math Achievement	-0.08	***	0.02	0.93
	College Preparatory Track	-0.34		0.21	0.71
	Math Course Beyond Alg II	-0.56	*	0.22	0.57
	Extracurricular Involvement	-0.21		0.21	0.81
High MA, Low MSE (13.9%)	Female	0.29		0.32	1.34
	Latino	-0.51		0.50	0.60
	African American	0.01		0.39	1.01
	Asian	0.90		0.83	2.46
	Other Race	-1.10		1.11	0.33
	First Generation	-0.63		1.78	0.53
	Low SES	-0.62		0.36	0.54
	10th Grade Math Achievement	-0.13	***	0.02	0.88
	College Preparatory Track	-0.42		0.31	0.66
	Math Course Beyond Alg II	-0.07		0.34	0.93
	Extracurricular Involvement	0.06		0.30	1.06

Note. N = 1,160. Class percentages are noted in parentheses. Reference class is High Math Attitude, High Math Self-Efficacy (18.5%); Low MA, High MSE = Low Math Attitudes, High Math Self-Efficacy; Med MA, Low/High MSE = Medium Math Attitude, Low/High Math Self-Efficacy; Low MA, Low MSE = Low Math Attitude, Low Math Self-Efficacy; High MA, Low MSE = High Math Attitude, Low Math Self-Efficacy; OR=odds ratio.
* $p < .05$. ** $p < .01$. *** $p < .001$.

Non-native English speakers. The relationships of the attitudinal classes with the covariates for non-native English speaking community college graduates are presented in Table 14, where the reference class is *HMH*. It is important to note that there is a large negative logit for the "other race" covariate, which indicates that there were not many non-native English speaking community college graduates who reported "other race". Another significant covariate is prior math achievement, where students with higher 10^{th} grade math achievement scores were more likely to be in the *HMH* class compared to the *HL* class.

Table 14

Covariate Table for 3-Class Model (Non-native English Speaking Community College Graduates)

Latent Classes	Effect	Logit		SE	OR
High MA, Low MSE (21.0%)	Female	-1.01		0.57	0.36
	Latino	-0.40		0.98	0.67
	African American	0.27		1.41	1.31
	Asian	1.27		0.92	3.57
	Other Race	31.37	***	1.14	4.21 e13
	First Generation	-0.17		0.55	0.84
	Low SES	0.43		0.67	1.54
	10th Grade Math Achievement	-0.07	*	0.04	0.93
	College Preparatory Track	-0.73		0.57	0.48
	Math Course Beyond Alg II	-0.15		0.71	0.86
	Extracurricular Involvement	0.43		0.53	1.53
Low MA, Low MSE (36.1%)	Female	-0.33		0.43	0.72
	Latino	-0.34		0.68	0.71
	African American	-0.83		1.65	0.44
	Asian	0.20		0.74	1.23
	Other Race	28.86		0.00	3.41 e12
	First Generation	-0.44		0.44	0.65
	Low SES	-0.29		0.45	0.75
	10th Grade Math Achievement	-0.06		0.03	0.95
	College Preparatory Track	-0.78		0.44	0.46
	Math Course Beyond Alg II	0.47		0.47	1.60
	Extracurricular Involvement	-0.16		0.43	0.86

Note. N =190. Class percentages are noted in parentheses. Reference class is High Math Attitude, Medium-High Math Self-Efficacy (42.9%); 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

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

Comparison between native and non-native English speakers. The only significant covariate that is worth comparing is 10^{th} grade math achievement, where non-native English speaking students with higher 10^{th} grade math achievement were more likely to be in the *HMH* class compared to the *HL* class. This finding is similar for native English speakers, where students with higher scores on their 10^{th} grade math achievement tests were more likely to be in the *HH* compared to the *MLH, LL,* or *HL* classes. This finding highlights the importance of positive math attitudes and math self-efficacy with math achievement.

Research Question 3 (Community College): To what extent do students' math attitudes and math self-efficacy contribute to their 12^{th} grade math achievement, and how does this differ between non-native English speakers and native English speakers?

Native English speakers. As seen in Table 15, non-native English speakers in the *HH* class had the highest 12^{th} grade math standardized test score, with a mean of 52.67. It is interesting to point out that those in the *LH* class were not far behind in achievement scores compared to the *HH* class, where students in the *LH* class had a mean score of 52.02. This comparison was not statistically significant from the *HH* class.

Non-native English speakers. Table 16 displays the math achievement test scores among non-native English speaking community college graduates. Students with high math attitudes and medium to high math self-efficacy (*HMH*) had the highest math achievement scores among the other classes, with a mean of 46.78. It is also evident that students in the *HL* and *LL* do not have much difference in math achievement scores since the comparison is not statistically significant.

Table 15

12th Grade Math Achievement for Native English Speaking Community College Graduates

Latent Classes	Mean (SE)
LH vs. MLH (Class 1 vs. Class 2)	**52.02 (0.85) vs. 49.37 (0.82)**
LH vs. LL (Class 1 vs. Class 3)	**52.02 (0.85) vs. 47.45 (0.38)**
LH vs. HL (Class 1 vs. Class 4)	**52.02 (0.85) vs. 44.60 (0.73)**
LH vs. HH (Class 1 vs. Class 5)	52.02 (0.85) vs. 52.67 (0.66)
MLH vs. LL (Class 2 vs. Class 3)	**49.37 (0.82) vs. 47.45 (0.38)**
MLH vs. HL (Class 2 vs. Class 4)	**49.37 (0.82) vs. 44.60 (0.73)**
MLH vs. HH (Class 2 vs. Class 5)	**49.37 (0.82) vs. 52.67 (0.66)**
LL vs. HL (Class 3 vs. Class 4)	**47.45 (0.38) vs. 44.60 (0.73)**
LL vs. HH (Class 3 vs. Class 5)	**47.45 (0.38) vs. 52.67 (0.66)**
HL vs. HH (Class 4 vs. Class 5)	**44.60 (0.73) vs. 52.67 (0.66)**

Note. N = 1,160. LH = *Low Math Attitudes, High Math Self-Efficacy*; MLH = *Medium Math Attitude, Low-High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HL = *High 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 16

12th Grade Math Achievement for Non-Native English Speaking Community College Graduates

Latent Classes	Mean (SE)
HL vs. HMH (Class 1 vs. Class 2)	44.06 (1.04) vs. 46.78 (1.08)
HL vs. LL (Class 1 vs. Class 3)	44.06 (1.04) vs. 44.12 (0.93)
HMH vs. LL (Class 2 vs. Class 3)	46.78 (1.08) vs. 44.12 (0.93)

Note. N = 190. HL = *High Math Attitude, Low Math Self-Efficacy*; HMH = *High Math Attitude, Medium-High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*.

Comparison between native and non-native English speakers. Figure 10 displays students' 12^{th} grade math achievement for native and non-native English speaking community college graduates. From this bar graph, it is clear that native English speakers' in the *HH* class had the highest average 12^{th} grade math achievement score with a mean of 52.67, and the *HL* class had the lowest average math achievement score with a mean of 44.60. A similar pattern emerges for non-native English speaking students, where the highest average 12^{th} grade math achievement is from the *HMH* class with a mean of 46.78, and the lowest average is from the *HL* class with a mean of 44.06.

For non-native English speakers, students in the *HL* class looked very similar to the *LL* class in terms of math achievement. In other words, even with high math attitudes, the average math achievement scores were the lowest for this *HL* class, suggesting that high math self-efficacy is more important in predicting 12^{th} grade math achievement. A similar pattern holds for native English speakers, where there was no significant difference in 12^{th} grade math achievement between the *LH* and the *HH* class. This suggests that students in the *LH* class look similar to students in the *HH* class in terms of 12^{th} grade math achievement. Furthermore, this suggests that having high math self-efficacy is important for having high 12^{th} grade math achievement scores, regardless of math attitudes. These combined results suggest that math self-efficacy is more important that math attitudes in predicting 12^{th} grade math achievement.

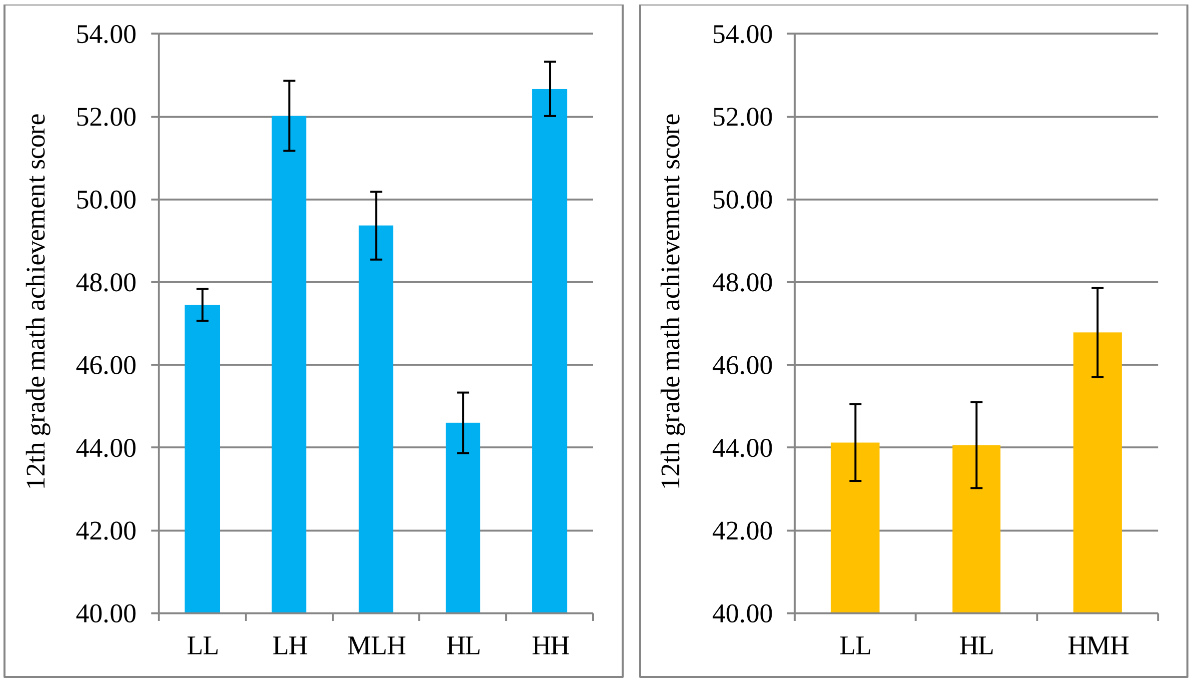

Figure 10. Community College: 12th grade math achievement by class for native English speakers (left) and non-native English speakers (right). Error bars represent standard error of the mean.

Research Question 4 (Community College): To what extent do students' math attitudes and math self-efficacy contribute to their STEM degree? How does this differ between non-native English speakers and native English speakers?

One of the distal outcomes used in this study was whether or not students attained a degree in STEM. Results are presented for native and non-native English speaking community college graduates below.

Native English speakers. Table 17 displays the STEM degree results for native English speaking community college graduates. Students in the *HH* class had the highest proportion of students with a STEM associate's degree or undergraduate certificate (17%), and this was statistically different from students with low math self-efficacy, which includes the *LL* class with 7% of students with a STEM degree and the *HL* class with 8% of students with a STEM degree. This finding suggests that having high math self-efficacy is more important in predicting STEM degrees regardless of math attitudes. In addition, students in the *MLH* class had 14% of students with a STEM degree and this was statistically significant from the 7% of students in the *LL* class.

Table 17

Proportion of Native English Speaking Community College Graduates with a STEM Degree

Latent Classes	Mean (SE)
LH vs. MLH (Class 1 vs. Class 2)	.12 (0.03) vs. .14 (0.03)
LH vs. LL (Class 1 vs. Class 3)	.12 (0.03) vs. .07 (0.01)
LH vs. HL (Class 1 vs. Class 4)	.12 (0.03) vs. .08 (0.03)
LH vs. HH (Class 1 vs. Class 5)	.12 (0.03) vs. .17 (0.03)
MLH vs. LL (Class 2 vs. Class 3)	**.14 (0.03) vs. .07 (0.01)**
MLH vs. HL (Class 2 vs. Class 4)	.14 (0.03) vs. .08 (0.03)
MLH vs. HH (Class 2 vs. Class 5)	.14 (0.03) vs. .17 (0.03)
LL vs. HL (Class 3 vs. Class 4)	.07 (0.01) vs. .08 (0.03)
LL vs. HH (Class 3 vs. Class 5)	**.07 (0.01) vs. .17 (0.03)**
HL vs. HH (Class 4 vs. Class 5)	**.08 (0.03) vs. .17 (0.03)**

Note. N = 1,160. LH = *Low Math Attitudes, High Math Self-Efficacy*; MLH = *Medium Math Attitude, Low-High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HL = *High Math Attitude, Low Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*. Bolded values indicate significant differences at the p = .05 level.

Non-native English speakers. Table 18 displays the STEM degree results for non-native English speaking community college graduates. There were 13% of students in the *HMH* class with a STEM associate's degree or undergraduate certificate, but this was not significantly different from the other classes (i.e., *HL* or *LL*) with 8% of students with a STEM degree.

Table 18

Proportion of Non-Native English Speaking Community College Graduates with a STEM Degree

Latent Classes	Mean (SE)
HL vs. HMH (Class 1 vs. Class 2)	.08 (0.05) vs. .13 (0.04)
HL vs. LL (Class 1 vs. Class 3)	.08 (0.05) vs. .08 (0.04)
HMH vs. LL (Class 2 vs. Class 3)	.13 (0.04) vs. .08 (0.04)

Note. N = 190. HL = *High Math Attitude, Low Math Self-Efficacy*; HMH = *High Math Attitude, Medium-High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*.

Comparison between native and non-native English speakers. Figure 11 shows the proportion of STEM degree attainment by class for both English proficiency groups. From this bar graph, it is apparent that students in the *HH* class had the highest proportion of STEM degree recipients with a mean of .17 for native English speakers, compared to .13 for the *HMH* class for non-native English speakers. The lowest proportion of STEM degree recipients for both groups was from students in the *LL* class, where the average was .07 for native English speakers and .08 for non-native English speakers.

A clear pattern emerges for native English speakers, where given the same math attitudes, but increasing in math self-efficacy, there is an increasing proportion of students pursuing a STEM degree. For example, when examining students with low math attitudes (i.e., *LL* and *LH*), students with higher math self-efficacy (i.e., *LH*) had higher proportion of students with a STEM degree. The same is true for students with high math attitudes (i.e., *HL*, *HH*). This shows the importance and significance of math self-efficacy on STEM degree attainment, where those with higher math self-efficacy have a higher proportion of students with a STEM degree, regardless of math attitude. A similar pattern is evident for non-native English speakers, where regardless of math attitudes, those with low math self-efficacy had a lower proportion of STEM degree recipients compared to students with high math self-efficacy. This suggests that non-native English speakers in the *HL* class look similar to those in the *LL* class in terms of STEM degree attainment and that increasing in math self-efficacy results in an increase in the proportion of non-native English speakers with a STEM degree.

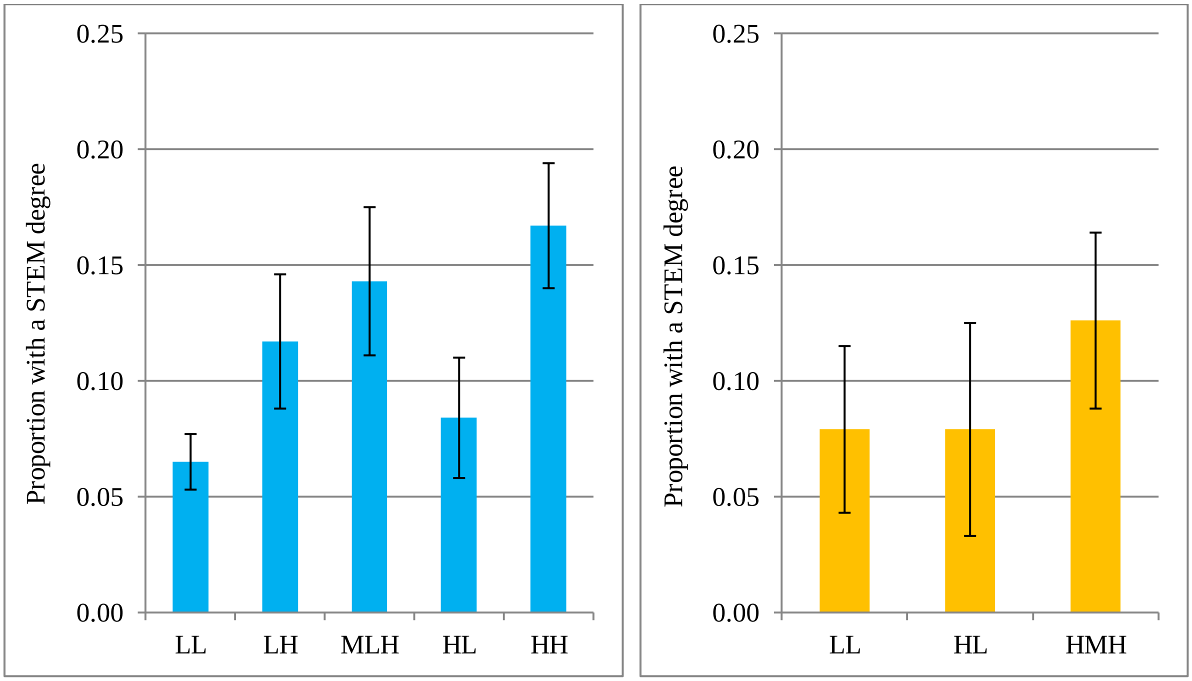

Figure 11. Community College: Proportion of students with a STEM degree by class for native English speakers (left) and non-native English speakers (right). Error bars represent standard error of the mean.

Research Question 5 (Community College): To what extent do students' math attitudes and math self-efficacy contribute to their STEM career? How does this differ between non-native English speakers and native English speakers?

The second distal outcome used in this study was a dichotomous variable indicating whether or not students attained an occupation in a STEM field. Results are presented for native and non-native English speaking community college graduates respectively.

Native English speakers. Table 19 displays the STEM career results for native English speaking community college graduates. Students in the *HH* class had the highest proportion of students with a STEM occupation (7%) as of the third follow up data collection, and this was significantly different from the 2% of students in the *HL* class. It is interesting to note that there were 2% of students in the *HL* class that pursued a STEM career compared to the 3% of students in the *LL* class; however this was not statistically significant.

Table 19

Proportion of Native English Speaking Community College Graduates with a STEM Occupation

Latent Classes	Mean (SE)
LH vs. MLH (Class 1 vs. Class 2)	.05 (0.02) vs. .05 (0.02)
LH vs. LL (Class 1 vs. Class 3)	.05 (0.02) vs. .03 (0.01)
LH vs. HL (Class 1 vs. Class 4)	.05 (0.02) vs. .02 (0.01)
LH vs. HH (Class 1 vs. Class 5)	.05 (0.02) vs. .07 (0.02)
MLH vs. LL (Class 2 vs. Class 3)	.05 (0.02) vs. .03 (0.01)
MLH vs. HL (Class 2 vs. Class 4)	.05 (0.02) vs. .02 (0.01)
MLH vs. HH (Class 2 vs. Class 5)	.05 (0.02) vs. .07 (0.02)
LL vs. HL (Class 3 vs. Class 4)	.03 (0.01)vs. .02 (0.01)
LL vs. HH (Class 3 vs. Class 5)	.03 (0.01) vs. .07 (0.02)
HL vs. HH (Class 4 vs. Class 5)	**.02 (0.01) vs. .07 (0.02)**

Note. N = 1,160. LH = *Low Math Attitudes, High Math Self-Efficacy*; MLH = *Medium Math Attitude, Low-High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HL = *High Math Attitude, Low Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*. Bolded values indicate significant differences at the $p = .05$ level.

Non-native English speakers. Table 20 displays the STEM degree results for non-native English speaking community college graduates. There were 6% of students in the *HMH* class with a STEM career, but this was not significantly different from the *HL* or *LL* classes with 3% and 2% of students with a STEM degree, respectively.

Table 20

Proportion of Non-Native English Speaking Community College Graduates with a STEM Occupation

Latent Classes	Mean (SE)
HL vs. HMH (Class 1 vs. Class 2)	.03 (0.03) vs. .06 (0.03)
HL vs. LL (Class 1 vs. Class 3)	.03 (0.03) vs. .02 (0.02)
HMH vs. LL (Class 2 vs. Class 3)	.06 (0.03) vs. .02 (0.02)

Note. N = 190. HL = *High Math Attitude, Low Math Self-Efficacy*; HMH = *High Math Attitude, Medium-High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*.

Comparison between native and non-native English speakers. Figure 12 displays the proportion of students with a STEM career by latent class for native and non-native English speakers. This graph shows that the highest proportion of STEM career seekers were from individuals in the *HH* class for native English speakers, with a mean of .07, and individuals in the *HMH* class for non-native English speakers, with a mean of .06. On the other hand, the lowest proportion of STEM career seekers was from the *HL* class for the native English speakers, with a mean of .02, and for the *LL* class for non-native English speakers, with an average of .02. For non-native English speakers, there was an increasing trend of positive math attitudes and math self-efficacy associated with more STEM career seekers. For instance moving from low math self-efficacy to medium-high math self-efficacy resulted in an increase in the proportion of students with a STEM career. However this pattern was not true for native English speakers, where the *HL* class had a lower proportion of individuals with a STEM career (.02) compared to the *LL* class (.03). These results suggest that math attitudes and math self-efficacy operate differently for each English proficiency group. What is interesting to note is that the students in the *HL* class had the lowest STEM career seekers, suggesting that maybe researchers and educators should focus interventions directed at improving their math self-efficacy instead of focusing on only the *LL* group.

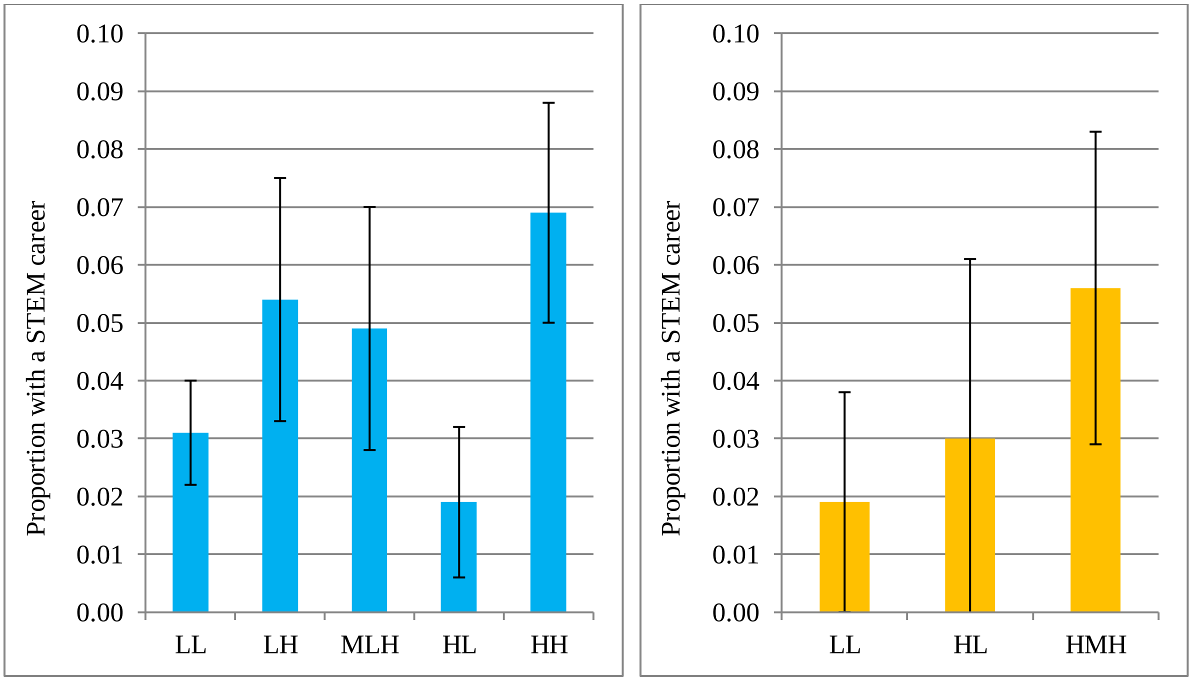

Figure 12. Community College: Proportion of students with a STEM career by class for native English speakers (left) and non-native English speakers (right). Error bars represent standard error of the mean.

University Graduates

The third set of latent class analyses was conducted on university graduates who attained a bachelor's degree or higher as of the third follow up of data collection. The results presented in the following section address the research questions for native and non-native English speakers accordingly.

Native English speakers. Table 21 displays the fit statistics for native English speaking university graduates. Although several fit statistics indicate a seven class model (i.e., the non-significant *p*-value of the LMRT for the eight-class solution and small ABIC value), a six-class solution was selected based on the smallest BIC value and large cmP value and applying the parsimony principle.

Table 21

Latent Class Analysis Fit Indices for Native English Speaking University Graduates

Number of classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of LMRT	BF	cmP
1	-17785.26	35635.72	35610.30	-	-	0.00	0.00
2	-13380.43	26899.43	26845.41	< .001	< .001	0.00	0.00
3	-12958.47	26128.87	26046.25	< .001	< .001	0.00	0.00
4	-12656.86	25599.00	25487.79	< .001	< .001	0.00	0.00
5	-12531.97	25422.58	25282.77	< .001	.003	0.00	0.00
6	-12464.53	**25361.06**	25192.66	< .001	< .001	1.94 e6	**1.00**
7	-12440.03	25385.42	**25188.41**	< .001	**.001**	**1.05 e8**	0.00
8	-12421.82	25422.36	25196.76	< .001	.358	N/A	0.00

Note. N = 3,470. BIC=Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT=Bootstrap Likelihood Ratio Test; LMRT=Lo-Mendell-Rubin Adjusted Likelihood Ratio Test; BF=Bayes Factor; cmP=Correct Model Probability. Bolded values indicate the preferred model by the given fit index.

Non-native English speakers. Table 22 displays the fit statistics for non-native English speaking university graduates. The *p*-value for the LMRT suggests a five-class solution, while the smallest BIC value and large cmP values suggest a four-class solution. The four-class solution was selected using the parsimony principle. Results from Tables 21 and 22, illustrate the differences in the number of classes of math attitudes and self-efficacy beliefs among native and non-native English speaking students with a STEM occupation.

Table 22

Latent Class Analysis Fit Indices for Non-Native English Speaking University Graduates

Number of classes	Log likelihood	BIC	ABIC	*p*-value of BLRT	*p*-value of LMRT	BF	cmP
1	-2768.75	5588.13	5562.731	-	-	0.00	0.00
2	-2141.77	4391.11	4337.146	< .001	< .001	0.00	0.00
3	-2075.12	4314.77	4232.232	< .001	< .001	0.00	0.00
4	-2017.03	**4255.53**	4144.425	< .001	.002	86.79	**0.99**
5	-1993.02	4264.46	4124.782	< .001	**.024**	**7.91 e5**	0.01
6	-1978.12	4291.62	4123.373	< .001	.117	N/A	0.00

Note. N = 560. BIC=Bayesian Information Criterion; ABIC = Adjusted BIC; BLRT=Bootstrap Likelihood Ratio Test; LMRT=Lo-Mendell-Rubin Adjusted Likelihood Ratio Test; BF=Bayes Factor; cmP=Correct Model Probability. Bolded values indicate the preferred model by the given fit index.

Research Question 1 (University): How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?

Native English speakers. The item probability plot presented in Figure 13 was used to identify a six-class model, which include the following labeled classes: (1) *Low math attitudes, High math self-efficacy (LH)* (14.7%); (2) *High math attitudes, High math self-efficacy (HH)* (27.6%); (3) *Low math attitudes, Low math self-efficacy (LL)* (24.7%); (4) *High math attitudes, Medium-High math self-efficacy (HMH)* (8.7%); (5) *High math attitudes, Low math self-efficacy (HL)* (10.5%); and (6) *Low math attitudes, Medium-High math self-efficacy (LMH)* (13.9%).

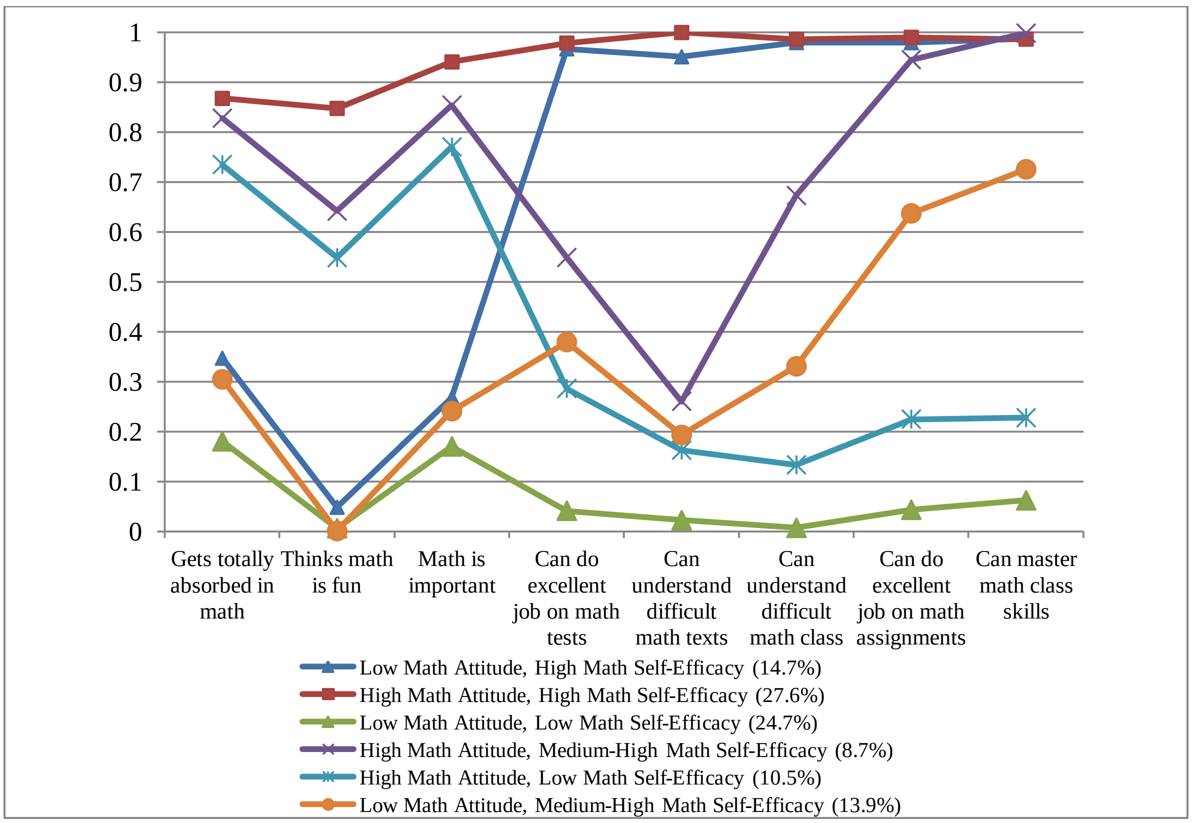

Figure 13. Item probability plot for native English speaking university graduates

Non-native English speakers. Figure 14 displays the item probability plot for non-native English speaking university graduates. A four-class model was identified and labeled as follows: (1) *Low math attitudes, Low math self-efficacy (LL)* (23.0%); (2) *High math attitudes, Low math self-efficacy (HL)* (21.5%); (3) *Low math attitudes, High math self-efficacy (LH)* (20.1%); and (4) *High math attitudes, High math self-efficacy (HH)* (35.4%).

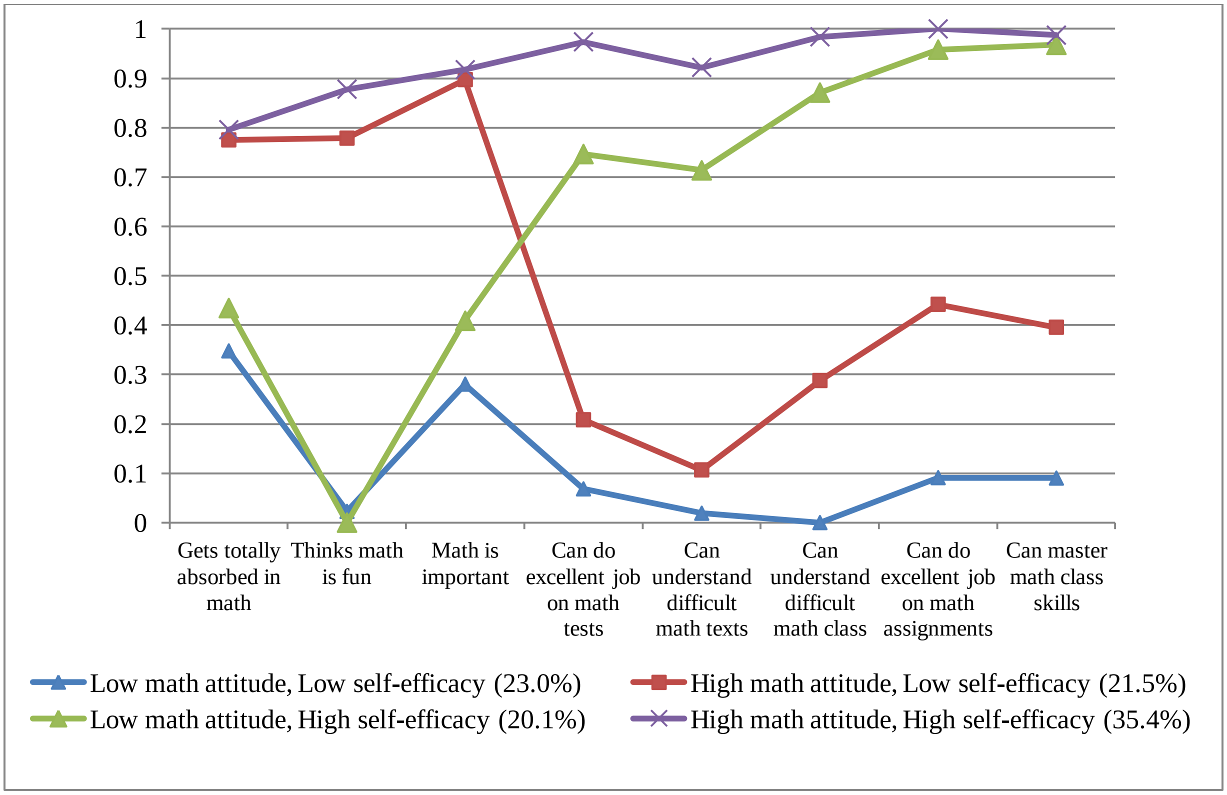

Figure 14. Item probability plot for non-native English speaking university graduates

Comparison between native and non-native English speakers. By looking at Figures 13 and 14, it is clear that there are differences in the types of classes of math attitudes and math self-efficacy for native and non-native English speakers. There were six latent classes for native English speakers and four latent classes for non-native English speakers. There is more heterogeneity in the latent classes for native English speakers, where there's variation in the medium-high math self-efficacy. This pattern does not emerge for the non-native English speakers. Instead, what does emerge is an ordered latent class with highs and lows for both math attitude and math self-efficacy.

Research Question 2 (University): What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?

Native English speakers. The relationships of the attitudinal classes with the covariates are presented in Table 23, where the reference class is *HH*. Table 23 reveals that female native English speaking university graduates were more likely to be in the *LL*, *HL*, or *LMH* class compared to the *HH* class, relative to male native English speaking university graduates. In terms of racial/ethnic differences, Latino and African American native English speaking students were more likely to be in the *HH* class compared to the *LH*, *LL*, or *LMH* classes, relative to their white counterparts. In addition, Asian students were more likely to be in the *HL* class than the *HH* class, while students of other race were more likely to be in the *HH* class compared to the *LMH* class, relative to their white counterparts. In addition, students coming from low SES backgrounds were more likely to be in the *HH* class compared to the *LL* class, relative to students from higher SES backgrounds. Similarly, students with higher 10^{th} grade math achievement scores were significantly more likely to be in the *HH* class compared to the other five classes. Students whose highest math courses were above Algebra II were significantly more likely to be in the *HH* class compared to the *LH* or *LL* classes. In addition, those involved in extracurricular activities were more likely to be in the *HH* class compared to the *LH*, *LL*, or *HL* classes.

Table 23

Covariate Table for the 6-Class Model for Native English Speaking University Graduates

Latent Classes	Effect	Logit		SE	OR
Low MA, High MSE (14.7%)	Female	0.02		0.15	1.02
	Latino	-1.25	*	0.48	0.29
	African American	-0.88	*	0.36	0.42
	Asian	0.23		0.42	1.25
	Other Race	-0.40		0.38	0.67
	First Generation	-1.30		0.77	0.27
	Low SES	-0.57		0.39	0.56
	10th Grade Math Achievement	-0.04	**	0.01	0.96
	College Preparatory Track	-0.29		0.18	0.75
	Math Course Beyond Alg II	-0.47	*	0.21	0.63
	Extracurricular Involvement	-0.42	*	0.21	0.65
Low MA, Low MSE (24.7%)	Female	0.76	***	0.13	2.13
	Latino	-0.71	*	0.31	0.49
	African American	-1.29	***	0.28	0.28
	Asian	0.38		0.38	1.46
	Other Race	-0.21		0.29	0.81
	First Generation	-0.75		0.43	0.47
	Low SES	-0.57	*	0.27	0.57
	10th Grade Math Achievement	-0.13	***	0.01	0.88
	College Preparatory Track	-0.13		0.16	0.88
	Math Course Beyond Alg II	-1.02	***	0.17	0.36
	Extracurricular Involvement	-0.51	**	0.17	0.60
High MA, Med-High MSE (8.7%)	Female	0.35		0.21	1.41
	Latino	0.25		0.39	1.28
	African American	-0.28		0.38	0.76
	Asian	0.97		0.51	2.65
	Other Race	-0.60		0.57	0.55
	First Generation	-0.30		0.67	0.74
	Low SES	-0.01		0.38	0.99
	10th Grade Math Achievement	-0.09	***	0.02	0.92
	College Preparatory Track	-0.32		0.24	0.73
	Math Course Beyond Alg II	-0.36		0.27	0.70
	Extracurricular Involvement	-0.07		0.29	0.94
High MA, Low MSE (10.5%)	Female	0.41	*	0.18	1.51
	Latino	-0.36		0.40	0.70
	African American	-0.11		0.30	0.90
	Asian	1.35	**	0.39	3.87
	Other Race	-1.35		0.76	0.26
	First Generation	-0.86		0.61	0.42
	Low SES	-0.33		0.37	0.72
	10th Grade Math Achievement	-0.10	***	0.01	0.90
	College Preparatory Track	-0.29		0.21	0.75

	Math Course Beyond Alg II	-0.33		0.24	0.72
	Extracurricular Involvement	-0.59	*	0.23	0.56
Low MA, Med-High MSE (13.9%)	Female	0.55	**	0.17	1.73
	Latino	-1.30	*	0.52	0.27
	African American	-0.91	**	0.34	0.40
	Asian	0.24		0.54	1.28
	Other Race	-1.21	*	0.57	0.30
	First Generation	-1.40		1.12	0.25
	Low SES	-0.38		0.35	0.68
	10th Grade Math Achievement	-0.13	***	0.01	0.88
	College Preparatory Track	-0.07		0.20	0.93
	Math Course Beyond Alg II	-0.34		0.22	0.71
	Extracurricular Involvement	-0.12		0.24	0.89

Note. N =3,110. Class percentages are noted in parentheses. Reference class is High Math Attitude, High Math Self-Efficacy (27.6%); Low MA, High MSE = Low Math Attitude, High Math Self-Efficacy; Low MA, Low MSE = Low Math Attitude, Low Math Self-Efficacy; High MA, Med-High MSE = High Math Attitude, Medium to High Math Self-Efficacy; High MA, Low MSE = High Math Attitude, Low Math Self-Efficacy; Low MA, Med-High MSE = Low Math Attitude, Medium to High Math Self-Efficacy; OR = odds ratio
* $p < .05$. ** $p < .01$. *** $p < .001$.

Non-native English speakers. The relationships of the latent classes with the covariates are presented in Table 24, where the reference class is *HH*. Non-native English speaking female students were more likely to be in the *LL* or *LH* class compared to the *HH* class, which suggest that they tended to have lower math attitudes than their male peers. Latino students were more likely to be in *HH* than the *HL* class, relative to their white peers. In addition, first generation immigrant students were more likely to be in the *HH* class than the *LL* or *LH* classes. Also, students with higher 10th grade math achievement scores were more likely to be in the *HH* class than the *HL* or *LL* classes. Additionally, university graduates who were on the college preparatory track were more likely to be in the *HH* class than the *HL* class. Also, university graduates who were involved in extracurricular activities were more likely to be in the *HH* class compared to the *LL* class.

Table 24

Covariate Table for the 4-Class Model Non-native English Speaking University Graduates

Latent Classes	Effect	Logit		SE	OR
Low MA, Low MSE (23.0%)	Female	1.16	***	0.35	3.18
	Latino	-0.58		0.63	0.56
	African American	0.23		1.01	1.25
	Asian	-0.31		0.59	0.74
	Other Race	-0.11		1.00	0.90
	First Generation	-0.80	*	0.32	0.45
	Low SES	0.02		0.35	1.02
	10th Grade Math Achievement	-0.08	***	0.02	0.92
	College Preparatory Track	-0.16		0.37	0.85
	Math Course Beyond Alg II	-0.35		0.39	0.71
	Extracurricular Involvement	-0.68	*	0.34	0.51
High MA, Low MSE (21.5%)	Female	0.09		0.35	1.09
	Latino	-1.39	*	0.66	0.25
	African American	-0.28		1.23	0.76
	Asian	-0.05		0.59	0.95
	Other Race	0.58		0.96	1.78
	First Generation	-0.64		0.34	0.53
	Low SES	0.48		0.37	1.62
	10th Grade Math Achievement	-0.09	***	0.02	0.91
	College Preparatory Track	-0.72	*	0.36	0.49
	Math Course Beyond Alg II	-0.30		0.41	0.74
	Extracurricular Involvement	0.01		0.39	1.01
Low MA, High MSE (20.1%)	Female	0.78	*	0.35	2.18
	Latino	-0.59		0.76	0.55
	African American	-1.42		1.43	0.24
	Asian	-0.42		0.73	0.66
	Other Race	0.08		1.11	1.08
	First Generation	-1.00	*	0.44	0.37
	Low SES	-0.71		0.45	0.49
	10th Grade Math Achievement	-0.04		0.03	0.96
	College Preparatory Track	-0.60		0.43	0.55
	Math Course Beyond Alg II	0.64		0.53	1.90
	Extracurricular Involvement	-0.32		0.42	0.72

Note. N = 450. Class percentages are noted in parentheses. Reference class is High Math Attitude, High Math Self-Efficacy (35.4%); High MA, Low MSE = High Math Attitude, Low Math Self-Efficacy; Low MA, High MSE = Low Math Attitude, High Math Self-Efficacy; Low MA, Low MSE = Low Math Attitude, Low Math Self-Efficacy; OR = odds ratio

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

Comparison between native and non-native English speakers. There are both similarities and differences when comparing the relationship between the latent classes and covariates. In terms of similarities, for both native and non-native English speakers, female students were more like to be in the *LL* class, while Latinos were more likely to be in the *HH* class. Another similarity is that students who had high 10th grade math achievement scores were more likely to be in the *HH* class. In terms of differences, there were some racial/ethnic differences captured among native English speakers that were not captured among non-native English speakers. For instance, African Americans and students of other race were more likely to be in the *HH* class, and Asian students were more like to be in the *HL* class. There were no statistically significant differences for other race/ethnic backgrounds for non-native English speakers. Another difference was that native English speakers who took a math course beyond Algebra II were more likely to be in the *HH* class, but this was not significant for non-native English speakers. In addition non-native English speakers who were on the college preparatory track were more likely to be in the *HH* class, but this was not significant for native English speakers.

Research Question 3 (University): To what extent do students' math attitudes and math self-efficacy contribute to their 12th grade math achievement, and how does this differ between non-native English speakers and native English speakers?

Native English speakers. Results from Table 25 suggest that native English speaking university graduates in the *HH* class had the highest 12th grade math standardized test score, with a mean of 61.26 and this was statistically significant compared to the other five classes. Students in the *LH* class had an average 12th grade math achievement score of 59.59, and the *HMH* class had an average score of 56.62. Students in the *HL* class had an average math achievement score of 55.88. The lowest average math achievement score was from the *LL* class, with a mean of 53.82.

Table 25

12th Grade Math Achievement for Native English Speaking University Graduates

Latent Classes	Mean (SE)
LH vs. HH (Class 1 vs. Class 2)	**59.59 (0.38) vs. 61.26 (0.27)**
LH vs. LL (Class 1 vs. Class 3)	**59.59 (0.38) vs. 53.82 (0.29)**
LH vs. HMH (Class 1 vs. Class 4)	**59.59 (0.38) vs. 56.62 (0.62)**
LH vs. HL (Class 1 vs. Class 5)	**59.59 (0.38) vs. 55.88 (0.52)**
LH vs. LMH (Class 1 vs. Class 6)	**59.59 (0.38) vs. 55.02 (0.44)**
HH vs. LL (Class 2 vs. Class 3)	**61.26 (0.27) vs. 53.82 (0.29)**
HH vs. HMH (Class 2 vs. Class 4)	**61.26 (0.27) vs. 56.62 (0.62)**
HH vs. HL (Class 2 vs. Class 5)	**61.26 (0.27) vs. 55.88 (0.52)**
HH vs. LMH (Class 2 vs. Class 6)	**61.26 (0.27) vs. 55.02 (0.44)**
LL vs. HMH (Class 3 vs. Class 4)	**53.82 (0.29) vs. 56.62 (0.62)**
LL vs. HL (Class 3 vs. Class 5)	**53.82 (0.29) vs. 55.88 (0.52)**
LL vs. LMH (Class 3 vs. Class 6)	**53.82 (0.29) vs. 55.02 (0.44)**
HMH vs. HL (Class 4 vs. Class 5)	56.62 (0.62) vs. 55.88 (0.52)
HMH vs. LMH (Class 4 vs. Class 6)	**56.62 (0.62) vs. 55.02 (0.44)**
HL vs. LMH (Class 5 vs. Class 6)	55.88 (0.52) vs. 55.02 (0.44)

Note. N = 3,110. LH = *Low Math Attitudes, High Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HMH = *High Math Attitude, Medium-High Math Self-Efficacy*; HL = *High Math Attitude, Low Math Self-Efficacy*; LMH = *Low Math Attitude, Medium-High Math Self-Efficacy*. Bolded values indicate significant differences at the p = .05 level.

Non-native English speakers. Table 26 displays the 12th grade math achievement test scores among non-native English speaking university graduates. Similar to the native English speaking students, students in the *HH* class had the highest math achievement score with an average score of 61.14, and this is significantly different from the achievement score of students in the *LL* or *HL* classes. It is interesting to note that 12th grade math achievement of the students in the *LL* (M = 52.87) or *HL* (M = 55.05) classes were not significantly different, which suggests that these two classes may not be that much different from each other. Similarly the 12th grade math achievement of the students in the *LH* (*M* = 59.02) or *HH* (*M* = 61.14) classes were not significant, suggesting that these two high math self-efficacy groups look similar.

Table 26

12th Grade Math Achievement for Non-native English Speaking University Graduates

Latent Classes	Mean
LL vs. HL (Class 1 vs. Class 2)	52.87 (0.89) vs. 55.05 (1.07)
LL vs. LH (Class 1 vs. Class 3)	**52.87 (0.89) vs. 59.02 (1.11)**
LL vs. HH (Class 1 vs. Class 4)	**52.87 (0.89) vs. 61.14 (0.66)**
HL vs. LH (Class 2 vs. Class 3)	**55.05 (1.07) vs. 59.02 (1.11)**
HL vs. HH (Class 2 vs. Class 4)	**55.05 (1.07) vs. 61.14 (0.66)**
LH vs. HH (Class 3 vs. Class 4)	59.02 (1.11) vs. 61.14 (0.66)

Note. N = 450. LL = *Low Math Attitude, Low Math Self-Efficacy*; HL = *High Math Attitude, Low Math Self-Efficacy*; LH = *Low Math Attitudes, High Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*. Bolded values indicate significant differences at the $p = .05$ level.

Comparison between native and non-native English speakers. Figure 15 displays the 12th grade math achievement by latent class for each English proficiency group. Across both native English speakers and non-native English speakers, a distinct pattern emerges. Individuals in the HH class had the highest 12th grade math standardized test score, while individuals in the LL class had the lowest 12th grade math standardized test score. Students in the *LL* class had the lowest math achievement with a mean of 53.82 for native English speakers and a mean of 52.87 for non-native English speakers. Similarly for both groups, the *HH* classes had the highest average 12th grade math achievement score with a mean of 61.26 for native English speakers and a mean of 61.14 for non-native English speakers. It is interesting to note that the highest math achievement for both groups was close, although this comparison is only descriptive and not statistical. This finding sheds light that the achievement gap for native and non-native English speaking students could be closing among students who attained at least a bachelor's degree. These results suggest that regardless of English proficiency, students with higher math attitude and math self-efficacy on average, had higher 12th grade math achievement scores.

Another point worth mentioning is as math attitudes and self-efficacy increases, there is an increase in average 12th grade math achievement. For example, looking at the three latent classes with low math attitudes (i.e., *LL, LMH, LH*), going from low math self-efficacy to high math self-efficacy results in an increase in 12th grade math achievement scores. Similarly for students with high math attitudes (i.e., *HL, HMH, HH*), there is an increase in average math achievement scores. This suggest that having more positive math attitudes and self-efficacy beliefs are important predictors for higher math achievement scores in 12th grade. This trend is similar for non-native English speakers, where having higher math attitudes and self-efficacy positively relates to higher 12th grade math achievement.

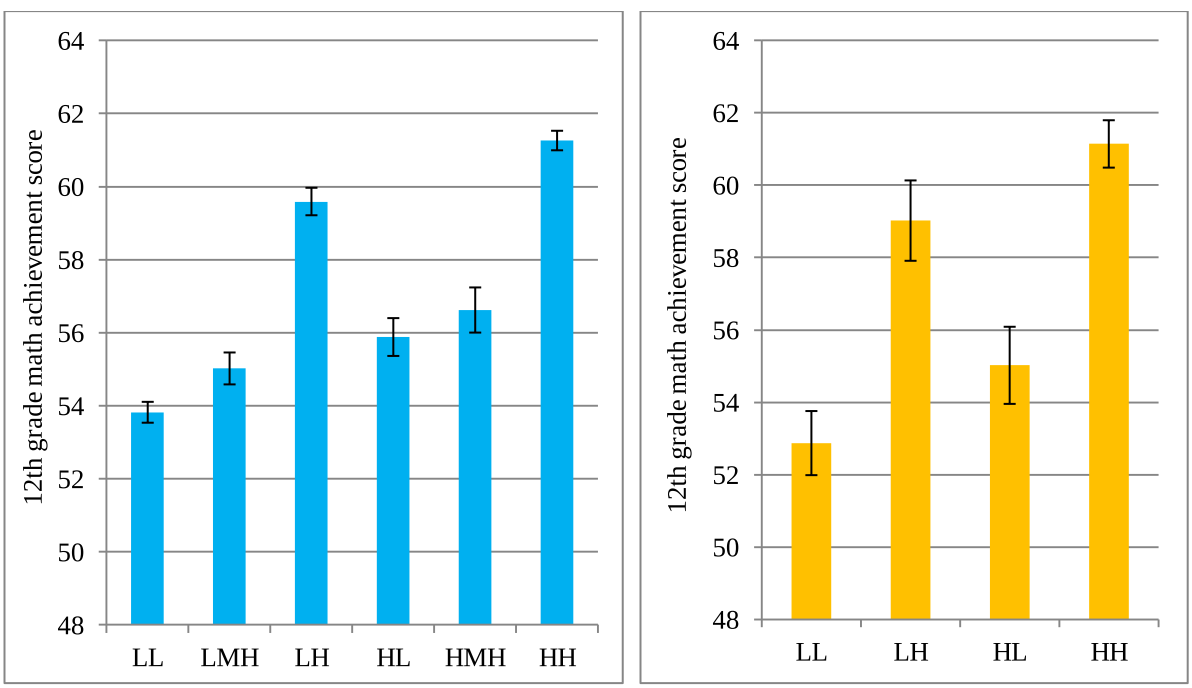

Figure 15. University: 12th grade math achievement by class for native English speakers (left) and non-native English speakers (right). Error bars represent standard error of the mean.

Research Question 4 (University): To what extent do students' math attitudes and math self-efficacy contribute to their STEM degree? How does this differ between non-native English speakers and native English speakers?

Native English speakers. Table 27 displays the proportion of native English speaking university graduates with a STEM degree. Students in the *HH* class had the highest proportion of students with a STEM degree (.29), and this was statistically different from the five other classes, where the mean of STEM degree recipients was .17 for the *LH* class, .08 for the *LL* class, .13 for the *HL* class, .10 for the *LMH* class, and .17 for the *HMH* class.

Table 27
STEM Major for Native English Speaking University Graduates

Latent Classes	Mean (SE)
LH vs. HH (Class 1 vs. Class 2)	**.17 (0.02) vs. .29 (0.02)**
LH vs. LL (Class 1 vs. Class 3)	**.17 (0.02) vs. .08 (0.01)**
LH vs. HMH (Class 1 vs. Class 4)	.17 (0.02) vs. .17 (0.03)
LH vs. HL (Class 1 vs. Class 5)	.17 (0.02) vs. .13 (0.02)
LH vs. LMH (Class 1 vs. Class 6)	**.17 (0.03) vs. .10 (0.02)**
HH vs. LL (Class 2 vs. Class 3)	**.29 (0.02) vs. 08 (0.01)**
HH vs. HMH (Class 2 vs. Class 4)	**.29 (0.02) vs. .17 (0.03)**
HH vs. HL (Class 2 vs. Class 5)	**.29 (0.02) vs. .13 (0.02)**
HH vs. LMH (Class 2 vs. Class 6)	**.29 (0.02) vs. .10 (0.02)**
LL vs. HMH (Class 3 vs. Class 4)	**.08 (0.01) vs. .17 (0.03)**
LL vs. HL (Class 3 vs. Class 5)	.08 (0.01) vs. .13 (0.02)
LL vs. LMH (Class 3 vs. Class 6)	.08 (0.01) vs. .10 (0.02)
HMH vs. HL (Class 4 vs. Class 5)	.17 **(0.03)** vs. .13 (0.02)
HMH vs. LMH (Class 4 vs. Class 6)	**.17 (0.03) vs. .10 (0.02)**
HL vs. LMH (Class 5 vs. Class 6)	.13 (0.02) vs. .10 (0.02)

Note. N = 3,110. LH = *Low Math Attitudes, High Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HMH = *High Math Attitude, Medium-High Math Self-Efficacy*; HL = *High Math Attitude, Low Math Self-Efficacy*; LMH = *Low Math Attitude, Medium-High Math Self-Efficacy*. Bolded values indicate significant differences at the *p* = .05 level.

Non-native English speakers. Table 28 displays the STEM degree results for non-native English speaking university graduates. There were 37% of students in the *HH* class with a STEM degree and this was statistically significant compared to the other three classes, *LL*, *HL*, and *LH*, where the proportion was .15, .24, and .21, respectively.

Table 28

Proportion of Non-native English Speaking University Graduates with a STEM Degree

Latent Classes	Mean (SE)
LL vs. HL (Class 1 vs. Class 2)	.15 (0.04) vs. .24 (0.05)
LL vs. LH (Class 1 vs. Class 3)	.15 (0.04) vs. .21 (0.05)
LL vs. HH (Class 1 vs. Class 4)	**.15 (0.04) vs. .37 (0.04)**
HL vs. LH (Class 2 vs. Class 3)	.24 (0.05) vs. .21 (0.05)
HL vs. HH (Class 2 vs. Class 4)	**.24 (0.05) vs. .37 (0.04)**
LH vs. HH (Class 3 vs. Class 4)	**.21 (0.05) vs. .37 (0.04)**

Note. N = 450. LL = *Low Math Attitude, Low Math Self-Efficacy*; HL = *High Math Attitude, Low Math Self-Efficacy*; LH = *Low Math Attitudes, High Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*. Bolded values indicate significant differences at the p = .05 level.

Comparison between native and non-native English speakers. Figure 16 displays the proportion of students with a STEM degree for native and non-native English speakers by latent classes. A common finding between the native and non-native English speakers is how similar the lowest and highest math attitude and math self-efficacy classes fare on STEM degree attainment. For both groups, the class with the smallest proportion of STEM degree seekers was the *LL* class with a mean of .08 for native English speakers and .15 for non-native English speakers. Similarly for both groups, the highest proportion of STEM degree holders were from students in the *HH* class, where the mean was .29 for native English speakers, and .37 for non-native English speakers. The proportion of non-native English speakers with a STEM degree is higher compared to native English speakers, but this comparison is simply descriptive and not statistical.

Similar to the pattern of increasing math attitudes and self-efficacy relating to positive 12th grade achievement, there is a clear trend of increasing math attitudes and self-efficacy with the increasing percentage of STEM degree recipients. As illustrated in this figure, it is evident that going from low math attitudes to high math attitudes and from low math self-efficacy to high math self-efficacy, there is an increasing proportion of individuals pursuing a STEM degree and that the same is true for both English proficiency groups. These results suggest that having positive math attitudes and math self-efficacy are positively related to STEM degree attainment.

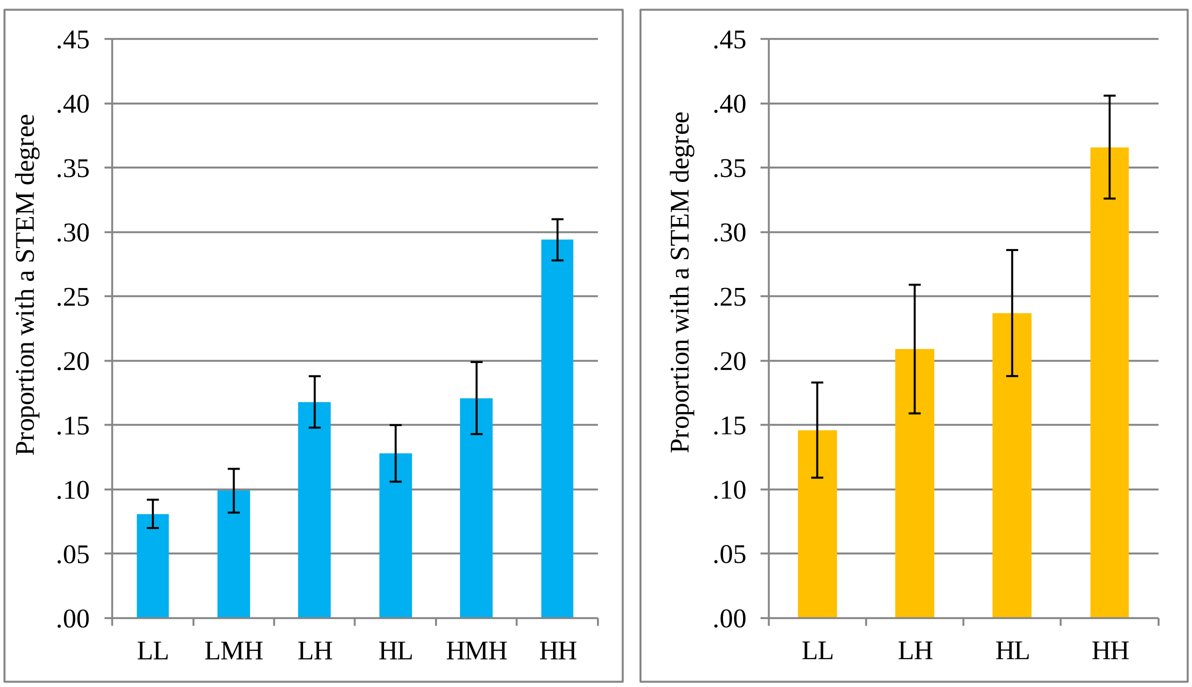

Figure 16. University: Proportion of students with a STEM degree by class for native English speakers (left) and non-native English speakers (right). Error bars represent standard error of the mean.

Research Question 5 (University): To what extent do students' math attitudes and math self-efficacy contribute to their STEM career? How does this differ between non-native English speakers and native English speakers?

Native English speakers. Table 29 displays the proportion of native English speaking university graduates with a STEM career. Students in the *HH* class had the highest proportion of students with a STEM occupation (19%) as of the third follow up data collection, and this is significantly different from the five other classes, where the average was .11 for the *LH* class, .05 for the *LL* class, .10 for the *HMH* class, .07 for the *LMH* class, and .11 for the *HL* class.

Table 29

Proportion of Native English Speaking University Graduates with a STEM Occupation

Latent Classes	Mean (SE)
LH vs. HH (Class 1 vs. Class 2)	**.11 (0.02) vs. .19 (0.01)**
LH vs. LL (Class 1 vs. Class 3)	**.11 (0.02) vs. .05 (0.01)**
LH vs. HMH (Class 1 vs. Class 4)	.11 (0.02) vs. .10 (0.02)
LH vs. HL (Class 1 vs. Class 5)	.11 (0.02) vs. .11 (0.02)
LH vs. LMH (Class 1 vs. Class 6)	.11 (0.02) vs. .07 (0.01)
HH vs. LL (Class 2 vs. Class 3)	**.19 (0.01) vs. .05 (0.01)**
HH vs. HMH (Class 2 vs. Class 4)	**.19 (0.01) vs. .10 (0.02)**
HH vs. HL (Class 2 vs. Class 5)	**.19 (0.01) vs. .11 (0.02)**
HH vs. LMH (Class 2 vs. Class 6)	**.19 (0.01) vs. .07 (0.01)**
LL vs. HMH (Class 3 vs. Class 4)	**.05 (0.01) vs. .10 (0.02)**
LL vs. HL (Class 3 vs. Class 5)	**.05 (0.01) vs. .11 (0.02)**
LL vs. LMH (Class 3 vs. Class 6)	.05 (0.01) vs. .07 (0.01)
HMH vs. HL (Class 4 vs. Class 5)	.10 (0.02) vs. .11 (0.02)
HMH vs. LMH (Class 4 vs. Class 6)	.10 (0.02) vs. .07 (0.01)
HL vs. LMH (Class 5 vs. Class 6)	.11 (0.02) vs. .07 (0.01)

Note. N = 3,110. LH = *Low Math Attitudes, High Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*; LL = *Low Math Attitude, Low Math Self-Efficacy*; HMH = *High Math Attitude, Medium-High Math Self-Efficacy*; HL = *High Math Attitude, Low Math Self-Efficacy*; LMH = *Low Math Attitude, Medium-High Math Self-Efficacy*. Bolded values indicate significant differences at the p = .05 level.

Non-native English speakers. Table 30 displays the STEM degree results for non-native English speaking university graduates. There were 23% of students in the *HH* class with a STEM career, and this is significantly different from the *HL* and *LL* class with 9% and 11% of students with a STEM degree, respectively.

Table 30

Proportion of Non-native English Speaking University Graduates with a STEM Occupation

Latent Classes	Mean (SE)
LL vs. HL (Class 1 vs. Class 2)	.11 (0.03) vs. .09 (0.04)
LL vs. LH (Class 1 vs. Class 3)	.11 (0.03) vs. .13 (0.04)
LL vs. HH (Class 1 vs. Class 4)	**.11 (0.03) vs. .23 (0.04)**
HL vs. LH (Class 2 vs. Class 3)	.09 (0.04) vs. .13 (0.04)
HL vs. HH (Class 2 vs. Class 4)	**.09 (0.04) vs. .23 (0.04)**
LH vs. HH (Class 3 vs. Class 4)	.13 (0.04) vs. .23 (0.04)

Note. N = 450. LL = *Low Math Attitude, Low Math Self-Efficacy*; HL = *High Math Attitude, Low Math Self-Efficacy*; LH = *Low Math Attitudes, High Math Self-Efficacy*; HH = *High Math Attitude, High Math Self-Efficacy*. Bolded values indicate significant differences at the *p* = .05 level.

Comparison between native and non-native English speakers. Figure 17 depicts the proportion of STEM career seekers by latent class for native and non-native English speakers. Similar to the results found for university graduates' 12th grade math achievement and STEM degree attainment, there was a similar pattern for students with a STEM career, where students in the *HH* class had the highest proportion of individuals in STEM careers. However what is different is how there is no clear trend with increasing math attitude and math self-efficacy beliefs. In contrast to the results from the 12th grade math achievement and STEM degree attainment, there is a different pattern in terms of the lowest and highest proportion of STEM career seekers. The highest proportion of STEM career seekers was .19 for native English speakers and .23 for non-native English speakers in the *HH* classes. However, the lowest proportion of STEM career holders was .05 for native English speakers in the *LL* class and .09 for non-native English speakers in the *HL* class. This finding suggests there are differences in how math attitudes and self-efficacy function for native and non-native English speakers in terms of STEM career attainment and that there may be other influential factors that are not explained by students' math attitudes and self-efficacy. Another interesting point to note is that regardless of math attitudes, students with high math self-efficacy (i.e., *LH* or *HH*) had the highest proportion of students in a STEM career and this was true for both native and non-native English speakers. This finding also suggests that perhaps having high math self-efficacy matters more, where individuals are likely to pursue a job in which they feel confident.

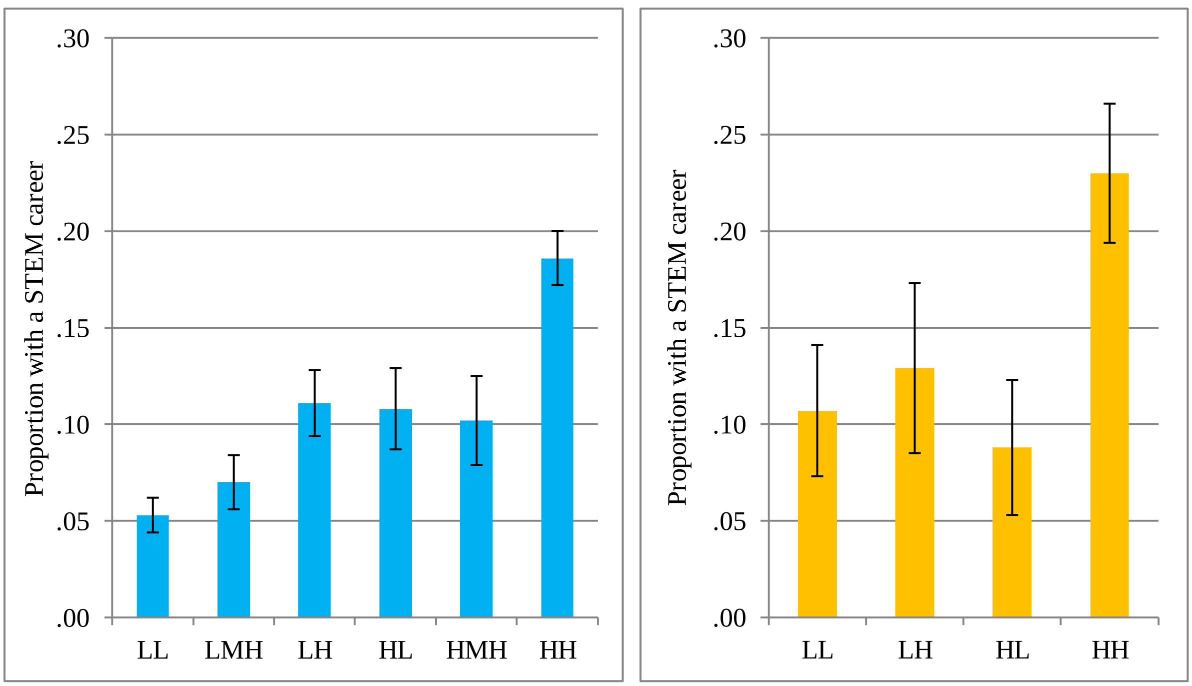

Figure 17. University: Proportion of students with STEM careers by class for native English speakers (left) and non-native English speakers (right). Error bars represent standard error of the mean.

The following two research questions uses regression mixture analysis to examine differential effects for native and non-native English speaking university graduates holding at least a bachelor's degree.

Research Question 6 (University): Are there differential effects in the relationship between 12th grade math achievement and STEM degree for students holding at least a bachelor's degree? Does this differ between native and non-native English speakers?

Native English speakers. Table 31 displays the results from regression STEM degree attainment on 12th grade math achievement for each class for native English speaking university graduates. These results suggest that for students in the *LL* class, scoring higher on 12th grade math achievement is significant for predicting STEM degree attainment. For a one unit increase in math score, there is an 8% increase in the odds of attaining a STEM degree for those in the *LL* class. Similarly for students in the *HH* class, 12th grade math achievement significantly predicted STEM degree attainment. More specifically, for a one unit increase in 12th grade math achievement, there is a 9% increase in the odds of attaining a STEM degree. When comparing the point estimates across classes, there were no significant differences.

Table 31

Parameter Estimates for Regressing STEM Degree on 12th Grade Math Achievement for Native English Speakers, By Class

Latent Classes	Logit		SE	OR
Low Math Attitude, Low Math Self-Efficacy (24.7%)	.08	*	.03	1.08
High Math Attitude, Low Math Self-Efficacy (10.5%)	.07		.04	1.07
Low Math Attitude, Medium-High Math Self-Efficacy (13.9%)	.05		.05	1.05
High Math Attitude, Medium-High Math Self-Efficacy (8.7%)	.05		.03	1.05
Low Math Attitude, High Math Self-Efficacy (14.7%)	.04		.03	1.04
High Math Attitude, High Math Self-Efficacy (27.6%)	.09	***	.02	1.09

Note. $N = 3{,}050$

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

Non-native English speakers. Table 32 displays results from regressing STEM degree attainment on 12th grade math achievement for each class for non-native English speaking university graduates. The results indicate that for those in the *LL* class, for an increase in math achievement test score, there is significant increase in the likelihood of attaining a STEM degree, where a one point increase in 12th grade math score resulted in an 11% increase in the odds of attaining a degree in STEM. For individuals in the *HH* class, there was also a significant relationship between 12th grade math achievement score with STEM degree attainment, where a one point increase on math test score resulted in a 9% increase in the odds of attaining a STEM degree. This is interesting to note and will be discussed in further detailed in the discussion chapter.

Table 32

Parameter Estimates for Regressing STEM Degree on 12th Grade Math Achievement for Non-Native English Speakers, By Class

Latent Classes	Logit		SE	OR
Low Math Attitude, Low Math Self-Efficacy (23.0%)	.10	*	.04	1.11
High Math Attitude, Low Math Self-Efficacy (21.5%)	.06		.04	1.06
Low Math Attitude, High Math Self-Efficacy (20.1%)	.06		.05	1.06
High Math Attitude, High Math Self-Efficacy (35.4%)	.09	**	.03	1.09

Note. $N = 440$
* $p < .05$, ** $p < .01$, *** $p < .001$

Comparison between native and non-native English speakers. There are similarities in the results presented in Tables 31 and 32, where the logit coefficients were statistically significant for both *LL* and *HH* classes for native and non-native English speakers. This suggests that the path from 12th grade math achievement to STEM degree attainment is significant for the *LL* and *HH* classes for both native and non-native English speakers. There was a difference in the magnitude of the logit coefficient for the *LL* and *HH* classes, but this difference was not compared statistically across proficiency groups.

Research Question 7 (University): Are there differential effects in the relationship between STEM degree and STEM career for students holding at least a bachelor's degree? Does this differ between native and non-native English speakers?

Native English speakers. Table 33 displays the results from regressing STEM occupation on STEM degree attainment for each latent class for native English speaking university graduates. For every class, there was a significant path from STEM degree to STEM career. These results suggest that regardless of latent class, STEM degree is a significant predictor for STEM occupation for native English speakers.

Table 33

Parameter Estimates for Regressing STEM Occupation on STEM Degree Attainment for Native English Speakers, By Class

Latent Classes	Logit		SE	OR
Low Math Attitude, Low Math Self-Efficacy (24.7%)	2.05	***	.55	7.77
High Math Attitude, Low Math Self-Efficacy (10.5%)	3.12	***	.56	22.65
Low Math Attitude, Medium-High Math Self-Efficacy (13.9%)	3.69	***	.79	40.04
High Math Attitude, Medium-High Math Self-Efficacy (8.7%)	2.59	***	.72	13.33
Low Math Attitude, High Math Self-Efficacy (14.7%)	3.16	***	.47	23.57
High Math Attitude, High Math Self-Efficacy (27.6%)	2.99	***	.25	19.89

Note. N = 3,050. Standard errors in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Non-native English speakers. Table 34 displays the results from regression STEM occupation on STEM degree attainment for each class for non-native English speaking university graduates. These results suggest that for individuals in the *LL* and *HH* class, there is a significant relationship between STEM degree attainment and STEM occupation attainment. More specifically, for individuals in the *LL* class, holding a STEM degree results in a 40% increase in the odds of attaining a STEM occupation. For individuals in the *HH* class, holding a STEM degree results in a 21% increase in the odds of attaining a STEM occupation. Discussion and implications of these results as well as future areas of research are discussed in the following chapter.

Table 34

Parameter Estimates for Regressing STEM Occupation on STEM Degree Attainment for Non-Native English Speakers, By Class

Latent Classes	Logit		SE	OR
Low Math Attitude, Low Math Self-Efficacy (23.0%)	3.70	***	1.04	40.45
High Math Attitude, Low Math Self-Efficacy (21.5%)	2.66		2.41	14.30
Low Math Attitude, High Math Self-Efficacy (20.1%)	1.98		1.04	7.24
High Math Attitude, High Math Self-Efficacy (35.4%)	3.07	**	0.63	21.54

Note. N = 440. Standard errors in parentheses.
* $p < .05$, ** $p < .01$, *** $p < .001$

Comparison between native and non-native English speakers. There are similarities and differences when comparing the regression mixture models of STEM occupation on STEM degree attainment between native and non-native English speakers. For native English speakers, this regression was positive and significant for all six latent classes. However for non-native English speakers, only two of the four latent classes had positive and significant logit coefficients. This suggests that there are differences in how this relationship of STEM degree and STEM career attainment operates for each of the latent classes, particularly for non-native English speakers. Conducting this analysis allowed for the differential effects to emerge for each class and each proficiency group.

The next chapter provides a discussion of the results from the study as well as the limitations and future areas of research.

V. Discussion

Overall, the findings from this study support and refine the theoretical framework of social cognitive career theory developed by Lent et al. (1994). More specifically, the results from this study extend social cognitive career theory to non-native and native English speakers, and also provide information on how math attitudes and math self-efficacy beliefs differ within each English proficiency group at each educational attainment level. The findings from this study support the logical basis of SCCT that there are many complex factors that influence students' STEM outcomes. The result of fitting independent LCAs on each of the non-native and native English speakers for each educational attainment levels revealed that there were different patterns of math attitudes and math self-efficacy for each English proficiency group. Combining the English proficiency groups into one group masks these differences. Thus, without doing this analysis, this interesting result would have been overlooked and it would not have been known that there was 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 non-native English speakers are the same, but that they have different profiles and experiences, which lead to different STEM outcomes.

Summary of Results

Given the numerous results presented thus far, a table summarizing the results for each research question, educational attainment level, and English proficiency group is provided in Table 35. In summary, the findings revealed that there are both common and unique findings, which will be presented in the following section.

Table 35

Summary of Results

Research Question	HS Non-Native English Speakers (*n*=560)	HS Native English Speakers (*n*=3,070)	CC Non-Native English Speakers (*n*=250)	CC Native English Speakers (*n*=1,360)	Univ Non-Native English Speakers (*n*=560)	Univ Native English Speakers (*n*=3,470)
How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?	1. HL (24.3%) 2. LL (31.1%) 3. HH (44.6%)	1. HL (17.7%) 2. LH (21.1%) 3. LL (39.7%) 4. HH (21.5%)	1. HL (21.0%) 2. HMH (42.9%) 3. LL (36.1%)	1. LH (13.0%) 2. MLH (14.3%) 3. LL (40.2%) 4. HL (13.9%) 5. HH (18.5%)	1. LL (23.0%) 2. HL (21.5%) 3. LH (20.1%) 4. HH (35.4%)	1. LH (14.7%) 2. HH (27.6%) 3. LL (24.7%) 4. HMH (8.7%) 5. HL (10.5%) 6. LMH (13.9%)
What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?	1. Female: More likely to be in LL vs. HH 2. Latino: More likely to be in the HH vs. LL or HL 3. 10th Grade Math Standardized Test Score: More likely to be in the HH vs. LL or HL	1. Female: More likely to be in the LL vs. HH 2. African American students: More likely to be in the HH vs. LH or LL 3. 10th Grade Math Standardized Test Score: More likely to be in the HH vs. other classes 4. College Prep: More likely to be in HH vs. LL 5. Math Course Beyond Alg II: More likely to be in HH vs. HL or LL 6. Extracurricular: More likely to be in HH vs. LL	1. Other Race: More likely to be in HL vs. HMH 2. 10th Grade Math Standardized Test Score: More likely to be in the HMH vs. HL	1. Female: More likely to be in LL vs. HH 2. Latino: More likely to be in HH vs. LL 3. African American: More likely to be in HH vs. MLH or LL 4. 10th Grade Math Standardized Test Score: More likely to be in HH vs. MLH, LL, HL 5. Math Course: More likely to be in HH vs. LH or LL	1. Female: More likely to be in LL or LH vs. HH 2. Latino: More likely to be in HH vs. HL 3. First Generation: More likely to be in HH vs. LL or LH 4. 10th Grade Math Standardized Test Score: More likely to be in HH vs. HL or LL 5. College Prep Track: More likely to be in HH vs. HL 6. Extracurricular: More likely to be in HH vs. LL	1. Female: More likely to be in LL, HL, or LMH vs. HH 2. Latino: More likely to be in HH vs. LH or LL or LMH 3. African American: More likely to be in HH vs. LH or LL or LMH 4. Asian: More likely to be in HL vs. HH 5. Other Race: More likely to be in HH vs. LMH 6. Low SES: More likely to be in HH vs. LL 7. 10th Grade Math Standardized Test Score: More likely to be in the HH vs. all other classes 8. Math Course Beyond Alg II: More likely to be in HH vs. LH or LL 9. Extracurricular: More likely to be in HH vs. LH, LL, HL

To what extent do students' math attitudes and math self-efficacy contribute to their 12th grade math achievement, and how does this differ between non-native and native English speakers?	1. HL: 44.83 (1.13) 2. LL: 44.35 (0.94) 3. HH: 51.40 (0.83)	1. HL: 45.43 (0.51) 2. LH: 50.70 (0.48) 3. LL: 47.24 (0.28) 4. HH: 53.64 (0.44)	1. HL: 44.06 (1.04) 2. HMH: 46.78 (1.08) 3. LL: 44.12 (0.93)	1. LH: 52.02 (0.85) 2. MLH: 49.37 (0.82) 3. LL: 47.45 (0.38) 4. HL: 44.60 (0.73) 5. HH: 52.67 (0.66)	1. LL: 52.87 (0.89) 2. HL: 55.05 (1.07) 3. LH: 59.02 (1.11) 4. HH: 61.14 (0.66)	1. LH: 59.59 (0.38) 2. HH: 61.26 (0.27) 3. LL: 53.82 (0.29) 4. HMH: 56.62 (0.62) 5. HL: 55.88 (0.52) 6. LMH:55.02 (0.44)
To what extent do students' math attitudes and math self-efficacy contribute to their STEM degree, and how does this differ between non-native and native English speakers?	N/A	N/A	1. HL: .08 (0.05) 2. HMH: .13 (0.04) 3. LL: .08 (0.04)	1. LH: .12 (0.03) 2. MLH: .14 (0.03) 3. LL: .07 (0.01) 4. HL: .08 (0.03) 5. HH: .17 (0.03)	1. LL: .15 (0.04) 2. HL: .24 (0.05) 3. LH: .21 (0.05) 4. HH: .37 (0.04)	1. LH: .17 (0.02) 2. HH: .29 (0.02) 3. LL: .08 (0.01) 4. HMH: .17 (0.03) 5. HL: .13 (0.02) 6. LMH: .10 (0.02)
To what extent do students' math attitudes and math self-efficacy contribute to their STEM career, and how does this differ between non-native and native English speakers?	1. HL: .03 (0.02) 2. LL: .04 (0.02) 3. HH: .08 (0.02)	1. HL: .05 (0.01) 2. LH: .05 (0.01) 3. LL: .03 (0.01) 4. HH: .07 (0.01)	1. HL: .03 (0.03) 2. HMH: .06 (0.03) 3. LL: .02 (0.02)	1. LH: .05 (0.02) 2. MLH: .05 (0.02) 3. LL: .03 (0.01) 4. HL: .02 (0.01) 5. HH: .07 (0.02)	1. LL: .11 (0.03) 2. HL: .09 (0.04) 3. LH: .13 (0.04) 4. HH: .23 (0.04)	1. LH: .11 (0.02) 2. HH: .19 (0.01) 3. LL: .05 (0.01) 4. HMH: .10 (0.02) 5. HL: .11 (0.02) 6. LMH: .07 (0.01)
Are there differential effects in the relationship between 12th grade math achievement and STEM degree for students holding at least a bachelor's degree? Does this differ between native and non-native English speakers?	N/A	N/A	N/A	N/A	Significant for LL (OR=1.11) and HH (OR = 1.09)	Significant for LL (OR=1.08) and HH (OR = 1.09)
Are there differential effects in the relationship between STEM degree and STEM career for students holding at least a bachelor's degree? Does this differ between native and non-native English speakers?	N/A	N/A	N/A	N/A	Significant for LL (OR=40.45) and HH (OR = 21.54)	Significant for all classes 1. LH (OR = 23.57) 2. HH (OR = 19.89) 3. LL (OR = 7.77) 4. HMH (OR = 13.33) 5. HL (OR = 22.65) 6. LMH (OR = 40.04)

Common findings. What is common among native and non-native English speakers across all three educational attainment levels is that female students were less likely to be in the high math attitude, high math self-efficacy (*HH*) class, which suggests they have lower math attitudes and math self-efficacy compared to their male counterparts. This finding is consistent with research that suggest female students perceive to have more negative attitudes and have lower math self-efficacy beliefs compared to male students (Betz & Hackett, 1983; Hackett & Betz, 1981; Ing & Nylund-Gibson, 2013; Luzzo et al., 1999).

Another commonality is the positive relationship between math attitudes and math self-efficacy with 10th grade math achievement and STEM outcomes across all educational levels and English proficiency levels, where students in classes with higher math attitudes and higher math self-efficacy beliefs had higher 10th grade math achievement scores and had higher STEM outcomes. This is consistent with previous research that suggests prior academic achievement is positively associated with math attitudes and math self-efficacy (Li & Moschkovich, 2013). In terms of extracurricular involvement, another similarity between native and non-native English speaking university graduates who were involved in extracurricular activities were more likely to be in the *HH* class; and the same was true for high school native English speakers, but this was not for either groups at the community college level.

Among all three educational attainment levels, native English speaking students whose highest math course was beyond Algebra II were more likely to be in the *HH* class compared to the other classes. However, this commonality was not significant for non-native English speaking students at the high school, community college, or university level. This could be due to non-native English speakers not being afforded the opportunity to take courses beyond Algebra II due to tracking policies in place (Callahan, 2005; Mosqueda, 2010; Oakes, 2005) or unequal resources at school (Gándara et al., 2003). This has implications for policymakers and administrators to review tracking policies and other inequitable conditions in schools to ensure that every student has equal educational opportunities.

Another common result was the importance of math self-efficacy. The results from this study suggest that having high math self-efficacy was important in predicting STEM outcomes for both native and non-native English speakers, and this was true across all levels of educational attainment. Although having positive math attitudes is important for STEM outcomes, the findings from this study suggest that math self-efficacy had a larger role in predicting STEM outcomes. For example, non-native English speaking high school and community college graduates in the *HL* and *LL* class look similar to one another, but these groups were significantly different from the *HH* group. In fact for native English speaking community college graduates, students in the *HL* class had the lowest 12th grade math achievement scores and lowest proportion of students with a STEM career compared to other groups. This suggests that even having high math attitudes does not necessarily equate to having successful STEM outcomes.

This is important for researchers and policymakers to understand and to develop interventions to focus on promoting positive math self-efficacy. Implementing an LCA contributes to our understanding on how to develop specific interventions for different English proficiency groups. For example, an intervention for students with high math attitudes and low math self-efficacy can focus specifically on improving students' math self-efficacy, while an intervention for students with low math attitudes and high math self-efficacy can focus on improving students' math attitudes. Thus using LCA improves our understanding of how to design different interventions for different latent classes.

Unique findings. Although there were many similarities in comparing the English proficiency groups and educational levels, there were also some differences. A unique finding among the native and non-native English speaking groups is how race/ethnicity functions differently, where Latino non-native English speaking students at the high school and university level were more likely to be in classes with higher math attitudes and/or high math self-efficacy compared to the other latent class, and African American native English speaking students were more likely to have higher math self-efficacy beliefs compared to their white peers. Although the results from the study suggest that Latinos and African Americans tend to have higher math attitudes and/or math self-efficacy beliefs, this does not necessarily translate to higher math achievement as demonstrated in the 2013 Mathematics Assessment from the National Assessment of Educational Progress (NAEP, 2013) results. The NAEP (2013) results revealed that 12th grade Latino and African Americans performed significantly lower on the math assessments compared to their White counterparts.

Future research is needed to study this attitude-achievement paradox (Ma, 2009) and investigate why Latinos and African American students expressed comparably higher math attitudes and math self-efficacy beliefs than their White peers, yet performed lower on math performance tests than their White peers. Perhaps there are other factors that impact Latinos' and African Americans' mathematical performance, which may include poor academic preparation (Ma, 2009), lack of exposure to advanced math or science coursetaking (Wang, 2013), or lack of positive role models (Lent et al., 1996). Nevertheless, what is important is for parents and educators to continue to foster these positive attitudes and self-efficacy beliefs that will keep these underrepresented populations interested in STEM and motivated to pursue STEM fields.

Another unique finding from this study is how significant immigrant generation status was in the university sample, where students classified as first generation immigrant non-native English speakers were more likely to be in the *HH* class compared to the *LL* or *HL* class. This finding provides evidence beyond previous research focusing on elementary school samples that parents of ELL children tend to hold high academic expectations for their children (Goldenberg et al., 2006; Tseng, 2006). Tseng (2006) argues that children of immigrants rate their English skills lower than would be expected based on their standardized test scores and that these self-ratings motivate them to pursue STEM areas that are less dependent on verbal and written English skills. This finding would not have been uncovered if an LCA was not implemented. Thus, this study contributed to the literature by providing evidence that math attitudes and math self-efficacy varies within English proficiency and immigrant generation status.

STEM outcomes. In terms of STEM outcomes, i.e., 12^{th} grade math achievement, STEM degree and STEM career attainment, it is not surprising that students' with high math self-efficacy and math attitudes have higher STEM outcomes. Results from this study revealed that students with high math attitudes and high math self-efficacy had the highest 12^{th} grade math achievement scores, and had the highest proportion of individuals with STEM degrees and STEM careers. More specifically, the results from this study found that having higher math self-efficacy had a more important role on STEM outcomes than math attitudes. This finding is consistent with the SCCT framework, where individuals with higher math self-efficacy have increased interest in pursuing STEM careers (Lent et al., 1994). Overall, this study provided evidence that math attitudes and self-efficacy beliefs operate differently for native and non-native English speakers, and that they also vary at each educational attainment level. This was possible through the use of latent class analysis. This dissertation contributes to the literature since there has been no research to date that has applied a latent class analysis to examine the influence of math attitudes and math self-efficacy on STEM outcomes for native and non-native English speakers using a nationally representative dataset.

One important finding to note is the similarities in 12^{th} grade math achievement for university native and non-native English speaking graduates. The *HH* classes in both groups had the highest average 12^{th} grade math achievement score with a mean of 61.26 for native English speakers and a mean of 61.14 for non-native English speakers. Although this difference was not compared statistically, this finding sheds light that our prior assumptions of under-achievement may be changing for non-native English speakers. In other words, the achievement gap for native and non-native English speaking students could be closing among students who attained at least a bachelor's degree. This finding also suggests that non-native English speakers who overcome obstacles (Gándara, et al.,2003), traverse through the pipeline and attain a bachelor's degree or higher, and with high math attitudes and math self-efficacy beliefs are among the groups with the highest proportion of individuals with a STEM degree and/or STEM career. Thus, having high math attitude and high math self-efficacy is important for persisting through the pipeline and attaining successful STEM outcomes, regardless of English proficiency.

When examining the results across educational attainment levels, it is interesting to note how the STEM outcomes differ for the latent classes with low STEM outcomes. For instance, there were differences in which latent class had the lowest math achievement and smallest proportion of STEM degree and STEM career holders across educational levels. In terms of 12^{th} grade math achievement, the latent classes with the lowest average math achievement scores were from individuals in the *HL* class (for high school native English speakers, community college native and non-native English speakers) or the *LL* class (for high school non-native English speakers, university native and non-native English speakers).

Similarly, across educational levels, students in the *HL* class (i.e., high school non-native English speakers, community college native English speakers, and university non-native English speakers) or the *LL* class (i.e., high school native English speakers, community college non-native English speakers, and university native English speakers) had the smallest proportion of individuals in a STEM career. These results suggest that math attitudes and math self-efficacy operate differently for each English proficiency group and for each educational level. These findings speak to the complexity of educational and career trajectories among native and non-native English speakers in the STEM pipeline. This suggests that perhaps the students in the *HL* class were not significantly different from the students in the *LL* class. This has implications for researchers to not only focus on developing interventions for students in the *LL* class, but also to include students in the *HL* class.

Regression mixture analysis. The results from the regression mixture analysis suggest that for those who have at least a bachelor's degree, regardless of English proficiency, 12th grade math achievement significantly predicts STEM degree attainment for those in the *LL* or *HH* classes. In addition, when examining the extent to which having a STEM degree predicts having a STEM career or not, there were significant differences for individuals in the *LL* and *HH* classes for non-native English speakers, and significant differences for all six latent classes for native English speakers. This is an important contribution to the literature as it suggests that not all non-native English speakers are the same in regards to their math attitudes, math self-efficacy, and STEM outcomes. In addition the finding that students in the *LL* class had significant regression coefficients suggests that math attitudes and math self-efficacy might not be the only factors explaining success in

STEM, but there could be other individual or structural characteristics that were not analyzed in the study. Future research is needed to investigate what other contextual factors contribute to the success of individuals in classes that were not statistically significant. It may be that there are other reasons for their success in STEM, but that it was not related to their 12th grade math achievement or STEM degree attainment.

It is also important to note that the results from the regression mixture analysis reveals groups that have significant paths from 12th grade math achievement to STEM degree attainment to STEM career attainment. It does not necessarily reveal which groups ends up in STEM careers. In other words, there may be groups aside from students in the *HH* or *LL* that may go into a STEM career, but it was not significantly related to their 12th grade math achievement or their STEM degree attainment. For example, a hypothetical student in the *LH* class may have high 12th grade math achievement scores, but may not major in a STEM field, yet still pursue a STEM career. This student would not have been captured in the regression mixture modeling analysis. Regression mixture modeling provides significant predictors, but it does not reveal which latent classes end up in a STEM career. This relationship, however, can be explained through a latent class analysis with distal outcomes. The regression mixture analysis was included in my dissertation to supplement the latent class analysis and to show how each of the STEM outcomes relate to one another. It was also included to have a better understanding of the STEM pipeline from high school to postsecondary education to the work force.

Furthermore, the results from the regression mixture analysis provide evidence that non-native English speaking university graduates can be successful in pursuing STEM careers. This particular finding suggests that educators and researchers should move away from viewing non-native English speakers from a deficit perspective (MacSwan, 2000), but instead focus on the assets of non-native English speakers and recognize that they may play important roles in creating a diverse, multilingual STEM workforce. Shifting the perspective from a deficit to an asset perspective requires researchers, educators, and administrators to shift their thinking of intervention programs that were intentionally aimed to increase achievement, but in reality, were detrimental to students' learning outcomes (Oakes, 2005).

For example, Oakes (2005) noted that tracking has been argued in the literature to be beneficial since students learn better when they are grouped in similar academic ability, but in fact, Oakes argued that tracking further disadvantaged students in the lower track and widens the achievement gap between native and non-native English speakers. Non-native English learners already face many barriers such as language demands in high stakes tests (Abedi & Lord, 2001); coming from low socioeconomic backgrounds (Halle et al., 2012); and lack of access to advanced math coursetaking (Finn et al., 2002; Mosqueda & Maldonado, 2013). Koelsch (2011) suggest that ELL students have a better chance to succeed at high levels when such barriers are removed. This has implications for policymakers to remove programs that hinder students' success and instead offer support and guidance to maximize students' potential to succeed.

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 the base year and first follow up data to capture those respondents who have at least graduated from high school. This is a limitation because 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). In addition, this study included students with non-missing responses on the covariates and distal outcomes. This is a limitation because it is uncertain whether the students in the analytic sample are representative of those students who dropped out from the study. Furthermore, this is a limitation because the estimates of the distal outcome variables may be overestimated because it includes responses from students who persisted throughout the ELS:2002 data collection waves and does not include students who were dropped from the analysis.

To make this point more clear, say a hypothetical student in the *LL* class completed the base year survey in 10^{th} grade, but did not complete the follow up survey in 12^{th} grade. Then this student would not be included in my dissertation. This student might be among the lowest of the *LL* group in terms of STEM outcomes because he/she might have had dropped out from high school. Thus the students remaining in the analytic sample of my dissertation who were classified as *LL* might actually not be the lowest of the *LL* group since the lowest of the *LL* group were not included in the dissertation. This is important to keep in mind that there may be some overestimation when interpreting these results. This suggests that perhaps the students in the *LL* class in the analytic sample might actually look different compared to the students in the *LL* class in the complete ELS:2002 sample.

Second, the sample excludes students with low English proficiency skills who were unable to read or respond to the base year survey. Thus, the non-native English speakers in the sample might not be truly representative of the non-native English speaking population in the U.S. as a whole. Similar to the first limitation, non-native English speaking students who were unable to complete the survey might have different STEM outcomes and were not included in the analytic sample. Therefore there may be some overestimation in the results, and readers should take caution in interpreting these results. Furthermore, it is important to note that non-native English speakers who persisted in the longitudinal data collection were likely to persist in attaining their educational and career goals compared to those who did not respond to all of the data collection waves. Despite this limitation, this study is one of few studies to examine non-native students' outcomes beyond high school. Therefore this study can be a springboard for future research on non-native English speakers.

Third, the ELS:2002 data relies on students' self-reported measures, where responses to critical variables could be left blank or filled in with false information. For example, respondents' English proficiency status was classified on one critical question that asked students whether English is their native language. Students might choose "Yes" even if English was not their native language. This could underestimate the number of non-native English speaking students in the sample. Therefore, some underestimation should be assumed in the study when interpreting results for non-native English speakers.

Fourth, data examined in this study relied on secondary data, thus some critical variables for the analysis were unavailable. In this study, self-efficacy beliefs are central to the social cognitive career theory, 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 relied on math self-efficacy as a proxy for STEM self-efficacy beliefs. This study assumes that math attitudes and math self-efficacy beliefs influence STEM outcomes. Having the combination of science, technology, engineering, and math attitudes and self-efficacy would provide a better profile of students' STEM attitudinal and self-efficacy beliefs and would help researchers understand the complex factors associated with STEM outcomes. Future studies should consider including these STEM attitudinal and self-efficacy measures to predict STEM outcomes.

Fifth, this study used math attitude and math self-efficacy items that were measured in 10th grade to predict STEM degrees four years later when most students were in college, and to predict STEM careers 10 years later when most students were in the work force. This is a limitation because students' math attitudes and math self-efficacy beliefs may change over time. Although these measures were included in the first follow up survey, they were not included in the second or third follow up surveys. Future research should examine including math attitude and math self-efficacy measures in all base year and follow up surveys to track math attitudes and math self-efficacy longitudinally.

Sixth, although regression mixture modeling is a powerful tool in identifying differential effects, it is not clear whether the interpretation of the findings is a result of the underlying variables of interest or whether it is driven by other features of the data (Van Horn et al., 2012). Along these lines, it should be noted that the native English speakers in university graduate group had the largest sample size among the three levels of educational attainment and also had the largest number of classes. It is possible that the number of classes that is selected as a final model might not reflect the "true" number distinct groups in the population (Masyn, 2013). Mixture models can be sensitive to sample size, where smaller samples might not have enough power to detect smaller and/or poorly separated classes (Lubke, 2010).

Despite these limitations, the results from this study are important due to the fast growing population of non-native English speakers and the lack of research conducted on this population. This study contributes to the literature by jointly analyzing students' math attitudes and math self-efficacy beliefs and how that differs among native and non-native English speaking students at different educational attainment levels. This study aims to bridge the gap in knowledge of non-native English speaking students' academic and career opportunities beyond secondary and postsecondary education. Findings from this study will contribute to the emerging body of literature of non-native English speakers in STEM fields.

Future Research

These limitations provide opportunities to conduct future research on native and non-native English speakers in STEM. The following section presents some preliminary analysis attempts, future research in examining other variables, causal inference studies, and interventions worth developing and implementing.

Preliminary analysis attempts. In an attempt to differentiate latent classes further, a preliminary analysis of this study included language spoken at home for non-native English speakers, which included Spanish, West/South Asian language, Pacific Asian/Southeast Asian language, and other European language. However, this variable was not significant and thus was not included in the final model. Further analyses, possibly with a different dataset might yield significance. In addition, to test the conditional independence assumption and to examine the relationship between indicators above and beyond what is explained by the latent factors, the correlations of the math attitude and math self-efficacy items' residuals were examined. Results from this preliminary analysis yielded similar results to the results without residual associations. Thus applying the parsimony principle, the latent class models without residual associations were selected as the final models in this study.

Another preliminary analysis that was conducted but not included in the final study was examining additional regression mixture models. Initially, a variable that indicated whether or not a students' declared major in 2006 was STEM or not was included to see the persistence of STEM degrees in 2012. This variable was considered because a student's initial major may change during the course of their postsecondary education, and thus was explored to see if students persisted with their initial declared major when it came to graduation. In terms of the regression mixture analysis, the regression of students' degree in 2012 was regressed on students' declared degree in 2006. However, this analysis failed to converge possibly due to the large sample size required to run regression mixture models (Van Horn et al., 2015). Thus this variable was not included in the final model.

Examining other variables. Given the limitation that this study used a large-scale dataset with a limited number of variables, future research should examine other datasets and explore other variables that may be related to STEM outcomes. One example study is to run a similar analysis using the NELS:88 data and compare the results. Another example is to examine a variable on when students became English proficient or when students were reclassified as linguistic minorities. Some research suggest that the earlier non-native English speakers gain proficiency in English, the faster they will be able to close the math achievement gap between their native English speaking peers (Halle et al., 2012; Mulligan, Halle, Kinukawa, 2012). Halle et al. (2012) suggest that the timing of when students obtain English proficiency is critical for math performance, where students who achieve English proficiency by kindergarten entry fare better on reading and math standardized tests than their peers who achieved English proficiency by the spring of the first grade. It is therefore important to identify which factors best support non-native English speakers' academic development, especially for those with low English proficiency skills.

Although variables on parental education and parental involvement were available in the ELS:2002, this study did not examine these variables. Future research should investigate how these factors influence students' math attitudes and STEM outcomes. There is some research suggesting that regardless of English proficiency, students with highly educated mothers had higher scores in reading, math, and science (Mulligan et al., 2012). Although the SES variable in this study was calculated as a composite score with parental education, it would be interesting to see how a student's mother's and father's educational background (in disaggregated form) influences their math attitudes and math self-efficacy, and in turn, influences their STEM outcomes. Research suggests that having parents involved is important for students' success. Although this would be ideal, Castro, Espinosa, and Paez (2011) argues that the main barrier to parental involvement in school is the lack of resources available such as having bilingual staff or documents translated in Spanish.

It is also worth investigating other variables that are related to students' STEM outcomes. The results from this study revealed that there were students in the *HH* class whose highest educational attainment was graduating from high school or graduating from community college. This implies that not all students with *HH* go on to pursue a bachelor's degree or higher. There may be other factors or barriers that may influence a student's decision to not pursue a four-year degree including financial aid (Wang, 2013), poor academic preparation for college (Mosqueda, 2012; Oakes, 2005); or intense academic environment at college (Wang, 2013) that may deter a student from attaining a bachelor's degree. Future studies should consider these variables and determine the impact of these factors on students' STEM outcomes.

Investigating the STEM pipeline. Due to the nature of the way the study was set up in terms of analyzing groups of students' highest educational attainment (i.e., graduates from high school, community college, and university), the results from this study cannot directly speak to the STEM pipeline issues since it did not examine the same group of students across the STEM pipeline from high school to postsecondary education to the work force. However, this data is available in the ELS:2002 and should be investigated in future research. Future studies may want to examine students' transition from high school to college to the work force and identify points where students drop out from the STEM pipeline. Studying this "leaky" pipeline is important because it may help researchers understand where students veer off from the pipeline and pinpoint where to implement interventions to keep these students in the STEM pipeline. Knowing and understanding this point can patch the leak and prevent further drop outs from the pipeline. Doing so will increase the number of STEM professionals to meet the demands of the STEM labor market.

Causal inference studies. Although this study did not implement a quasi-experimental design to infer causality, it is possible to design a study that uses causal inference methods with LCA. Propensity score matching methods can be used to estimate the average causal effect and differences in treatment effect among those who received the treatment (Lanza, Coffman, & Xu, 2013). This propensity score matching method attempts to make the control group and treatment group look similar and estimate the treatment effect. This method is advantageous as it has the ability to eliminate potential bias due to differences across individuals (Murnane & Willet, 2011). Another example could be to stratify the sample on the covariates, (i.e., SES, tracking) and examine the effects of math attitudes and math self-efficacy on STEM outcomes for each of the stratum. The following section presents some interventions that are worth developing and implementing for the future.

Interventions. The results from this study have implications for educators, researchers, and policymakers to develop interventions for students, while taking into account a host of non-linguistic factors. Focusing on only linguistic factors is not enough and may end up backfiring. For instance placing students in ESL classes limit students’ access to take advanced level courses (Callahan et al., 2010), which limits students' opportunities for postsecondary education (Adelman, 2006) and future careers. Instead future interventions should examine non-linguistic factors such as improve math attitudes and math self-efficacy, increasing STEM awareness, and creating professional development for teachers. These interventions are discussed in more detail in the following section.

Improving math attitudes and math self-efficacy. Results from this study suggest that math self-efficacy was important in predicting STEM outcomes, regardless of students' math attitudes. The results showed that students with high math attitude and low self-efficacy (*HL*) did not look different from students with low math attitude and low math self-efficacy (*LL*). Therefore, future research should examine interventions to improve students' math self-efficacy beliefs. The results from my study also suggest that female students were less likely to be in the *HH* class when compared to male students. This suggests that interventions are necessary to promote positive attitudes and self-efficacy beliefs, while also encouraging female students to study STEM fields and pursue STEM careers.

Future researchers can use a self-efficacy based intervention designed by Betz and Schifano (2000) that aimed to increase female undergraduate students' math self-efficacy and interests to pursue a STEM career through engaging in activities such as assembling, building, and operating machinery. Another intervention that researchers can use is the Talented At-Risk Girls: Encouragement and Training for Sophomores project (TARGETS) (Kerr & Robinson Kurpius, 2004). This intervention was designed to emphasize STEM identity and the importance of leadership and mentorship in the persistence in STEM. The authors noted that after exposure to a full-day intervention program, female students, who ranged from the ages 11 to 20, had significantly improved STEM attitudes, self-efficacy, future-related self-efficacy, and increased interest in pursuing a STEM career after a four-month follow-up. This suggests that even a short one-day intervention program can be successful in improving female students' STEM attitudes and self-efficacy and increased interests in STEM. This study also highlights the importance of early interventions as attitudes and self-efficacy tend develop early on in a student's life.

There is also research that suggests a teacher's support and care in the classroom can increase non-native English speaking students' self-efficacy and math achievement (Lewis et al., 2012). In addition, interest and students' perceptions of their teachers' support and care has been demonstrated to increase students' likelihood in attaining a STEM career (Nylund-Gibson, Ing, & Park, 2013). These interventions of increasing math attitudes and math self-efficacy beliefs, as well as increasing teachers' support and care in the classroom is important for all students, especially for female and non-native English speaking students. Implementing these interventions is important and critical in increasing the number of students pursuing STEM and addressing the need for producing one million more STEM professionals in the next decade (PCAST, 2012).

Increasing STEM degree and STEM career awareness. Not only is it important to increase math attitudes and math self-efficacy beliefs, but it is also important to increase the awareness of STEM professions early in a student's life. Based on the SCCT framework (from Figure 1), there is an indirect path where an individual's math attitudes and self-efficacy influence his/her career interests, and in turn motivates an individual to set goals and take actions towards performance domains and attainment. Results from my dissertation suggest that there are groups of students in the *HH* class that do not pursue a STEM degree or STEM field. It is possible that these groups of students may not be aware of the opportunities to study a STEM major or have a career in STEM. Thus it is important to study their underlying, indirect pathways to gain a better understanding of their decisions to pursue a non-STEM career. Again, this may help researchers understand factors that relate to the "leaky" STEM pipeline. It can also be an opportunity to implement interventions to continue to promote positive attitudes and self-efficacy beliefs. Although my dissertation focused on the direct path of math attitudes and self-efficacy to performance attainment, this indirect path is worth investigating. Future research should consider how student's interest and awareness of STEM fields influence his/her goals and actions to pursue a STEM field.

One recommendation for an intervention is to have more discussions in classrooms and describe the types of jobs available in STEM. In addition, instructors could invite guest speakers from STEM organizations and have students engage with these STEM representatives to increase STEM career awareness as well as improve attitudes and self-efficacy beliefs about STEM jobs. More interventions such as the Mother Daughter program are needed. This program, which was developed by the University of Texas at El Paso, aimed to help sixth grade Latino female students and their mothers work together to set goals for academic and career success (Excelencia in Education, 2010). Such intervention programs are necessary to promote Latino female students' attitudes and self-efficacy, promote early awareness of different career opportunities, and involve mothers with their daughter's academic and career goals.

Professional development. Another type of intervention worth studying is professional development for teachers. Teachers play an important role in students' success. Therefore future research should create professional development opportunities to help teachers address the unique instructional demands for non-native English speakers. Such support can help non-native English students attain full proficiency (Fillmore, 2014). One type of intervention is to use research-based curricular and instructional practices that support students' language development and also incorporate culture into the curriculum (Gándara et al., 2003). This curriculum could be effective in building students' prior knowledge that supports learning of new concepts in a second language. Given the growing population of ELLs (Kena et al., 2015), it is important for teachers to be prepared in teaching students who come from diverse cultural and linguistic backgrounds. It is also important for school principals and counselors to offer educational support and provide equitable opportunities for students.

In conclusion, more studies like this dissertation as well as these future studies aforementioned are necessary to unpack the complex interplay of factors involved in students' math attitudes and math self-efficacy with STEM outcomes, and the additional layers of English proficiency and educational attainment levels. Such research is needed to inform policy and practice to ensure the future success of native and non-native English speakers in STEM fields. In doing so, educators, researchers, and policymakers have a real opportunity to prepare one of the fastest growing U.S. population and create the next generation of scientific talent to fill STEM job vacancies.

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Appendix A

Table A1

Summary of Study Research Questions, Variables, and Analysis Models

Highest Educational Level	Research Questions	DVs	IVs.	Covariates	Analytic Method
High school graduates	1. How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?	Within latent classes	1. Math attitudes: a. Gets totally absorbed in mathematics (BYS87A) b. Thinks math is fun (BYS87C) c. Mathematics is important (BYS87F) 2. Math self-efficacy: a. Can do excellent job on math tests (BYS89A) b. Can understand difficult math texts (BYS89B) c. Can understand difficult math class (BYS89L) d. Can do excellent job on math assignments (BYS89R) e. Can master math class skills (BYS89U)	None	Traditional Latent Class Analysis (LCA): Step 1 of the three-step LCA (unconditional model)

High school graduates	2.	What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?	Within latent classes	1. Math attitudes: a. Gets totally absorbed in mathematics (BYS87A) b. Thinks math is fun (BYS87C) c. Mathematics is important (BYS87F) 2. Math self-efficacy: a. Can do excellent job on math tests (BYS89A) b. Can understand difficult math texts (BYS89B) c. Can understand difficult math class (BYS89L) d. Can do excellent job on math assignments (BYS89R) e. Can master math class skills (BYS89U)	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. Immigrant Generation Status (BYP17, BYP20, BYP23) 4. SES (BYSES2QU) 5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	Step 3 of the three-step LCA (adding covariates)
High school graduates	3.	To what extent do students' math attitudes and math self-efficacy contribute to their 12th grade math achievement, and how does this differ	12th grade math achievement test scores (F1TXM1IR)	Latent class membership	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. Immigrant Generation Status (BYP17, BYP20, BYP23) 4. SES (BYSES2QU) 5. 10th grade math achievement	Step 3 of the three-step LCA (adding proximal outcomes)

		between non-native English speakers and native English speakers?			(BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	
High school graduates	4.	To what extent do students' math attitudes and math self-efficacy contribute to their STEM career, and how does this differ between non-native English speakers and native English speakers?	Dichotomous variable: STEM Career (F3ONET6CURR)	Latent class membership	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. Immigrant Generation Status (BYP17, BYP20, BYP23) 4. SES (BYSES2QU) 5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	Step 3 of the three-step LCA (adding distal outcomes)

Community College Graduates	1.	How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?	Within latent classes	1. Math attitudes: a. Gets totally absorbed in mathematics (BYS87A) b. Thinks math is fun (BYS87C) c. Mathematics is important (BYS87F) 2. Math self-efficacy: a. Can do excellent job on math tests (BYS89A) b. Can understand difficult math texts (BYS89B) c. Can understand difficult math class (BYS89L) d. Can do excellent job on math assignments (BYS89R) e. Can master math class skills (BYS89U)	None	Traditional Latent Class Analysis (LCA): Step 1 of the three-step LCA (unconditional model)

Community College Graduates	2.	What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?	Within latent classes	1. Math attitudes: a. Gets totally absorbed in mathematics (BYS87A) b. Thinks math is fun (BYS87C) c. Mathematics is important (BYS87F) 2. Math self-efficacy: a. Can do excellent job on math tests (BYS89A) b. Can understand difficult math texts (BYS89B) c. Can understand difficult math class (BYS89L) d. Can do excellent job on math assignments (BYS89R) e. Can master math class skills (BYS89U)	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. Immigrant Generation Status (BYP17, BYP20, BYP23) 4. SES (BYSES2QU) 5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	Step 3 of the three-step LCA (adding covariates)
Community College Graduates	3.	To what extent do students' math attitudes and math self-efficacy contribute to their 12th grade math achievement, and how does this differ	12th grade math achievement test scores (F1TXM1IR)	Latent class membership	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. English Proficiency Level (composite variable of BYS70A, BYS70B, BYS70C, BYS70D) 4. SES (BYSES2QU)	Step 3 of the three-step LCA (adding proximal outcomes)

	between non-native English speakers and native English speakers?			5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	
Community College Graduates	4. To what extent do students' math attitudes and math self-efficacy contribute to their STEM degree, and how does this differ between non-native English speakers and native English speakers?	Dichotomous variable: Bachelor Degree STEM major: a. F31CREDGEN_1 b. F31CREDGEN2_1 c. F31CREDGEN2_2	Latent class membership	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. Immigrant Generation Status (BYP17, BYP20, BYP23) 4. SES (BYSES2QU) 5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	Step 3 of the three-step LCA (adding distal outcomes)

Community College Graduates	5.	To what extent do students' math attitudes and math self-efficacy contribute to their STEM career, and how does this differ between non-native English speakers and native English speakers?	Dichotomous variable: STEM Career (F3ONET6CURR)	Latent class membership	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. Immigrant Generation Status (BYP17, BYP20, BYP23) 4. SES (BYSES2QU) 5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	Step 3 of the three-step LCA (adding distal outcomes)
University Graduates	1.	How do the math attitudes and math self-efficacy beliefs differ between non-native English speakers and native English speakers?	Within latent classes	1. Math attitudes: a. Gets totally absorbed in mathematics (BYS87A) b. Thinks math is fun (BYS87C) c. Mathematics is important (BYS87F) 2. Math self-efficacy: a. Can do excellent job on math tests (BYS89A) b. Can understand difficult math texts (BYS89B)	None	Traditional Latent Class Analysis (LCA): Step 1 of the three-step LCA (unconditional model)

				c. Can understand difficult math class (BYS89L) d. Can do excellent job on math assignments (BYS89R) e. Can master math class skills (BYS89U)		
University Graduates	2.	What is the relationship between the different math attitudes and math self-efficacy beliefs and the following selected variables: gender, race/ethnicity, immigration generation status, socioeconomic status, prior math achievement, tracking program, math coursework, and extracurricular involvement? How does this differ between non-native English speakers and native English speakers?	Within latent classes	1. Math attitudes: a. Gets totally absorbed in mathematics (BYS87A) b. Thinks math is fun (BYS87C) c. Mathematics is important (BYS87F) 2. Math self-efficacy: a. Can do excellent job on math tests (BYS89A) b. Can understand difficult math texts (BYS89B) c. Can understand difficult math class (BYS89L) d. Can do excellent job on math assignments (BYS89R) e. Can master math class skills (BYS89U)	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. Immigrant Generation Status (BYP17, BYP20, BYP23) 4. SES (BYSES2QU) 5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	Step 3 of the three-step LCA (adding covariates)

University Graduates	3.	To what extent do students' math attitudes and math self-efficacy contribute to their 12th grade math achievement, and how does this differ between non-native English speakers and native English speakers?	12th grade math achievement test scores (F1TXM1IR)	Latent class membership	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. English Proficiency Level (composite variable of BYS70A, BYS70B, BYS70C, BYS70D) 4. SES (BYSES2QU) 5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	Step 3 of the three-step LCA (adding proximal outcomes)
University Graduates	4.	To what extent do students' math attitudes and math self-efficacy contribute to their STEM degree, and how does this differ between non-native English speakers and native English	Dichotomous variable: Bachelor Degree STEM major: a. F31CREDGEN_1 b. F31CREDGEN2_1 c. F31CREDGEN2_	Latent class membership	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. Immigrant Generation Status (BYP17, BYP20, BYP23) 4. SES (BYSES2QU) 5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework	Step 3 of the three-step LCA (adding distal outcomes)

		speakers?	2		(F1RMAPIP) 8. Extracurricular involvement (BYS42)	
University Graduates	5.	To what extent do students’ math attitudes and math self-efficacy contribute to their STEM career, and how does this differ between non-native English speakers and native English speakers?	Dichotomous variable: STEM Career (F3ONET6CURR)	Latent class membership	1. Gender (BYSEX) 2. Race (BYRACE_R) 3. Immigrant Generation Status (BYP17, BYP20, BYP23) 4. SES (BYSES2QU) 5. 10th grade math achievement (BYTXMSTD) 6. Track status (BYS26) 7. Math coursework (F1RMAPIP) 8. Extracurricular involvement (BYS42)	Step 3 of the three-step LCA (adding distal outcomes)
University Graduates	6.	Are there differential effects in the relationship between 12th grade math achievement and STEM degree for students holding at least a bachelor’s degree? Does this differ between native	Dichotomous variable: Bachelor Degree STEM major: a. F31CREDGEN_1 b. F31CREDGEN2_1 c.	12th grade math achievement test scores (F1TXM1IR)	None	Regression mixture modeling

		and non-native English speakers?	F31CREDGEN2_ 2			
University Graduates	7.	Are there differential effects in the relationship between STEM degree and STEM career for students holding at least a bachelor's degree? Does this differ between native and non-native English speakers?	Dichotomous variable: STEM Career (F3ONET6CURR)	Dichotomous variable: Bachelor Degree STEM major: a. F31CREDGEN_1 b. F31CREDGEN2_1 c. F31CREDGEN2_2	None	Regression Mixture Modeling

Note. BY = Base year (2002) of study; F1 = First follow-up (2004) of study; F2 = Second follow up (2006); F3 = Third follow up (2012)

Table A2

Variables included in Study with Recoded Values

Construct	**ELS:2002 variable name**	**Description**	**Original coding**	**New Coding**
Math attitudes	BYS87A	When I do mathematics, I sometimes get totally absorbed	1=Strongly Agree, 2=Agree, 3= Disagree, 4= Strongly Disagree	1 & 2=1; 3 & 4=0
Math attitudes	BYS87C	Because doing mathematics is fun, I wouldn't want to give it up	1=Strongly Agree, 2=Agree, 3= Disagree, 4= Strongly Disagree	1 & 2=1; 3 & 4=0
Math attitudes	BYS87F	Mathematics is important to me personally	1=Strongly Agree, 2=Agree, 3= Disagree, 4= Strongly Disagree	1 & 2=1; 3 & 4=0
Math self-efficacy	BYS89A	I'm confident that I can do an excellent job on my math tests	1=Almost never, 2= Sometimes, 3= Often, 4=Almost always	1 & 2=0; 3 & 4=1
Math self-efficacy	BYS89B	I'm certain I can understand the most difficult material presented in math texts	1=Almost never, 2= Sometimes, 3= Often, 4=Almost always	1 & 2=0; 3 & 4=1
Math self-efficacy	BYS89L	I'm confident I can understand the most complex material presented by my math teacher	1=Almost never, 2= Sometimes, 3= Often, 4=Almost always	1 & 2=0; 3 & 4=1
Math self-efficacy	BYS89R	I'm confident I can do excellent job on my math assignments	1=Almost never, 2= Sometimes, 3= Often, 4=Almost always	1 & 2=0; 3 & 4=1
Math self-efficacy	BYS89U	I'm certain I can master the skills being taught in my math class	1=Almost never, 2= Sometimes, 3= Often, 4=Almost always	1 & 2=0; 3 & 4=1

English Proficiency	BYS70A	How well 10th grader understands spoken English	1=Very well, 2=Well, 3=Not well, 4=Not at all	1 & 2=1; 3 & 4=0
English Proficiency	BYS70B	How well 10th grader speaks English	1=Very well, 2=Well, 3=Not well, 4=Not at all	1 & 2=1; 3 & 4=0
English Proficiency	BYS70C	How well 10th grader reads English	1=Very well, 2=Well, 3=Not well, 4=Not at all	1 & 2=1; 3 & 4=0
English Proficiency	BYS70D	How well 10th grader writes English	1=Very well, 2=Well, 3=Not well, 4=Not at all	1 & 2=1; 3 & 4=0
English Proficiency	BYSTLANG	Whether English is student's native language - composite. Missing values were imputed	0=No; 1=Yes	N/A
English Proficiency	BYTM12B	Student behind due to limited proficiency in English language (math)	0=No; 1=Yes	N/A
Gender (covariate)	BYSEX	Gender	1=male, 2=female	Female: 0=male, 1=female
Race (restricted) (covariate)	BYRACE_R	Race	1=American Indian/Alaska Native, 2=Asian, 3=African American, 4=Hispanic (no race specified), 5=Hispanic (race specified), 6=More than one race (non-Hispanic), 7=Native Hawaiian/Pacific Islander, 8=White	*Latino*: 0=non-Hispanic; 1=Hispanic (4,5) *African American:* 0=non-African American; 1=African American (3) *Asian:* 0=non-Asian; 1=Asian (2); *Other Race*: 1= other (1,6,7); 0 otherwise
Immigration generation status (covariate)	BYP23	Student's birthplace (United States or elsewhere)	1=United States, 2=Puerto Rico, 3=Another country/area	1=0; 2,3=1

Immigration generation status (covariate)	BYP17	Mother’s birthplace (United States or elsewhere)	1=United States, 2=Puerto Rico, 3=Another country/area	1=0; 2,3=1
Immigration generation status (covariate)	BYP20	Father’s birthplace (United States or elsewhere)	1=United States, 2=Puerto Rico, 3=Another country/area	1=0; 2,3=1
Students’ socioeconomic status (covariate)	BYSES2QU	SES composite variable based on the 1989 GSS occupational prestige scores used instead of the SES1, which used the 1961 Duncan SEI values	1=lowest quartile, 2=second lowest quartile, 3=second high quartile, 4=highest quartile	Low_SES: 1=1; 2, 3, 4 = 0
10th grade math achievement (covariate)	BYTXMSTD	10th grade math test standardized score	Ranges from [19.38, 86.68]	N/A
Tracking (covariate)	BYS26	High school program-student self-report	1=General, 2=College prep-academic, 3=Vocational-including technical/business	College_prep: 2=1; 1, 3=0;
Highest math course taken beyond Algebra II (covariate)	F1RMAPIP	Math course taking pipeline	1=No math, 2=Non-academic, 3=Low academic, 4=Middle academic, 5=Middle academic II, 6=Advanced I, 7=Advanced II/Pre-Calculus, 8=Advanced III/Calculus	Math course taken beyond Algebra II: 1, 2, 3, 4, 5: 0 6, 7, 8: 1
Extracurricular involvement (covariate)	BYS42	Hours/week spent on extracurricular activities	0=0 hours, 1=1 hour, … 21 = 21 or more hours	0=1; 1-21=0
12th grade math achievement (proximal outcome)	F1TXMSTD	12th grade math test standardized score	Ranges from [23.26, 29.85]	N/A

College degree major (distal outcome)	F3ICREDGEN_1	Credential #1 (highest or only credential from the given institution): field-of-study 2-digit (general) code		*stem_major*: 0=non-STEM major; 1=STEM major
College degree major	F3ICREDGEN2_1	Credential #1: second major field-of-study 2-digit (general) code		*stem_major*: 0=non-STEM major; 1=STEM major
College degree major	F3ICREDGEN_2	Credential #2 (additional credential from the given institution): field- of-study 2-digit (general) code		*stem_major*: 0=non-STEM major; 1=STEM major
College degree major	F3ICREDGEN2_2	Credential #2: second major field-of-study 2-digit (general) code		*stem_major*: 0=non-STEM major; 1=STEM major
Highest level of education earned as of F3	F3ATTAINMENT	Respondent's highest level of education as of the third follow-up interview	1=No HS credential, no PS attendance; 2=HS credential, no PS attendance; 3=Some PS attendance, no PS credential, 4=Undergraduate certificate; 5=Associate's degree; 6=Bachelor's degree; 7=Post-Baccalaureate certificate; 8=Masters degree; 9=Post-Masters certificate; 10=Doctoral degree	A. High school graduates: F3ATTAINMENT = 2 or 3 B. Community college graduates: F3ATTAINMENT= 4 or 5 C. University graduates: F3ATTAINMENT=6, 7, 8, 9, or 10
Occupation	F3ONET2CURR	2-digit ONET code for current/most recent job		*stem_job*: 0=non-STEM job; 1=STEM job
Occupation	F3ONET6CURR	6-digit ONET code for current/most recent job		*stem_job*: 0=non-STEM job; 1=STEM job

Appendix B

Table B1

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 C

Table C1

Classification of STEM Major Field of Study in ELS:2002

2-Digit Code	Description
01	Agriculture, Agriculture Operations, and Related Sciences
03	Natural Resources and Conservation
11	Computer and Information Sciences and Support Services
14	Engineering
15	Engineering Technologies/Technicians
26	Biological and Biomedical Sciences
27	Mathematics and Statistics
29	Military Technologies
40	Physical Science
41	Science Technologies/Technicians

Note. STEM majors were adopted from Chen & Ho (2013)

Table C2

Classification of Non-STEM Major Field of Study in ELS:2002

2-Digit Code	Description
04	Architecture and Related Services
05	Area, Ethnic, Cultural, and Gender Studies
09	Communication, Journalism, and Related Programs
10	Communications Technologies/Technicians and Support Services
12	Personal and Culinary Services
13	Education
16	Foreign Languages, Literatures, and Linguistics
19	Family and Consumer Sciences/Human Sciences
22	Legal Professions and Studies
23	English Language and Literature/Letters
24	Liberal Arts and Sciences, General Studies, and Humanities
25	Library Science
30	Multi/Interdisciplinary Studies
31	Parks, Recreation, Leisure, and Fitness Studies
38	Philosophy and Religious Studies
39	Theology and Religious Vocations
42	Psychology
43	Security and Protective Services
44	Public Administration and Social Service Professions
45	Social Sciences
46	Construction Trades
47	Mechanic and Repair Technologies/Technicians
48	Precision Production
49	Transportation and Materials Moving
50	Visual and Performing Arts
51	Health Professions and Related Clinical Sciences
52	Business, Management, Marketing, and Related Support Services
54	History
60	Residency Programs

Note. STEM majors were adopted from Chen & Ho (2013)

Appendix D

Table D1

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

Appendix E

Mplus Input files for University Non-Native English Speakers

Step 1

```
Title: STEP 1 of the 3-step
Data: File is BY_F3.dat;
Variable: Names are STU_ID BYPARED BYTXMSTD F1TXMBIR F1TXM1IR
F1TXMSTD eng_prof low_ses nonacademic_track college_prep high_math extracurric
        non_eng_spkr firstgen stem_major declarestem stem_job stem_composite
        math_absorb math_fun math_important mathtest mathtext mathclass mathasgn
        mathskill female native_amer asian african_amer latino multirace hawaiian white
        minority other_race spanish asianlang otherlang riskfc;
usevariables =  math_absorb math_fun math_important mathtest mathtext mathclass
        mathasgn mathskill ;
categorical = math_absorb math_fun math_important mathtest mathtext mathclass mathasgn
        mathskill ;
auxiliary = female latino african_amer asian other_race firstgen low_ses BYTXMSTD
        college_prep high_math  extracurric F1TXMSTD  stem_major declarestem stem_job;
Missing are all (-9999);
classes = c(4);

Analysis:
type = mixture;
starts = 0;
optseed = 210870;
lrtstarts = 0 0 200 40;

Model:
Plot: type=plot3;
series = math_absorb(*) math_fun(*) math_important(*) mathtest(*) mathtext(*)
        mathclass(*) mathasgn(*) mathskill(*) ;
Savedata:
file is 4clca.dat;
save=cprob;
missflag=-9999;

Output: tech11 tech14;
```

Step 2

```
Title: STEP 2 of the 3-step
Data: File is 4clca.dat;
Variable: Names are MATH_ABS MATH_FUN MATH_IMP MATHTEST MATHTEXT
MATHCLAS MATHASGN MATHSKIL FEMALE LATINO AFRICAN ASIAN OTHER
        FIRSTGEN LOW_SES BYTXMSTD COLLEGE   HIGH_MAT EXTRACUR
        F1TXMSTD  STEM_MAJ DECLARES STEM_JOB CPROB1 CPROB2 CPROB3
        CPROB4 n;
nominal = n;
Usev = n;
classes = c(4);
Analysis:
type = mixture;
starts = 0;

Model:
%c#1%
[n#1@5.071]
[n#2@2.130]
[n#3@1.596]

%c#2%
[n#1@0.410]
[n#2@2.755]
[n#3@-0.430]

%c#3%
[n#1@-0.569]
[n#2@-1.264]
[n#3@2.432]

%c#4%
[n#1@-6.097]
[n#2@-4.147]
[n#3@-2.870]

Output:tech1;
```

Step 3

```
Title: STEP 3 in 3-step
Data: File is 4clca.dat;
Variable: Names are MATH_ABS MATH_FUN MATH_IMP MATHTEST MATHTEXT
MATHCLAS MATHASGN MATHSKIL FEMALE LATINO AFRICAN ASIAN OTHER
FIRSTGEN LOW_SES BYTXMSTD COLLEGE  HIGH_MAT EXTRACUR F1TXMSTD
STEM_MAJ DECLARES STEM_JOB CPROB1 CPROB2 CPROB3 CPROB4 n;
nominal = n;
Usev = n FEMALE LATINO AFRICAN ASIAN OTHER FIRSTGEN LOW_SES
BYTXMSTD COLLEGE HIGH_MAT EXTRACUR F1TXMSTD STEM_MAJ
STEM_JOB;
auxiliary = F1TXMSTD(e) STEM_MAJ(e) STEM_JOB(e);
Missing are all (-9999);
classes = c(4);
Analysis:
type = mixture;
starts = 0;

Model:
%overall%
c on FEMALE LATINO AFRICAN ASIAN OTHER FIRSTGEN LOW_SES
        BYTXMSTD COLLEGE  HIGH_MAT EXTRACUR;
%c#1%
[n#1@5.071]
[n#2@2.130]
[n#3@1.596]
%c#2%
[n#1@0.410]
[n#2@2.755]
[n#3@-0.430]
%c#3%
[n#1@-0.569]
[n#2@-1.264]
[n#3@2.432]
%c#4%
[n#1@-6.097]
[n#2@-4.147]
[n#3@-2.870]
Output: tech1;
```

Regression Mixture

```
Title: Regression mixture
12th grade math achievement -> STEM Degree -> STEM Job

Data: File is 4clca.dat;
Variable: Names are MATH_ABS MATH_FUN MATH_IMP MATHTEST MATHTEXT
        MATHCLAS MATHASGN MATHSKIL FEMALE  LATINO AFRICAN ASIAN
        OTHER FIRSTGEN LOW_SES BYTXMSTD COLLEGE  HIGH_MAT
        EXTRACUR F1TXMSTD  STEM_MAJ DECLARES STEM_JOB  CPROB1
        CPROB2 CPROB3 CPROB4 n;
nominal = n;

Usev = n FEMALE LATINO AFRICAN ASIAN OTHER FIRSTGEN LOW_SES
        BYTXMSTD COLLEGE  HIGH_MAT EXTRACUR F1TXMSTD STEM_MAJ
        STEM_JOB;
categorical =  STEM_JOB STEM_MAJ;
Missing are all (-9999) ;
classes = c(4);

Analysis:
type = mixture;
starts = 0;
ALGORITHM = INTEGRATION;

Model:
%overall%
c on FEMALE LATINO AFRICAN ASIAN OTHER FIRSTGEN LOW_SES
        BYTXMSTD COLLEGE  HIGH_MAT EXTRACUR;
STEM_MAJ on F1TXMSTD;
STEM_JOB on STEM_MAJ;

%c#1%
[n#1@5.071];
[n#2@2.130];
[n#3@1.596];
STEM_MAJ on F1TXMSTD (a1);
STEM_JOB on STEM_MAJ (b1);
```

```
%c#2%
[n#1@0.410];
[n#2@2.755];
[n#3@-0.430];
STEM_MAJ on F1TXMSTD (a2);
STEM_JOB on STEM_MAJ (b2);

%c#3%
[n#1@-0.569];
[n#2@-1.264];
[n#3@2.432];
STEM_MAJ on F1TXMSTD (a3);
STEM_JOB on STEM_MAJ (b3);

%c#4%
[n#1@-6.097];
[n#2@-4.147];
[n#3@-2.870];
STEM_MAJ on F1TXMSTD (a4);
STEM_JOB on STEM_MAJ (b4);

!Test the point estimates for each of the regression coefficients
Model constraint:
New(w1 w2 w3 w4 w5 w6);
w1 = a1-a2;
w2 = a1-a3;
w3 = a1-a4;
w4 = a2-a3;
w5 = a2-a4;
w6 = a3-a4;

New(x1 x2 x3 x4 x5 x6);
x1 = b1-b2;
x2 = b1-b3;
x3 = b1-b4;
x4 = b2-b3;
x5 = b2-b4;
x6 = b3-b4;

Output: tech1;
```