SUCCESSFUL TRANSITION FOR ALL STUDENTS FROM SECONDARY TO POST-SECONDARY EDUCATION IN SCIENCE, TECHNOLOGY, ENGINEERING, AND MATHEMATICS

By

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ABSTRACT

SUCCESSFUL TRANSITION FOR ALL STUDENTS FROM SECONDARY TO POST-SECONDARY EDUCATION IN SCIENCE, TECHNOLOGY, ENGINEERING, AND MATHEMATICS

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This dissertation addresses two important aspects of college and career readiness in the fields of science, technology, engineering, and mathematics (STEM) using the High School Longitudinal Study of 2009 (HSLS: 2009). The first chapter focuses on students' coursework in mathematics and science and examines optimal combinations of mathematics and science courses in high school that lead to students' successful transition to STEM majors in college. The first study identifies high school students' course-taking patterns to determine which combinations of mathematics and science courses, including corresponding credits, are related to students' enrollment in different college STEM majors. Results obtained from multilevel latent profile analysis and multilevel generalized linear models showed that four discrete high school mathematics and science course-taking combinations were identified. Moreover, students' gender, interest in math courses, and previous math performance levels were differently associated with these respective combinations. Out of the four identified course-taking combinations, the pattern of a balanced course load combined with high numbers of credits earned in Chemistry, Physics, Pre-calculus, and Calculus indicated a higher association with students' enrollment in any STEM majors in college. Students with this course-taking combination were more likely to enroll in the four categories of STEM majors—Biology/Physics, Computer Science, Engineering, and Mathematics—than non-STEM majors in college. The finding that a certain course-taking combination uniquely contributes to higher likelihoods of being enrolled in a STEM major in college suggests that educators and school and

district leaders should ensure students who want to explore or select a STEM major in college have access to such curricula exposure when they design curriculum in their high schools. This research could also help educators develop protocols to guide students' course selection for those who have an interest in potentially becoming a STEM major.

The second chapter investigates college and career readiness in math and science of underrepresented student populations. In response to comprehensively identifying multiple student subgroups' college and career readiness, I examine students' college and career readiness by race/ethnicity groups as well as groups by different English learner (EL) status that also takes into account their race/ethnicity. Results suggest that different race/ethnicity and EL status subgroups experience disparities in different types of college and career readiness assessments. Except Asian students, most racial minority student populations exhibited a lower degree of college and career readiness in performance-oriented ACT and SAT scores than White students. For the advanced coursework opportunity aspect of college and career readiness measured by AP/IB course credits, Asian students earned more credits than White students whereas other race/ethnicity groups did not show statistically significant differences with White students. In addition, current ELs showed consistent underperformance in ACT and SAT scores when parceled out from student characteristics including their race/ethnicity and other background variables. The results suggest that students' EL status should be independently investigated in identifying patterns of student subgroups' college and career readiness. Such an approach is helpful for acknowledging existing disparities surrounding current ELs and informs efforts to devise policy measures to mitigate the grave differences.

To my parents.
Thank you for always believing in me.

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CHAPTER 1 INTRODUCTION

The common definition of college and career readiness indicates the status where high school graduates possess knowledge and skills to succeed in both postsecondary education and their chosen careers (Mishkind, 2014). The attainment and demonstration of college and career readiness is shown when students enrolled in higher education are able to successfully complete entry-level college work without need for remediation (Sambolt & Blumenthal, 2013). This smooth entry is consequently connected to an easy transition into careers in the workplace (Sambolt & Blumenthal, 2013).

College and career readiness standards have garnered much attention from states, districts, and schools in response to preparing students for postsecondary education in a competitive global economy with its fast-changing demands for a workforce with enhanced knowledge and skill sets. One such short-term issue concerns the substantial time and costs associated with remediation courses for students who enroll in postsecondary education with inadequate academic preparation (Jimenez et al., 2016). For instance, approximately half of high school graduates took at least one remedial course during college, with ranges from 40% of high school graduates who enrolled in four-year institutions to 68% of those who attended two-year colleges (Chen, 2016). Additional remedial courses prolong the timeline to graduation and put students at more risk regarding degree completion (Jimenez et al., 2016). Given that the total cost of remediation exceeds $2.3 billion a year and remedial students have more risk of dropping out of college (The Atlantic, 2014, as cited in Strong American Schools, 2008), it is paramount to address college and career readiness to ensure high school students' successful transition.

Furthermore, in the long run, the failure to equip students with college and career readiness will turn into a mismatch between the increasing demand in the workforce for middle- and high-skill jobs and the ability to secure such qualified workers (Carnevale et al., 2010; Organization for Economic Co-operation and Development [OECD], 2013). Approximately 65% of all jobs and 92% of traditional STEM jobs will necessitate a tertiary level of education and training support (Carnevale et al., 2011). These figures support the necessity of ensuring college and career readiness for all students, helping them chart their career paths after high school graduation and achieve their career goals without being unnecessarily delayed or placed at greater risk for college incompletion.

With this in mind, it is important to note that students' college and career readiness is addressed in the Every Student Succeeds Act (ESSA) which was enacted in 2015. ESSA has two main goals: 1) integrating college and career readiness standards into education programs and 2) offering educational opportunities for underserved student populations including racial and ethnic minorities and English learners (Young et al., 2017). As can be seen from the goals, ESSA includes provisions that are written to help to assure college and career readiness for all students and enhance equity in educational opportunity across diverse student populations.

In my dissertation reflecting the foci of ESSA, I addressed two important topics in college and career readiness: 1) identifying high school math and science course-taking combinations that prepare students to be college-and-career-ready and 2) examining underserved student populations' degree of college and career readiness to enhance equity across diverse student populations. Firstly, college and career readiness can be improved by course-taking as student exposure to advanced subjects is positively related to college and career readiness indicators (ACT, 2013). Previous studies demonstrate the positive relationship between students' rigorous high school coursework and their higher performance in achievement tests (e.g., Froiland & Davison, 2016). Expanding on these findings, I look at whether and to what degree students' *course-taking patterns* have an association with students' STEM majors in college. Thus, my first study focuses on course-taking in mathematics and science to devise an indicator for students' college and career readiness in terms of coursework combinations in high school and their relationship to students' college career choice in relevant STEM fields.

Secondly, underserved students face more difficulties in achieving college and career readiness than other student populations (Lee, 2012). Racial minorities and minority students that learn English as their second language (English learners) encounter fewer opportunities to be exposed to subject content knowledge (Callahan, 2005). Moreover, researchers tend to focus on other student demographics when studying college and career readiness, such as race/ethnicity or gender, leaving a scholarly gap in similar research on English learners (Wang et al., 2012). This necessitates a complete and systematic examination of the college and career readiness status for such students in order to identify factors that influence existing disparities, if they exist. In addition, as college and career readiness standards utilized across states have a variety of standards, a study on diverse student populations' college and career readiness necessitates examining their college and career readiness using different indicators, such as SAT and ACT scores, as well as credits earned in AP/IB courses in mathematics and science. These indicators will, in turn, shed light on which aspects of college and career readiness a certain group of students need for improvement in comparison to other groups. Hence, the second topic I address is the understudied relationship that comprehensively considers both English language learner status and the race/ethnicity of high school students with regard to their college and career readiness in mathematics and science.

CHAPTER 2 HIGH SCHOOL COURSE-TAKING AND ENROLLMENT IN SCIENCE, TECHNOLOGY, ENGINEERING, AND MATHEMATICS MAJORS: A HOLISTIC PICTURE OF THE "GOLDEN COMBINATION" OF MATHEMATICS AND SCIENCE[1]

Introduction

In the current knowledge-and-technology-intensive economy, scientific research and development of technologies are the main driving forces of a nation's prosperity due to their innovative and economic contributions (Koebler, 2011). Responding to this structure of the economy, demands on the STEM workforce are already high and continue to grow. The U.S. Bureau of Labor Statistics anticipated that there will be more than 2.6 million STEM job openings from 2014 to 2024 (Fayer et al., 2017; Petrucci & Rivera-Figueroa, 2020). Contrary to this growing demand and necessity, the current pace that workers with STEM knowledge in the workforce are becoming available is not predicted to keep up with the future demands in the U.S. (National Science Board [NSB], 2015). The gap between projected needs and available workforce may grow as currently the least represented demographic groups in STEM degree programs are the fastest growing populations in the U.S. (Fayer et al., 2011).

As suggested from these projections, the sustainable development of science and technology largely relies on acquiring strong human capital in science, technology, engineering, and mathematics (STEM) fields. Building such human capital should be approached by both

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sufficiently securing a STEM-capable workforce from diverse backgrounds to expand the STEM pipeline and ensuring the quality of the trained workforce (NSB, 2015). To that end, bolstering STEM education to support the preparation of the workforce with STEM competency through different levels of education is paramount. In particular, as STEM jobs typically require a post-secondary level of education, STEM education that paves the road to enable individuals to fully acquire skills and knowledge from tertiary education plays a significant role in filling the gap. For instance, 92% of traditional STEM jobs necessitate such a level of education and training (Carnevale et al., 2011).

Despite these promising trends in STEM fields, not many students enter STEM programs. Many students are hesitant to pursue a STEM major and career. One of the reasons is that STEM fields are seen as difficult among young adults, who also simultaneously feel that they are underprepared. For example, a single-choice survey conducted by the Lemselson-MIT Invention Index indicated the main reasons that prevent young adults (ages 16-25) from pursuing education or work in STEM: one third of respondents said that “STEM fields [are] too challenging” and 28% said “they were not well-prepared at school to seek further education in STEM fields.” As a result, scholars assert that it is essential to prepare college and career readiness for high school students in those fields and support them to meet any challenges (Means et al., 2016; Schmidt et al., 2013).

To tackle this issue, previous studies have delved into how students’ college-and-career readiness in mathematics and science can be enhanced. In response, researchers have consistently found that taking advanced courses in mathematics and/or science in high school is positively related to subsequent academic performance in those subjects (e.g., Long et al., 2012) and their entrance into STEM majors (e.g., Byun et al., 2015; Wang, 2013).

With this in mind, taking advanced mathematics and science courses should be a priority for students who want to pursue STEM fields. Indeed, students who took Trigonometry, Precalculus, or Calculus in high school have a higher probability of entering STEM fields (Chen, 2009). Given that the required knowledge for STEM majors consists of multiple courses, examining diverse combinations of high school mathematics and science courses would offer insights into students' curricular exposure and its influence on subsequent college-level outcomes. Extant examinations of course-taking combinations have left a gap in the holistic picture. Thus, studies identifying combinations of high school mathematics and science courses and corresponding credits would be most beneficial.

However, there are few studies that comprehensively examine which course-taking combinations are most related to choosing a STEM major. Considering only one course at a time does not fully reflect the knowledge students need to learn when pursuing STEM majors. Moreover, most studies on course-taking have examined mathematics course-taking, and relatively little research has been done on the role of science course-taking in college and career readiness in STEM fields, as well as the students' choice of a STEM major. Hence, this study investigates the relationship between students' course-taking combinations in key mathematics and science courses and choices of college majors.

Research Questions

To address the needs outlined above, this study aims to identify mathematics and science course-taking combinations in high school, examine school and student background variables to predict students' course-taking, and investigate the relationship between the combinations and students' choice of college majors.

This study answers the following research questions:

> **Research Question 1:** Using information on students' completion of the main mathematics (namely Algebra I, Algebra II, Integrated Math, Pre-calculus, Calculus, Geometry, Statics/Probability, and Trigonometry) and science (Biology, Chemistry, Geology/Earth Science, and Physics) courses, what are the significant combinations of students' course-taking in mathematics and science?
>
> **Research Question 2:** To what extent do students' course-taking patterns in high school math and science vary based on school context and students' background characteristics, controlling for students' previous mathematics achievements?
>
> **Research Question 3:** To what degree are high school math and science course-taking combinations associated with students' enrollment in different categories of STEM majors in college, controlling for school context and students' background characteristics and mathematics achievements in high school?

Conceptual Framework

High school students' career planning and choices can be made based on multiple individual and social factors and the interactions with them. Krumboltz's (1976) social learning theory of career decision making explains how the process is influenced largely by the interaction among four categories: 1) individuals' characteristics, 2) environmental conditions and events, 3) learning experiences, and 4) task approach skills.

To briefly explain each component, individuals' inherited qualities refer to race, sex, intelligence, and special abilities that are related to people's occupational preferences and skills (Krumboltz, 1979). Environmental conditions and events indicate social, cultural, political, and economic aspects as well as the location of natural resources and disasters (Krumboltz, 1979). These include characteristics of job and training opportunities in society and policies, laws, and economic returns for occupations, educational systems, and natural events such as droughts and hurricanes. The previous learning experiences people have also play an important role in shaping their decisions related to their career path, and yet the routes of stimuli and reinforcement surrounding learning experiences are complex when attempting to uncover them completely. Lastly, task approach skills refer to the skills, including work habits, standards, and values, that each individual uniquely utilizes when coping with the environmental influences and interpreting them with regards to self-observation and making their future projections. For my study, my conceptual framework is built especially from the third category of influence, as it includes schooling and can be enhanced by systematic efforts in schools.

Learning experiences are essential not only in creating career preferences, but also building cognitive and performance skills that individuals need to career plan and develop their career path pursuits. In practice, individuals can observe themselves engaging in a performance that can demonstrate their skills and capabilities and can obtain reactions from others about the quality of that performance. The consequences of each learning experience, in turn, lead to individuals' future engagement in similar learning experiences. This sequence of experiences is also connected to the improvement of their skills. Through these series of processes, individuals create ideas about their career and make selections related to their career.

In this sense, Krumboltz's (1976) social learning theory of career decision making suggests that high school coursework is related to students' enrollment in STEM majors in college. As course-taking in high school is a part of an individual's learning experiences (Krumboltz, 1979), it therefore contributes to their later educational and occupational preferences and decision-making (Eccles, 1994). The mechanism for producing this outcome is a high school student's learning experiences generating self-judgments, preferences, and interests, and the student gains the cognitive and performance skills needed to deal with future situations related to that experience. All of these increase the probability that the student will select similar training and educational experiences (e.g., college major) in the future.

Literature Review

Growing needs of the workforce in science, technology, engineering, and mathematics

College and career readiness in STEM fields is important in regard to the growing needs of the workforce in the fields. Jobs in STEM fields are expected to substantially outpace other jobs as STEM job growth is increasing twice as fast as non-STEM jobs (National Math+ Science Initiative, 2013). Indeed, from 2009 to 2015, STEM occupations increased by 10.5% while non-STEM occupations increased by 5.2% over the same period of time (Fayer et al., 2017). When considering jobs that are traditionally defined as non-STEM occupations such as sales and management yet still require STEM critical thinking and technical skills (competency), the demand for a qualified workforce is increased even more to meet the complex needs of business and industry (Fayer et al., 2017).

However, it is estimated that the current supply of STEM workers will not be sufficient to meet the future projected need of approximately one million STEM workers due to a lack of personnel with qualified skills in STEM, whereas another estimate indicated that the shortage is more related to skills as opposed to a lack of personnel itself (Hanushek et al., 2011). In addition, people with STEM-field skills and jobs tend to have benefits including higher wages and job stability. On average, individuals with STEM occupations earn 29% higher wages (Noonan, 2017). Also, no matter what their occupations, STEM-degree holders are likely to have higher earnings (U.S. Department of Commerce [DOC], 2011). The benefit continues for STEM major graduates as they have a lower risk of underemployment once they are employed in STEM jobs (Sigelman et al., 2018).

High school course-taking in math and science that better position students' completion of advanced courses to attain college and career readiness

Previous findings suggest that high school coursework is essential for college and career readiness, as its influence affects students' access and achievement in more advanced courses throughout high school and in college (Adelman, 2006; Long et al., 2009). In particular, the relationship between taking more mathematics coursework in high school and college and career readiness is well established (Musoba, 2011). The reasoning behind the relationship of coursework and readiness can be explained as follows: completing math courses functions as a stepping stone for more advanced math and science courses, which subsequently improve performance levels in college and career readiness assessments in math and science.

Inversely, not completing an Algebra I course early in high school, for instance, can result in failing to take Algebra II before graduation, thus influencing college and career readiness (Leow et al., 2004; Zelkowski, 2010). Furthermore, some math courses, such as Algebra I, can function as gatekeepers for advanced science courses (U.S. Department of Education [ED], 2018), although there is generally no set sequence within high school science courses (Montgomery & Allensworth, 2010; Schneider et al., 1997). Additionally, as the math course sequence typically begins with Algebra I followed by Geometry, Algebra II, Pre-

Calculus, and Calculus (Montgomery & Allensworth, 2010), students who are not exposed to the preceding courses are not likely to take any Calculus courses by the end of high school.

These studies on uncovering the link between high school course-taking and college and career readiness are concentrated on the ends of mathematics courses and the most advanced level of math courses that students completed. The reason that studies on advanced course-taking have mostly been conducted on mathematics is that the studies relied on hierarchical characteristics of mathematics course-taking patterns. On the other hand, as there is no explicit hierarchy and sequence in science courses, there have been few studies that took such courses into account when examining advanced course-taking. Thus, devising and utilizing measures that provide a holistic picture of the diverse combinations of science and mathematics course-taking is urgently needed.

High school course-taking in math and science and college and career readiness: College enrollment and attainment

Students who have access to college-level academics in high school are more likely to seek higher education and succeed in it (McGee, 2013). Empirical evidence shows that course-taking in high school is strongly associated with postsecondary enrollment and performance (ACT, 2005; Adelman, 1999). The reason for this is twofold: taking advanced courses is positively related to student academic achievement in high school, and college admission often necessitates completing these courses for entrance into college (Crisp et al., 2009).

Echoing this point, previous research found that completion of Algebra II shows a positive effect on students' first-year GPA in college by 0.7 points, as well as their cumulative college GPA by 0.83 points (Gaertner et al., 2014). The augmented increase across years indicates that the influence of Algebra II is stronger on longer-term outcomes measured later in college (Gaertner et al., 2014).

Due to the growing interest in promoting STEM majors, previous research also investigated course-taking patterns that involve college enrollment in STEM fields as well as the attainment of STEM degrees in college. Studies found that overall advanced course-taking in math and science matters in students' pursuit of STEM fields at the college level (e.g., Tyson et al., 2007; You, 2013). Regarding students' entrance to STEM majors in college, Chen (2009) found that students who took Trigonometry, Precalculus, or Calculus in high school are more likely to enter STEM fields. You (2013) also found that taking any advanced mathematics courses was positively related to STEM major choice, especially for Asian males and White females. The author posited that completing calculus has a strong positive association with the decision to major in STEM fields across all subgroups.

In addition, when it comes to college degree attainment in STEM, advanced course-taking in math and science also plays a role towards degree completion in STEM. Employing Burkam and Lee's (2003) course-taking categories in math and science, Tyson et al. (2007) found that high school students whose highest levels of math courses took was Calculus are more likely to complete a STEM degree in college within 6 years than students who did not reach that level of math course category. In addition, the researchers found that high school students who move on to taking Chemistry I are more likely to graduate with a STEM degree than their peers whose highest level of science courses is Life sciences. Also, students who took the highest levels of science courses (Physics I and Chemistry II or Physics II) were more likely to obtain a STEM degree in college than students whose highest level of science courses was Chemistry I.

Nevertheless, compared to general college entrance, there have not been many studies aiming to determine what factors policymakers and school practitioners should use in policy implementation to encourage students' pursuing STEM majors. Moreover, when studying students' entrance or choice of majors in STEM fields in college as an outcome variable, most studies approach post-secondary enrollment or choice of post-secondary major as dichotomous (STEM major vs. non-STEM major). Given that STEM majors are composed of diverse and heterogeneous sub-disciplines, utilizing the different categories of STEM majors in research models is indispensable to addressing the gap in the literature.

Student backgrounds, course-taking, and STEM majors in college

Empirical evidence shows that students' course-taking and exposure to mathematics and science content is associated with their socioeconomic status (SES) (Schmidt et al., 2015). High-SES students have more access to content coverage in science and mathematics and are more likely to take advanced courses (Schmidt & McKnight, 2012; Wenglinsky, 2002). Students' course-taking patterns in advanced courses are more apparent in mathematics, which has a more explicit hierarchical structure to its courses than science. For example, high SES students tend to take at least one advanced course in mathematics that ultimately better prepares them for college-level education: progressing from Trigonometry to Precalculus to Calculus (Byun et al., 2015). In contrast, lower SES students are inclined to take courses required specifically for high school graduation (Shifrer et al., 2013). Unevenly distributed educational opportunities among students from different SES backgrounds worsen existing achievement gaps and disparities in readiness for pursuing STEM majors in college. An empirical study provided evidence that students from low-income families are less likely than their peers from higher-income families plan to major in a STEM field when they enter college (National Academies of Sciences, Engineering, and Medicine, 2016).

In addition, studies suggest that unevenly distributed access to and completion of advanced courses lead to different levels of academic achievement and college readiness among different racial/ethnic groups. Though various ethnic and racial groups show positive inclinations and aspirations for STEM careers across the board (Crisp et al., 2009), some studies maintain that racial/ethnic minority students are presented with fewer opportunities to take advanced math and science courses, which then results in discrepancies in educational attainment (Dalton et al., 2007; Ingels & Dalton, 2008; Riegle-Crumb & Grodsky, 2010). For example, 21% of White students took Precalculus in the U.S., while only 14% and 15% of Black and Hispanic/Latino students took it, according to examinations of statistics from 2004 (Byun et al., 2015; Dalton et al. 2007; Ingels & Dalton, 2008). The logic behind this conclusion is that the number of courses minority students take are limited, and those students tend to not be as well-prepared for high school- and college-level STEM coursework (Crisp et al., 2009; Oakes, 1990; Peng, Wright, & Hill, 1995; Simpson, 2001). Supporting this point, an empirical study suggests that these disparities in high school course-taking across students' race/ethnicity explain their differences in STEM pathways in college. For instance, while Black and Hispanic students are less likely to complete STEM degrees in college than White students in general, Black and Hispanic students who took high-level math and science courses are just as likely as White students to obtain STEM degrees (Tyson et al., 2007).

Previous findings show that students' SES and race/ethnicity are important background variables that must be considered in order to provide a more accurate picture regarding whether and to what degree course-taking patterns are associated with students' demographic characteristics. The results also suggest a crucial interplay among these students' backgrounds and high school course-taking in students' college major choice in STEM. While maintaining the position that students' high school coursework is related to their college entrance into STEM majors, some researchers provide additional exploratory factors for the differential entrance into STEM college majors across students' race/ethnicity and SES backgrounds. Research using NELS:88 longitudinal study uncovered that in addition to the courses they took in these subjects, high school students' attitudes toward math and science help explain the different likelihoods of entering a science and engineering major in college, in conjunction with students' race/ethnicities and socioeconomic backgrounds (Huang et al., 2000). Hence, students' interest in math and science is an aspect that also needs to be taken into consideration when examining students' enrollment in STEM majors, besides controlling for their demographic backgrounds.

Need for holistic indicators in relation to high school course-taking in math and science

Although there is growing interest in investigating whether and to what degree taking advanced courses in mathematics and science is related to students' college readiness and their entrance into STEM majors, most previous findings were derived using traditional course-taking measures in mathematics at the high school level. For high school course-taking indicators, advanced courses in math have often been the main focus in relation to college enrollment as math courses have explicit course sequences derived from a hierarchical standardization of mathematics course progressions. Given that students are required to develop their body of knowledge beyond math courses in pursuing STEM majors in college, devising indicators that include high school science coursework in the indicator will provide a holistic picture about different course-taking patterns in both math and science and their link to college enrollment in STEM majors.

Some studies utilized a binary variable for taking advanced mathematics courses, simply indicating whether or not students took at least one math course beyond Algebra II (e.g., Riegle-Crumb & Grodsky, 2010). This type of indicator does not parcel out much variation in students' course-taking; about 50% of students in a nationally representative sample were considered to have taken advanced math courses when this measure was employed (Byun et al., 2015). Similarly, another approach to measurement that considers one course at a time, controlling for course-taking in other subjects (e.g., Trusty, 2002), also only partially reflects the knowledge students need to learn when pursuing STEM majors, given that multiple courses compose the needed body of knowledge.

There have been efforts to more comprehensively understand the relationship between students' course-taking and post-secondary outcomes. For example, based on the hierarchical structure of some STEM-related courses, Schneider et al. (1997) utilized course-taking sequence variables in mathematics and science with respect to low, intermediate, and high levels of rigor for courses taken in the 10^{th}, 11^{th}, and 12^{th} grades. These researchers identified 10 mathematics course sequences and six science course sequences for courses in 12^{th} grade and found that students with more advanced 12^{th} grade mathematics course sequences were more likely to have some type of postsecondary education. In addition, Burkam and Lee (2003) developed course-taking categories of the most advanced levels attained for each math and science "pipeline" during high school. Utilizing a natural sequence of the mathematics courses, they developed eight math course-taking categories from no mathematics to advanced academic III level that refers to Calculus. They also devised seven science course categories from no science to

Chemistry 2 or Physics 2, taking into account the average grade level students achieved within each science course pipeline (Life Science, Chemistry, and Physics) and sequences within each pipeline. Despite their improved approaches to better represent students' course-taking histories, these two course-taking indicators look at math and science course-taking history separately, leaving a space that still needs course-taking indicators which parse out detailed information on different combinations of high school coursework in both math and science.

Previous findings show that high school course-taking should be studied to allow for the connection between variations in course-taking with major choice in college during analysis. There are many important, unanswered aspects when investigating the role high school students' coursework plays in students' college and career readiness. For example, few studies took into account the dimension of course-taking duration or the time students spend on each course in high school (credits students earned). In this sense, building on these studies for creating comprehensive course-taking indicators (e.g., Burkam & Lee, 2003; Schneider et al., 1997), the present study aims to construct course-taking combination profiles that indicate credits students earned in each course, to further enrich the studies on course-taking in mathematics and science and their relationship to STEM major selection in college.

Data

Sample

The data for this study is from the High School Longitudinal Study of 2009 (HSLS:09), which is a dataset with a nationally representative sample. HSLS:09 has been implemented across multiple data collection waves in 2009 (the base year), 2012 (first follow-up), 2013 (update and high school transcripts), and 2016 (second follow-up) to gather information on students' educational experience and outcomes in high school and postsecondary level after graduation. The base year data was collected during the 2009-10 school year, following a stratified two-stage random sample design. In the first stage, schools were selected as the primary sampling units; students were then randomly selected from the sampled schools in the second stage. The initial target sample was fall-term 9th graders in more than 900 public and private high schools. The information on their high school transcripts was collected in the 2013-14 academic year and contained students' coursework during high school, including course names and how many credits students earned in Carnegie units by each course. The second follow-up, which was conducted three years after high school graduation, provides young adults' postsecondary outcomes, including students' college enrollment and major.

The HSLS:09 is particularly well-suited to answer this study's research questions because the high school transcripts provide information both on the courses that students took and the credits they earned in the courses during high school in Carnegie units. The Carnegie credit is a time-based standard which can compare students' exposure to subject content using coursework time (Silva et al., 2015). Hence, the HSL:09 enables the inclusion of the durations students spend in each type of course in its analysis of the high school transcript. Also, these data include rich sets of covariates on students' demographics, their interests in mathematics and science, family backgrounds, math and science test scores, and schools' demographic characteristics. As both students' course-taking patterns and their choices in college major are correlated with students' gender, socioeconomic status, motivational factors, school location, and demographic characteristics (Carroll & Muller, 2018; Schiller et al., 2010), being able to control for these covariates contributes to reducing the selection bias of the sample used in my analyses.

Variables used in the analysis

The variables used in the analysis are presented in Table 1.A1. In addition to student and school background characteristics, this study includes two additional sections of variables: 1) the high school math and science courses and 2) college majors that students enrolled in. To run the analysis for identifying high school students' course-taking patterns, course-taking variables were created using the data from high school transcripts. First, common math and science courses were categorized into 12 courses: Algebra I, Algebra II, Integrated Math, Pre-calculus, Calculus, Geometry, Statistics/Probability, Trigonometry, Biology, Chemistry, Geology/Earth science, and Physics.

AP/IB courses were not included into this categorization (e.g., AP/IB courses in Calculus, Statistics/Probability, Biology, Chemistry, and Physics) as the main scope of this study is regular high school math and science courses rather than college-level courses offered by high schools. The categorization was conducted based on information from the School Courses for the Exchange of Data (SCED) code, which is the common system for classifying course content that enables comparing course information across divergences in course names. In addition to the SCED code, a course name variable was utilized for cross reference purposes. Then, the corresponding total number of credits individual students earned for each course category during high school were computed using a variable that indicates the number of Carnegie credits students earned for courses (the variable, T3SCRED, as presented in Table 1.A1). A Carnegie unit in this high school transcript in HSLS:09 is defined as the time that a student spends on studying a one-year academic course taken one period a day, five days a week (Dalton et al., 2016). This Carnegie credit provides information on the aspect of opportunity-to-learn standard (durations students spend in coursework), and it does not refer to students' achievement levels in each course that test scores or grades indicate.

The variables for students' enrollment in a college major have been created by recategorizing the HSLS:09's original variable of 23 college degree major categories. One variable constructed indicates whether students' major in college is either STEM or non-STEM. Another variable created provides more detailed information on students' STEM majors in college by grouping majors into six STEM major categories (Agriculture, Biology/Physics, Computer science, Engineering, Health, and Mathematics) and a non-STEM major category. This variable for different categories of STEM majors was based on the list of STEM disciplines from Higher Education Research Institute (HERI) (2019) and the available information gathered from the HSLS: 09. By employing this variable in the analysis, my study accounts for heterogeneity within STEM majors in college in the analysis model and provides more detailed information on multiple course-taking patterns and variety within STEM majors.

Methods

This study employed multilevel latent profile analyses (MLPA) to answer research question 1. Latent profile analysis, which is a special case of finite mixture models, does not require the assumption of homogeneity in the population to be met. With this flexibility, latent profile analysis enables identifying those subpopulations exhibiting different patterns in terms of values for certain variables of interests (Muthén & Muthén, 2000). Hence, distinct sets of estimates are produced for naturally different latent subpopulations under the latent profile analysis (McLachlan & Peel, 2000). In this sense, latent profile analysis provides useful information on subgroups' categorization that is not revealed in the explicit categorical variables (Asparouhov & Muthén, 2008).

Nevertheless, uniformly applying latent profile analysis to a data set while ignoring the nature of the data structure can produce biased estimates of the number of classified latent classes and standard errors when the assumption of independent observations does not hold (Henry & Muthén, 2010; Vermunt, 2008). For hierarchical data, which is often the case in educational data in which students are nested within schools, the assumption of independent observation is not met. Therefore, to assess latent profiles with consideration of the nested data structure and obtain accurate estimates, MLPA is needed. With the advantage of accounting for different levels of data from the hierarchical data structure, MPLA provides information beyond the scope of what a single-level latent profile analysis can offer. MPLA allows not only for latent profiles at level 1, but also level 2 latent classes derived by utilizing the level 2 variations in the relative frequency of level 1 profiles (Mäkikangas et al., 2018). The information allows us to examine the influence of level 2 on level 1 membership of latent profile. Equations for MLPA are presented in Appendix B.

I utilized MLPA because the HSLS:09 has a nested structure—students (Level 1) are nested within schools (Level 2)—deriving from its stratified two-stage random sampling design. Also, since individual students' course-taking in mathematics and science can be closely related to their schools' overall course-taking patterns, incorporating school-level information can provide more accurate estimates. For generalizable results, final student weights and school weights corresponding to analyses were used for within and between weights, respectively. In implementing MPLA, I used full information maximum likelihood (FIML) estimation with robust standard errors for estimation, which is the MLR estimator option in Mplus. This estimation approach is robust to non-normal and non-independent distributions of observations. Given the range of students' earned credits in math and science and the nested structure of the data, the FIML estimation with robust standard errors is suited for addressing these issues. Also, maximum likelihood estimation produces more accurate parameter estimates in data with missingness compared to traditional methods for handling missing data including listwise deletion, arithmetic mean imputation, and stochastic regression imputation across all missing pattern conditions (Enders, 2010). This approach produces unbiased parameter estimates and standard errors under missing at random (MAR) and missing completely at random (MCAR) conditions (Cham et al., 2017; Enders, 2010). Furthermore, even if the estimates using maximum likelihood are biased, the bias from maximum likelihood is inclined to be limited to a subset of the analyses, while traditional techniques are prone to be distributed broadly throughout the analysis model (Enders, 2010).

Modeling MLPA was conducted in the following steps: (1) model specification and tests of alternative models to identify latent profiles that describe students' underlying course-taking patterns regarding mathematics and science at the student level; (2) model specification and tests of alternative models for identifying school-level latent classes derived from the variations in the size of students' course-taking profiles; (3) including covariates that take into account the classified latent profiles (level 1) and latent classes (level 2); and (4) examining the relationship between identified latent profiles and outcome variables.

First, single-level (level 1) latent profile analysis was conducted to determine the optimal number of profiles that indicate high school students' course-taking combinations in mathematics and science. Latent profile solutions were produced using variables on the credits that students achieved for eight math courses (Algebra I, Algebra II, Integrated Math, Precalculus, Calculus, Geometry, Statics/Probability, and Trigonometry) and four science courses (Biology, Chemistry, Geology/Earth Science, and Physics). Models were built with an incremented number of profiles through an iterative process, and the models with different numbers of classes were compared based on model fit indices including sample-size Adjusted BIC (SABIC), Akaike information criterion (AIC), and Bayesian information criterion (BIC), as well as entropy and interpretability of the results. Specifically, the SABIC is an index based on a log-likelihood estimate and the model with lower SABIC value indicates that the model has a better fit with fewer parameters for the data (Tein et al., 2013). The entropy is related to the degree of aggregated classification uncertainty. The normalized entropy is scaled to the interval [0,1], and the higher value represents a better fit that identified latent classes or profiles are more distinguishable (discriminating) from each other. In general, the entropy values larger than .80 indicate that the latent classes/profiles are highly discriminating (Muthén & Muthén, 1998-2017).

All of these pieces of information contribute to assessing the appropriateness of each model, and, as a result, a model was selected as the final solution for single-level analysis. Once the number of classes at student level was determined, solutions for school-level latent classes were derived. Incorporating school-level latent classes in the model is mainly due to taking into account the dependency in observations and to obtain more accurate solutions for student-level latent profiles for high school course-taking patterns. As the focus is more towards determining student level latent profiles, the number of latent classes at school level is determined by considering all factors including the interpretability that shows distinguishability across latent classes, the number of schools corresponding for each identified latent class, and the distribution of latent profiles in each latent class.

After obtaining the final unconditional latent profile solution, I used two-level hierarchical multinomial logistic regression to examine school and student background variables to predict student-level course-taking combinations (latent profiles) and school-level latent classes, respectively (research question 2). Following the MLPA model framework, student background characteristics are specified to predict student-level latent profiles and school backgrounds are specified to predict school-level latent classes. No direct path was set from school backgrounds to student-level latent profiles because, in this MLPA model**,** school characteristics are set to be related to student-level profiles through direct paths from school-level classes to student-level profiles. These covariates were added to assess their differential relationship with latent classes and to evaluate whether the derived latent profiles represent heterogeneous populations.

In this analytic model, students' gender, math course interest, science course interest, previous math test scores, socioeconomic status, race/ethnicity, as well as percent of racial minority students (Black and Hispanic) in the school, percent of free/reduced lunch students in school, percent of students enrolled in AP courses in school, and percent of students enrolled in a 4-year college in school were included as covariates. In particular, the school background variables were incorporated in the model as indicators reflecting characteristics that are related to course-offering. Students' course-taking can be shaped by course-offering in school, which differs by school characteristics, in addition to students' choice of course-taking made by multiple factors. The limited information on course-offering in each school in the data does not allow for this study to address this area. Hence, to complement the limited information on course-offering in each school and to indirectly take it into account, the relationship between other school characteristics concerning school offering and school latent classes as well as the relationship between school latent classes and student latent profiles were utilized in the model.

For the analysis of this model with covariates, the previous starting values of MPLA without covariates were used, thereby ensuring level 1 profiles were not switched. Simulation results show that the covariates should be included in the models only after the final unconditional solution has been determined and not during the procedure of determining the number of latent profiles (Diallo & Lu, 2017; Diallo et al., 2017). In addition, multilevel multinomial logistic regression was conducted to investigate which identified course-taking profiles are most related to choosing different types of STEM majors in college, controlling for covariates (research question 3). The two versions of variables for STEM majors (a binary variable and a categorical variable with six categories) were used as outcome variables. Being consistent with previous multilevel analyses, FIML estimation with robust standard errors for estimation was employed to handle non-normal distribution of data with missing cases. The multilevel multinomial logistic regression approach serves better for my study than applying post hoc ANCOVA to examine such relationships as suggested by some studies (e.g., Agasisti et al., 2019). The rationale for this is that the outcomes in my studies are categorical variables rather than continuous variables that ANCOVA is designed for and multilevel multinomial logistic regression using Mplus can handle missingness, non-normality, and nested structure present in the data. Equations for this model are also presented in Appendix B.

Results

Descriptive statistics

Table 1.C1 shows credits that students earned for eight math and four science subjects during high school as well as total credits students earned across all 12 math and science subjects (represented as Math and Science Total in Appendix Table 1.C1) and the earned credits across 8 math subjects and 4 science subjects, respectively (represented as Math total and Science total in Table 1.C1, respectively). The credits are based on Carnegie units, where a unit of Carnegie credit equates to the time of course-related work for a one-year academic course taken one period a day, five days a week (Dalton et al., 2016). In this sense, the credits students earned for each course in high school represent duration of coursework for a corresponding course.

As shown in Table 1.C1, on average, high school students earned more than one credit across different math and science courses, with exceptions of slightly lower credits in advanced math courses: Precalculus (0.93 credits), Calculus (0.93 credits), and Statistics (0.82 credits). Looking at course credits specifically by subject, among the eight math courses, students earned the most credits in integrated math (1.28 credits), spending the most time on integrated math course-taking (approximately 61.44 hours). Biology is the subject that students earned the most credit and spent the majority of their time on course-taking among the four science courses (1.40 credits, 67.2 hours). In terms of variation in course credits, Integrated Math has the largest variation (SD=0.94) out of these 8 math courses, and earth science has the largest variation (SD=0.72) right followed by Biology (SD=0.71) across 4 science subjects. Students earned 3.32 credits across all math subjects and 3.48 credits across all science subjects, which equate to 159.36 and 167.04 hours of course-related exposure, respectively. The average credits students earned in both math and science during their high school coursework are 6.73 (approximately equivalent to 323.04 hours).

Table 1.C2 shows the correlation between credits high school students earned in math and science subjects as well as the relationship between the earned credits and students' enrollment in a STEM major. In general, credits that students earned in each math and science subjects during high school are positively related to each other with a few exceptions. The increase in credits in Algebra I is not related to credits in Calculus, Statistics/Probability, and Trigonometry. The credits earned in Earth Science are not associated with credits in Calculus and Statistics/Probability. In addition, credits in Integrated Math and Chemistry as well as credits in Geometry and Statistics/Probability do not show any statistically significant relationship. Among math courses, credits earned in Calculus and Statistics/Probability have the strongest relationship (r=.35, p<.05). Among science courses, credits earned in Biology and Chemistry have the strongest relationship (r=.22, p<.05). The strongest association between math and science courses come from Algebra I and Earth Science (r=.29, p<.05).

Increase in time spent in Algebra I during high school has a weak and negative relationship with students' enrollment in a STEM major (r=-.04, p<.05). Among math courses, increase in time spent on Calculus coursework has the strongest positive relationship with students' enrollment in a STEM major (r=.11, p<.05). In science courses, three subjects of Biology, Chemistry, and Physics all have the highest association with being enrolled in a STEM major in college (r=.14, p<.05).

Enrollment in Agriculture/Natural resources is most positively related to increase in earning credits in Earth Science although the magnitude of the correlation is small (r=.03, p<.05). Course-taking durations in math courses are not significantly related to students' enrollment in Agriculture/Natural Resources in college. Enrollment in Biological and Physical Sciences majors is most positively related to increase in duration (the earned credits) in taking Calculus out of the eight math courses (r=.12, p<.05) and Biology (r=.15, p<.05) among the four science courses. Out of the small magnitude of the significant correlation coefficients, the enrollment in Computer and Information Sciences is most positively associated with Trigonometry (r=.04, p<.05) and Physics (r=.06, p<.05) for math and science courses, respectively. The college enrollment in Engineering and Engineering technology majors has the highest correlation with credits earned in Precalculus (r=.05, p<.05) and Physics (r=.17, p<.05) from the math and science courses, respectively. Student enrollment in Health Care fields in college is most related to enrollment increase in Algebra II among math courses and Biology among science courses (r=.06, p<.05) during high school. Students' enrollment in a Mathematics major has the largest association with Precalculus (r=.03, p<.05) and Physics (r=.05, p<.05) out of math and science courses, respectively, but the magnitude of each correlation is very small. The correlation results show that increase in students' spent time in math and science coursework (durations of courses measured by credits they earned in the courses) generally have a positive relationship with students' enrollment in a STEM major. However, increases in the duration of some courses have a negative association with student enrollment. Hence, we should holistically look at students' course-taking patterns in terms of types and durations (credits they earned) of courses to understand the relationship comprehensively rather than looking at the individual relationship one by one.

Multilevel latent profile analysis

I first conducted single-level latent profile analysis to obtain information on the number of classes in the student level (profiles) that explain student patterns of course-taking in high school math and science courses. The model fit indices including ABIC, AIC, and BIC have largely decreased as models have increased the number of latent profile solutions until a model is specified with four profiles. The decreases are relatively level from four profiles to five profiles (Table 1.C3). To represent this pattern, ABIC values across the number of latent profile solutions are shown in Figure 1.D1. Also, entropy for the four-profile model is 0.94, while entropy for the five-profile model is 0.87. These indices suggest that the four-profile solution is superior based on both its model fit and clear delineation of latent profiles. Moreover, in terms of interpretability of the profiles, the four-profile solution is clearer than the five-profile solution.

Then, I conducted MLPA with four profiles at level 1 (student-level) and two classes at level 2 (school-level). The ABIC for the MLPA model with four profiles and two classes is 147131.781 and the corresponding entropy is 0.913. The ABIC for MLPA model with four profiles and three classes is 145857.330 and the entropy is 0.913. Given the number of sampled schools, ABIC index, and interpretability, the MLPA model with four profiles at the student level and two classes at the school level has finally been chosen. In other words, four course-taking profiles at the student level were identified based on information on credits students earned for each subject (duration they spent per subject). Students' course-taking patterns by each profile are presented in Table 1.C4 and Figure 1.D2.

Students can be categorized into four groups based on their course-taking combinations. Students with Profile 1 earned the highest credits across seven subjects, except Precalculus, Calculus, Chemistry, Earth Science, and Physics. Their time spent on coursework in these five courses is around one credit and similar to the patterns of Profile 3. Hence, they are labeled as *generally highest course-takers*. Students with Profile 2 show overall balanced and higher course-taking patterns around one Carnegie credit across eight math subjects with more time spent across four science subjects. They also spent a little more time on Precalculus and Calculus than Profile 1. Hence, they are labeled as *generally balanced and higher advanced math and science course-takers*. Profile 3 indicates students who attained about one Carnegie credit across all 12 subjects, and they are labeled as *tightly balanced course takers*. Students with Profile 4 are called *the lowest course-takers* as they earned the lowest amount of credits across subjects relative to the other groups except their notable surge (focus) on integrated math and earth science.

14.74% of schools were identified as Class 1 and 85.26% were identified as Class 2. The percent of each course-taking Profile of students in Class 1 schools is 20.32%, 33.56%, 44.08%, and 2.05%, respectively for Profiles 1-4. The percent of each course-taking Profile of students in Class 2 schools is 5.31%, 2.41%, 86.52%, and 5.76%, respectively for Profiles 1-4. Class 2 schools consist of mostly Profile 3 students who earned approximately one credit across all math and science courses. Compared to Class 2 schools, Class 1 schools have a relatively balanced proportion of students with different profiles from 1 to 3 with low percent of Profile 4 students.

Table 1.C6 shows a direct relationship between school-level latent class membership and student-level latent profile membership. The parameter estimates indicate the extent to which the class one's school belongs to is related to the class to which individual students belong. The reference categories are Class 2 at the school level and Profile 4 at the student level. Students attending schools in Class 1 are more likely to belong to Profile 1 than the students attending schools in Class 2 ($b=2.45$, $p<.05$). The membership of schools that students attend does not

have a statistically significant association with students' being classified as Profile 2 and Profile 3.

Multilevel latent profile analysis with covariates

Regarding answering research question 2 to identify course-taking profiles and whether and to what degree covariates are related to predict course-taking profiles, Table 1.C7 is presented. Students with higher math scores and higher SES are more likely to be classified as Profile 1 than Profile 4. For example, being classified as Profile 1 is 1.05 times higher in 1-point math score increase and 2.64 times higher in 1-unit increase in SES composite score, compared to being classified as Profile 4. Students' increased interest in math courses is associated with being classified as Profile 2 than Profile 4. Students who have a 1-unit higher interest in math courses and 1-unit higher math test score are 1.5 times and 1.13 times more likely classified as Profile 2 than Profile 4, respectively. Students' 1-unit increase in SES score means that they are 3.26 times more likely to be classified as Profile 2 than Profile 4. Compared to male students, female students are 2.23 times more likely to have Profile 3 course-taking patterns than Profile 4. Students with higher math score and SES are more likely to show Profile 3 course-taking patterns than Profile 4, 1.48 and 3.08 times, respectively.

Multilevel logistic regression and multilevel multinomial regression

Table 1.C9 shows logistic regression results concerning the association between students' course-taking profiles and their enrollment in a STEM major in college. Students who have course-taking patterns of Profile 2 in their math and science courses are 2.57 times more likely to be enrolled in a STEM major in college than the reference group of students who have Profile 4.

In other words, students who have balanced yet higher Chemistry, Physics, and advanced math (Pre-calculus and Calculus) courses are more likely to pursue a STEM major in college than those who earned the least credit across all math and science courses except integrated math.

In terms of enrolling in any type of STEM major overall, female students are 1.29 times more likely to be enrolled in a STEM major in college than male students. As students' interest in math courses in grade 9 increase by 1 factor score, it is expected to see about 24% increase in the enrollment in a STEM major in college. As students' interest in science courses in grade 9 increases by 1 factor score, they are 1.30 times more likely to be enrolled in a STEM major. In addition, when schools have an increase in the percentage of free and reduced priced lunch students by 1 percent, students who attend the schools will be 1.01 times more likely to be enrolled in a STEM major in college.

Table 1.C10 shows multilevel multinomial logistic regression results related to students' enrollment in six categories of STEM majors in college (Agriculture, Biology/Physics, Computer Science, Engineering, Health, and Mathematics). The reference group for the outcome variable (college major) is non-STEM major students. When it comes to an Agriculture major in college, students' high school course-taking profiles do not have any statistically significant association with their enrollment in an Agriculture major than non-STEM majors. As students have a higher science course interest score, they are 1.39 times more likely to be enrolled in an Agriculture major in college. Asian, Hispanic, and other race group students are 25 times (1÷0.04), 5.56 times (1÷0.18), and 8.33 times (1÷0.12) less likely to be enrolled in an Agriculture major in college. Students who are in a school with a higher percent of free and reduced priced lunch students are 1.03 times more likely to enroll in an Agriculture major.

High school students with course-taking profiles of 1, 2, and 3 are more likely to be enrolled in a Biology/Physics major in college (2.74, 4.90, and 2.87 times higher, respectively) than Profile 4 students. The increase in math course interest, science course interest, and math test score are related to 22%, 51%, and 7% increase in the enrollment in a Biology/Physics major in college. In addition, Asian students are 2.32 times more likely to enroll in a Biology/Physics major in college. High school students who have Profiles 1, 2, and 3 tend more to enroll in a Computer Science major in college (1.78, 2.92, and 2.60 times more likely than Profile 4 students, respectively). Female students are 5 times less likely to enroll in a Computer Science major while Asian and Black students have 4.45 times and 2.71 times greater odds for being enrolled in such a major than White students.

Enrollment in an Engineering major is also related to students' course-taking profiles. Students with Profile 1 are 1.53 times more likely to enroll in an Engineering major while Profile 2 students and Profile 3 students are 1.57 times and 1.07 times more likely to be enrolled in such a major. Students' higher interest in math and science courses is related to greater odds for being enrolled in an Engineering major in college (1.38 times and 1.34 times greater, respectively). Female students are 5.88 times less likely to pursue an Engineering major than male students. Asian students have 2.28 times greater odds for being enrolled in such an Engineering major than White students.

Being enrolled in a Health-related major in college is not predicted by students' course-taking profiles. Students' backgrounds are related to their enrollment in a Health major in college. Females are 5.01 times more likely to enroll in a Health major and students with higher math course interest and science course interest are more likely to enroll in such a major (the corresponding odds ratios are 1.23 and 1.25, respectively). On the other hands, compared to

White students, Black students are 2.5 times (1÷0.4) less likely to be enrolled in a Health major than a non-STEM college major. Dissimilar to Biology/Physics and Mathematics majors, students with higher math scores in grade 9 are less likely to enroll in a health major in comparison to a non-STEM major in college. One unit increase in math score will decrease the odds ratio by 1.03 times (1÷0.97).

In addition, being enrolled in a Mathematics major in college have a significant relationship with students' course-taking patterns of Profile 2. Students with Profile 2 are 2.20 times more likely to enroll in a Mathematics related major in college than Profile 4 students. Black students are less likely to enroll in a Mathematics major in college. The log odds of being enrolled in a Mathematics major vs. a non-STEM major decreases by 8.41 if students' race is Black (White is a reference group). Also, a one-unit increase in math test score is associated with the increase in log odds of being enrolled in a Mathematics major than a non-STEM major in college by 0.15, suggesting that students with a one-unit higher math test score are 1.16 times more likely to enroll in such a major. In general, compared to students with Profile 4, students with course-taking pattern of Profile 2 will more likely to being enrolled in Biology/Physics, Computer science, Engineering, and Mathematics majors over non-STEM majors in college.

Discussion

As the first study applying a new methodological approach of MPLA to students' high school course taking, the findings reported in this study extend the literature on high school math and science course-taking and its connection to students' achievement of college-level outcomes in STEM fields in multiple ways.

New approach to devise indicators for high school math and science course-taking

The present study classified four distinct course-taking patterns that show students' different exposure to coursework across 12 math and science high school courses in terms of credits students earned in Carnegie credit units (which also serves as an indirect indicator for time students spent for completing coursework). Profile 1, in which 7.87% of students were classified, shows a pattern of earning the highest course credits across the high school math and science courses compared to the other three profiles. However, while the students earned the highest number of credits in lower level courses such as Algebra I, Algebra II, and Biology, they did not achieve the highest number of credits in more advanced courses identified in previous literature as Calculus, Chemistry, and Physics. A notable point in Profile 1 is that students earned approximately two times as many credits on average (2.73 Carnegie credits) in Integrated Math than the other three profiles while attaining the highest credits earned in Algebra I, Geometry, and Algebra II. In addition, 8.47% of students were classified as Profile 2, which exhibits balanced course-taking patterns around one Carnegie credit across high school math courses with a slight deviation in the Statistics and Probability course (0.81 credits on average). Students with Profile 2 earned the highest credits in both Calculus and Physics; courses that are considered as the most advanced course sequence in Burkam and Lee (2003)'s classification of high school course sequence. They also attained the highest credits in Pre-calculus and Chemistry, showing a particularly large increase in credits achieved in Chemistry (2.15 credits), whereas students in Profile 1 who earned the second highest credits in Chemistry only earned 1.23 credits. Students with Profile 3 that shows balanced course-taking patterns (close to one Carnegie credit) across math and science courses make up 77.73% of the participants in the data. Profile 3 students earned the second to the highest number of credits in Calculus (0.92) and Physics (1.02), next to

Profile 2. Lastly, 5.93 % of students are identified as having Profile 4 course-taking combinations; these students attained the least credits of any other Profile across all 12 math and science courses.

Studies on high school math and science coursework have utilized different measures ranging from looking at whether students took any advanced level math courses as a binary indicator (e.g., Byun et al., 2013) to more detailed course sequences for math and science that capture more variations in students' course completion (e.g., Burkam and Lee, 2003; Schneider et al.,1997). These approaches relied heavily on the natural course sequence based on hierarchical structure of the courses. To further develop a measure for identifying high school students' course completion in math and science, this study incorporated diverse math and science courses to construct comprehensive indicators for high school course-taking combinations in both fields by simultaneously incorporating the specific courses students took and the duration of their study in each course (i.e., the credits they earned). These indicators capture different aspects of information and nuance that have not been provided in previous studies on high school course-taking patterns beyond the more commonly used binary variable for advanced course-taking.

In addition to these contributions, the results of Profile 1 indicate interesting patterns that need further examination to determine the reasoning behind school and district level course structure policies beyond individual students' choice of coursework. For instance, some schools that these students attend might be transitioning to change their course offerings from a traditional sequence of math courses in high school (usually provided in order from Algebra I, Geometry, Algebra II, to Probability and Statistics) to an integrated pathway that combines and reorganizes content from those math courses for grades 9-11 (simply put, Math I, Math II, and

Math III). Based on school and district policy, school counselors and teachers might encourage or provide students the opportunity to take these Integrated Math courses due to their structural leeway; these courses can serve as an alternative for advanced level courses after Geometry to strengthen their knowledge and skills in solving complex problems while schools continue to provide the Algebra I, Algebra II, and Geometry courses that they traditionally offer to prepare developing instruction and curriculum design suited to the transition.

Factors linked to the course-taking combinations of high school math and science courses

Applying the MLPA approach, the present study found that students' previous math test scores, socioeconomic status, math course interest, and gender are related to different likelihoods of certain course-taking profiles. To obtain a more accurate picture about the relationship, I included students' math test scores in the beginning of grade 9. Students' access to more advanced courses is cumulative from their previous course-taking experiences—students who have access to certain courses in the lower level course sequence tend to take more advanced courses because they are equipped with the knowledge and skills to do so from previous courses. This differential readiness through the cumulative process applies to course-taking within high school, which is the final educational stage in K-12 prior to post-secondary education**.** Therefore, it is important to take into account students' prior achievement levels as a variable that shows students' previous educational experience in their respective school system.

By considering how individual students' previous educational opportunities and subsequent performance levels can influence students' course-taking in high school, this study includes students' math achievement levels in the beginning of grade 9 as a control variable for the following two purposes: 1) to examine whether students' previous achievement is related to shaping students' course-taking patterns and 2) to provide a better understanding regarding the diverse factors that have a link to distinct course-taking patterns, controlling for students' initial achievement levels. Results from this study showed that students' previous math achievement level is related to high school students' different likelihoods of having different course-taking profiles. Students with a higher performance level in the beginning of grade 9 are more likely to be classified as Profile 1 (*generally highest course-takers*), Profile 2 (*generally balanced and higher advanced science and math including Chemistry, Physics, Pre-calculus, and Calculus*), and Profile 3 (*tightly balanced course takers*), all of which have more exposure to course-taking than Profile 4 (*the lowest course-takers*). The findings bolster previous research that students' previous performance levels act as a gatekeeper by either preparing or hampering their access to advanced coursework in high school.

The results in this study also support the assertion that students' socioeconomic status is related to students' different course-taking patterns in math and science. An increase in students' socioeconomic status is related to an increase in likelihoods of having course-taking combinations of Profile 1 (*generally highest course-takers*), Profile 2 (*balanced and higher advanced science and math courses including Chemistry, Physics, Pre-calculus, and Calculus*), and Profile 3 (*tightly balanced course-takers*) than Profile 4 (*the lowest course-takers*). The Profiles 1, 2, and 3 show course-taking patterns that earn higher credits in high school courses across all 12 math and science courses with different focuses on certain sets of courses compared to Profile 4. Moreover, students with higher SES are more likely to be classified as Profile 2, in which students earned the highest level of credits in Calculus and Physics courses that comprise the most advanced sequence of math and science courses, respectively. These findings are in line with previous studies that students' socioeconomic status plays a role in high school students' differential course-taking patterns in math and science, and is closely related to completing more advanced courses as well (e.g., Conger et al., 2009). Moreover, these findings expand on previous research to show that students' higher socioeconomic status is positively related to the increase in the duration of coursework (credits students earned) in both general and more advanced high school math and science courses beyond students' access to the course-taking.

The present study also found that students' interest in math courses in the beginning of high school is a predicting factor of their course-taking in high school math and science. Compared to the *lowest course-takers* (Profile 4), students' with higher math course interest are more likely to be *tightly balanced course-takers* (Profile 3) and *balanced and higher takers in advanced science and math courses including Chemistry, Physics, Pre-calculus, and Calculus* (Profile 2). This finding is in line with previous research showing that interest is closely related to students' course-taking—specifically, increase in STEM topic interest is associated with students' behavior of taking more elective math and science courses during high school (Harackiewicz et al., 2012). The underlying mechanism is that enhanced interest improves students' attention to and engagement for a subject that leads to further intentional efforts to engage with and explore the material (Harackiewicz et al., 2008).

However, students' math course interest does not predict the likelihood of being classified as *generally highest course-takers* (Profile 1) over *the lowest course-takers* (Profile 4) who earned the highest credits in Algebra I, Algebra II, Integrated Math, Geometry, Trigonometry Biology, and Earth Science among the total 12 courses. Given that the *generally highest course-takers* (Profile 1) have a tendency to earn the highest credits overall in most math courses and notably earn much higher credits (i.e., spend substantially more time) in Integrated Math and Algebra I among math courses than all other 3 profiles, the pattern cannot be simply explained with the quantitative aspect of reasoning. Therefore, further investigation is needed to determine a contributing reason for why students' increase in math course interest is not significantly related to the likelihood of being classified as the *generally highest course-takers* given its course-taking combinations. In addition, somewhat dissimilar results were found regarding the relationship between students' interest in science course and course-taking: student interest in science courses was not a statistically significant predictor regarding the likelihood of having different students' course-taking profiles compared to Profile 4. Although the four identified profiles show distinct patterns in their science courses, students' interest in science courses did not have a statistically significant relationship. A potential reason might be that math courses often serve as a stepping stone for both science and more advanced math courses in high school (e.g., ED, 2018). Another possible reason would be that students' interest in math courses are a more stable predictor of students' course-taking during high school years than their interest in science courses over time. Hence, future studies are needed to uncover the relationship between science course interest and high school course-taking in math and science, as well as the relationship between math course interest and science course interest in their role in high school course-taking in math and science.

Regarding students' demographic characteristics, female students are more likely to have tightly balanced yet lower credit-bearing course-taking patterns (Profile 3) than the least course-taking patterns (Profile 4). However, there are no statistically significant differences in likelihoods of being classified as Profile 1 or Profile 2 over Profile 4 by student gender, respectively. This finding shows that female high school students have a higher likelihood than male students of earning about one credit, which indicates a year-long course of study across math and science courses. However, gender does not predict the higher completion of course credits in advanced high school math and science courses (i.e. Precalculus, Calculus, Chemistry, and Physics) as shown in Profile 2. These new findings highlight the necessity for further investigation; particularly interviewing students to explore what the encouraging factors are that function differently across gender and bring about the different course-taking patterns and students' decisions on and processes in course-taking.

In this study, high school students' course-taking profiles in math and science do not differ by racial/ethnic groups after controlling for other variables including their previous math performance level, math course interest, and science course interest in the beginning of grade 9. When looking at the credits high school students earned in math and science without controlling for these variables, the results employing HSLS: 09 show that the total credits students earned in high school math and science courses, as well as the percentage of students who completed Calculus courses, differ by race/ethnicity groups. For example, according to National Center for Education Statistics [NCES] (2016, August), Asian students on average earned the most high school credits in math (3.9 credits) followed by White students (3.7 credits), Hispanic students (3.5 credits), and multi-race groups (3.5 credits). Also, for average science credits, Asian students (3.9 credits) earned more credits than White students (3.4 credits) by 0.5 credits and both of these race/ethnicity student groups earned more credits than students in any other group (NCES, 2016, August). In addition, when it comes to the percentage of students who earned their highest math course credit in Calculus, the percentage by race/ethnicity differs: 45 percent of Asian students, 18 percent of White students, 11 percent of multi-race students, 10 percent of Hispanic students, and 6 percent of Black students earned course credit in Calculus as their highest math course (NCES, 2016, August).

These results from previous research emphasize that the examination of high school course-taking patterns would produce different results depending on whether other backgrounds including student initial achievement level and interest in math and science courses are taken into account in the analysis. Based on this discrepancy, future studies need to conduct research on whether and to what degree the association between race/ethnicity and course-taking—after taking into account these diverse aspects of backgrounds—differs across education or grade levels. Whether students' race/ethnicity is a significant predictor of their course-taking patterns after holding other variables constant might be dissimilar across education levels (elementary, middle, and high school) or grade levels—over time, students form their interest in math and science courses from their experience with their coursework and classes, and their achievement level is also influenced by previous course-taking. Hence, further examination on whether statistically significant variations in course-taking by racial and ethnic groups exist in the earlier education levels or grade levels would contribute to build a more comprehensive understanding about the relationship among these variables.

Also, school background characteristics identified from previous studies that are closely related to students' course-taking patterns did not show significant association with school latent classes, which indirectly predict student course-taking latent profiles. One possible explanation is that within the MLPA framework, school-level backgrounds are set to indirectly influence student latent profiles via school latent classes, rather than the directly specified path from school backgrounds to student latent profiles. To further uncover the relationship between schools' characteristics and school-level course-taking patterns derived from students' course-taking profiles, future work should examine whether other school characteristics—including school location (urbanicity) and enrollment size—significantly predict school-level course-taking latent classes. Moreover, obtaining information on each school's course-offering list will be helpful in shedding light on how school characteristics have a relationship with school course-offerings, which in turn shape students' course-taking patterns.

Parceling out heterogeneity of STEM majors in examination of its relationship with course-taking

This study also takes into account the diversity and heterogeneity of STEM disciplines when examining the relationship between course-taking in mathematics and science and students' enrollment in STEM majors in college. Previous studies relied on a binary indicator (whether students' college major is in STEM or non-STEM) when examining factors that predict students' choice, enrollment, or completion of STEM majors as an indicator for students' pursuit of STEM fields (e.g., Ackerman et al., 2013). Using this approach, prior studies have contributed to distinguishing students' college enrollment or persistence in STEM fields from general college outcomes and found that variations in high school course-taking led to a different likelihood of choosing a STEM major in college. However, growing empirical evidence supports that STEM is an umbrella term for the unity of heterogeneous subfields and addressing the heterogeneity in investigating the topic is necessary (Su & Rounds, 2015).

In response to the necessity of further developing the line of inquiry to this topic, the present study takes a new approach that enables the identification of useful information regarding how different combinations of course-taking are related to enrollment in certain categories of STEM majors that a binary indicator of whether students choose a STEM major simply cannot capture. As a result, I found that students with the same high school course-taking profile do not lead to having the identical likelihood of being enrolled in a STEM college major across diverse subdisciplines. For example, when the binary measure for enrollment in STEM major is used, only Profile 2 (the patterns of balanced and higher course-taking in advanced science and math courses) has significant differences in the likelihood of being enrolled in a college STEM major when compared to Profile 4 (the lowest course-taking patterns). Students with other types of course-taking profiles do not have statistically significant differences in the likelihoods of entering into a STEM major in college from Profile 4. Students with balanced and higher course-taking in advanced science and math courses are more likely to enroll in a STEM major in college than students with the lowest earned credits across the math and science courses.

In contrast, using a categorical variable with seven levels of the enrollment in STEM majors as the outcome variable captures more information about the relationship between course-taking patterns and enrollment in specific STEM majors in college. Profile 2 is most related to higher likelihoods of the enrollment of STEM majors for many subdisciplines of STEM majors—Biology/Physics, Computer Science, Engineering, and Mathematics—than Profile 4. Both Profile 1 and Profile 3 course-taking combinations are related to students' higher likelihoods of enrolling in STEM majors in Biology/Physics, Computer Science, Engineering, and Mathematics than Profile 4. However, these two course-taking profiles do not predict students' entrance into a Mathematics major. For Agriculture and Health majors, students' variations in course-taking profiles do not have a significant relationship with STEM college enrollment.

These results from this study support that lumping diverse STEM disciplines into one STEM category does not parcel out important information that can be utilized for preparing students to be college and career ready in a specific STEM field that students intend to pursue.

Regarding their college and career readiness in certain STEM fields, students need to be equipped with common sets of curricular knowledge and skills, but acknowledging unique characteristics in each subfield and preparing students to better position themselves to be ready in pursuing a specific field will be useful for not only students but also educators. Also, different course exposure following different course completion patterns in high school would contribute to establishing their interest in a specific STEM field and their course-taking choice in college would combine with this earlier educational experience to influence students' enrollment in a certain STEM subfield. In this sense, this work will form a foundation for further studies on how best to advise students interested in STEM fields in terms of course-taking to sufficiently prepare them for future educational experiences in those fields. From these efforts, this study will assist in the development of a curricular pipeline to support students' successful transitions from secondary to post-secondary education with relevant and adequate course-taking experiences.

APPENDICES

APPENDIX A A LIST OF VARIABLES

Table 1.A1 Variables Used in the Study

Variable Name	Description	Research Question
Outcome variables		
X4RFDGMJ123	Degree major categories (23 categories)	RQ3
X4RFDGMJSTEM	Degree’s major is STEM	RQ3
Course-taking variables		
T3SSCED	SCED code	RQ1
T3SCRSNAM	Course name	RQ1
T3SCRED	Carnegie credit received for course	RQ1
Control variables		
Student characteristics		
X1SEX	Student’s gender	RQ2,3
X1RACE	Student's race/ethnicity	RQ2,3
X1SES	Student’s socio-economic status composite	RQ2,3
X1TXMTSCOR	Mathematics standardized score (base-year)	RQ2,3
X1SCIINT	Student’s interest in science course	RQ2,3
X1MTHINT	Student’s interest in math course	RQ2,3
School characteristics		
A1FREELUNCH	% of student body receiving free or reduced-price lunch (base-year)	RQ2,3
A1BLACKSTU	% of student body of Black/African American	RQ2,3
A1HISPSTU	% of student body of Hispanic	RQ2,3
A1AP	% of student body enrolled in AP courses	RQ2,3

Source. High School Longitudinal Study of 2009 (HSLS:09)

APPENDIX B EQUATIONS FOR ANALYTIC MODELS

Latent profile analysis models

Level 1:

$$y_{ijku} = \mu_{jk} + \varepsilon_{ik}\ , \varepsilon_{ik} \sim N\ (0, \sigma_k^2)$$

Level 2:

$$Cj_u \sim N\ (\mu_j, \sigma_j^2), j = 1, \ldots, J - 1$$

where individual, latent profile, math and/or science course-taking variables, and Level 2 (school) units are represented as i, j, k, and μ, respectively.

y_{ijku} is an observed variable that indicates an individual student's credits earned in subject *k*.

Cj_u is a latent categorical profile variable. p_j is the mean proportion of latent profile *j* where

$p_j = \frac{e^{\mu_j}}{1+\sum_{j=1}^{J-1} e^{\mu_j}}$, *j*=1,…,*J*-1 and $p_J = \frac{1}{1+\sum_{j=1}^{J-1} e^{\mu_j}}$

Hierarchical generalized linear model

Mixed model:

$$\eta_{ijk} = \log\frac{\pi_{ijk}}{\pi_{ijK*}}$$

$$= \gamma_{00k} + \boldsymbol{\gamma_{01k}}(\mathbf{SCH}_{\boldsymbol{j}}) + \boldsymbol{\gamma_{10k}}(\mathbf{STU}_{\boldsymbol{ij}}) + \boldsymbol{\gamma_{20k}}(\mathbf{Coursetaking}_{\boldsymbol{ij}}) + \mu_{0jk} + \varepsilon_{ijk}$$

π_{ijk} is a student's probability of enrolling in a specific category of STEM majors (*k*) in college. K* indicates a reference group (i.e., non-STEM major group). $\mathrm{Coursetaking}_{ij}$ indicates dummy variables for the course-taking combinations (latent profiles) identified from answering RQ1. SCH_j and STU_{ij} are vectors of school context variables and student characteristics, respectively. μ_{0jk} is the school-level random effect, and ε_{ijk} is the student-level random effect.

APPENDIX C TABLES FOR CHAPTER 2

Table 1.C1 Descriptive Statistics for Students' Course-taking in Math and Science

Courses taken by students for credits	M	SD
Algebra I	1.14	0.58
Algebra II	1.03	0.41
Integrated Math	1.28	0.94
Pre-calculus	0.93	0.31
Calculus	0.93	0.31
Geometry	1.06	0.42
Statistics	0.82	0.28
Trigonometry	0.94	0.34
Biology	1.40	0.71
Chemistry	1.07	0.45
Earth Science	1.34	0.72
Physics	1.04	0.37
Math total	3.32	1.30
Science total	3.48	1.33
Math and Science Total	6.73	2.41
N	21,870	

Source. High School Longitudinal Study of 2009 (HSLS:09)
Note. Estimates are weighted using 2013 Update weight (W3STUDENT).

Table 1.C2 Correlations between Credits Earned in Math and Science Courses and Enrollment in STEM Majors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)
(1)	1																					
(2)	.08*	1																				
(3)	.05*	.05*	1																			
(4)	.03*	.19*	.07*	1																		
(5)	-.003	.07*	.24*	.22*	1																	
(6)	.28*	.26*	.13*	.11*	.09*	1																
(7)	.04	.08*	.14*	.17*	.35*	.04	1															
(8)	.02	.08*	.10*	.30*	.14*	.12*	.24*	1														
(9)	.23*	.19*	.08*	.15*	.18*	.26*	.09*	.15*	1													
(10)	.08*	.23*	.03	.19*	.16*	.21*	.11*	.19*	.22*	1												
(11)	.29*	.12*	.19*	.10*	-.02	.27*	.03	.07*	.09*	.05*	1											
(12)	.05*	.17*	.10*	.15*	.32*	.12*	.09*	.28*	.10*	.21*	.03*	1										
(13)	.52*	.47*	.24*	.31*	.47*	.53*	.31*	.28*	.41*	.29*	.26*	.20*	1									
(14)	.28*	.28*	.18*	.25*	.30*	.35*	.13*	.24*	65*	.53*	.47*	.43*	.64*	1								
(15)	.44*	.43*	.24*	.34*	.46*	49*	.26*	.31*	.59*	.48*	.39*	.38*	.91*	.91*	1							
(16)	-.04*	.05*	-.003	.06*	.11*	-.01	-.01	.07*	.14*	.14*	-.03*	.14*	.05*	.19*	.13*	1						
(17)	.003	-.02	.04	.02	-.01	-.03*	-.004	.03	.02*	-.01	.03*	.02	.004	.02*	.01	-	1					
(18)	-.004	.03*	-.04	.02	.12*	-.002	-.07*	.03	.15*	.13*	-.03*	.06*	.08*	.18*	.15*	-	-.04*	1				
(19)	-.01	.01	-.02	-.01	.06	-.004	.002	.04*	-.06*	.03*	.02	.06*	.01	.03*	.02	-	-.03*	-.06*	1			
(20)	-.07*	-.03*	.02	.05*	.02	-.02*	.02	-.01	-.04*	.09*	-.05*	.17*	-.02	.07*	.03*	-	-.05*	-.08*	-.06*	1		
(21)	.003	.06*	.014	.02	-.02	.01	.02	.03	.12*	.003	-.004	-.06*	.002	.04*	.02*	-	-.07*	-.13*	-.10*	-.14*	1	
(22)	-.001	.01	-.004	.03*	-.02	.004	.03	.02	-.01	.03*	-.02*	.05*	.03*	.02	.03*	-	-.01	-.02*	-.02	-.02*	-.04*	1

*p<.05

Source. High School Longitudinal Study of 2009 (HSLS:09)

Notes.
Correlations between credits earned in courses are weighted using W3STUDENT. Correlations between course-taking (earned credits) and STEM major categories are weighted using W4W1STU. (*N*=21,870)

(1) ALG1: credits earned in Algebra 1
(2) ALG2: credits earned in Algebra 2
(3) INTM: credits earned in integrated math
(4) PREC: credits earned in precalculus

(5) CALC: credits earned in calculus
(6) GEO: credits earned in geometry
(7) STAT: credits earned in statistics/probability
(8) TRIG: credits earned in trigonometry
(9) BIOL: credits earned in biology
(10) CHEM: credits earned in chemistry
(11) ESCI: credits earned in earth science
(12) PHYS: credits earned in physics
(13) TMTH: credits earned in the 8 math subjects
(14) TSCI: credits earned in the 4 science subjects
(15) TMTHSCI: credits earned in both math and science subjects
(16) STEM: enrollment in a STEM major in college
(17) AGNR: enrollment in Agriculture/Natural Resources majors in college
(18) BPS: enrollment in Biological and Physical sciences majors in college
(19) CIS: enrollment in Computer and information sciences majors in college
(20) ENGT: enrollment in Engineering and engineering technology majors in college
(21) HLTH: enrollment in Healthcare fields majors in college
(22) MTHM: enrollment in Mathematics majors in college

Table 1.C3 Model Fit Indices for the Single-level Latent Profile Analysis

The number of Profiles	ABIC	AIC	BIC	Entropy
1	189365	189249.5	189441.3	-
2	177781.3	177603.1	177898.8	0.942
3	169977.6	169736.9	170136.5	0.925
4	160388.1	160084.8	160588.3	0.937
5	158886	158520.1	159127.5	0.870

Source. High School Longitudinal Study of 2009 (HSLS:09)

Table 1.C4 Means of Credits Students Earned for Each Subject by Profile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Profile 1	1.77	1.33	2.73	0.98	0.82	2.10	0.82	1.13	1.87	1.23	1.99	1.01
Profile 2	1.15	1.06	1.10	1.05	1.14	1.01	0.81	1.01	1.78	2.15	1.39	1.15
Profile 3	1.10	1.01	0.97	0.97	0.92	1.00	0.82	0.94	1.39	0.97	1.27	1.02
Profile 4	0.82	0.47	1.04	0.58	0.54	0.23	0.54	0.45	0.78	0.43	1.00	0.51

Source. High School Longitudinal Study of 2009 (HSLS:09)

Note.
(1) ALG1: credits earned in Algebra 1
(2) ALG2: credits earned in Algebra 2
(3) INTM: credits earned in integrated math
(4) PREC: credits earned in precalculus
(5) CALC: credits earned in calculus
(6) GEO: credits earned in geometry
(7) STAT: credits earned in statistics/probability
(8) TRIG: credits earned in trigonometry
(9) BIOL: credits earned in biology
(10) CHEM: credits earned in chemistry
(11) ESCI: credits earned in earth science
(12) PHYS: credits earned in physics

Table 1.C5 Weighted Proportion of Students' Major in College

College major	%	College major	%
Non-STEM	60%	Non-STEM	60.8%
STEM	40%	Agriculture	2.2%
		Biology/Physics	7.5%
		Computer science	3.9%
		Engineering	7.6%
		Health	17.4%
		Mathematics	0.6%

Source. High School Longitudinal Study of 2009 (HSLS:09)

Note. The number of observations is around 11,050 and the population size is about 2,470,040.

Table 1.C6 Multinomial Regression Results

	Estimate	Standard error	Estimate/Standard error
School Class 1—> Student Profile 1	2.45	0.83	2.97*
School Class 1—> Student Profile 2	3.47	2.15	1.61
School Class 1—> Student Profile 3	0.41	1.44	0.28

*$p<.05$

Source. High School Longitudinal Study of 2009 (HSLS:09)

Table 1.C7 Multinomial Regression Results for the Association between Student Level Covariates and Profiles

Variable	Profile 1		Profile 2		Profile 3	
	Coefficient (s.e.)	Odds Ratio	Coefficient (s.e.)	Odds Ratio	Coefficient (s.e.)	Odds Ratio
Student background						
Female	0.57		1.14		0.80*	2.23
	(0.31)		(0.35)		(0.23)	
Math course interest	0.27		0.39*	1.50	0.39*	1.48
	(0.16)		(0.14)		(0.12)	
Science course interest	0.10		-0.05		0.04	
	(0.17)		(0.18)		(0.17)	
Math test score	0.05*	1.05	0.12*	1.13	0.07*	1.07
	(0.02)		(0.04)		(0.01)	
Socioeconomic status	0.97*	2.64	1.18*	3.26	1.13*	3.08
	(0.24)		(0.25)		(0.25)	
Asian	0.34		1.72		0.23	
	(1.18)		(1.19)		(1.12)	
Black	0.41		1.03		-0.42	
	(0.63)		(0.59)		(0.35)	
Hispanic	0.26		0.36		0.45	
	(0.39)		(0.52)		(0.41)	
Other	-0.18		0.81		-0.29	
	(0.42)		(0.65)		(0.41)	

*$p<.05$

Source. High School Longitudinal Study of 2009 (HSLS:09)

Note. Profile 4 students are a reference group.

Table 1.C8 The Association between School-level Covariates and Classes

School background	Class 1 (School)
% of racial minority students (Black and Hispanic) in school	0.01 (0.02)
% of free/reduced lunch students in school	-0.01 (0.02)
% of students enrolled in AP courses in school	0.003 (0.04)
% of students enrolled in 4-year college in school	0.02 (0.02)

**p*<.05
Source. High School Longitudinal Study of 2009 (HSLS:09)
Note. Class 2 schools are a reference group.

Table 1.C9 Multilevel Logistic Regression Results

Variable	STEM major (binary)	Odds ratio
Course-taking		
Profile 1	0.39	
	(0.26)	
Profile 2	0.95*	2.57
	(0.31)	
Profile 3	0.48	
	(0.28)	
Student backgrounds		
Female	0.26*	1.29
	(0.10)	
Math course interest	0.21*	1.24
	(0.08)	
Science course interest	0.26*	1.30
	(0.08)	
Math test score	0.01	
	(0.01)	
Socioeconomic status	0.11	
	(0.08)	
Asian	0.39	
	(0.25)	
Black	-0.28	
	(0.29)	
Hispanic	-0.20	
	(0.22)	
Other	-0.08	
	(0.27)	
School backgrounds		
% of racial minority students (Black and Hispanic) in school	0.001	
	(0.002)	
% of free/reduced lunch students in school	0.009*	1.01
	(0.003)	
% of students enrolled in AP courses in school	-0.001	
	(0.005)	
% of students enrolled in 4-year college in school	-0.002	
	(0.002)	

*$p<.05$
Source. High School Longitudinal Study of 2009 (HSLS:09)
Note. Profile 4 is a reference group for students' course-taking Profiles. Non-STEM major is a reference group. Standard errors are in parenthesis.

Table 1.C10 Multilevel Multinomial Logistic Regression

	Agriculture		Biology/Physics		Computer science		Engineering		Health		Mathematics	
	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio
Course-taking												
Profile 1	-0.61 (0.82)		1.004* (0.47)	2.73	1.78* (0.63)	5.90	1.53* (0.58)	4.60	-0.04 (0.33)		2.00 (1.16)	
Profile 2	-0.11 (0.85)		1.59* (0.45)	4.90	2.92* (0.61)	18.54	1.57* (0.46)	4.82	0.50 (0.48)		2.20* (1.11)	9.02
Profile 3	0.96 (0.73)		1.05* (0.44)	2.87	2.60* (0.59)	13.50	1.07* (0.46)	2.92	0.01 (0.35)		1.18 (1.06)	
Student backgrounds												
Female	0.20 (0.24)		0.22 (0.15)		-1.62* (0.32)	0.20	-1.76* (0.21)	0.17	1.61* (0.17)	5.01	0.11 (0.56)	
Math course interest	-0.08 (0.20)		0.20* (0.09)	1.22	0.35 (0.22)		0.32* (0.09)	1.38	0.21* (0.09)	1.23	0.31 (0.21)	
Science course interest	0.33* (0.15)	1.39	0.41* (0.10)	1.51	-0.11 (0.12)		0.29* (0.13)	1.34	0.22* (0.10)	1.25	0.31 (0.35)	
Math test score	0.02 (0.03)		0.07* (0.01)	1.07	0.02 (0.02)		0.03 (0.02)		-0.03* (0.01)	0.97	0.15* (0.04)	1.16
Socioeconomic status	0.11 (0.19)		0.26 (0.15)		0.13 (0.20)		0.25 (0.14)		-0.02 (0.10)		-0.03 (0.30)	
Asian	-3.32* (0.58)	0.04	0.84* (0.37)	2.32	1.49* (0.51)	4.45	0.83* (0.39)	2.28	-0.38 (0.40)		-0.17 (0.64)	
Black	-1.44 (0.81)		0.49 (0.30)		0.10* (0.37)	2.71	-0.31 (0.33)		-0.91* (0.44)	0.40	-8.41* (0.65)	0.0002
Hispanic	-1.71* (0.77)	0.18	-0.25 (0.38)		0.25 (0.50)		0.56 (0.38)		-0.48 (0.26)		1.21 (0.77)	
Other	-2.09* (0.51)	0.12	0.18 (0.28)		0.73 (0.53)		-0.02 (0.36)		-0.34 (0.40)		0.96 (0.65)	
School backgrounds												
% of racial minority students (Black and Hispanic) in school	-0.004 (0.01)		0.003 (0.01)		-0.01 (0.01)		0.003 (0.004)		0.01 (0.004)		0.001 (0.01)	

Table 1.C10 (cont'd)

	Agriculture		Biology/Physics		Computer science		Engineering		Health		Mathematics	
	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio	Coefficient	Odds ratio
% of students enrolled in AP courses in school	0.00 (0.01)		-0.003 (0.01)		-0.004 (0.01)		0.00 (0.01)		0.001 (0.01)		-0.01 (0.02)	
% of students enrolled in 4-year college in school	0.001 (0.01)		0.002 (0.004)		0.002 (0.01)		-0.001 (0.01)		-0.01 (0.003)		-0.01 (0.01)	

*$p<.05$

Source. High School Longitudinal Study of 2009 (HSLS:09)

Note. Standard errors are in parenthesis.

APPENDIX D FIGURES FOR CHAPTER 2

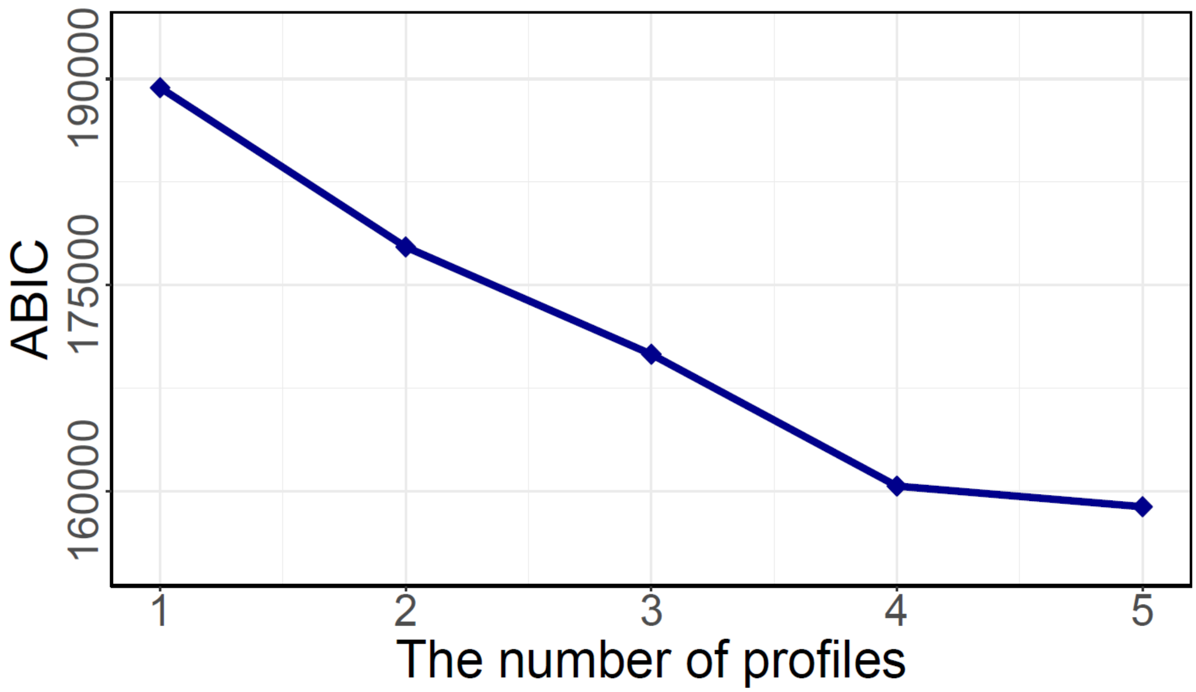

Figure 1.D1 The Sample-Size Adjusted BIC (ABIC) for Single-level Latent Profile Solutions

Source. High School Longitudinal Study of 2009 (HSLS:09)

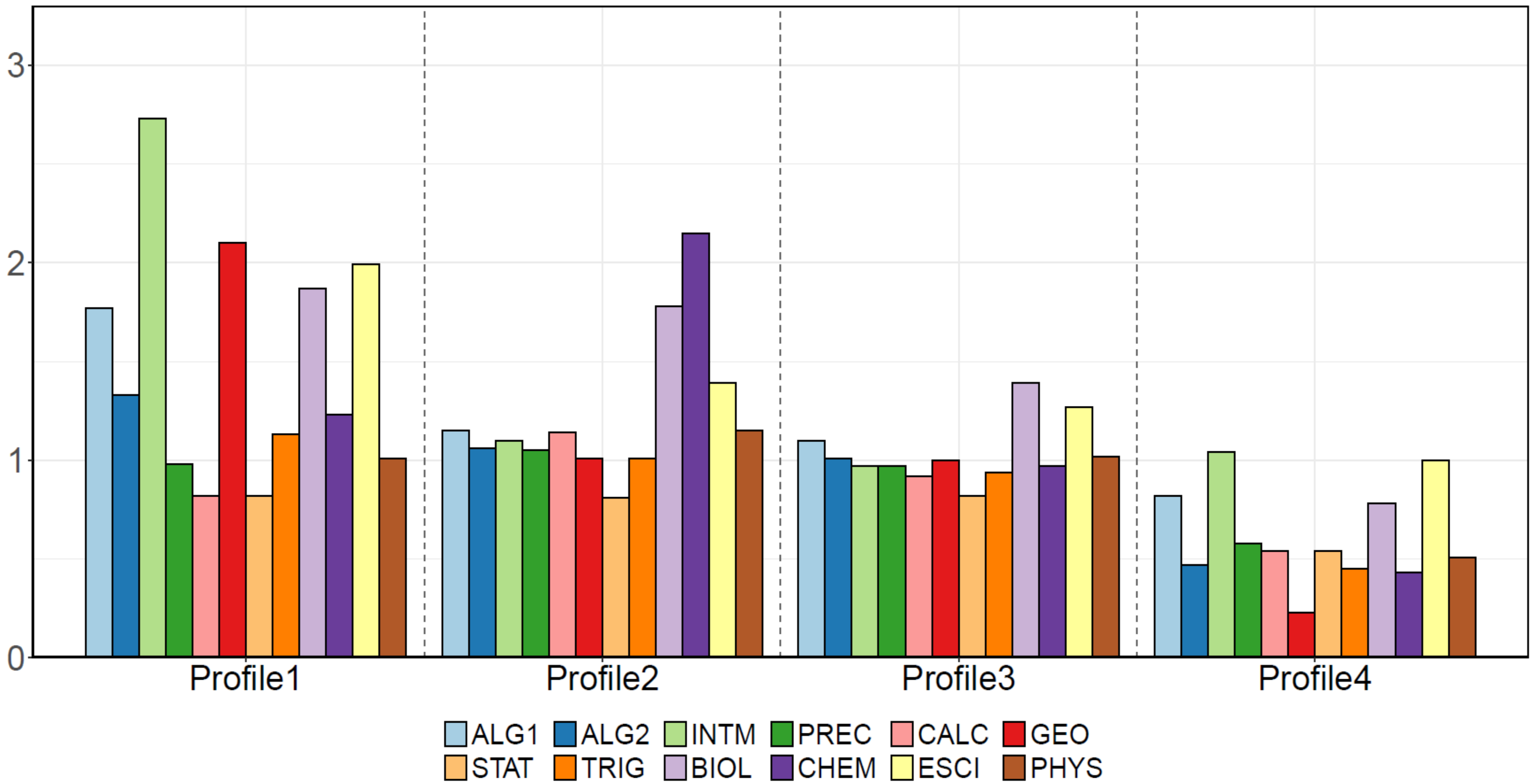

Figure 1.D2 Students' Course-taking Patterns by Each Profile

Source. High School Longitudinal Study of 2009 (HSLS:09)
Note. (1) ALG1: credits earned in Algebra 1
(2) ALG2: credits earned in Algebra 2
(3) INTM: credits earned in integrated math
(4) PREC: credits earned in precalculus
(5) CALC: credits earned in calculus
(6) GEO: credits earned in geometry
(7) STAT: credits earned in statistics/probability

Figure 1.D2 (cont'd)

(8) TRIG: credits earned in trigonometry
(9) BIOL: credits earned in biology
(10) CHEM: credits earned in chemistry
(11) ESCI: credits earned in earth science
(12) PHYS: credits earned in physics

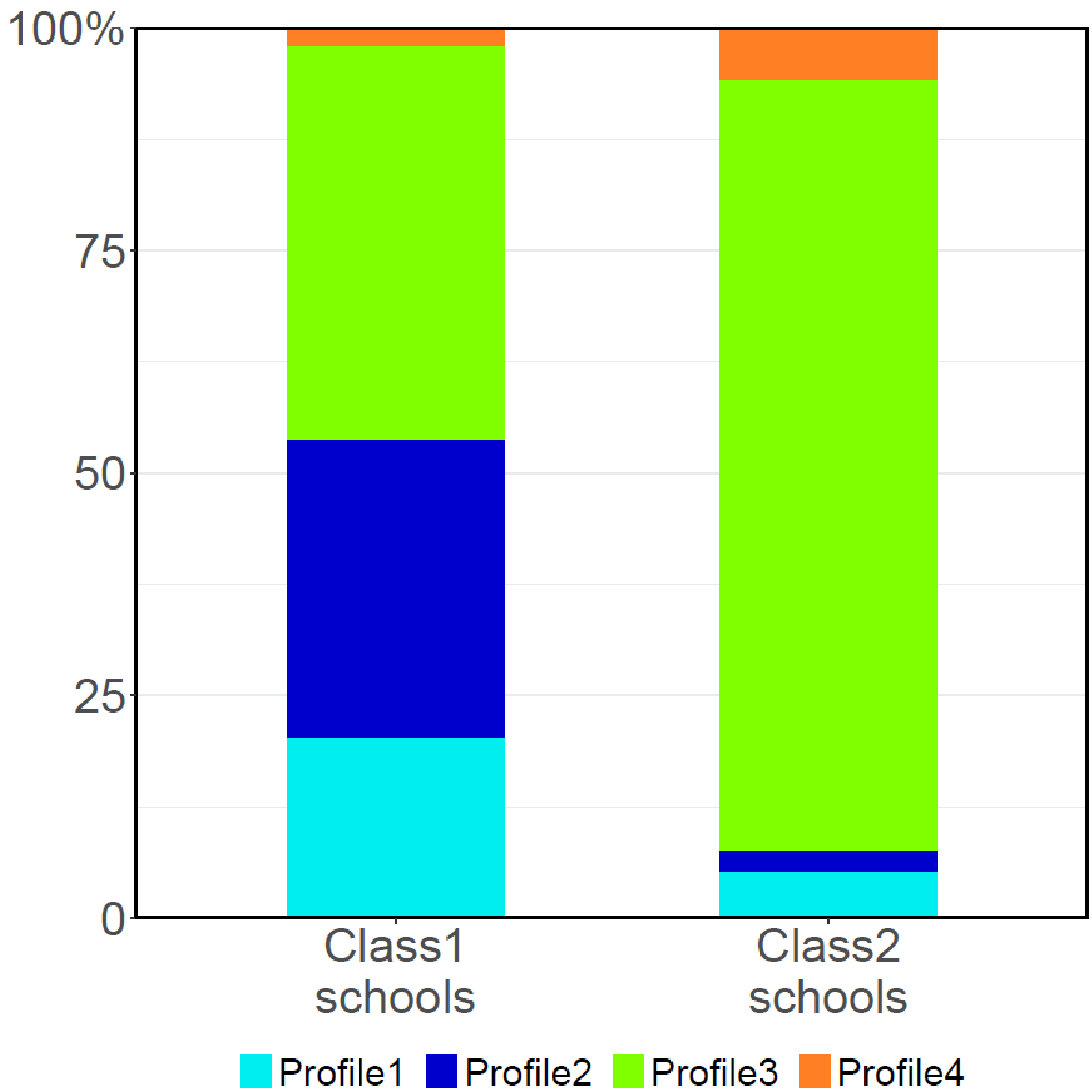

Figure 1.D3 Level 2 classes (at the school-level) Based on the Relative Frequency of the Level 1 Profiles (student-level)

Source. High School Longitudinal Study of 2009 (HSLS:09)

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CHAPTER 3 COLLEGE AND CAREER READINESS FOR ALL: UTILIZING MULTIPLE INDICATORS FOR THE EXAMINATION OF ENGLISH LEARNERS' COLLEGE AND CAREER READINESS

Introduction

In recent years, the importance of postsecondary education has increased significantly, as the current economy demands a workforce with high skill levels and advanced knowledge (Organization for Economic Co-operation and Development [OECD], 2012). For example, as of 2018, some level of postsecondary education is required by about 60% of all U.S. jobs and 90% of new jobs in growing industries (Carnevale et al., 2010). Aligning with these statistics, the unemployment rate for high school graduates (9.4%) is higher than college graduates (3.9%). As such, median weekly earnings for individuals with a bachelor's degree are higher by 60 percent, compared to those who have a high school diploma (Bureau of Labor Statistics [BLS], 2017). Additionally, students with higher educational backgrounds are expected to be better positioned to perform the needed job demands from the rapidly changing economy (Sambolt & Blumenthal, 2013). These positive contributions of college-level education to both society and individuals elevate the importance of preparing students to be college and career ready upon students' graduation in high school.

As a result of current economic demands for preparing a qualified workforce, college and career readiness has been emphasized as one of the major goals in the Every Students Success Act (ESSA) of 2015, which aims to build an accountability system that ensures students' success in both college and careers (Carnevale et al., 2010). The ESSA also attends to the equity aspect of college and career readiness, including provisions that require all students in the U.S. to have access to high academic standards and eliminate achievement gaps, and bringing underserved students into the scope of preparation for college and career readiness. With these approaches, the ESSA endeavors to help these student populations meet the demands associated with a rapidly evolving knowledge-based economy.

Amid this increasing attention, the school quality indicators in K-12 education have shifted from high school graduation rates to college and career readiness measures (Malin et al., 2017). The reasoning behind the change is simple: whether students complete high school does not provide information on whether they followed a college-and-career-ready course of study in high school (Bromberg & Theokas, 2016). Moreover, while high school graduation rates continue to increase, high school graduation does not guarantee whether and the degree to which students are ready for successfully transition into their postsecondary education and career (Achieve, 2016). Therefore, employing college and career readiness measures is more appropriate to serve the goals of ESSA (Bromberg & Theokas, 2016).

States are increasingly gathering students' college and career readiness data and utilizing it to evaluate schools' quality and accountability. Each state selects its own indicators for the academic aspects of college and career readiness, and the range of the indicators varies, including AP course-taking, college remediation rates for public high school graduates, as well as SAT, ACT, or AP scores (U.S. Department of Education [ED], 2010). Moreover, students' academic performance measured by tests constructed for college and career readiness are utilized to examine readiness and compare the degree of readiness across subpopulations of students. Acquiring relevant information and identifying potentially existing discrepancies across subgroups using multiple types of college and career readiness indicators will be a stepping stone to devising policy measures that improve underserved students' college and career readiness.

However, although students' test scores are disaggregated based on student characteristics for this purpose, states' public reports on college and career readiness benchmarks are mainly divided based on gender and race/ethnicity and not linguistic or English Learner (EL) status (e.g., Tyson et al., 2007).

Addressing this equity issue surrounding ELs is essential as nearly five million ELs attend schools in the U.S. (Sanchez, 2017)—and the number of ELs is rapidly growing (National Center for Education Statistics [NCES], 2019). Nevertheless, ELs have not been a major focus of college and career readiness studies, and information on ELs' college and career readiness benchmarks is infrequently available (Wang et al., 2012). As such, this lack of information makes it difficult to identify ELs' degree of college and career readiness and to ensure educational equity for this already underserved group. ELs often have reduced access to rigorous mathematics and science content because their academic achievement is often conflated with their English proficiency which, in turn, leads many educators to engage ELs in less-rigorous academic instruction and funnel them into less challenging coursework than their peers who are reclassified ELs (former ELs) and never ELs (native English speakers) (Callahan, 2005; Callahan & Shifrer, 2016). These unique characteristics of ELs also raise the necessity of investigating students' college and career readiness by their EL status beyond the examination of college and career readiness just by racial and ethnic groups. Thus, systematic research on students' college and career readiness, which comprehensively takes into account their multiple backgrounds, will allow educators and researchers to better understand the college and career readiness of diverse student subgroups.

Research Questions

To contribute to studies of underserved student populations' successful transition from secondary education to postsecondary education with a focus on ELs, whose college and career readiness have received relatively less attention, I have three research questions. These questions were designed to better understand ELs educational path by connecting students' college and career readiness outcomes by the time of high school graduation with course-taking gaps as represented in the time point of taking Algebra I as an indicator for a middle checkpoint towards their future college and career readiness.

Research Question 1: To what degree does students' performance aspect of college and career readiness in math and science (SAT and ACT scores) differ among *current ELs*, *former ELs*, and *never ELs,* after controlling for student and school background characteristics?

Research Question 2: To what degree does students' curricular opportunity aspect of college and career readiness (AP course-taking) in math and science differs among *current ELs*, *former ELs*, and *never ELs*, after controlling for student and school background characteristics?

Research Question 3: Does EL status make a unique contribution in predicting high school students' college and career readiness across multiple types of indicators, even after controlling for students' race/ethnicity as well as other student and school backgrounds?

Literature Review

College and career readiness

College and career readiness refers to the status in which students are able to successfully progress in a postsecondary, credit-bearing education program without taking remedial education courses (Conley, 2012). College and career readiness is a continuum with various degrees of readiness from not ready to ready in their postsecondary education and career. It consists of academic (e.g., SAT, ACT, and AP/IB course-taking) and non-academic aspects (e.g., social and emotional learning). Equipping students to be college and career ready is important because a lack of college and career readiness hampers students' college attainment and on-time graduation within four years (Conley, 2012). This setback consequently affects the capabilities of the labor force, specifically the workforce in STEM fields. Hence, there have been growing efforts to incorporate college and career readiness indicators into accountability measures, rather than solely focusing on high school completion.

Academic college and career readiness, which is the main interest in this study, emphasizes that all students should master core curricular content that helps their smooth transition to their college education and career. Nearly every state has devised and adopted college and career readiness standards in English language arts and mathematics and implemented these standards for all students, and invested in supporting teachers and school leaders help students to meet these standards (American Institutes for Research [AIR], 2020). Some of the examples of states utilizing college and career readiness standards include AP course-taking (31 states), college remediation rates for public high school graduates (32 states), dual-credit courses (25 states), percentage of high school graduates who enter college (21 states), college GPA and credit attainments (14 states), and to SAT, ACT or AP scores (9 states) (ED, 2010).

These indicators measure different aspects of college and career readiness, which suggests the necessity of employing multiple indicators that measure a wide range of college and career readiness. For example, SAT and ACT tests are well-established assessments often utilized in college and career readiness studies that measure both students' content knowledge and critical thinking skills, although they do not reflect students' readiness with the aspect of content exposure (Conley, 2012). In addition, AP course-taking assesses college and career readiness with respect to their college-level content exposure opportunity and earn college credits in high school (Warne, 2017). Nevertheless, this AP course-taking indicator is less likely to follow normal distribution that allows clear comparison between students compared to standardized SAT and ACT tests. Hence, rather than solely rely on uni-type indicators, using multiple measures of college and career readiness will help capture diverse aspects of college of career readiness and provide meaningful and useful information concerning the quality of education students have received for educators, parents, and students (Chester, 2005; Darling-Hammond et al., 2014).

Discrepancies in college and career readiness by student subgroups: Examining math and science ACT performance

Examining gaps in college and career readiness assessments across subgroups of students has centered around students' race and ethnicity. Results based on ACT scores in math and science indicate that students' college and career readiness in these academic areas show a different pattern by their racial and ethnicity groups. For example, regarding the mathematics

ACT scores of 2017 graduates from the national population, the average scores of Asians, Whites, Hispanics, Blacks, Multi-race groups were 25.2, 21.9, 18.9, 17.1, 20.7, respectively (ACT, 2017). For science ACT scores, Asian students had an average score of 24, followed by White students (22.3 points), Multi-race group students (21.2 points), Hispanic students (19.1 points), and Black students (17.4 points) (ACT, 2017).

These scores can be compared with the college readiness benchmark scores for each subject, which is empirically derived from students' actual performance in college. A benchmark score refers to the minimum score required for students to have a 50% chance of obtaining a B or higher or a 75% chance of obtaining a C or higher in the corresponding academic area of college courses (ACT, 2017). Regarding ACT math assessments, the benchmark score is 22, which can be interpreted as 70% of Asian students, 51% of White students, 40% of multi-race students, 26% of Hispanic students, and 13% of are considered ready for college-level mathematics (ACT, 2017). The benchmark score for science ACT assessment is 23, meaning 58% of Asian students, 47% of White students, 38% of multi-race students, 22% of Hispanic, and 11% of Black students are college ready in science-related coursework (ACT, 2017).

The examination of students' performance in ACT math and science assessments college and career readiness has also been done by student gender. For instance, in the math ACT, the average score of female students was 20. 4 (39% of female students are college ready in math courses), and the average score of male students was 21.2% (44% of male students are college ready in math) (ACT, 2017). In terms of science ACT assessment, on average, female students have 20.8 points while male students have 21.3 points, indicating 35% of female students and 40% of male students are college ready in science courses (ACT, 2017). However, EL status has not been widely used for this systematic comparison by subgroups, leading to a critical oversight that must be addressed in the literature.

Reclassification of English learners

When examining ELs' education, there has been growing scholarly evidence for the necessity of accounting for different EL subgroups derived from their changes over time. Traditionally, studies addressing the EL population compare ELs with non-ELs. However, such dichotomous comparison does not fully capture variations in students' educational opportunities and outcomes based on their EL status. Further breaking down the two categories into more detailed subcategories allows for better understanding of educational opportunities and outcomes for each student group (Mavrogordato & Harris, 2017; Saunders & Marcelletti, 2013; Thompson, 2017a). One such recategorization, which I employ in this study, consists of current, former, and never ELs. Current ELs are those who are classified at present as ELs, former ELs refer to those who used to be EL and have been successfully reclassified as English proficient, and never ELs include those who have never been designated as ELs (Hopkins et al., 2013). This refined categorization limits the overestimation of achievement gaps between different EL subgroups, and, where simpler, binary comparisons between ELs and non-ELs do not capture the variations between subgroups, thus giving an inaccurate picture of many ELs' academic achievements (Mavrogordato & Harris, 2017; Saunders & Marcelletti, 2013).

Course-taking, educational equity, and English learners

When studying educational equity in secondary education, researchers have generally paid attention to the aspects of students' course placement that are used to measure content-area access and exposure to advanced subjects (Callahan, 2005). This is because a student's access and exposure to academic content has a positive relationship with their academic achievement (Schmidt et al., 2015). Especially in mathematics, course-taking is an important factor for students' academic performance because mathematics learning is a highly sequential process; if students are not offered lower-level core courses, they will not be able to progress to more advanced courses (Gamoran, 2010). For example, Gamoran and Hannigan (2000) found that students' placement in Algebra I in grade 8 was an important indicator for their later access to rigorous mathematics. Hence, having the opportunity to take this key course on time is a significant aspect of improving knowledge and skills in mathematics.

Building on the above studies of educational equity, some researchers have begun exploring ways to enhance ELs' curricular equity and/or college preparation (e.g., Callahan et al., 2010; Thompson, 2017b; Umansky, 2016). For instance, Lee (2018) examined the alignment between English language proficiency (ELP) standards and content standards in mathematics, science, and English language arts. She found that although the ESSA mandates that every state must adopt ELP standards aligned with its academic content standards, the standards are mismatched in each of these subjects in terms of "disciplinary practices across content areas" and "cognitive expectations across proficiency levels" (p. 8).

In addition, Callahan and Shifrer (2016) found that ELs have less academic access than former ELs and never ELs in terms of completion of high school graduation course requirements and four-year-college preparatory courses. These course-taking gaps remained even after controlling for students' linguistic, social, and academic characteristics. In essence, current ELs face two separate barriers—their lack of both English proficiency and opportunities to be exposed to advanced academic content—that the other two groups face less. In addition, current

ELs are more likely to be taught by underprepared teachers and cover less rigorous content than if they were taught in mainstream classes (Dabach, 2014). Although these two recent studies did touch on college preparation curricula, they did not specifically address college and career readiness; to date there has been scant research directly related to ELs' college and career readiness outcomes and how the equity gaps in curricula play out in outcomes across time.

School linguistic composition and ELs' educational opportunity

School composition is an instrumental factor, especially for ELs. Previous studies determined that EL students in schools with low percentages of ELs have limited content-area exposure due to limited school resources. Callahan et al. (2009) determined that second-generation ELs in schools with low concentrations of linguistic minorities exhibited a more negative relationship between ESL placement and their math and science course-taking than first-generation ELs in schools with high concentrations of linguistic minorities. Furthermore, regarding academic performance, the researchers found that ESL placement brought lower levels of academic achievement for ELs in schools with low concentrations of linguistic minority students than ELs in schools with higher concentrations.

Data

The dataset for this study comes from the National Center for Educational Statistics' restricted version of High School Longitudinal Study of 2009 (HSLS:09). HSLS:09 is a longitudinal study with a nationally representative sample of U.S. 9th graders in 2009 as the base year, and it has multiple waves of data collection occurring until 2017 for postsecondary transcripts. Currently, data from the base year to the second follow-up study in 2016 are available.

The data sets have useful information on not only students' performance in college and career readiness standards in general, but also information specifically tied to math and science. Using this rich information enables us to understand students' college and career, in relation to their diverse educational and career paths, in a multifaceted way. For example, in addition to several college and career readiness measures used by states (e.g., AP course-taking and SAT and ACT scores), these data include information on students' mathematics test scores in the beginning of grade 9, course-taking, demographic characteristics, and school backgrounds. Therefore, HSLS:09 serves well for the purpose of studying the educational experiences of specific subgroups of students during high school with regards to their readiness in college and career.

Sample

The sample is restricted to the students who participated in both the base year and a follow-up wave when college and career readiness outcomes were assessed. SAT and ACT scores were measured in the second follow-up and the information on credits that students earned in Advanced Placement (AP) or International Baccalaureate (IB) courses were obtained in the 2013 update. This decision was made in order to increase the available information in the analysis given that attrition increases as the wave of assessment progresses. Consequently, the final sample size for the analyses including SAT and ACT scores is 16,110, and the final sample size for the analyses including math and science AP/IB course credits is 17,310[2]. To address missingness at the variable level, multiple imputation was applied (see below for more information).

Students' EL status was identified using two sources of information: 1) a variable derived from high school transcripts indicating that a student had taken courses designated for ELs in grade 9, and 2) responses from parent surveys about students' experiences of being enrolled in programs for ELs prior to grade 9. Specifically, those who were in grade 9 taking a program specifically for ELs were identified as current ELs. Students whose parents indicated that they had participated in a program for ELs before grade 9 but who were not taking a program/course customized for ELs during high school starting grade 9 were identified as former ELs. Also, students who had never been enrolled in a program/course for ELs both in grade 9 and before were identified as never ELs. Broken down by EL status at the time of grade 9, former ELs, current ELs, and never ELs make up the 8%, 4%, and 88% of the weighted sample, respectively.

With this group identification approach, the number of current ELs are likely underrepresented relative to the actual number as some students were identified as ELs but did not take any classes or were not involved in a program designed for ELs. Furthermore, the academic performance of these students identified as current ELs in this study might be lower than the entire current EL student populations identified by each school district. The reasoning behind this is that students who were directly involved in programs for ELs tended to have achievement levels in the lower bounds due to the fact that these students usually ended up having less English language development and lower previous achievement levels that direct

[2] All numbers of the unweighted sample size of students and schools, including subgroups of students, are rounded to the nearest ten, following the Institute of Education Sciences' guidelines for reporting results using restricted-use data from a restricted data.

them into EL programs as is inferred from the difference between current ELs and former ELs (Mavrogordato & Harris, 2017). Nevertheless, such current EL students included in this study those who might be a subsection of the larger current EL population need closer attention from researchers and school educators. They are more likely to face doubly challenges in their preexisting learning difficulties and English language proficiency which makes it hard for the students to attain college and career readiness that are necessary to transition into higher education.

To situate the proportions of student populations by their EL status in this study, I also compared the proportions obtained from this national data set with statistics collected from the Local Education Agency in the U.S. The average percentage of current ELs in the U.S. across grade levels (K-12) were 9.6% in the school year of 2009-2010 when students' EL status for U.S. 9th graders in this study were identified (Keaton et al., 2012). The proportion of these student populations decrease as grade levels increase with reclassification of ELs (McFarland et al., 2019). Hence, the statistics for percentage of current ELs in grade 9 provide a better picture for understanding the percentage of current EL populations in grade 9 in this data set. Based on the availability of such data in different years than the school year when students' EL status was identified (2009-2010), information from the nearest school year was presented for approximate comparison. For example, the school year, 2013-2014, was chosen for the purpose of comparison with the proportions of the EL population in grade 9 in the school year 2009-2010 derived from the HSLS:09 data as the statistics in the year of 2013-2014 is the available information nearest to the data in my study. According to the State Nonfiscal Survey of Public Elementary and Secondary Education, ELs in grade 9 in U.S. public schools in the school year 2013-2014 composed 6.6% of 9th graders[3] (Kena et al., 2016). The statistics suggest that the proportion of Current ELs identified in the HSLS:09 data (4%) is slightly under identified than the figures provided by school districts across the U.S. (about 6%).

Multiple imputation for handing missing data

Missing data might reduce the representativeness of the sample and consequently generate biased estimates (Enders, 2010). Hence, to address the issue and to prepare data before analysis, I first tested for missing data patterns in this data set. The examination of missing data patterns supports that the missing data pattern for the variables that were included in the analysis is at least missing at random because it is shown that missingness on a variable was predicted by other variables in the data set. Studies support that multiple imputation is superior to employing traditional methods of handling missing data regardless of missing data patterns (e.g., Enders, 2010). I implemented multiple imputation using multivariate normal distribution to minimize bias while maximizing the use of available information as well as ensuring adequate power for detecting significant differences among subgroups. The multiple imputation, based on the multivariate normal distribution model, assumes that variables in the model follow a multivariate normal distribution. Previous simulation studies showed that the imputation model can produce reliable estimates even when the normality assumption does not hold if the sample size is sufficiently large (Demirtas et al., 2008; Lee & Carlin, 2010).

The multiple imputation consists of imputation and analysis and pooling phases. In the imputation phase, I created 25 complete data sets in which the missing data were imputed by

[3] As additional information to provide approximate proportion of ELs across the time point, the proportion of EL students in grade 9 in the school years of 2014-2015 and 2015-2016 were 6.5% and 6.7%, respectively (Kena et al., 2016).

STATA. I then conducted analyses and reported combined estimates. For the imputation, in addition to all variables to be used in the analyses, students' 10th grade math test scores were included as an auxiliary variable in the imputation model. Adding auxiliary variables that have moderate to high correlations with other variables contributes to reducing bias and improving the imputation quality (Enders 2010; Graham, 2009). In addition, a given variable has a moderate or high correlation (correlation coefficients larger than .4) with at least one variable in the model except dummy variables used in the analysis. However, dummy variables also have statistically significant association with most of the variables in the model. In future studies, different approaches to multiple imputation, such as incorporating a cluster variable in the computation or imputing data separately across clusters, can be compared with the approach adopted in this study to reach more appropriate methods to handle the data structure[4].

Analytic Methods

Regression with cluster-robust standard errors

Multiple regression with cluster-robust standard errors was employed to analyze the 25 multiply imputed complete data sets prepared through multiple imputations with longitudinal analytic weights, based on currently available options in STATA software. Students' responses are nested in the schools in HSLS:09. In that sense, the cluster-robust standard error estimation is used to account for clustering by allowing for intragroup correlation in standard errors and relaxing the required assumption that the observations be independent.

4 In addition to these analyses, presenting results concerning comparison of the observed and imputed data (e.g., quantile–quantile and cumulative distribution plots) would be beneficial in terms of checking the multiple imputation model. COVID-19 pandemic did not allow me to access a restricted data lab to conduct such work.

Five models are specified for each of the four types of college and career readiness standards (Models 1A-5A, 1B-5B, 1C-5C, and 1D-5D). The first set of models (Models 1A, 1B, 1C, and 1D) in each type of college and career readiness standard shows a baseline relationship of high school students' race/ethnicity and their performance in a type of college and career readiness. The second set of models (Models 2A, 2B, 2C, and 2D) adds student related variables into the first models and the third models additionally include school backgrounds into the previous second models. The third set of models (Models 3A, 3B, 3C, and 3D) across college and career readiness standards shows the relationship between students' race/ethnicity and performance in college and career readiness standards after controlling for student and school covariates. The fourth set of models (Models 4A, 4B, 4C, and 4D) are set for baseline relationship between EL status and performance in college and career readiness standards. The fifth set of models (Models 5A, 5B, 5C, and 5D) are models of main interest in this study that specifically show the comprehensive examination of whether and to what degree EL status uniquely contributes to predicting students' performance in college career readiness holding race/ethnicity constant.

The research models are constructed in this way to understand students' performance in college and career readiness using two important student grouping variables (racial and ethnic groups and EL status) with no controls, respectively, and with the additions of student and school controls. In addition, these models are specified to compare whether the relationship between race/ethnicity and college and career readiness change after taking EL status into account, as well as whether and to what extent students' college and career readiness show statistically significant differences by EL status after controlling for other variables.

Corresponding equations for Models 5A, 5B, 5C, and 5D (equations 1-1 to 1-4) are presented in a simplified form as seen in equation (1). The dependent variable (Y_i) indicates SAT, ACT, AP course credits earned in math, and AP course credits earned in science in equations from (1-1) to (1-4), respectively. Equations (1-1) and (1-2) are formulated for the SAT composite score and ACT composite score, respectively. Equations (1-3) and (1-4) are built for credits earned in AP math and science courses, respectively. Equations (1-1) and (1-2) are concerned with answering research question 1, and the coefficients of interest in these two equations are, which represents the mean difference in SAT and ACT score between former ELs and never ELs, and, which indicates the mean difference in SAT and ACT score between current ELs and never EL. Equations (1-3) and (1-4) are specified to answer research question 2. In equations (1-3) and (1-4), β_1 and β_2 are the coefficients of interest that present dummy variables for former ELs and current ELs with never ELs as the reference group. Research question 3 was addressed using information obtained across equations (1-1) through (1-4). As the main focus of examination in research question 3, the coefficients for former ELs (β_1) and current ELs (β_2) were examined, as well as estimates for dummy variables regarding racial and ethnicity groups (β_3, β_4, β_5, β_6) with White students as a reference group.

$$\begin{aligned} Y_i = \ & \beta_0 + \beta_1(\mathrm{frmEL}_i) + \beta_2(\mathrm{CrnEL}_i) + \beta_3(\mathrm{AS}_i) + \beta_4(\mathrm{BL}_i) + \beta_5(\mathrm{HS}_i) + \beta_6(\mathrm{MR}_i) + \\ & \boldsymbol{\beta_7}(\mathbf{Stucontrols}_{\boldsymbol{i}}) + \boldsymbol{\beta_8}(\mathbf{Schcontrols}_{\boldsymbol{i}}) + \varepsilon_i \end{aligned} \tag{1}$$

Robustness check towards omitted variable bias

This study employed extensive sets of controls that account for different aspects of student and school characteristics. However, as omitted variable bias could still reside in the models, the robustness of the inference for estimates need to be checked. To that end, Frank et al.'s (2013) approach presented in equation (2) was applied to situate some of the estimated results that constitute the main interests of this study in a probability-based causal framework. This robustness check analysis quantifies how many unobservable cases with no estimate effect (null hypothesis) replacing the observable cases would be required to invalidate an estimated inference. Accordingly, the potential confounding effects of estimates that indicate the mean differences in college and career readiness assessments between current ELs and never ELs were assessed, and the differences that racial minorities have in comparison to White students were also examined. In addition, the robustness for the estimated effect of taking Algebra I after grade 9 on college and career readiness was examined.

$$\text{\% bias necessary to invalidate an inference} = 1 - \frac{\text{threshold for inference}}{\text{estimated effect}} \quad (2)$$

$$\text{where threshold} = \text{s.e.} \times t_{cv,df}$$

Obtaining a large value from equation (2) indicates that a higher percent of bias must exist in an estimate to invalidate the result, thus showing the robustness of the inference. Approximately, a value of .3 refers to a moderate level of robustness in educational studies, meaning that in this case a 30% bias would be required to refute the null hypothesis about an estimated effect (Frank et al., 2013).

Results

To begin with descriptive statistics, the means and standard deviations of continuous variables used in the analysis are shown in Table 2.E1 in Appendix E. In addition, Table 2.E2 presents the proportions of each category for categorical variables.

Results on the relationship between EL status and SAT and ACT scores and unique contribution of EL status predicting SAT and ACT scores.

Table 2.E3 presents regression models that show the relationship between student and school characteristic variables and SAT composite scores. As seen in the results for Model 1A, when no covariates are included in the model, Asian students (β=53.36, p<.05) have higher SAT composite scores than White students while Black (β=-195.72, p<.05), Hispanic (β=-138.93, p<.05), and Multi-race (β=-85.93, p<.05) groups have lower SAT composite scores than White students. Model 2A shows that when all student related variables are incorporated in the model, Asian students did not show any statistically significant differences with White students in their SAT composite scores. However, the differences between Black, Hispanic, and Multi-race groups with White students still remained.

Model 3A includes both all student and school characteristics, and the results indicate that Black (β=-65.17, p<.05), Hispanic (β=-36.40, p<.05), and Multi-race (β=-26.10, p<.05) students have 65.17, 36.40, and 26.10 points lower SAT scores than White students, holding other variables constant. Asian students did not show any significant differences with White students. There is no gender difference in students' SAT composite scores. Students' socioeconomic status SES and 9th grade math test score had a positive relationship with their

SAT composite score. A one unit increase in socioeconomic score is associated with a 43.06-point SAT score increase, and students had a higher SAT score by 12.15 points when their previous math test score increased by a 1-point T-score. Compared to students' who took Algebra I before grade 9 or in grade 9, students who took Algebra I after grade 9 had a decreased SAT composite score by 46.19 points. School characteristics also are related to students' performance on the SAT. When schools have a higher percentage of free and reduced priced lunch students, students' SAT composite score decreased by 0.86 of a point. Schools' higher percentage of ELs was also associated with a 0.51-point decrease in SAT composite score.

Model 4A provides estimates for the performance differences that both current and former ELs have in comparison with never ELs. Without any controls, former ELs (β=-70.55, p<.05) have 70.55 points lower SAT scores than never ELs whereas current ELs (β=-199.29, p<.05) have a larger difference of 199.29 points with never ELs. Model 5A shows the results in regards to whether students' SAT composite score differed by their EL status, holding other variables included in Model 3A constant. Current EL status predicted students would have lower SAT scores by 62.05 points than never ELs (β=-62.05, p<.05). Former ELs did not have statistically significant differences in SAT composite scores when compared to never ELs (β=-1.82, p>.05). The results suggest that examining students' performance by EL status is also needed when examining college and career readiness by subgroups of student populations as including EL status explained differences between such groups not taken into account by previous race/ethnicity groups.

Table 2.E4 presents the relationship between different students' groups and their performance in ACT composite tests. Models 1B-5B indicate similar patterns with the results of SAT composite scores. When only students' race/ethnicity groups were included in the model,

there was a statistically significant difference in Asian (β=1.34, p<.05), Black (β=-4.59, p<.05), Hispanic (β=-3.31, p<.05), and Multi-race (β=-2.07, p<.05) groups, compared to White students. Model 2B indicates that after taking into account all other student related characteristics, there still remained differences between Black-White, Hispanic-White, and Multirace-White.

Model 3B is a final model that indicates the association between students' race/ethnicity and ACT composite scores. Compared with White high schoolers, Black students have a 1.45 lower ACT composite scores (β=-1.45, p<.05), while Hispanic students (β=-0.84, p<.05) and Multi-race students (β=-0.63, p<.05) have a lower ACT scores 0.84 and 0.63 points, respectively. In addition, students with a one unit higher socioeconomic status IRT score have a 1.07 higher ACT composite score (β=1.07, p<.05). Also, students' increase in math test score in grade 9 by a point is associated with a 0.29 increase in their ACT scores (β=0.29, p<.05). Students who completed Algebra I after grade 9 had ACT scores that were lower by 1.18 points (β=0.29, p<.05). Schools with higher percentage of free and reduced priced lunch students (β=-0.02, p<.05) as well as increased percentage of ELs (β=-0.01, p<.05) are both negatively related to students' ACT composite scores.

The baseline results concerning EL status are presented in Model 4B. The results show that on average former ELs have lower performance levels than never EL peers (β=-1.69, p<.05), and the difference between current ELs and never ELs are exacerbated (β=-4.64, p<.05). Results for Model 5B that include all other controlling variables indicate that current ELs have lower performance levels on the ACT when compared with never ELs (β=-1.33, p<.05). In this model, the difference between former ELs and never ELs were not statistically significant (β=-0.04, p>.05).

Results on the relationship between EL status and AP/IB course-taking in math and science and unique contribution of EL status predicting AP/IB course-taking

The results in Models 1C, 2C, and 3C (meant to examine the relationship between race/ethnicity and math credits) in Table 2.E5 indicate whether and to what degree student and school variables are related to how many credits students earned in math AP/IB courses. Model 1C shows that Asian students (β=0.44, p<.05) earned more AP/IB math credits than white students, while Black (β=-0.12, p<.05), Hispanic (β=-0.06, p<.05), and Multi-race (β=-0.06, p<.05) groups tend to earn fewer credits, without incorporating any control variables.

After including student characteristics in Model 2C, there was no significant difference between multi-race and White high school students. Asian, Black, and Hispanic students earned more credits than White students by 0.33, 0.04, and 0.04, respectively. However, after also adding controls for school backgrounds, the results for Model 3C indicate that only Asian students completed 0.30 credits more than White students (β=0.30, p<.05), while other race/ethnicity groups did not have any statistically significant differences in credits they earned in AP/IB courses, compared to White students. Students' socioeconomic status (β=0.06, p<.05) and their math test scores (β=0.01, p<.05) are positively related to the number of credits they earned in AP/IB math courses. In addition, students who had late exposure to Algebra I after grade 9 tend to earn fewer credits than their peers who had earlier completion of Algebra I (β=-0.19, p<.05). Dissimilar to the estimate results for models where students' test scores were examined as an outcome variable, both schools' increased percentage of free and reduced priced lunch students and ELs have a positive association with credits students earned in AP/IB math courses.

Model 4C provides information on the baseline relationship between students' EL status and the numbers of credits they earned in AP/IB math courses. On average, current ELs attained less credits than never ELs (β=-0.10, p<.05). Former ELs did not show any significant difference with never ELs (β=0.01, p>.05). Lastly, the results for Model 5C indicate that students' EL status was not related to AP/IB math credits they attained, controlling for other student and school variables. The difference related to student race/ethnicity groups still remained. Asian students still earned more AP/IB math credits than White students, while other race/ethnicity groups did not show any significant differences from White students in terms of credits achieved.

The results presented in Table 2.E6 concerning the credits students earned in AP/IB science classes also showed similar patterns from the previous results related to math credits in Table 2.E5. As seen in Model 1D, Asian high school students attained 0.50 more Carnegie unit credits in AP/IB science courses than White peers whereas Black, Hispanic, and Multi-race peers attained 0.11, 0.08, and 0.05 less of such credits, respectively, compared to White students. After controlling for students' socio-economic status, previous achievement levels, and an indicator for time point when completing Algebra I, Asian students still achieved more credits by 0.39 than White students as presented in Model 2D. The difference still existed by 0.37 credits after holding both student and school background variables in Model 3D. On the other hand, the science credits that other race/ethnicity groups earned did not differ from the credits White students attained, and the preexisting differences were explained by school characteristics as presented in Model 3D. Results for Models 4D and 5D also exhibited similar patterns compared to the results in Models 4C and 5C. The statistically significant difference between current ELs and never ELs in Model 4D found in the simple comparison between groups were explained by other variables. In Model 5C, there was no association found between students' EL status and the credits they earned in science AP/IB courses.

Robustness check for inference

In observational studies in education, 30% of the calculated proportion of bias for changing an inference valid indicates a moderate level of robustness (Frank et al., 2013). In light of this figure, the estimate for the mean difference in SAT scores between current ELs and never ELs is robust. To invalidate the inference of a negative impact of current EL status on SAT scores, 48% of the data (about 7,730 out of 16,110 students) would necessarily be replaced with cases that have an effect of zero. Also, the estimate for the mean difference between current ELs and never ELs regarding predicting ACT scores is robust. 41% of the data (about 6,610 out of 16,110 students) would need to be replaced with cases that have no association.

Estimates for race dummy variables also showed quite a high level of robustness. Based on the negative association of Black, Hispanic, and Multi-race groups with SAT scores shown in Model 5A, the results would be invalidated if 74% (about 11,930 out of 16,110 students), 58% (about 9,330 out of 16,110 students), and 41% (6,540 out of 16,110 students) of the data had cases with a zero association. In addition, estimates for race dummy variables regarding ACT scores are also robust. In order to invalidate the inference about the negative impacts on the variables in Model 5B, 71% of the estimate for Black race/ethnicity, 57% of the estimate for Hispanic, and 42% of the estimate for Multi-race would have to be attributed to bias. The estimate for the mean difference in math credits between Asian and White students in Model 5C is also robust—70% of cases (12,070 out of 17,310 students) would have to be replaced with unobserved cases in which there was no association in order to invalidate the inference. Lastly, the estimate for Asian students predicting the mean difference in science credits in comparison to White students in Model 5D shows strong robustness as well. 75 % of cases (about 13,010 out of 17,310 students) would have to stem from bias to invalidate the inference. Across Models 5A, 5B, 5C, and 5D, the negative effects of taking Algebra I after grade 9 are quite robust. In order to invalidate such negative effects, the required non-observable cases supporting null hypothesis should replace 77% (about 12,280 out of 16,110 participants), 78% (about 13,710 out of 16,110 participants), 79% (about 13,710 out of 17,310 participants), and 71% (about 12,280 out of 17,310 participants) of cases in each model, respectively.

Discussion

The present study investigates high school students' college and career readiness with a focus on underserved student populations by EL status and racial and ethnic groups. Results show that subgroups of students have a dissimilar pattern in their discrepancies with a reference group across different types of college and career readiness standards. Regarding academic performance-based college and career readiness standards such as ACT and SAT scores, Black, Hispanic, and Multiracial groups have consistently lower scores than White students. Moreover, after controlling for student race/ethnicity, in addition to student and school backgrounds, current ELs have a lower performance level in ACT and SAT compared to never ELs. However, former ELs did not have statistically significant discrepancies in their ACT and SAT scores compared to never ELs. When it comes to the curricular exposure aspect of college and career readiness represented by credits earned in AP courses, the mean difference is shown between Asian and White students, with Asian students earning more credits in both AP math and science courses. EL status does not have a statistically significant relationship with AP credits students earned in math and science after taking into account their Algebra I course-taking time point and other controls.

These results suggest that EL status still exhibits a unique association with ACT and SAT scores after taking account for students' race/ethnicity and other controls. Information on effect size and the coefficient of determination is necessary for interpreting statistical significance further in terms of the estimates' practical significance in the near future follow-up steps. Also, the consistent results within test scores and AP course-taking credits and different results across the two types of standards indicate that a comprehensive examination of college and career readiness using various types of indicators would elucidate more than what a study utilizing a uni-type measure is able to uncover. In this sense, future studies on college and career readiness using HSLS:09 can expand investigation by utilizing college grade point average, which will be available in the near future in a study to see how and to what degree college and career readiness measured in high school and the actual performance in college are related across different student groups.

This study also comprehensively examines the relationship between EL status and college and career readiness, including individual students' opportunities to take Algebra I. Expanding on previous studies that investigated the relationship between EL status and opportunity to learn (e.g. Callahan, 2005), this study examined to what degree different EL statuses are associated with college and career readiness, taking into account variations arising from one of the important stepping-stone courses in high school studies. As current ELs have less opportunity to be exposed to academic course-taking and the time point of course-taking of Algebra I is known to play an important role in math achievement (Gamoran & Hannigan, 2000; Thompson, 2017b), incorporating such information in this study's models strengthens its conclusions and contributes a deeper understanding of the issues around how ELs transition from secondary to post-secondary education.

Finally, the results of this study suggest that mere exposure to a course is not completely sufficient to explain the achievement gap evident between current ELs and never ELs. The results suggest that current ELs' underperformance should not only be understood as linked to their less rigorous curricular exposure, but also instruction practice considering that many educators engage such ELs in less-rigorous academic instruction than their peers who are reclassified ELs and never ELs (Callahan, 2005). Furthermore, as courses with the same title might have different qualities and variations in terms of specific covered topics, this work will help to improve organizational stakeholders' efforts to design curricula and instruction programs for ELs.

APPENDIX

APPENDIX E TABLES FOR CHAPTER 3

Table 2.E1 Means and Standard Deviations for Continuous Variables Used in this Study

	M	*SD*
Outcome variables		
SAT composite score	970.07	207.71
ACT composite score	20.69	5.02
AP math credits earned	0.17	0.47
AP science credits earned	0.18	0.53
Student backgrounds		
Socioeconomic status	-0.06	0.75
9^{th} grade math test score	50.09	9.97
10^{th} grade math test score	49.94	9.99
School backgrounds		
% of free and reduced priced lunch students in school	38.79	24.91
% of English learners in school	6.02	10.05
% of students who took AP courses in school	16.25	13.28

Source. High School Longitudinal Study of 2009 (HSLS:09)
Notes. Estimates related to SAT and ACT scores are weighted using second follow-up analytic weight (W4STUDENT). Estimates regarding student and school backgrounds are weighted using base-year student analytic weight (W1STUDENT).

Table 2.E2 Proportions of Categorical Variables Used in this Study

	Proportion
English learner status	
Former English learner	.08
Current English learner	.04
Never English learner	.88
Race	
White	.52
Asian	.03
Black	.14
Hispanic	.22
Multi-race	.09
Gender	
Male	.50
Female	.50
Grade level that students took Algebra I	
Before grade 9	.24
In or after grade 9	.76

Source. High School Longitudinal Study of 2009 (HSLS:09)
Note. Estimates are weighted using base-year student analytic weight (W1STUDENT).

Table 2.E3 Student and School Factors Predicting SAT Composite Score

	Model 1A	Model 2A	Model 3A	Model 4A	Model 5A
Student backgrounds					
Asian	53.36*	-18.05	-10.51		-2.36
	(19.05)	(10.74)	(10.10)		(9.93)
Black	-195.72*	-77.80*	-65.17*		-66.31*
	(11.55)	(9.12)	(8.80)		(8.78)
Hispanic	-138.93*	-48.70*	-36.40*		-32.24*
	(9.42)	(6.80)	(6.58)		(6.93)
Multi-race	-85.93*	-33.68*	-26.10*		-26.25*
	(12.50)	(8.12)	(7.93)		(7.96)
Female		-5.23	-5.78		-5.67
		(4.12)	(4.08)		(4.09)
Socio-economic status		53.48*	43.06*		42.29*
		(3.14)	(3.07)		(3.02)
9^{th} grade math test score		12.51*	12.15*		12.05*
		(0.28)	(0.29)		(0.29)
Taking Algebra I after grade 9		-46.32*	-46.19*		-46.05*
		(5.62)	(5.49)		(5.47)
Former ELs				-70.55*	-1.82
				(15.66)	(10.55)
Current ELs				-199.29*	-62.05*
				(21.49)	(16.47)
School backgrounds					
% of free and reduced priced lunch students in school			-0.86*		-0.84*
			(0.11)		(0.11)
% of English learners in school			-0.51*		-0.32
			(0.26)		(0.26)
% of students who took AP courses in school			0.30		0.33
			(0.19)		(0.19)
Number of students	16110	16110	16110	16110	16110
Number of schools	940	940	940	940	940

Source. High School Longitudinal Study of 2009 (HSLS:09)
Notes. Estimates are weighted using base-year to second follow-up weight (W4W1STU).
Coefficients are unstandardized. Standard errors are in parenthesis.
*p<.05

Table 2.E4 Student and School Factors Predicting ACT Composite Score

	Model 1B	Model 2B	Model 3B	Model 4B	Model 5B
Student backgrounds					
Asian	1.34*	-0.38	-0.20		-0.03
	(0.47)	(0.27)	(0.25)		(0.25)
Black	-4.59*	-1.74*	-1.45*		-1.48*
	(0.27)	(0.23)	(0.22)		(0.22)
Hispanic	-3.31*	-1.12*	-0.84*		-0.75*
	(0.22)	(0.16)	(0.16)		(0.17)
Multi-race	-2.07*	-0.80*	-0.63*		-0.63*
	(0.29)	(0.19)	(0.19)		(0.19)
Female		-0.16	-0.18		-0.17
		(0.10)	(0.10)		(0.10)
Socio-economic status		1.31*	1.07*		1.05*
		(0.08)	(0.08)		(0.07)
9th grade math test score		0.30*	0.29*		0.29*
		(0.01)	(0.01)		(0.01)
Taking Algebra I after grade 9		-1.18*	-1.18*		-1.18*
		(0.14)	(0.13)		(0.13)
Former ELs				-1.69*	-0.04
				(0.38)	(0.26)
Current ELs				-4.64*	-1.33*
				(0.51)	(0.39)
School backgrounds					
% of free and reduced priced lunch students in school			-0.02* (0.003)		-0.02* (0.003)
% of English learners in school			-0.01*		-0.01
			(0.01)		(0.01)
% of students who took AP courses in school			0.01 (0.005)		0.01* (0.004)
Number of students	16110	16110	16110	16110	16110
Number of schools	940	940	940	940	940

Source. High School Longitudinal Study of 2009 (HSLS:09)
Notes. Estimates are weighted using base-year to second follow-up weight (W4W1STU).
Coefficients are unstandardized. Standard errors are in parenthesis.
**p*<.05

Table 2.E5 Student and School Factors Predicting AP Math Course Credits

	Model 1C	Model 2C	Model 3C	Model 4C	Model 5C
Student backgrounds					
Asian	0.44*	0.33*	0.30*		0.30*
	(0.06)	(0.04)	(0.05)		(0.05)
Black	-0.12*	0.04*	-0.00003		-0.0006
	(0.01)	(0.01)	(0.01)		(0.01)
Hispanic	-0.06*	0.04*	0.001		0.0005
	(0.02)	(0.02)	(0.02)		(0.02)
Multi-race	-0.06*	0.01	-0.01		-0.01
	(0.02)	(0.02)	(0.01)		(0.01)
Female		-0.01	-0.01		-0.01
		(0.01)	(0.01)		(0.01)
Socio-economic status		0.06*	0.06*		0.06*
		(0.01)	(0.01)		(0.01)
9^{th} grade math test score		0.01*	0.01*		0.01*
		(0.001)	(0.001)		(0.001)
Taking Algebra I after grade 9		-0.20*	-0.19*		-0.19*
		(0.02)	(0.02)		(0.02)
Former ELs				0.01	0.02
				(0.03)	(0.02)
Current ELs				-0.10*	-0.04
				(0.04)	(0.03)
School backgrounds					
% of free and reduced priced lunch students in school			0.001* (0.0003)		0.001* (0.0003)
% of English learners in school			0.0003		0.0003
			(0.001)		(0.001)
% of students who took AP courses in school			0.005* (0.001)		0.005* (0.001)
Number of students	17310	17310	17310	17310	17310
Number of schools	940	940	940	940	940

Source. High School Longitudinal Study of 2009 (HSLS:09)
Notes. Estimates are weighted using base-year to 2013 Update weight (W3W1STU).
Coefficients are unstandardized. Standard errors are in parenthesis.
*p<.05

Table 2.E6 Student and School Factors Predicting AP Science Course Credits

	Model 1D	Model 2D	Model 3D	Model 4D	Model 5D
Student backgrounds					
Asian	0.50*	0.39*	0.37*		0.37*
	(0.05)	(0.05)	(0.05)		(0.05)
Black	-0.11*	0.05*	0.01		0.01
	(0.02)	(0.02)	(0.02)		(0.02)
Hispanic	-0.08*	0.05*	0.002		0.002
	(0.02)	(0.01)	(0.02)		(0.02)
Multi-race	-0.05*	0.02	-0.003		-0.003
	(0.02)	(0.02)	(0.02)		(0.02)
Female		0.01	0.01		0.11
		(0.01)	(0.01)		(0.01)
Socio-economic status		0.10*	0.09*		0.09*
		(0.01)	(0.01)		(0.01)
9th grade math test score		0.01*	0.01*		0.01*
		(0.001)	(0.001)		(0.001)
Taking Algebra I after grade 9		-0.15*	-0.13*		-0.13*
		(0.02)	(0.02)		(0.02)
Former ELs				0.01	0.02
				(0.03)	(0.02)
Current ELs				-0.10*	-0.06
				(0.04)	(0.03)
School backgrounds					
% of free and reduced priced lunch students in school			0.001* (0.0003)		0.001* (0.0003)
% of English learners in school			0.0002		0.0003
			(0.001)		(0.001)
% of students who took AP courses in school			0.005* (0.001)		0.005* (0.001)
Number of students	17310	17310	17310	17310	17310
Number of schools	940	940	940	940	940

Source. High School Longitudinal Study of 2009 (HSLS:09)
Notes. Estimates are weighted using base-year to 2013 Update weight (W3W1STU).
Coefficients are unstandardized. Standard errors are in parenthesis.
*p<.05

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