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Examining the Smarter Balanced Assessment Consortium Exams, Scholastic Aptitude Test, and High School Grade Point Average as Predictors of College Readiness

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Approval of the Dissertation Committee

This dissertation has been duly read, reviewed and critiqued by the Committee listed below, which hereby approves the manuscript of Carol Alexander as fulfilling the scope of quality requirement for meriting the degree of Doctor of Philosophy in Education.

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Abstract

Examining the Smarter Balanced Assessment Consortium Exams, Scholastic Aptitude Test, and High School Grade Point Average as Predictors of College Readiness

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The lack of college readiness in the United States is a critical issue that jeopardizes our economy. The demographic inequality of the crisis, particularly for low-income as well as Black and Latinx students, emerges from systemic problems of race and class in American education and society which suppress students' educational and economic mobility. As part of the national reform efforts, state-based standardized tests such as the Smarter Balanced Assessment Consortium (SBAC) were designed to be better aligned with K-12 Common Core standards and provide a more efficient and equitable measure of academic performance and college readiness in middle and high school when compared to traditional measures such as the Scholastic Aptitude Test (SAT) and grade point average (GPA). Although the SBAC test is being used across the nation, there is a large research gap regarding how the SBAC compares with GPA and the SAT for prediction of college readiness and the degree to which it is unbiased by demographic or school variables.

Therefore, the research problem of this study was to investigate the predictive power of the 8th-grade and 11th-grade SBAC tests, as compared to GPA, the SAT, curricular intensity, and college aspirations, for college readiness as measured by college enrollment and persistence, and how such predictability may be biased by nonacademic factors of poverty, race, and school size. The purpose of this quantitative, ex post facto study, which was conducted on archived data from

a large, urban, and demographically diverse school district in southern California, was to investigate the problem using rigorous statistical analyses of path analysis, discriminant function analysis, and logistic regressions.

There were several important findings. Both middle and high school SBAC tests were not reliable predictors of college readiness, despite their intended design, in contrast to high school GPA, SAT, curricular intensity, and college aspirations which tended to strongly and reliably predict college readiness either directly or indirectly via their positive effects on other predictors. However, the middle school SBAC tests reliably and positively predicted the high school SBAC tests, even when controlling for middle school GPA. Moreover, middle school SBAC scores were stongly related to middle school GPA, and high school SBAC scores were strongly related to high school GPA. These various results provide evidence of high internal consistency within SBAC assessments and suggests that these tests can accurately and reliably track students' academic progress between middle and high school.

In addition, there was evidence of demographic or school bias in the scores of all academic indicators based on the findings of significant direct effects from those demographic and school variables towards the academic variables. There was also evidence of bias in the predictive validity of the academic indicators for college enrollment and persistence based on the findings of reduced predictive effects when controlling for the demographic and school variables or different predictive effects for different demographic groups. Importantly, the degree of theses biases in SBAC was less than the degree of biases in SAT but similar to GPA. Based on these results, the overall conclusion and recommendation for educational policy is that the SBAC tests seem ideal for monitoring students' academic progress, instruction, and needs throughout middle and high school but less ideal for predicting college enrollment and persistence.

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CHAPTER 1

Background of the Study

College readiness and access are critical issues in the United States since public high school (HS) graduation rates are at an all-time high of 85% (Atwell et al., 2020), but four-year university enrollment rates are declining (National Student Clearinghouse, 2020a; St. Amour, 2020), and there is little movement in the percentage of students earning a bachelor's degree, especially among low-income students and students of color (National Center for Education Statistics [NCES], 2020b). Approximately 78% of students aspire to attend college (Jaschik, 2019; Stephan et al., 2015). Yet only 28% of college-going students enrolled in four-year universities in 2020, and only 39% of all students in any college or university completed a degree within six years in 2019 (National Student Clearinghouse, 2021). There is a considerable discrepancy in degree attainment between Black or Latinx students and White or Asian students. In 2019, only 21% of Latinx and 29% of Blacks obtained a bachelor's degree compared to 71% of Asians and 45% of Whites (NCES, 2020b). The racial structures of inequality that are stubbornly rooted in the American educational system and society persistently suppress the educational and economic mobility of students of color in the United States (Carter, 2016).

College readiness, enrollment, persistence, and degree completion are critical issues because two-thirds of jobs require a college degree (Carnevale et al, 2016; Di Giacomo et al., 2013), but the current low rate of attainment, especially in California (California Competes, 2015), hinders the nation's economic progress. At the current rate of bachelor's degree attainment, which is 39% (NCES, 2020b), there will be a national shortage of college-educated workers, with California alone projected to have a deficit of over one million such workers by 2030 (California Competes, 2015; Johnson et al., 2015), jeopardizing the state and nation's capability to compete in a global economy. There are many long-term benefits of earning a college degree including a path out of poverty, increased social and economic mobility (Abel & Deitz, 2019; Baum et al., 2013; Carter, 2016; Hussar et al., 2020), and increased physical and mental health (Tinto, 2012; Zimmerman et al., 2015). Establishing a national K-12 focus on college readiness, former president Obama highlighted the urgency of increasing the number of HS students graduating college-ready and earning postsecondary degrees (White House, 2015).

As part of the national focus on college readiness, 41 states adopted the more rigorous K-12 Common Core Standards (Webster & Thatcher, 2015) and several states have adopted reform policies mandating more rigorous courses in HS curricula to better align with college curricula in order to improve college readiness and access (Buddin & Croft, 2014; Jimenez & Sargrad, 2018). At least four states, Louisiana, Michigan, South Dakota, and Tennessee have aligned their HS graduation requirements to four-year state university requirements (Jimenez & Sargrad, 2018). Several districts in California, including the local site of this study, have done so as well with the implementation of the mandatory a-g course sequence for graduation, which covered seven content areas: history/social science ("A"), English ("B"), mathematics ("C"), laboratory science ("D"), foreign language ("E"), visual and performing arts ("F"), and college preparatory elective ("G"). While there remain racial and socioeconomic disparities in rigorous college preparatory courses (Kirst & Brasco, 2004; Price, 2020), districts and schools have expanded opportunities for advanced placement (AP) or International Baccalaureate (IB) classes as well as concurrent and dual enrollment courses as selective universities have them as a default criterion for admissions (Austin, 2020; Price, 2020).

Apart from increasing curricular intensity, in 2015, some states began to administer associated standardized assessments from either the Smarter Balanced Assessment Consortium

(SBAC) or Partnership for Assessment of Readiness for College and Careers (PARCC) that are specifically designed to measure college readiness (Webster & Thatcher, 2015). In his framework of "the four keys to college and career readiness," Conley (2008) defines college readiness as "the level of preparation a student needs in order to enroll, succeed, and successfully progress in credit-bearing general education courses" (p.4), where success is defined as the student's continued college enrollment into the second year of college. Regarding the measures that colleges are considering to assess college readiness (Gordon, 2020; Strauss, 2020; Tang, 2018; Watanabe, 2021), a national shift is occurring. While over 200 colleges and universities now use SBAC test scores for course placement (Gewertz, 2015), relatively little is known about the role of these test scores in college admissions as compared to the role of the Scholastic Aptitude Test (SAT), grade point average (GPA), or the completion of more rigorous courses such as AP and the a-g course sequence that universities have traditionally relied upon (Barnett & Reddy, 2017; Clinedinst & Patel, 2018). To increase degree attainment and close persistent gaps between ethnicities and levels of poverty (Finney et al., 2014), colleges need effective indicators of college readiness (Barnett & Reddy, 2017).

Research Problem

There is a large research gap regarding how SBAC examinations compares with GPA and the SAT as measures of college readiness. Although standardized tests usually predict college success (Huh & Huang, 2016; Westrick et al., 2019; Zwick, 2017, 2019), they often do not provide an accurate assessment of student ability or prediction of college readiness for Black and Latinx youth or students in poverty (Dixon-Roman et al., 2013; Zwick, 1999) or those students that live in low-income communities (Geiser, 2015; Gonzales Canché, 2019). Many studies have also demonstrated that poverty, race and ethnicity, and school type also strongly bias GPA as a measure of college readiness (Allensworth & Clark, 2020; Preston et al, 2017; Zwick, 2013). In this literature, such bias often appears as direct effects of demographic variables on the academic measures based on regression results, or differences in the academic scores across demographic subgroups based on ANOVA results, or reduced ability of the academic measures to predict the college variables when controlling for those demographic or school variables in the same regression model. However, relatively little is known about these potential biases for SBAC tests (Kurlaender & Cohen, 2019).

Another research gap is that few studies have assessed middle school (MS) indicators for predicting academic success despite the acknowledged importance of early assessment (Dougherty, 2014). Unlike the SAT or American College Testing (ACT), the eighth-grade SBAC test is aligned with K-12 curriculum and assessment, so it is necessary to investigate as a potential early indicator of college readiness. Finally, there is mixed evidence in the research literature regarding the relationship between increasing curricular intensity and improving college readiness in comparison to GPA or standardized tests as well as the racial and socioeconomic biases that exist in course access and preparation (Buddin & Croft, 2014; Plunk et al., 2014; Preston et al., 2017). To conclude, the overall research problem in this study was the need to examine the predictive power of the eighth and 11th-grade SBAC tests, as compared to GPA, the SAT, curricular intensity, and college aspirations, for college success as measured by college enrollment and persistence, and how such predictability may be biased by nonacademic factors of poverty, race, and school type.

Purpose

The purpose of this quantitative, ex post facto study was to conduct empirical research using statistical analysis to examine the extent to which the variance in college readiness, as measured by college enrollment and persistence, can be uniquely explained or predicted by various indicator variables in MS and HS including the SBAC tests (eighth-grade SBAC, and 11th-grade SBAC tests), MS and HS GPA (Middle School GPA, High School GPA), curricular intensity in HS, the SAT admission test, and college aspirations, which may be confounded by the influences of school type; college aspirations; and student demographics of ethnicity, poverty, language classification, and gender. The first goal was to assess how well the 11th-grade SBAC test can predict college readiness, as measured by college enrollment and persistence, in comparison to traditional academic indicators of GPA, SAT, and curricular intensity while controlling for HS type; college aspirations; and student demographics of ethnicity, poverty, language classification, and gender. The second goal was to examine the predictive validity of the eighth-grade SBAC test for college readiness, as measured by college enrollment and persistence, in comparison to MSGPA while controlling for 11th-grade SBAC; HSGPA; SAT; curricular intensity; HS type; college aspirations; and student demographics of ethnicity, poverty, language classification, and gender. The third goal was to assess how well the eighth-grade SBAC test can predict the 11th-grade SBAC test scores in comparison to MSGPA while controlling for HS type; college aspirations; curricular intensity; and demographics of ethnicity, poverty, language classification, and gender. The fourth goal was to determine to what extent the eighth-grade or 11th-grade SBAC tests and their predictive validity for college readiness suffer from the same biases of ethnicity, poverty, and school type that have been shown to bias the SAT and GPA.

Research Questions

RQ1: To what extent does the 11th-grade SBAC test predict college readiness, as measured by college enrollment and persistence, in comparison to SAT, HSGPA, and curricular intensity while controlling for HS type; and college aspirations; and student demographics of ethnicity, poverty, language classification, and gender?

RQ2: To what extent does the 8th-grade SBAC test predict college readiness, as measured by college enrollment and persistence, in comparison to MSGPA while controlling for 11th-grade SBAC test; HSGPA; SAT; curricular intensity; HS type; college aspirations; and student demographics of ethnicity, poverty, language classification, and gender?

RQ3: To what extent does the 8th-grade SBAC test predict the 11th-grade SBAC test in comparison to MSGPA while controlling for HS type; college aspirations; curricular intensity; and student demographics of ethnicity, poverty, language classification, gender?

RQ4: To what extent do the eighth or 11th-grade SBAC test scores and their predictive validity for college readiness suffer from the same biases of school type, ethnicity, and poverty that have been shown to bias the SAT and GPA?

Significance of the Study

This study is important for several reasons. First, colleges need indicators that lead to highly valid and reliable inferences about college readiness and success to better inform the admissions process and intake of college-ready students because the current educational crisis continues to threaten state and national economies with more jobs requiring college degrees (Carnevale et al., 2016). Second, this study added to the body of research literature on the newly implemented SBAC examinations for measuring college readiness and their predictive power compared to traditional indicators of the SAT, HSGPA, and rigorous course completion. If the SBAC examination is equally predictive, then it may provide a more equitable, affordable, and time-saving option for students in the college admissions process. Third, there is a substantial knowledge gap in the research literature concerning the predictive validity of the SBAC examination for college readiness and its effect on racial inequalities, poverty (Dam, 2019; Kurlaender & Cohen, 2019), and school type (González Canché, 2018; Kurlaender & Cohen, 2019). Fourth, it is important to know whether increasing curricular intensity in HS has a positive impact on college readiness without creating or worsening equity issues. For example, California State University (CSU) is currently negotiating whether to add a fourth quantitative reasoning course as a necessary HS requirement for CSU admission (Gordon, 2020; Strauss, 2020; Tang, 2018; Watanabe, 2021), despite the mixed evidence in the research literature about the effectiveness of mandating more rigorous courses to improve college readiness (Buddin & Croft, 2014; Preston et al., 2017). Finally, whether SBAC tests have predictive utility will be relevant to K-12 and postsecondary educators, stakeholders, and policymakers concerned with improving students' college readiness and college admissions processes. It is becoming increasingly urgent to more rigorously assess the SBAC tests, especially within the local site under investigation in this study, for two reasons: (1) it was recently decided that the University of California (UC) and CSU systems will no longer consider the SAT or ACT in their admissions procedures (Douglass, 2020), and (2) over 200 universities across 10 states, including the UC system in California, are already including SBAC tests in their course placement decisions (Smarter Balanced, 2016) and are now considering using the SBAC scores for admission decisions (Burke, 2021; Gordon, 2020).

Summary

This study addressed the ongoing crisis of the lack of college readiness in high school graduates across the nation. The research problem was the uncertain predictive validity of the middle school and high school SBAC tests for college readiness, as measured by college enrollment and persistence, and the uncertain degree of demographic and school bias in SBAC scores and prediction when compared to GPA, SAT, curricular intensity, and college aspirations. There were four research questions that focused on different aspects of the research problem. The study is very important because higher education institutions need more valid and reliable indicators of college readiness and relatively little is known about SBAC measurement and prediction of college readiness, and potential demographic and school bias, when compared to SAT and GPA. The following chapter contains a thorough review of the theoretical and quantitative research literature on the topics of college readiness, academic indicators, and potential demographic and school biases.

CHAPTER 2

Literature Review

The purpose of this literature review is to present prior research discussing the predictive validity of standardized assessments, HSGPA, and the completion of more rigorous courses in making college admissions decisions and how they relate to student ethnicity, student poverty, and HS type. All scholarly research is built on the studies and knowledge that came before in order to increase understanding of the topic and factors explored, assess the methods used, assess major findings upon which concepts and ideas are built, uncover different perspectives, and find gaps in the literature. I begin by describing the strategy used to conduct the literature search, followed by providing an overview of the national focus on college access and explore the concept of college readiness. I then examine the indicators used in college admissions and the development and use of standardized assessments. This is followed by a description of the SAT, a discussion of the research on the predictive power for college success, and an exploration of the issues of equity and bias that plague the SAT. I then examine HSGPA, followed by rigorous course completion, discussing the predictability and the equity and bias related weaknesses found in each of these traditional college readiness indicators. The literature review continues with a review of the literature on the SBAC tests, its use as part of the California Assessment of Student Performance and Progress (CASPP), and a discussion of the relevant knowledge gaps in research on the predictive power of SBAC examinations for college success that inform the scope of this study. Next, I examine the use of the SBAC as an MS indicator of college readiness and highlight the gap in the literature relating to whether the eighth-grade SBAC is predictive of the 11th-grade SBAC or college enrollment and persistence. Finally, I turn to an important component of college readiness and examine student aspirations. The literature review ends with a review of how this study will address current gaps and add to the body of knowledge.

I conducted the literature search across multiple databases such as Google Scholar, Education Resources Information Center, and SAGE, with combinations of specific key words or phrases relevant to each major theme. I used the following keywords and phrases interchangeably and in combination: "college admissions,"" college readiness," "standardized educational assessments," "HS, grade point average," "college persistence," "Smarter Balanced Assessment Consortium," "value of college degree," "national educational reform," "Every Student Succeeds Act," "SAT," "ACT," "Advanced Placement," "college preparatory curriculum," "college aspirations,"" middle school," and "theoretical framework." The inclusion criteria were the relevance of the sources to the keywords, study themes, and questions and articles being peer-reviewed. However, I did not exclude other relevant sources.

I conducted the following steps when assessing sources: First, I read the title and abstract to determine the relevance to the research focus or subtopic. Second, I read or skimmed the study to determine its relevance to the focus of my study by examining the relationship between the problem, purpose, and questions addressed; the methods and theoretical framework used; the findings; and the insights and arguments presented. Third, I paraphrased and took notes on the purpose, methods, findings, and important sections or segments from the article for use in an applicable subsection of the study along with the full American Psychological Association reference citation for that article. Fourth, I investigated pertinent sources cited in the article. Fifth, I explored other studies that referenced the article by clicking on, "cited by" in Google Scholar to find more recent articles that referenced the source. Through this process, I discovered additional reviewed sources because many relevant articles include citations to other relevant articles. Finally, I filtered my search to only peer-reviewed articles and repeated the first five steps. I also noted recurring authors and searched for them by name to find other articles they had published. I included over two dozen peer-reviewed articles; however, I also included many non-journal articles in the six-step procedure to gather information not described in the research articles.

National Focus on College Readiness

In 2015, under President Obama, No Child Left Behind (NCLB) was replaced by the Every Student Succeeds Act (ESSA), which focuses on increasing college and career readiness and eliminating disparities in student outcomes, college access, and degree attainment (U.S. Department of Education, 2015; Duncheon, 2015). ESSA retained the mandated standardized testing requirement from NCLB as part of state, district, and school site accountability of student progress toward college readiness (Sharp, 2016). States were able to choose to participate in one of the developed Common Core assessments (i.e., an SBAC or PARCC examination) or to use one of their own standards-aligned assessments (Sharp, 2016). As the national focus shifted to college readiness, most states adopted the Common Core Standards (Polikoff et al. 2016; Porter et al., 2011) and began contemplating the adoption of the associated SBAC or PARCC assessments (Common Core State Standards Initiative, 2021). A total of 41 states adopted the Common Core Standards (Common Core State Standards Initiative, 2021), with 20 states adopting SBAC assessments, 15 states adopting PARCC assessments, and 19 states using their own assessments aligned with state standards (Gewertz, 2017). The intended use of these standardized assessments is to inform and monitor student performance on the Common Core Standards (National Governors Association & Council of Chief State School Officers, 2010) and to provide universities with a more accurate indicator of students' level of college readiness

(SBAC, 2020a). However, it's important to note that the degree to which teachers adequately adhere to the Common Core Standards in their individual course instruction is not usually sufficiently documented or monitored, so this can create potential limitations or challenges when interpreting the effects of assessments like the SBAC tests or curricular intensity.

College Readiness

College readiness is a complex and multidimensional concept that has been difficult for researchers and educators to effectively define. Conley (2003) discussed the challenges in creating a universal definition of college readiness. Jackson and Kurlaender (2014) emphasize similar difficulties, calling it a "nebulous term" (p. 955). In educational practice, college readiness has been conventionally defined by colleges and universities based on the rigor and grades of HS courses as well as performance on traditional admissions tests such as the SAT and ACT. However, many postsecondary institutions or states often have their own performance benchmarks for how they consider incoming students to be college ready. For example, in the CSU (2017) system, college readiness is defined as the ability to pass credit-bearing math and English courses at the college level that count toward a college degree.

The majority of U.S. states (33) have operationalized a definition of college readiness (Webster, 2015) with core features in common such as knowledge of core subjects (i.e., the most common feature occurring in 19 state definitions), problem-solving and critical thinking, collaboration and communication with others, persisting and persevering through adversity, and self-development of being a socially conscious and responsible citizen (Mishkind, 2014; Webster, 2015). All states regard the successful completion of rigorous college preparatory courses such as advanced math and science, AP, and the IB as indicating college readiness (English et al., 2017). Most states have specific college readiness standards for English and math courses as well as required proficiency tests for English and math courses in HS (Webster, 2015). Some states have rarer features in their definition of college readiness, such as technological aptitude (e.g., Maryland and Oregon), development into lifelong learners (e.g., Hawaii, Massachusetts, West Virginia), and environmental consciousness (e.g., Hawaii). This variability in state definitions further indicates some of the complexities inherent to defining college readiness.

Many educators and researchers have offered definitions of college readiness with a variety of factors involved. The National Office for School Counselor Advisory (NOSCA) promoted their own definition with eight key factors: college aspirations, academic planning with rigorous course-taking and good performance, extracurricular activities, exploring and selecting college and career, college test performance, budgeting, admission process, and college enrollment (College Board, 2010; Perusse et al., 2015). Similarly, Bryan et al. (2015) and Hatch (2013) suggest these important factors: HSGPA > 3.0, rigorous course-taking, taking the SAT or ACT, extracurricular and community activities, aspiring for college and/or career, meeting state benchmarks for math and reading, knowing how to do college applications, college enrollment, financial aid application, and ability to request transcripts and scores. Nagaoka et al. (2013) distinguish between academic factors of college readiness (such as GPA, test scores, and rigorous courses) and nonacademic factors of college readiness (such as mindset, attitude, study methods, skills), with both sets of factors being crucially relevant for accurately predicting college success.

Conley (2003, 2007) emphasizes the important connection between completing rigorous HS curricula with development of non-cognitive skills. In a survey study of faculty from 20 universities on the topic of the necessary knowledge and skills for college success, Conley

(2003) identified the importance of content knowledge in English, science, math, history, second language, and the arts, as well as the importance of non-cognitive skills such as problem solving, critical thinking, time management, note-taking and writing, persistence and grit, and communication. Notably, the faculty considered the non-cognitive skills to be as important as the content knowledge. These findings inspired the developments of future college readiness standards, including Conley's (2007) subsequent model of college readiness that integrated both academic and nonacademic factors into a more holistic view of what it means to be college ready. Conley (2007) also distinguished between academic knowledge, which indicates the successful understanding of ideas in specific fields, and academic skills, including abilities such as critical thinking, problem solving, and time management, which are always relevant no matter what field of study.

Several years later, Conley (2007) defined college readiness as "the content knowledge, strategies, skills, and techniques necessary to be successful in any of a range of postsecondary settings" (p. 15), where success means the ability to persist into the second year of college. In the "Four Keys to College and Career Readiness" framework (see Theoretical Framework section for more detail), Conley (2014, 2017) outlines the multidimensional nature of college readiness depending on the important factors of cognitive ability (Key 1: "think"), content knowledge (Key 2: "know"), academic skills (Key 3: "act"), and college-going mindset and transition (Key 4: "go"). This model of college readiness has been a grounding framework for many empirical studies on college readiness (Conley, 2014), and it is also used as a grounding framework for the currently proposed study. Conley's (2014) framework also overlaps substantially with other definitions of college readiness described above, most notably the inclusions of successfully completing a rigorous HS curriculum and the mix of both academic and nonacademic factors

(Bryan et al., 2015; College Board, 2010; Hatch, 2013; Nagaoka et al., 2013; Perusse et al., 2016).

College Admissions

The measures of college readiness used by colleges and universities for admissions has changed over time. During the 19th and early 20th century, colleges and universities used interviews, oral and essay exams to assess students for college admissions. Each university had their own exams, requirements and protocols for selecting students for admissions however these methods were not only time consuming but subjective (Giordano, 2005; Rothman, 1995) and allowed for the rejection of candidates meeting academic requirements but who were nevertheless "unwanted" due to various institutional biases (Thut, 1957). In an attempt to standardize admissions in 1900, Harvard University President, Charles William Eliot encouraged 12 prominent colleges to create the college entrance examination board, later known as the College Board, in order to develop a common set of essay exam that could be used in universities for college admissions across the United States (Zwick, 2019).

Development of Standardized College Admission Exams

However, these exams that measured achievement would be replaced by the innovation of an intelligence test that allegedly measured student aptitude. Inspired by the development of an intelligence test by French psychologist Alfred Binet in 1905 adapted by Terman, and standardized by Yerkes and Brigham, dozens of standardized tests were developed by researchers and scientists to measure mental ability (Gould, 1996, Lemann, 2000). Arthur Otis, a student of Terman created a multiple-choice format for intelligence tests allowing the exams to be administered to thousands of children and altering the scoring system to an average score of 100, which was more familiar to the public, and later referred to as the Stanford-Binet test for intelligence quotient (IQ) (Gould, 1996). However, Terman and Otis, like other biological determinists of the time, had a willful blindness to other factors and rejected the idea that environmental factors such as poverty, home life, or poor schooling had any significant influence on IQ levels (Gould, 1996).

Motivated by the development of the IQ test, Carl Brigham led the development of the Scholastic Aptitude Test (SAT) in 1926 to assess students' aptitude for learning on behalf of the College Board. The word "aptitude" was intentionally used to distinguish the exam from other standardized achievement tests, even though the SAT does not measure innate intelligence (Couse & Trusheim, 1988). The military allowed Brigham to use the SAT to assess applicants to West Point and then Annapolis and was able to collect data to support the idea that the SAT could predict academic performance as measured by freshman grades (Lemann, 2000). The SAT was viewed as a neutral yardstick by which to assess student academic ability and preparation for college-level courses and to predict college success (Gonzalez Canché, 2018, 2019). James Bryant Conant, President of Harvard University believed intelligence tests could potentially be used to assess college applicants potentially expand college access. In an attempt to expand college opportunities, Conant used Brigham's SAT to select students demonstrating academic promise for a national scholarship program (Lemann, 2000). Conant viewed intelligence test as superior to achievement tests, as he believed they gave an unfair advantage to students of privilege who receive the best instruction and was trying to identify and award scholarships to students from every social level across the country (Lemann, 2000). By the end of the 1930s, all Ivy League colleges required the SAT for admissions (Lemann, 2000). Intelligence tests were viewed as the ultimate tool for social justice and viewed as a systematic opportunity for the masses to enter postsecondary institutions.

In 1936, Thomas Watson founder of IBM developed a machine to score multiple-choice tests in mass enabling the mass expansion of standardized testing, including the SAT. With advances in technology, scoring machines were invented and later iterations of the SAT with multiple-choice questions began in 1935 (Linn, 1993). The breakthrough innovation of the SAT in contrast to previous standardized tests at that time was “an easily scored, multiple-choice instrument for measuring students’ general ability or aptitude for learning” (Atkinson & Geiser, 2009, p. 666). The SAT became completely multiple choice in 1956, enabling the efficient testing of thousands of students across the United States (Linn, 1993). The mechanical scoring of standardized tests removed any bias or variability in scoring.

With the advent of the GI Bill after WWII, there was a surge in college enrollment and students taking the SAT (Lemann, 2000). A national, centralized testing agency, the Educational Testing Service (ETS) was created in 1948 and assumed the responsibility for future iterations of the SAT for the College Board (Board of Admissions and Relations with Schools, 2002; Lemann, 2000). By 1961, the SAT was given to over 800,000 students (Lawrence et al., 2014). The California University system adopted the SAT as a requirement for admissions in 1968, which effectively reduced the number of Black and Latinx students admitted (Lemann, 2000). By 1970, over two million students took the SAT (Lawrence et al., 2014).

Measures of College Readiness Used by University Admissions

Today the measures of college readiness set by university admissions offices continue to include standardized college entrance exams scores such as the SAT or ACT as well as the types of courses completed, HSGPA (Clinedinst & Patel, 2018; Douglass, 2007). California state four-year public universities use one or more of the following indicators of college readiness specific to math and English: a high score on the SAT (e.g., above a 550 for math and a 500 for English);

a high score on the ACT (e.g., a score above a 23 in math and a 22 in English); an AP score of a 3 or higher in a relevant English or math course; obtaining a grade of a C or higher from a community college course in English or math; scoring at the "standard exceeded" level on the Early Assessment Program test; or scoring above a 50 in math and above a 147 in English on college placement exam (California State University, 2017). As one of the components of a university's success is measured by is their graduation rate (Fain, 2018), universities use the SAT or ACT, HSGPA, and rigorous course completion to predict which students will succeed in college (Allensworth et al., 2018, Barnett & Reddy, 2017).

Scholastic Aptitude Test

The SAT has evolved and changed over time. Initially, the SAT comprised nine sections two included math and seven assessed verbal skills and SAT scores were scaled to an average of 500 through 1941 (Lawrence et al., 2014). However, with the expansion of college enrollment, the average in student scores declined through the 1960s and 1970s (Lemann, 2000). Combating criticism and declaring that the SAT was not coachable, the College Board began releasing test question in 1978, expanding test preparation programs such as Kaplan and Princeton Review (Lemann, 2000). In 1994, the SAT dropped the use of antonym questions, included longer reading passages, and allowed the use of calculators (Lawrence et al., 2014). In 2005, the initial SAT (SAT I) was completely redesigned into SAT II (i.e., SAT revised or SAT-R) in order to address issues of racial and socioeconomic equity and test validity of the first version (Lawrence et al., 2014). The new exam added open-ended and higher-level math problems, eliminated analogies, and introduced a 2,400 point scoring system and a writing exam as a separate section, distinct from the verbal and mathematical reasoning sections (Lawrence et al., 2014). In 2016, the SAT changed again modifying the structure and scoring method from 2,400 to 1,600. The score of 1,600 comprised 800 for each the verbal and mathematics sections with the writing section using an 8-point scale (Lawrence et al., 2014). The new SAT also adopted the innovations of computer-based tests, adaptive testing, and automated essay scoring which greatly increased the testing and scoring efficiency (Lawrence et al., 2014). However, the new SAT has continued to struggle with similar equity and validity issues as well as misalignment with K-12 curricula and suboptimal prediction of college outcomes (Moncaleano & Russell, 2018).

Today, the overall SAT score is the sum of the Evidence-Based Reading and Writing (EBRW) score and the mathematics score, each ranging from 200 to 800 with a total score ranging from 400 to 1,600 (College Board, 2021). The EBRW reflects proficiency in standard English conventions of grammar, punctuation, and the organization of ideas; reading comprehension of informational, fictional, and non-fiction text and words in context; deciphering the meaning of words from surrounding text and evaluating word choice for meaning, style, and tone; expression of ideas; and use of evidence to support claims and interpreting visuals, charts, graphs, and assessing implications (College Board, 2021). The math scores reflect student proficiency in algebra concepts and operations; solving equations; problem-solving; interpretation of data tables, charts, and graphs; math; and some geometry and trigonometry concepts and skills (College Board, 2021). An optional written essay section worth 8 points is scored separately from the overall. Recent piloting of the revised SAT demonstrated improved content validity and reliability of SAT as well as good predictive validity for college performance and persistence (Westrick et al., 2019).

Predictability of the Scholastic Aptitude Test for College Readiness

The College Board's response to these concerns of bias consistently returned to the predictive power of the SAT for college success. The College Board formed a research consortium with universities to validate the predictive validity of the SAT on college success, such as student GPA, persistence, and degree completion. A study by Huh and Huang (2016) found that standardized tests are an accurate predictor of academic performance as seen by student grades after controlling for socioeconomic status. Another study by Mattern and Patterson (2011) examined the relationship between SAT scores with college persistence. Controlling for HSGPA, the researchers found that students with higher SAT scores had higher retention rates than those with lower SAT scores into the third year of college (2010) as well as into the fourth year (2011). Mattern, Shaw, and Marini's (2013) results demonstrated that students who met the college readiness benchmarks on the SAT had a 27% higher bachelor degree completion than those who did not meet the college readiness benchmarks. Study results have confirmed that standardized exams used for college admissions are predictive of college GPA, persistence, and degree attainment (Mattern & Patterson, 2014; Randunzel & Mattern, 2015; Radunzel & Noble, 2012; Shaw, 2015).

A robust number of studies not associated with the College Board document the relationship between standardized college admissions exams and college success. Research shows that the SAT is predictive of first-year college GPA (Krompecher, 2020; Roszkowski & Speat, 2016; Sackett et al., 2009) and persistence to the second year (Westrick et al., 2019). Several studies have found that standardized admissions exams are predictive of student college grades and degree completion (Sackett & Kuncel, 2018; Zwick, 2017, 2019). Furthermore, many studies have found the SAT and ACT to be uniquely predictive of college success over and above HS grades, while others highlight the importance of combining standardized test results and HSGPA (Huh & Huang, 2016; Krompecher, 2020; Mattern & Patterson, 2011; Mattern et al., 2013; Randunzel & Mattern, 2015; Roszkowski & Speat, 2016; Sackett & Kuncel, 2018;

Westrick et al., 2019; Woodruff & Ziomek, 2004; Zwick, 2019). For example, in a meta-analysis, Westrick et al. (2019) showed that ACT scores predicted first-year academic performance while controlling for HSGPA and that while both ACT scores and HSGPA predicted college performance, HSGPA was the stronger predictor. In a previous review of many large studies, Zwick (2019) reported that SAT or ACT scores are correlated with first-year college GPA but that the correlations increased on average when including HSGPA. Additionally, Westrick et al. (2019) report that using SAT scores alone was predictive of college performance but that including the SAT in the model with HSGPA explained 15% more variance. Results such as this highlight the potential need to consider both factors together.

Problems with the Scholastic Aptitude Test

There are long-standing concerns about how ethnicity, poverty, and school type can create inequity or bias in standardized tests (College Board, 2019; Geiser, 2015; Gonzales Canché, 2018; Kohn, 2001; Linn, 1990; Sackett et al., 2009; Zumbrun, 2014; Zwick, 1999). The findings of Linn (1990) increased the controversy over the validity of the standardized college admissions exams, SAT and ACT, and their efficacy for assessing minority student abilities. Linn (1990) found limited predictive validity, especially for Black and Latinx students, who scored a standard deviation below White students. Zwick (1999) found that socioeconomically disadvantaged and minority students do not score as well on the SAT, highlighting concerns of bias. In 1999, the U.S. Department of Education Office of Civil Rights publicly warned schools and universities on the use of standardized college admissions exams due to concerns over bias (Gose & Selingo, 2001). In response, the College Board revamped the SAT in 2005, eliminating sections on analogies and ambiguous questions deemed as culturally biased, added an essay section, and increased the level of rigor of the exam questions (Shaw & Kobrin, 2013). The exam was described by the College Board as “an integrated system of tests that measure what students are learning in class, and what they need to succeed in college” (College Board, 2019, p. 2). Although the revised SAT was designed to more accurately measure the academic ability of all students, researchers have continued to find that race, ethnicity, family income level, community wealth, and geographic factors bias SAT performance (College Board, 2019; Dixon et al, 2013; Geiser, 2015; Gonzales Canché, 2018). For example, Rothstein (2004) found that the relation between SAT scores and freshman GPA was determined by student poverty and ethnicity. Gonzalez Canché (2019) reports that geographical bias in SAT is based on factors including poverty. The author also discusses results indicating differences in SAT performance due to type of school (e.g., private vs. public) and school resources. These trends deny equity and access to students of color and students from low-income families and neighborhoods and promote the continuation of White privilege with increased opportunities for college.

According to Conley (2012), standardized college admissions tests provide a narrow and inaccurate assessment of college readiness as they do not consider other non-cognitive factors such as student interest and aspirations. This is evidenced by the fact that one-third of college freshmen must take at least one remedial English or math course (Ling & Radunzel, 2017) and fewer than 23% of students complete a college degree nationwide (Linderman & Kolenovic, 2013). A better predictor of college readiness is student HSGPA, which researchers have found to be more highly correlated with student performance than the ACT, a traditional college entrance exam (Hiss & Franks, 2014; Hodara & Cox, 2016; Hodara, & Lewis, 2017; Westrick et al., 2015). A major theme in the literature on college readiness, access, and success has been the search for indicator variables in HS and less so in MS that reliably and accurately predict variables such as college enrollment, first-year GPA, and persistence past the first year or through degree completion.

High School Grade Point Average

HSGPA has been identified as the strongest predictor of college success even when controlling for standardized tests and school or demographic variables (Allensworth & Clark, 2020; Balfanz et al., 2016; Fonteyne et al., 2017; Giersch, 2016; Hodara, & Lewis, 2017; Koretz & Langi, 2018; Mattern et al., 2018; Morgan et al., 2018; Westrick et al., 2015). Therefore, most universities have used HSGPA along with standardized tests for admission and prediction (Westrick, 2017). HSGPA is a multidimensional variable that reflects numerous cognitive and non-cognitive aspects of college readiness (Mattern & Patterson, 2014; Conley, 2014), and it features in many different frameworks and definitions of college readiness (Bryan et al., 2015; Conley, 2014, 2017; Hatch, 2013; Nagaoka et al., 2013; Perusse et al., 2015).

GPA is typically calculated on a continuous scale from 0 to 4 as an average across all course grades. For many decades, HSGPA along with standardized test scores has been used by most colleges as one of the most important factors for admission and predictors of academic performance (Westrick, 2017). HSGPA is a primary criterion for admission into many four-year public state university systems. The NOSCA recommends the use of HSGPA to reflect the performance aspect of academic preparation (Perusse et al., 2015). In college preparatory curricula, HSGPA is recognized as one of the strongest predictors of college success (Allensworth & Clark, 2019; Balfanz et al., 2016; Conley, 2014; Fonteyne et al., 2017; Giersch, 2016; Koretz & Langi, 2018; McNeish et al., 2015; Morgan et al., 2018; Sanchez & Mattern, 2018; Westrick et al., 2015; Williams et al., 2018).

Many researchers have argued for the necessary inclusion of GPA as an academic factor in theoretical or conceptual frameworks of college readiness (Bryan et al., 2015; Conley, 2014; Hatch, 2013; Nagaoka et al., 2013). For example, in the Four Keys model of Conley (2014, 2017), GPA features as "the strongest predictor of postsecondary success" (p. 14) because it reflects critical thinking (Key 1), content knowledge (Key 2), and learning skills (Key 3), as well as "a whole series of meta-cognitive learning skills such as time management, study skills, help-seeking strategies, persistence, and goal focus" (Conley, 2014, p. 14). Other scholars have discussed the role of HSGPA as both an academic and nonacademic factor (Mattern et al., 2014; Westrick, 2017). Mattern et al. (2014) explain that HSGPA not only reflects student academic achievement but also reveals non-cognitive aspects of study habits, organization, self-regulation, grit, and motivation that play an integral role in college readiness and postsecondary success.

Predictive Power of High School Grade Point Average for College Readiness

HSGPA has been used in numerous quantitative research studies to assess college readiness and to evaluate new graduation policies (Betts et al., 2016; Jackson & Kurlaender, 2014; Le et al., 2016; Preston et al., 2017). Many research studies have demonstrated that HSGPA outperforms the ACT or SAT when predicting college readiness (Allensworth & Clarke, 2020; Hiss & Franks, 2014; Hodara & Cox, 2016; Hodara, & Lewis, 2017; Westrick et al., 2015). Yet others have demonstrated the importance of combined effects for predicting college performance (Kobrin et al., 2008; Woodruff & Ziomek, 2004). For example, Kobrin et al. (2008) showed an only slightly stronger prediction of freshman GPA for HSGPA alone (R^2 = .13) versus SAT alone (R^2 = .10), but their combined effect was substantially greater (R^2 = .19). In a large cross-sectional study of universities across the United States, Bowen et al. (2009) found a strong relation between HSGPA and college achievement when controlling for SAT and ACT scores, and this relationship was larger than the relation between SAT and ACT and college success in an alternative model controlling for HSGPA. The ACT (2013) reported that including HSGPA with the ACT scores and other measures enables higher prediction of college success. Previous studies have found that students with an HSGPA of a 3.0 or higher are more likely to pass college courses and persist to earning a college degree (Balfanz et al., 2016; Hein et al., 2013; Jackson & Kurlaender, 2014). The substantial influence of GPA is often necessary to control for in studies assessing the influence of other HS variables on college readiness (e.g., Buddin & Croft, 2014; Kim et al., 2015).

Problems with High School Grade Point Average

A well-known problem with GPA is that, because it is an average over all grades, it tends to disguise the high variability of factors that influence grades, such as assignments, projects, tests, activities and behaviors that occur over time, as well as teachers and school (Bowers, 2011; Brookhart et al., 2016; Kelly, 2008). Grades can also be perceived as inconsistent because they differ between teachers and schools. Despite this variability, Allensworth and Clarke (2020) suggest that GPA is an ideal indicator precisely because they average this variability and the wide range of activities and tasks on which students are assessed. Similarly, Conley (2014) emphasized the importance of GPA as a predictor of college readiness primarily because it reflects a wide range of academic and nonacademic factors.

Another problem with GPA is the evidence of grade inflation over time contributing to less reliability when compared with standardized test scores (Gershenson, 2018; Hurwitz & Lee, 2018). It has also been shown that students matched on GPA can show large differences in standardized test scores (Woodruff & Ziomek, 2004). Buckley et al. (2018) relate that many proponents of standardized admission tests believe that such admission tests provide a more “neutral yardstick” (p. 2) for assessing students’ academic performance and potential amidst the high variability of courses available, variety, rigor, and grade inflation. Because standardized tests use the same questions and tasks to measure student performance, they are often perceived as more reliable, objective, and fair. Another problem mentioned by Northern and Petrilli (2018) is that, unlike standardized tests, grades come from courses that are often not aligned with state standards for college. It has also been reported that requiring students to take more challenging courses, such as AP, often decreases their grades and GPA (Sadler & Tai, 2007). One counterargument to this issue is that many colleges that are test optional place more emphasis on the completion of rigorous courses and HSGPA for their admissions. Hiss and Franks (2014) discovered that students not submitting SAT or ACT scores had similar or better outcomes, in the same colleges, than students who did submit their scores.

Poverty, race and ethnicity, and school type are three of the most important nonacademic factors that have been identified in the research literature as associated with bias and inequity in grades and GPA (Allensworth & Clarke, 2020; Betts et al., 2016; Koretz & Langi, 2018; Preston et al., 2017; Zwick, 2013; Zwick & Himelfarb, 2011). In an analysis of data from the CSU and UC, Rothstein (2004) found the relation between SAT and freshman GPA was determined by student poverty and ethnicity. Preston et al. (2017) discovered that the GPA of minority groups often decreased after new policies for increasing curricular rigor, reflecting an ongoing disparity in academic achievement for racial and ethnic or socioeconomic subgroups of students. Barrow et al. (2016) discovered that school context accounted for differences in grades of students with similar scores on assessment tests, such that students in schools with higher-performing students were lower than students in schools with more low-performing students. Koretz and Langi (2018) revealed that the size of the relationship between HSGPA and college GPA and completion was greater for students coming from the same HS than for those from different schools. The authors recommend that future studies should adjust for such school differences by including average achievement levels of schools. Allensworth and Clarke (2020) reported different rates of college graduation in students with the same ACT and HSGPA depending on which HS they attended. Finally, some researchers have suggested that low-income-neighborhood schools are more likely to give Black and Latinx students inflated grades, which could result in those students being underprepared in college and receiving lower freshman GPA, thereby decreasing the reliability of HSGPA for indicating college readiness (Zwick, 2013; Zwick & Himelfarb, 2011). These various studies demonstrate how strongly the factors of school type, poverty, and race and ethnicity can confound the relationship of GPA with college readiness. Therefore, it is important to control for these potential confounds when assessing relations between HS and college.

Curricular Intensity in High School

The importance of curricular intensity or rigorous course-taking in HS has been acknowledged for decades (Adelman, 1999, 2006; Austin, 2020). In this context and for the purpose of the present study, rigorous can be defined as above the minimum requirements for high school graduation. Conley (2007) associated curricular rigor in HS with the development of both cognitive (e.g., critical thinking, problem solving, writing) and non-cognitive skills (time management, persistence). Conley (2014) emphasized the disconnection between HS and college curricula and the need for alignment to improve college readiness. Rivkin and Schiman (2015) conducted regression analyses on data from the 2009 PISA worldwide survey of MS students and demonstrated a positive relationship between increasing instruction time and higher achievement in math and ELA depending on time spent learning, student effort, and quality of teaching.

Part of the national reform effort to adopt the Common Core Standards was focused on ways to improve the vertical alignment between HS and college-level curricula (Conley, 2008; Jimenez & Sargrad, 2018). The lack of alignment has been of growing concern because only 50% of HS students in the United States complete the courses required by four-year public university systems (Bromberg & Theokas, 2016). To increase vertical alignment and college readiness, many states have been adopting reform policies that mandate the addition of more rigorous courses for HS graduation (Buddin & Croft, 2014; Jimenez & Sargrad, 2018). Since 2004, at least 36 states have increased HS curricular intensity required for graduation (Achieve, 2015). For example, the school district under investigation in this study was one of several districts in California (Betts et al., 2016) to mandate a new a-g course sequence with seven content areas: history/social science (“A”), English (“B”), mathematics (“C”), laboratory science (“D”), foreign language (“E”), visual and performing arts (“F”), and college preparatory elective (“G”) as part of their HS graduation requirements. In this school district under investigation, the a-g course policy was implemented in 2012 (Martinez et al., 2012), making the class of 2016 the first affected cohort. Many researchers have also indicated the importance of completing at least three years of mathematics, including Algebra II, and four years ELA (Achieve, 2015; Bromberg & Theokas, 2016; WestEd, 2016). Many HSs also provide students with the option to take AP, IB, and concurrent community college courses so that students can earn early college credits and gain practice with the rigor of college-level curricula. Some studies have found that successful completion of AP or IB courses positively relates to achievement in college (Ackerman et al., 2013; Conley et al., 2014; Morgan et al., 2018).

Predictive Power of Curricular Intensity for College Readiness

Despite the prevalence of school districts and states adopting new policies for increasing course rigor of HS to improve college readiness, many researchers have noted it remains relatively unknown whether increasing HS course requirements can reliably improve college readiness and access for all students (Buddin & Croft, 2014; Plunk et al., 2014; Preston et al., 2017). For example, Preston et al. (2017) emphasized that racial and economic gaps in academic progress remain despite over three decades of dedicated reform policy, concluding that "the evidence is weak or mixed for any structural or organizational change alone leading to improved student outcomes" (p. 526). Similarly, Domina et al., (2015) note that "relatively few studies have attempted to estimate the effects of advanced course-taking in experimental or rigorous quasi-experimental settings, and those that do have returned sharply mixed results" (p. 277).

Indeed, the empirical evidence from the research literature on this topic provides inconclusive support for the beneficial link between increasing HS rigor and college readiness given that both positive and negative outcomes have been found for different measures of college readiness (Buddin & Croft, 2014; Byun et al., 2014; Howard et al., 2015; Kim et al., 2015; Long et al., 2012; Mazzeo, 2010; Preston et al., 2017; Rivkin & Schiman, 2015; Royster et al., 2015). The results of several exemplary studies are summarized below. Long et al. (2012) used multiple regression and propensity score matching in a large sample of HS students in Florida to show that more rigorous courses were associated with increased test scores, graduation rates, and college enrollment across different demographic groups. Using similar analysis, Byun et al. (2014) found in a large national sample of HS students from 2002 to 2006 that advanced math course-taking was associated with increased math scores on standardized tests, although for primarily high-income and White students compared to low-income and Black students, as well as increased college enrollment rates for all students. Plunk et al. (2014) used logistic regression to compare college readiness outcomes between pre-policy and post-policy groups across the nation from the 1980s to the 1990s. They reported mixed evidence of increased college graduation rates for Black and Latinx men and women as well as decreased HS graduation rates for Black and Latinx students and decreased college enrollment for Black women and Latinx students. Several studies on the Chicago public school reforms in 1997 (Allensworth et al., 2009; Montgomery & Allensworth, 2010; Jacob et al., 2016; Mazzeo, 2010) used analysis of variance and regression analyses to show mixed evidence of increased course-taking; no effects on math or English test scores, as well as several negative outcomes such as lower grades and GPA, lower course completion rates for lower-achieving students, lower HS graduation, and no change in college enrollment or persistence. In a literature review curricular intensity in HS aligned with college, Preston et al. (2017) reported a mix of both positive and negative outcomes, such as increased HS graduation, increased college enrollment and graduation, as well as higher dropout rates and lower GPA for ethnically diverse students. Jacob et al. (2017) conducted a longitudinal analysis using interrupted time series regression while controlling for eighth-grade performance and demographics and also found a mix of positive, negative, and neutral outcomes from a Michigan college-prep curriculum.

Kim et al. (2015) investigated the effects of increased advanced math requirements for HS graduation in a longitudinal study of over 750,000 students in Grades 7 to 12 in Florida using multiple logistic regressions and controlling for student demographics, HSGPA, SAT, and district and school-level differences. They found that successful completion of Algebra II predicted higher enrollment and completion for two-year colleges but not four-year universities. Cortes et al. (2015) also tested for the effects of increased algebra requirements in Chicago

Public Schools with a longitudinal regression discontinuity analysis controlling for demographics. They found that doubling the time that students spent in algebra class was associated with improved critical thinking and problem-solving skills, higher scores on standardized tests, higher HS graduation rate, and higher college enrollment. In another longitudinal analysis with logistic regression controlling for demographics, Royster et al. (2015) reported both positive effects of increased participation in college-prep math and English courses, such as higher college readiness ACT benchmarks, but also negative effects such as lower readiness for English and math courses in college. Woods et al. (2018) studied the relationship between curricular intensity in HS and performance in first-year college courses in over 28,000 first-generation students in Florida using logistic regression and controlling for demographics. While higher HS grades predicted higher college grades, many well-prepared students showed low passing rates in college courses (70% in English and 48% in intermediate algebra). These results suggest that HS curricular intensity can help but is insufficient on its own to guarantee college success.

At least three studies have directly investigated the potential effects of the a-g course policy on college readiness. In a statistical summary of data from several school districts, Betts et al. (2013) reported only a small increase in college-eligible HS graduates. In a follow-up study comparing between pre-policy and post-policy cohorts in San Diego, Betts et al. (2016) reported small increases in completion of college-level courses without any change in HSGPA. However, most of the students labeled as off-track (i.e., HSGPA below the minimum requirement of 2.0) were in minority subgroups (e.g., Latinx, Black, English learners). Finally, Gao (2016) reported summary statistics of new course policies in California from 2000 to 2014. These results were mostly positive, with small increases in course completion (i.e., around 10-20% on average, with over 50% for Latinx students) and a substantial (50%) increase in Algebra 2 course-taking although the overall rate was still low at 30%. However, ethnically diverse schools had only half the rate of course completion when compared to schools with less diversity.

As reviewed above, many states and school districts have tried to fix their college readiness problem by implementing new graduation course requirements to increase vertical alignment between HS and college curricula. However, previous studies have demonstrated that the results of these policies are overall quite mixed with various positive, negative, or absent effects with respect to grades, GPA, test scores, HS graduation, college enrollment, persistence, and completion. The uncertainty regarding the efficacy and mixed outcomes of such policies, especially for socioeconomically or ethnically diverse students, creates a major gap in educational research and practice.

Problems with Curricular Intensity

Mandating increased curricular intensity in HS has been shown to have unintended negative consequences such as decreased grades or GPA, or absence of expected positive results, especially for lower-performing students (Buddin & Croft, 2014; Jacob et al., 2016; Woods et al., 2018). Jacob et al. (2016) explained these results as being "caused by higher failure rates among low performing students pushed into more difficult courses by the new requirement" (p. 33). Both Woods et al. (2018) and Jacob et al. (2016) speculated that merely increasing curricular rigor is insufficient to substantially improve students' achievement and college readiness and can be particularly detrimental for the lowest-performing students. Betts et al., (2016) discussed the so-called "double jeopardy" problem (p. 13), where students are required to both complete more rigorous courses and increase their GPA, which could create "unintended negative consequences that harm the very students the policy seeks to assist" (p. 18). In light of the persistent racial, ethnic and socioeconomic gaps in academic achievement, Preston et al. (2017) suggested that "effective schools not only increase curricular rigor but also provide support systems and promote equal access to resources and create variability in options" (p. 536-537).

Another problem is that the effects of curricular intensity on college readiness often appear to be biased by student demographics, such as race and ethnicity and socioeconomic status (Betts et al., 2016; Byun et al., 2014; Plunk et al., 2014; Preston et al., 2017). It appears that most of the studies reviewed above did at least partly address this concern by controlling for student demographics and other potentially confounding variables in the analysis; for example, by including them as additional independent variables in the regression models so that the effects of increasing curricular rigor as the primary independent variable could be interpreted over and above the effects of those potential confounds. It is crucially important to evaluate potential bias in new course policies for curricular intensity given the ongoing racial and socioeconomic differences that can be found in many aspects of education including course-taking patterns (College Board, 2013), geographical access to and quality of education (Gonzalez Canché, 2019; Tienken et al., 2016), standardized test scores (College Board, 2013; Gonzalez Canché, 2019; Zwick, 2019), HSGPA (Roderick et al., 2006; Zwick, 2019), state-based assessment tests such as the SBAC (Warren, 2018), predictive validity of college readiness indicators (Klasik & Strayhorn, 2018; Koretz et al., 2016), and college enrollment (Douglass, 2020; Reed et al., 2019) and persistence (DeAngelo & Franke, 2016; Stewart et al., 2015).

Smarter Balanced Assessment Consortium

As part of the development of the Common Core Standards was the idea that the standards would be accompanied by aligned standardized assessments that used the latest smart technology. The government-appointed two multi-state consortia. The PARCC and the SBAC to develop these standardized assessments that would measure college and career readiness. One of the requirements was that the two consortia involve colleges and universities in the design of the assessment to ensure they measured student readiness for college level coursework (Camara, 2013).

Technological Innovation of Smarter Balanced Assessment Consortium

The SBAC tests were designed to not only reduce the socioeconomic and racial inequity issues associated with other standardized exams but also to enhance testing efficiency and validity with the introduction of technology-enhanced items (TEI) in addition to the computerized adaptive method already used in the revised SAT. A TEI uses the digital testing environment "to collect evidence of student achievement by requiring students to manipulate content or produce a product that is something other than a selected response" (Moncaleano & Russell, 2018, p. 14). Up to 25% of the SBAC uses TEI (Moncaleano & Russell, 2018). For example, a TEI math problem might require students to fill in the blanks by using the computer mouse to drag and drop pre-determined values into the blanks. Similar to SAT and other standardized tests, the SBAC was also designed with rigorous procedures such as extensive piloting, content and construct validation, and analysis of individual test items to assess and enhance the validity of test items. Although there is ongoing debate about the validity of SBAC test items in general and TEI items in particular (Moncaleano & Russell, 2018), it is clear that the SBAC takes advantages of the latest technological innovations in standardized testing in order to increase the efficiency and potentially also the validity of their testing procedure to enable fair access and assessment for as many students as possible.

The SBAC, the focus of this study, was first administered in California public school in 2015. According to Michelau (2015), with the implementation of the SBAC and PARCC assessments most states and universities are only now considering how to change their course placement and admissions policies to account for the new assessments. Meanwhile, while the SAT is not aligned with the Common Core K-12 content standards, the SBAC is completely aligned. Due to the use and predictability of the SAT by colleges and in an effort to reduce the number of tests HS students must take, various districts have attempted appeals to the state to replace the SBAC with the SAT (Festerwald, 2018) as the statewide accountability measure. However, a study by Achieve (2018) highlights the lack of alignment of college admissions exams to the Common Core K-12 standards and warns states and districts against using the SAT or ACT as statewide accountability measures. The new state-based assessments such as SBAC were designed to measure college readiness (Smarter Balanced Assessment Consortium, 2020), so empirical validation of their effectiveness as compared to traditional indicators is necessary.

The SBAC tests were specifically designed to better assess academic achievement and college readiness and be accessible for all students. Almost 5,000 educators participated in the design of test questions and how to define achievement levels aligned with college standards. Around 33,000 test questions and tasks have been created so far. The main SBAC tests are summative or “end-of-year” tests that measure student achievement in English and math by the end of the academic year for any students in Grades 3-8 and 11. Teachers can opt to also administer flexible “interim tests” to monitor student progress. The summative test, which contains both a computer adaptive test and a performance task, was designed for accurate assessment (Smarter Balanced, 2020f) of student achievement (i.e., total content or procedural knowledge by end of year) and student growth (i.e., change in knowledge relative to previous summative test). Irrespective of the student's grade level, the test includes writing and reading items and math items based on real-world problems to solve in a series of steps.

In order to ensure that the SBAC test fully covers the knowledge and skills that were identified by the Common Core State Standards (CCSS) as required for college and career readiness, each test item is based on corresponding content claims and assessment targets that track the relevance of the item for the specific CCSS standards. An example content claim for the problem-solving items in the math test is the following: "Students can solve a range of complex well-posed problems in pure and applied mathematics, making productive use of knowledge and problem solving strategies" (Smarter Balanced, 2020g). An example content claim for the reading items in the English test is the following: "Students can read closely and analytically to comprehend a range of increasingly complex literacy and informational texts" (Smarter Balanced, 2020h). The SBAC procedure also includes support for teachers to instruct their classes with formative assessment and actionable feedback so that they can modify their teaching practices to optimize student learning and readiness. SBAC provides an online repository of instructional and learning resources, aligned to the Common Core Standards that are curated and provided by other educators for the benefit of any other educators.

The SBAC test measures English and language arts (ELA) and Math knowledge (see example test items in Appendices A-B) in a computerized adaptive style customized to students' performance (Smarter Balanced, 2020h). This adaptive format means that correct answers elicit subsequently more difficult questions whereas incorrect answers prompt subsequently easier questions. SBAC proposes this advantage "allows students to better demonstrate what they know" (Smarter Balanced, 2020e) and it provides a substantial improvement over "old fashioned, fill in the bubble, paper-and-pencil assessments" because they are more efficient (i.e., fewer questions, less time, faster results, and a chance for intervention), more secure (i.e., larger bank of potential questions to avoid reusing items), and more accurate (i.e., individualized performance evaluation) (Smarter Balanced, 2020i). However, for optimal student accessibility, SBAC also provides a paper-and-pencil version of all tests to accommodate schools without technological resources or students with religious prohibitions.

SBAC tests have two primary scoring methods (Smarter Balanced, 2020j). The scaled scores are on a continuous distribution that is grade specific (usually from 2,000 to 3,000). These scaled scores are designed to reflect both current achievement and growth for individual students, or for specific student groups, schools, and districts when aggregated across student populations. Student percentiles at the population level can also be viewed although these percentiles do not seem to be considered for college readiness as much as the scaled scores or achievement levels. The scaled scores are typically converted into "achievement levels" which are approximate but less precise categories of college readiness: Level 1 (standard not met), Level 2 (standard nearly met), Level 3 (standard met), and Level 4 (standard exceeded). For example, for an 11th-grade math test, Level 3 requires a minimum score of 2,628 and Level 4 requires a minimum score of 2,717, whereas for the 11th-grade English test, Level 3 requires a minimum score of 2,583 and Level 4 requires a minimum score of 2,681. The achievement levels were decided on by a multi-phase review process (online panel, in-person panel, and cross-grade review committee) that included thousands of K-12 educators, administrators, researchers, parents, and community members to ensure optimal fairness and vertical alignment with college standards. SBAC emphasizes that the achievement levels are less precise than scaled scores and oversimplify the academic preparedness of a student. Therefore, educators (i.e., HS or college teachers and administrators) should never evaluate or enroll students solely on the basis of achievement levels but rather use these levels in combination with other information (i.e., scaled scores, growth history, other assessments of student work) for the best-informed decisions.

SBAC scores and vertical scaling appear to have strong validity and reliability due to extensive pilot testing, institutional review, and computer simulations that are performed annually (Smarter Balanced, 2016). For example, the SBAC technical report for 2018-2019 (Smarter Balanced, 2020d) provides a very detailed evaluation of (a) good validity based on different sources of evidence of test content and alignment, internal structure based on statistical analysis, and response process, which engages the appropriate cognitive skills, relation to other variables, and test consequences; (b) good test reliability and precision based on low measurement error, low measurement bias and high classification accuracy; (c) optimal fairness of test content and requirements for all students. This evaluation of validity, reliability, precision, and fairness is applied to all English and math test items, test categories, grade levels, and test types (summative, interim, or practice) with a high level of transparency so that anyone can see how the test is designed and maintained.

Because student accessibility is a core principle of SBAC, the tests were designed with additional supports for students with disabilities and English learners to be more accessible than other standardized tests (Smarter Balanced, 2020e). SBAC ensures that accessibility resources to address visual, auditory, and physical barriers with universal tools such as, scratch paper or digital notepad and accommodations such as Braille, foreign language translations, and other supports are available to meet the needs of all students (Smarter Balanced, 2020e). The SBAC team consulted and collaborated with expert panels on disabilities and English learning to ensure the tests were based on peer-reviewed research and universal design, for example, by carefully monitoring and adjusting the level and diversity of language complexity and “quantifying text density, language form and structure, and vocabulary" across test items (Smarter Balanced, 2020e).

The SBAC tests have seen rapid adoption in recent years. A total of 35 states are using either the SBAC or PARCC assessments, with 20 states adopting the SBAC, 15 states adopting the PARCC, and 19 states using their own assessments aligned with state standards (Gewertz, 2017). The intended use of these standardized assessments is to inform and monitor student performance on the Common Core Standards (National Governors Association & Council of Chief State School Officers, 2010) and to provide a more accurate indicator for colleges and universities about the level of student college and career readiness (Smarter Balanced, 2020a). According to SBAC (Smarter Balanced, 2016), over 6 million students in Grades 3-8 and HSs across 12 states and US Virgin Islands took the SBAC test in 2017. Over 200 higher education institutions across 10 states include SBAC as part of their multiple measures approach to determine the college readiness of incoming students in terms of course placement and remediation needed in the first year of college (Smarter Balanced, 2015). Additionally, six colleges in South Dakota already use SBAC for admission decisions (Gewertz, 2015). In the UC system, after almost 20 years of contention, the administration voted in 2020 to suspend SAT and ACT requirements for all CA applicants until fall 2024 (test optional) while they design their new and improved test or consider using the SBAC test to better align with UC curricula (Douglass, 2020). The decision was spurred by the COVID-19 pandemic, which prevented in-person test-taking such that SAT, ACT, and other tests had to be dropped for 2021 admissions (Douglass, 2020).

California Assessment of Student Performance and Progress

California uses the 11th-grade SBAC as the HS indicator of college readiness. As part of the state compliance to NCLB and later ESSA, California implemented the CASPP test in 2014 for 11th graders (California Department of Education, 2020). The CASPP program quickly transferred from using the California Standards Test to the new Smarter Balanced Assessments in 2015 to measure students' college and career readiness in ELA and math (California Department of Education, 2020). The idea behind the CASSPP was to provide information on student progress toward college readiness to identify any areas of need where students might improve before they finish HS, such that they graduate college ready (Gonzalez-Canché, 2019). Colleges and universities recognize the SBAC result of standards met, and standards exceeded the level in math and ELA as indicators of college readiness. Students scoring in the other levels rely on other evidence of college readiness, such as SAT or ACT scores, HSGPA, and success in advanced college preparatory courses.

Predictive Power of the Smarter Balanced Assessment Consortium for College Readiness

In contrast to SAT scores or HSGPA, there has been very little empirical research on the use and predictive validity of the relatively new state-based assessments such as the SBAC examinations (Michelau, 2015). Thus, there is a large gap in the literature that requires further empirical investigation. The focus of this study is on the SBAC tests, and few studies have examined the SBAC tests as predictors of college success. According to Michelau (2015), with the implementation of the SBAC and PARCC assessments most states and universities are only now considering how to change their course placement and admissions policies to account for the new assessments. The SBAC's role in college admissions remains far less well understood than that of standardized college admissions tests.

Concerned about the over testing of students, Dam (2019) compared the predictive power of the SBAC examinations against that of the SAT, ACT, and PSAT for college persistence at one public HS in Southern California. Results from multivariate analysis of variance indicate no differences in levels of persistence across examination types, but some differences exist within the ACT English and SAT math scores that appeared with higher levels of persistence. Results from a multiple regression indicated that only PSAT English scores uniquely and significantly predicted persistence over and above the other examinations, but the effect was negative and opposite to that expected since higher PSAT scores corresponded with lower levels of persistence. In this full regression model, neither the SBAC test scores nor SAT scores nor ACT scores significantly predicted persistence over and above the others. In a simplified model keeping only the significant PSAT English predictor and the marginally significant predictors of SAT math and ACT English, both SAT math and ACT English positively predicted persistence. However, it is important to emphasize that SAT and ACT scores did not significantly predict persistence when controlling for SBAC test scores, indicating some importance of accounting for SBAC examinations. These results highlight how varying results can arise from different types of analyses. Dam (2019) surmises that additional research, with a larger sample size and including multiple school sites, must be conducted. The present study expands on this initial research with a larger sample size ($n > 25{,}000$, compared to $n=142$ in Dam, 2019) and multiple school sites, and it also improves the tests of predictive power by controlling for ethnicity, poverty, and school type.

A recent study by Kurlaender and Cohen (2019) examined the predictive power of the SBAC test as compared to the SAT for first-year college GPA and persistence at CSU and UC and explored how the relationship between the SBAC examination and the SAT differed based on student ethnicity and socioeconomic status. The researchers found that the SBAC examination was comparable to the SAT as an indicator of college success. However, none of the indicators SBAC examination, SAT, and HSGPA, were strong predictors of student persistence into the second year of college. When comparing the different student groups, Kurlaender and Cohen (2019) found that lower-income students always had lower correlations of first-year college GPA with HSGPA (lower income: r=.43, higher income: r=.51), SAT scores (lower income: r=.37, higher income: r=.42), and SBAC test scores (lower income: r=.36, higher income: r=.42). HSGPA was found to be a stronger predictor of college freshman GPA than either the SBAC examination or the SAT. Kurlaender and Cohen (2019) also found that using HSGPA in conjunction with SBAC test scores was more inclusive of different student groups, especially socioeconomically disadvantaged students (Kurlaender & Cohen, 2019).

Evaluations of Other State Standardized Assessments

Prior to making the decision to adopt the SBAC or PARCC exams, several states evaluated their own state standardized assessments in relation to college readiness. Two studies D'Agostino and Bonner (2009) and Cimetta et al. (2010) examined the predictive power of the Arizona Instrument to Measure Standards (AIMS) for first-year college GPA. While the findings of both studies indicate that the AIMS math and writing scores were an effective predictor of first-year college GPA, the reading scores were not predictive (Cimetta et al., 2010; D'Agostino & Bonner, 2009). Similarly, Kingston and Anderson (2013) investigated the predictive power of the Kansas State Assessment (KSA) compared to the ACT for first-year college math and English grades using correlation and logistic regression. Unlike the other studies, the authors found that the KSA was a reliable predictor of first-year college math and English grades when compared with the ACT. These research findings indicate mixed results regarding the predictive power of state-specific standardized assessments.

Problems with the Smarter Balanced Assessment Consortium

Currently, little is known about whether the SBAC test results demonstrate the biases of race and ethnicity, poverty, and school type that have been found to affect SAT scores and student grades that comprise HSGPA. Despite SBAC's aim to more accurately and efficiently measure the college readiness of all students fairly, some limitations of the SBAC test have been identified. Locke (2019) found that socioeconomic status but not district size strongly predicted SBAC ELA and math scores. Merkel (2019) showed that factors of gender, ethnicity, special education and English learners all predicted SBAC math scores. Reed, Kurlaender, and Carrell (2019) found that students who were Black, Latinx, low socioeconomic status, or English learners were less likely to meet SBAC ELA or math levels of college readiness. Warren (2018) showed lower growth in SBAC math scores for minority, English learners, disability, and low-income students. Scaled math scores also differed drastically by race and ethnicity and were also confounded by socioeconomic status. Warren (2018) emphasizes that the SBAC test does not accurately measure achievement or growth equally for different subgroups. Moreover, while the achievement levels enable clear accountability and the long-term pattern of incremental growth is informative, the large measurement error of test scores impedes interpretation of large changes in aggregate scores at the population level, which further reduces state-level or district-level growth annually. Warren (2018) proposes a new "cohort growth measure" (p. 14) for tracking longitudinal changes of student subgroups. Kolluri and Tierney (2020) note the lack of cultural alignment or relevance in practically all SBAC test items; a major limitation that hinders the test validity for culturally diverse students. Another potential limitation of the 11^{th}-grade SBAC test is that many, if not most, high school students are probably aware that most colleges and universities still use GPA and SAT measures for their admission decisions, with the SBAC tests being used so far only for course placement decisions. This awareness could influence many students to treat the SBAC tests as less important for their chances to enroll in college, perhaps spending less time and effort to prepare for or take the test. However, as more colleges and universities move towards including SBAC and other state-based assessments for admission decisions, this imbalance in students' perceived importance could shift and reduce this problem with the SBAC tests.

In an opinion review, Cohen (2015) stated that while the SBAC tests have increased efficiency because they are easier to score, they are often not easy for students to use because many test items are developmentally inappropriate or create a technology gap for students with fewer resources, and the test itself can take up to 8 hours in total. Cohen (2015) reports that in a survey of 1,600 K-12 teachers sponsored by the Connecticut Education Association, 97% said the test fails to represent school effectiveness and takes away time and resources from important instruction. Echoing Cohen (2015), Moncaleano (2018) criticized SBAC's overemphasis on adaptive testing and TEI, which "require students to manipulate content or produce a product that is something other than a selected response" (p. 14). Up to 20-25% of test items on SBAC or PARCC tests uses this format. Moncaleano (2018) noted that although SBAC seems to be driven more by validity than efficiency, recent analysis indicated that many new items are merely TEI-forms of previously selected-response items and that most items, 40% did not have improved utility while 20% showed a moderate increase and 40% a substantial increase. The author concluded that SBAC design suffers from a disproportionate emphasis on testing efficiency rather than validity. Rasmussen (2015) also opined that the math test can be difficult to use because many test items appear to have poor user interaction or are confusing or ambiguous. Marachi (2015) noted that the SBAC's claims that the tests were scientifically valid, reliable, secure, accessible, and fair had not been independently verified. These issues found in SBAC test results when compared to SAT scores or GPA are vastly understudied, and much research must be done to address the need for equitable practices in college readiness, admissions, persistence, and degree completion.

Middle School Indicators of College Readiness

Colleges and universities rely on college readiness indicators, such as test scores and GPA, for reliable prediction of admission, course placement, and success in college so that they can improve their accountability and external evaluations (National Research Council, 2012; University of California Office of the President, 2019). The importance of these indicators for college transfers into the K-12 system where school districts also use these indicators to evaluate students' academic progress and college readiness so that these schools can improve their own accountability and ability to produce college-ready students (Allensworth et al., 2018, Barnett & Reddy, 2017). Indeed, the SBAC test was designed as a monitoring system for districts to be held accountable for the academic progress and college readiness of students (Gonzalez-Canché, 2019; SBAC, 2016). While the 11th-grade SBAC test provides an opportunity to identify underperforming students before their final year of HS, results of the 11th-grade SBAC are released too late to help struggling students better prepare for college admission (Gaertner & McClarety, 2015; Gonzalez-Canché, 2019; Mattern et al., 2016). Therefore, the eighth-grade SBAC test provides an even earlier opportunity to identify and help students who are off-track for college readiness. However, a major hole in the literature on college readiness is that relatively few studies have assessed the potential importance of early indicator variables from MS for predicting future HS and college success (Casillas et al., 2012; Mattern et al., 2016).

Gaertner and McClarty (2015) explain that most studies on college readiness have assessed indicators from 11th grade. Although these assessments late in HS are beneficial for school accountability, they impede intervention because they are performed when it is often too late for timely intervention in the progression of underprepared students to reduce the rates of college remediation (Gaertner & McClaerty, 2019). For example, students who are unprepared by 11th grade are usually required to take remediation courses in college, and such remediation is known for high rates of failure (Attewell et al., 2006; National Center for Education Statistics, 2004). Even more concerning, ACT (2008) shows that trailing students in eighth-grade are unlikely to catch up, and at-risk students fare even worse (Dougherty, 2014). The authors emphasize the importance of early K-12 measures for timely intervention. The authors propose a six-factor model of college readiness, comprised of both MS and HS variables, which include academic achievement, motivation, behavior, social engagement, family circumstances, and school characteristics. In support of this model, Mattern, Allen, and Camara (2016) propose that performance level indicators can be established by reverse mapping from college success to earlier grades in HS and MS.

Mattern et al. (2016) suggests that current college readiness benchmarks focus excessively on academic achievement without considering important nonacademic factors. They propose an MS index of college readiness with four domains: core academic skills, cross-cutting capabilities, behavioral skills, and education and career navigation skills. In a longitudinal study, Tienken et al. (2016) found that three demographic variables (percentage of high-income families in community, percentage of people in poverty in community, and percentage of people in community with college degree) predicted the percentage of students scoring at or above the proficiency level in the state tests of math and English for Grades 6-8 for more than 70% of schools across the state. Casillas et al. (2012) found that MS grades helped to predict college performance along with HSGPA and admission test scores, both having stronger effects, which Mattern et al. (2016) interpreted as "reinforcing the need for periodic assessment of multiple dimensions to accurately track students' progression toward college readiness" (p. 33).

In a unique study, Radcliffe and Bos (2013) conducted a "college culture" (p. 137) evaluation and intervention program, grounded in Conley's theoretical framework, with a diverse group of 100 students, starting in sixth-grade and ending in 11th grade, of whom half were in the treatment group and the other half were in the control group. As noted by the researchers, interventions beginning in MS are important because it has been estimated that two-thirds of eighth-grade students (and even higher for Latinx and Black groups) are below proficiency levels for math, science, reading, and writing. The intervention was designed with five specific goals to help students better understand what college is, why it is important, how to think positively about and aspire toward college, how to prepare for college admission, and how to set both short-term and long-term goals that promote their college readiness. The intervention was also designed with eight recommended strategies that students can use to improve their college readiness: (1) create digital stories (e.g., "my positive school experience", "my future career and how to prepare for it", or "how to be successful in middle school"), (2) visit colleges, (3) intensive writing during college visits, (4), academic tutoring, (5) attend presentations by college students, (6) attend presentations by college admission representatives, (7) develop school goals for improving readiness skills, and (8) apply to college including getting help from current college students. The results of this study were that the treatment group, as compared to the control group which did not participate in any of the goals or strategies training, showed higher academic improvement based on state-based assessments, higher perseverance in HS, and higher perceptions of college. Overall, more than two-thirds of all students said going to college was their major goal along with minor goals such as improving study skills.

In a similar study, Hollman et al. (2019) reported that a MS intervention to evaluate and boost students' information technology skills with problem-based learning successfully boosted student engagement in IT and related science, technology, engineering, and mathematics fields. In another intervention study, Nemelka (2018) conducted a nine-week college readiness course for 71 MS students from a racially and socioeconomically diverse school district, half of whom participated in the treatment group, which used customized digital badges and modules to enhance student learning, and the other half participated in the control group which used only standard feedback techniques. The results showed that the treatment group, relative to the control group, showed an increased understanding of optimal principles and strategies they would need to implement to improve their college preparation. These studies provide evidence that interventions conducted as early as MS can positively impact students' college readiness.

Several studies have assessed MS achievement and how it predicts HS tests in order to develop early warning indicators (Allensworth, 2013; Allensworth et al., 2014; Allensworth & Easton, 2005; Balfanz et al., 2007). Some studies have assessed learning trajectories of MS students and found growth inequalities based on race and ethnicity or gender (Downey et al., 2020; Kuhfeld et al., 2019; Reardon et al., 2015), but these studies did not relate these findings to college readiness. Very few studies have studied the connection between MS academic trajectory and college readiness. Lee (2012) conducted an early study on academic trajectories of MS students based on their math test scores in eighth, 10th, and 12th grade and how it relates to two-year college versus four-year university success. Lee (2012) found that it was necessary for a student to meet the math proficiency level in eighth-grade in order to successfully complete a bachelor's degree. Lee (2012) also found that Latinx and Black students were consistently off-track from late elementary to HS levels as compared to their White or Asian peers, similar to the reduced academic mobility of Latinx and Black students found by Quintana and Correnti (2020). Johnson et al. (2021) applied college readiness benchmarks for math and reading, based on six different ACT assessments administered to each student from sixth to eighth-grade, to a single cohort of more than 360,000 students from around 6,000 schools across the United States. In their analysis using hierarchical generalized linear models to convert each student's growth data across tests into a trajectory, it was found that on-track students tended to stay on-track, off-track students tended to stay off-track, and that demographic variables at student and school levels strongly predicted academic trajectories. Black and Latinx students were always off-track in MS relative to White and Asian students. For students who started sixth-grade on track, if a student was male, Black, Hispanic, and/or going to a school with high rates of low-income students, then they were more likely to fall off-track.

Research studies such as these have provided strong evidence for the necessary inclusion of MS variables, but more research is necessary to fully assess their predictive validity when compared to HS variables. The eighth SBAC test is crucial to evaluate because admissions tests such as the SAT are not designed or appropriate for assessment of K-12 and yet have often been used in this way (Atkinson & Geiser, 2009). Furthermore, results of the 11th-grade SBAC are released too late to help struggling students better prepare students for college admission (Gaertner & McClarety, 2015; Gonzalez-Canché, 2019; Mattern et al., 2016). Another hole in the evidence is that few studies have assessed how such MS indicators may also be influenced by nonacademic factors of poverty, race and ethnicity, and school type. Given the well-known confounding effects of these factors for understanding the relations of HS indicators and college readiness, it is equally important to also account for them in the MS context.

College Aspirations

In addition to test scores and academic performance, college aspirations are acknowledged by the NOSCA as one of the critically important components of college readiness that also anchors other components such as academic planning (College Board, 2010). The National Office of School Counselor Advocacy (NOSCA) defines college aspirations in the following way:

> Build a college-going culture based on early college awareness by nurturing in students the confidence to aspire to college and the resilience to overcome challenges along the way. Maintain high expectations by providing adequate supports, building social capital and conveying the conviction that all students can succeed in college (Bryan et al., 2015, p. 2).

College aspirations have been identified in previous research as a useful predictor of college readiness (Conley and French, 2014; Bryan et al., 2015; Perusse et al., 2015). According to Conley and French (2014), "students who did well academically were more likely to aspire to college, and vice versa" (p. 1,024). The rationale is that if a student does not have a college-oriented mindset, then it is unlikely that they will go to college or make preparations for transition into college. In other words, "students must have the desire to enroll in college in order to take rigorous coursework" (Royster et al., 2015, p. 210). College aspiration also aligns with the first (Key 1: "think") and second (Key 2: "know") components of Conley's college readiness framework because having higher education as a goal is likely to motivate students to excel and persevere in their college preparatory classes, building critical thinking and a strong knowledge base (Gaertner & McClarty, 2015; Perusse et al., 2015) and will also enhance students' ownership of their own learning, increasing college readiness (Conley & French, 2014). Furthermore, previous research has indicated that college aspirations have been increasing over recent decades as students are becoming more aware of the need for a college degree to maintain pace with the changing economic environment (Royster et al., 2015).

Some previous research has identified the important link between students' college aspirations and college readiness. In their quantitative study on math and English preparation for college in a Kentucky school district, Royster et al. (2015) did not directly define the concept, but indirectly referred to it as "the desire to enroll in college" (p. 210). Self-report information was taken from the student profile section from the authors' Educational Planning and Assessment System, which included a specific question about post-graduation plans that was coded into a dichotomous variable in the following way: "0 = No college, 1 = College (Not completing HS, HS only, job training via military, apprenticeship, undecided = 0; Career/tech school, community college, four-year university, graduate or professional = 1)". Students who had college aspirations were between 1.04 and 1.68 times more likely than those who did not demonstrate college readiness (as defined by standardized test scores such as the ACT), indicating a relatively small effect. Jacob et al. (2016), in their review of previous studies, suggested that the positive benefits of increasing curricular rigor may be "because requiring a set of college preparatory courses raises students' college aspirations" (p. 7). Perusse et al. (2015) report that aspirations (i.e., "encourage the highest possible career aspirations in students") was the highest-rated item of importance by respondents (76.2%). Cabrera and La Nasa (2001) found that students with college aspirations were 28% more likely to enroll in college.

Compared to other measures of college readiness such as GPA or college enrollment, it seems that relatively less quantitative research has been conducted to assess the relation between college aspirations and college readiness or to assess how college aspirations are impacted by new policies for increasing curricular rigor. This is surprising given that college aspirations have been identified as an important component of college readiness (College Board, 2010; Bryan et al., 2015; Perusse et al., 2015). Therefore, given these large knowledge gaps in the educational research literature, there is a dire need for more quantitative research studies to directly assess how college aspirations relate to college readiness; curricular intensity; and traditional academic indicators such as SAT, GPA, and SBAC tests.

Conclusion

This literature review has highlighted several important problems relevant to the proposed study. First, there is a national crisis of college readiness and equity of access for HS students of color and those in poverty because racial structures of inequality are stubbornly rooted in the American education system and society. Second, this crisis is a significant issue because there are many long-term benefits of obtaining a college degree, including a path out of poverty and increased economic and social mobility for disadvantaged students, and because California is currently facing a shortage of over 1 million college- educated workers by 2030 (California Competes, 2015; Johnson et al., 2015). Third, as colleges strive to increase degree attainment and close persistent gaps between ethnicities and levels of poverty (Finney et al., 2014) they need effective predictors to accurately assess the college readiness of potential students (Barnett & Reddy, 2017).

While some colleges have changed their admissions practices, many have maintained the same admissions practices for over five decades, one mired in a system of meritocracy that is aligned with White privilege (Garcia et al., 2018; Ladson-Billings, 1998; Sablan, 2018). Only recently has the University of California-Board of Regents announced that it will break with tradition by phasing out the SAT requirement by 2025 and exploring, other examination options such as the SBAC test for college admissions (Gordon, 2020; Strauss, 2020; Watanabe, 2021). Finally, there is a substantial knowledge gap in the research literature about the predictive validity of the standardized SBAC examinations for college readiness and success and potential issues of racial inequalities, poverty (Dam, 2019; Kurlaender & Cohen, 2019), and school type (Gonzalez-Canché, 2018; Kurlaender & Cohen, 2019).

Many colleges have been reluctant to abandon traditional indicators such as the SAT and GPA because of their long history of predictive validity (Clinedinst, 2019); however, the limitations of these measures in the contexts of racial, ethnic, and socioeconomic diversity reduces their predictive validity. Studies have shown that HSGPA does not fairly predict the abilities and potential of students of color, and students from low-income families (Allensworth & Clarke, 2020; Betts et al., 2016; Koretz & Langi, 2018; Preston et al., 2017; Zwick, 2013; Zwick & Himelfarb, 2011). Meanwhile, although the SAT is not aligned with the Common Core K-12 content standards, the SBAC examinations are completely aligned. Due to colleges' use of the SAT and its predictive power, and in an effort to reduce the number of tests HS students must take, various districts have attempted appeals to their states to replace the SBAC examination with the SAT (Festerwald, 2018) as the statewide accountability measure. However, a study by Achieve (2018) highlights the lack of alignment of college admissions examinations with the Common Core K-12 standards and warns states and districts against using the SAT or ACT as statewide accountability measures. The new state-based assessments such as the SBAC examination were designed to measure college readiness (Smarter Balanced Assessment

Consortium, 2020b); thus, empirical validation of their effectiveness as compared to traditional indicators is necessary.

The present study expands on previous research by investigating several gaps in the research literature with novel study designs. First, the evidence is either insufficient or mixed regarding the predictive validity of the SBAC examination for college readiness. Research Question 1 is designed to examine to what extent the HS SBAC examination can predict college enrollment and persistence in comparison to HSGPA, the SAT, and curricular intensity while controlling for HS type; and college aspirations; and student demographics of ethnicity, poverty, language classification, and gender.

Another major gap in the literature is that relatively few studies have assessed whether early indicator variables from MS can predict future HS and college success (Casillas et al., 2012; Mattern et al., 2016). This is critically important information, as timely intervention in the progression of underprepared students can reduce the rates of HS and college remediation (Gaertner & McClarty, 2019). The eighth-grade SBAC examination is also crucial since admissions tests such as the SAT or Preliminary SAT are not designed to assess the Common Core content standards even though they have been used in such a way (Atkinson & Geiser, 2009). Additionally, results of the 11th-grade SBAC examination are released too late to identify struggling students and help them better prepare for college admission (Gaertner & McClarty, 2015; Gonzalez-Canché, 2019; Mattern et al., 2016). Therefore, Research Questions 2 and 3 are designed to investigate to what degree the eighth-grade SBAC examination can uniquely predict college readiness as indicated by college entrance and persistence in comparison to MSGPA, while controlling for 11^{th}-grade SBAC scores; HSGPA; SAT; curricular intensity; HS type; college aspirations; and student demographics of ethnicity, poverty, language classification, and gender (RQ 2) and also predict achievement on the 11th-grade SBAC examination in comparison to MSGPA (RQ 3).

In addition, little is known regarding whether the SBAC examinations suffer from the same biases found in the SAT and HSGPA. This is important information as universities consider how to use SBAC test results in admission decisions (Gordon, 2020; Strauss, 2020; Tang, 2018; Watanabe, 2021), especially in the wake of many colleges' discontinuation of SAT use (Strauss, 2019). Research Question 4 is designed to investigate whether the effect of SBAC test scores on college enrollment and persistence vary by or interact with ethnicity, poverty, or school type.

Finally, an important critique is that many previous studies have not been explicitly grounded in any specific theoretical or conceptual frameworks of college readiness, so their assumptions and rationales for choosing variables or interpreting results are often unclear. Avoiding these limitations, the present study is based on Conley's (2014, 2017) theoretical framework of college and career readiness, which outlines the multidimensional nature of college readiness. The study is also grounded in quantitative critical race theory (QuantCrit), which emphasizes the influence of racism on educational opportunities that has led to inequalities in college access for ethnically diverse and socioeconomically disadvantaged students (Garcia et al., 2017; Kohli et al., 2017; Sablan, 2018). Using these two structures, this study will illuminate the relationships between SBAC testing and results and college readiness as evidenced by college admissions and persistence.

Objectives and Hypotheses

The first objective and research question of the proposed study concern the degree to which 11th-grade SBAC examination predicts college readiness, as measured by enrollment and persistence, in comparison to SAT, HSGPA, and curricular intensity while controlling for HS type; college aspirations; and student demographics of ethnicity, poverty, language classification, gender. Given that this SBAC examination was designed to be a better assessment of college readiness than traditional admission tests such as the SAT with more equitable racial and socioeconomic access (CCSSI, 2021; SBAC, 2020c) and has already been shown to uniquely predict some college measures (Dam, 2019; Kurlaender & Cohen, 2019), it is hypothesized that 11th-grade SBAC test results will positively predict both college enrollment and persistence (i.e., higher SBAC test results will be associated with higher enrollment and persistence) over and above the effects of the other independent variables. It is also hypothesized that HSGPA and SAT scores will positively predict college variables, in line with many previous studies (Westrick et al., 2017, 2020; Zwick, 2013). It is hypothesized that the SBAC test effect will be greater than the SAT effect, given that the SBAC test is more optimized for college readiness, but not greater than the HSGPA effect, which is reliably found to be the strongest predictor of college readiness (Allensworth & Clark, 2020; Westrick et al., 2015).

The second objective and research question pertains to the predictive validity of the eighth-grade SBAC examination for college enrollment and persistence in comparison to MSGPA while controlling for 11th-grade SBAC tests; HSGPA; SAT; curricular intensity; HS type; college aspirations; and student demographics of ethnicity, poverty, language classification, gender. Based on prior evidence of the predictive validity of the 11th-grade SBAC examination (Dam, 2019; Kurlaender & Cohen, 2019) and previous studies on the importance of assessing early indicators of college readiness (Dougherty, 2014), it is hypothesized that the eighth-grade SBAC test will also positively predict college enrollment and persistence over and above the other variables.

The third objective and research question related to the predictive validity of eighth-grade SBAC test scores for 11th-grade SBAC test scores in comparison to MSGPA while controlling for HS context; curricular intensity; college aspirations; and student demographics of ethnicity, poverty, language classification, and gender. It is hypothesized that eighth-grade SBAC test scores will positively predict 11th-grade SBAC test scores over and above the other variables given the acknowledged importance of early indicators for subsequent success (Dougherty, 2014) and the assumption that earlier performance on a test should predict later performance on the same test. It is also hypothesized that poverty and ethnicity wll not significantly predict 11th-grade SBAC test scores on the basis that the SBAC examinations were designed to reduce the biases of differences in access to testing explained by race and socioeconomic status (CCSI, 2021). Finally, it is hypothesized that eighth-grade SBAC test scores will predict 11th-grade SBAC test scores more strongly than MSGPA because MSGPA is less specifically related to such scores.

The fourth objective and research question addressed the extent to which the SBAC test suffers from the same biases of poverty, ethnicity, and school type that have been demonstrated for the SAT and GPA (Allensworth & Clark, 2020; Zwick, 2013). These biases are operationally tested in three different ways. The first approach assesses the degree to which poverty, ethnicity, and school type bias (i.e., statistically influence) SBAC scores in comparison to SAT scores or GPA. The second approach assesses the degree to which poverty, ethnicity, and school type bias (i.e., statistically influence) the ability of SBAC scores, in comparison to SAT or GPA, to reliably predict college enrollment or persistence. This can be determined in the analysis according to whether the SBAC scores, in comparison to SAT or GPA, can predict college variables while controlling for poverty, ethnicity, and school type. For the third approach, I will run a separate path analysis model to assess the different levels of each potentially confounding variable of ethnicity, poverty, gender, and language classification. For each of these tests of bias, it is hypothesized that these potentially confounding variables should have minimal influence associated with SBAC and a larger influence associated with SAT and GPA. However, it is acknowledged that such biases in SBAC may be present based on some previous inconclusive evidence (Locke, 2019; Merkel, 2019; Reed et al., 2019; Warren, 2018).

Research Questions

RQ1: To what extent does the 11^{th}-grade SBAC test predict college readiness, as measured by college enrollment and persistence, in comparison to SAT, HSGPA, and curricular intensity while controlling for HS type; and college aspirations; and student demographics of ethnicity, poverty, language classification, and gender?

RQ2: To what extent does the eighth-grade SBAC test predict college readiness, as measured by college enrollment and persistence, in comparison to MSGPA while controlling for 11^{th}-grade SBAC test; HSGPA; SAT; curricular intensity; HS type; college aspirations; and student demographics of ethnicity, poverty, language classification, and gender?

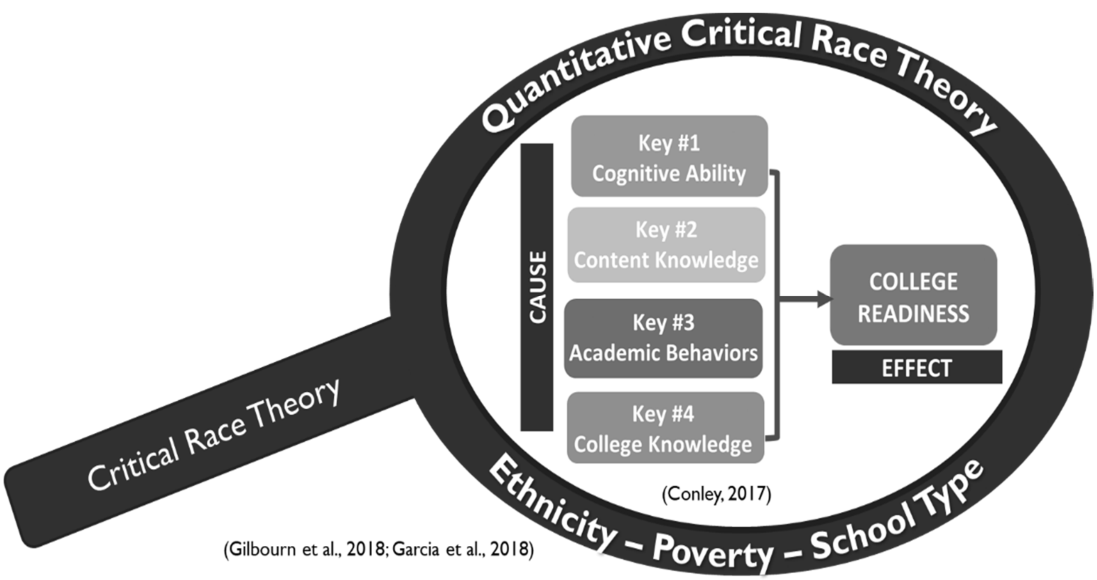
RQ3: To what extent does the eighth-grade SBAC test predict the 11^{th}-grade SBAC test in comparison to MSGPA while controlling for HS type; college aspirations; curricular intensity; and student demographics of ethnicity, poverty, language classification, and gender?

RQ4: To what extent do the eighth or 11^{th}-grade SBAC test scores and their predictive validity for college readiness suffer from the same biases of school type, ethnicity, and poverty that have been shown to bias the SAT and GPA?

Theoretical Frameworks

This study is grounded in two theoretical frameworks relating to higher education. The first framework is Conley's (2014, 2017) "four keys to college and career readiness," which outline the academic and nonacademic factors that influence students' readiness for college and beyond. The second framework is QuantCrit, which outlines how a quantitative research approach that is based on critical race theory (CRT; Ladson-Billings & Tate, 1995; Patton, 2015) can be used to both critique and positively change the racial and social inequalities of higher education (Garcia et al., 2018; Gilbourn et al., 2018). These theoretical frameworks are depicted in Figure 1, and the study variables that are grounded in them are further described below.

Figure 1. ***Grounding Theoretical Frameworks***



Note. Figure 1 illustrates the relationships between the three grounding theoretical frameworks such that the quantitative critical race theory framework, or QuantCrit, which is based on the original critical race theory, or CRT, and used as a lens to investigate and interpret college enrollment and persistence via Conley's "Four Keys to College Readiness" framework and while considering the potentially confounding effects from demographics and school variables.

Conley (2014) defines college readiness as "the content knowledge, strategies, skills, and techniques necessary to be successful in any of a range of postsecondary settings" (p. 15), where success is defined not only by enrollment in college but also by persisting through the second year and up to degree completion. In the "four keys to college and career readiness" framework, Conley (2014, 2017) outlines the multidimensional nature of college readiness depending on the important factors of cognitive ability (Key 1: "think"), content knowledge (Key 2: "know"), academic skills (Key 3: "act"), and college-going mindset and transition (Key 4: "go"). The domain of cognitive ability includes critical analysis of learning materials, problem-solving skills, scientific reasoning, and organization of content and work output. The domain of content knowledge includes all facts and information a student learns in school, particularly in the core subjects of college-preparatory curricula (e.g., math, English, history, arts, science, and foreign language). The domain of academic skills includes the ability to persist and learn efficiently, good study habits and time management skills, and awareness of one's own ability to learn and progress toward set goals. The domain of college mindset and transition involves a student's ambition or aspiration for college, self-advocacy for achieving what they need and desire, and knowledge of how to look for and apply to colleges and find financial aid.

The indicators of college readiness used in college admissions align with the different keys in Conley's framework. The SBAC, SAT, and curricular intensity are grounded in Conley's first two keys, with student performance representing student cognitive ability and content knowledge. The HSGPA is grounded in Conley's first three keys as a multidimensional variable influenced by a student's ability to think and reason, to remember important information, and learn effectively, as well as "a whole series of meta-cognitive learning skills such as time management, study skills, help-seeking strategies, persistence, and goal focus" (Conley, 2014, p. 14). Conley (2014) recommends HSGPA as "the strongest predictor of postsecondary success" (p. 14). HSGPA is included in many other guidelines and definitions of college readiness, and it is also one of the most empirically validated predictors of college readiness (Bryan et al., 2015; College Board, 2010; Hatch, 2013; Nagaoka et al., 2013; Perusse et al., 2015). I chose the dependent variables of college enrollment and persistence to measure HS transition to college. These variables are grounded in Conley's fourth key as an outcome measure of an HS student's mindset and ability to not only go to college but also persist beyond the first year. College enrollment and persistence are also commonly used by empirical studies to estimate predictive validities of HS variables such as GPA, curricular intensity, admission test scores (e.g., ACT and SAT scores), and state-based assessment tests (e.g., SBAC examinations).

QuantCrit (Garcia et al., 2018; Gilbourn et al., 2018) recently emerged as a guiding framework for the use of quantitative research on racial issues in education, a topic traditionally believed to be best studied by qualitative research (Baez, 2007). QuantCrit is anchored in the original CRT that emerged from the historical application of racial concepts for understanding and changing social and educational inequality (Ladson-Billings & Tate, 1995). There are three central propositions of CRT for modern education: 1) race, like gender and class, is a crucial factor of educational inequality; 2) property rights, not human rights, are the foundation of American society and education; and 3) race and property intersect to create social and educational inequality (Ladson-Billings & Tate, 1995; Ladson-Billings, 1998).

CRT explains important aspects of racial differences of curriculum quality and access, academic assessment, and school funding and geographical segregation. CRT can also explain higher education in the United States as a predominant vehicle for racial inequity due to racially biased admissions policies, curricular content, test-taking practices, and teaching practices (Patton, 2015). Castro (2013) argues that any framework or evaluation of college readiness in HS students must include the context of racial inequality given the many racial and ethnic differences observed in the research literature.

Based on CRT, Gilbourn et al. (2018) propose five key principles of QuantCrit for understanding the role of quantitative methodology in research on racial issues of higher education. First, racism is a complex and central aspect of much of society, but it cannot be easily reduced to a variable or simply quantified, and it can often be hidden in statistical analysis. This is an important limitation of the quantitative approach, but it also highlights the necessity of the quantitative researcher to integrate racial issues in the study design and analysis as transparently as possible. Second, quantitative analysis is not objective, but rather necessarily subjective depending on researchers' and funders' interests, personal and systemic biases, and perceptions (particularly those of predominantly White institutions). Therefore, it is crucial for quantitative research to be self-critical with regard to research positionality and institutional context (Garcia et al., 2018; Sablan, 2018). Third, the use of categories or labels such as race and ethnicity in analysis should be critically evaluated in terms of their usefulness versus their tendency to promote further bias. For example, race and ethnicity categories can be necessary to analyze given their predominant use in educational databases, but it is important to acknowledge that these labels do not necessarily define or capture the complexity of students' identities and experiences. Fourth, interpretations of quantitative data are ambiguous and open to multiple perspectives, so it is important to always consider alternative interpretations and implications of findings. Fifth, quantitative research should be used to support social justice and challenge oppressive norms (Garcia et al., 2018).

Grounded in QuantCrit the current study includes two independent variables of race and ethnicity and socioeconomic status, operationalized as "poverty." Their inclusion is relevant given the ongoing racial and socioeconomic differences that persist in course-taking patterns (College Board, 2013), geographical access to and quality of education (Gonzalez Canché, 2019; Tienken et al., 2016), standardized test scores (College Board, 2012; Gonzalez Canché, 2019; Zwick, 2019), HSGPA (Zwick, 2019), state-based assessment tests such as the SBAC examinations (Warren, 2018), predictive validity of college readiness indicators (Klasik & Strayhorn, 2018; Koretz et al., 2016), and college enrollment (Douglass, 2020; Reed et al., 2019) and persistence (DeAngelo & Franke, 2016; Stewart et al., 2015). It is necessary to include these variables in the analyses to control for their confounding effects when evaluating predictive validities of college readiness indicators such as HSGPA and test scores.

It is also important to test whether the effects of such indicators are biased by (i.e., interacts with or vary by) race and ethnicity and/or socioeconomic status in order to evaluate potential racial bias in these measures that can be improved by more progressive educational policies. Directly testing for the effects of race and ethnicity and poverty provides optimal transparency of these important issues in the statistical analysis. It is also necessary to include these variables because although they are widely used categories in educational databases and educational research, it is acknowledged that these categories do not capture the full spectrum of student identity or experience. As emphasized by the QuantCrit framework, labels matter in the sense that they can be as equally useful in addressing bias as they can in perpetuating such bias if not used responsibly (Gilbourn et al., 2018). Finally, QuantCrit is directly relevant in this proposed study as a grounding framework for social justice because the SBAC tests were designed and adopted to improve equity in college access. The use of a quantitative methodology in this study is ideal for testing the validity of the SBAC tests and other quantitative measures for predicting college readiness within the context of racial and socioeconomic biases because it allows testing of a model, generalization of results to the larger population of students, and identification of important variables that can be addressed by policy change (Sablan, 2018).

Summary

This chapter reviewed the previous literature on the topics of the national crisis and focus on college readiness, the complex concept of college readiness, the history and current landscape of college admissions and standardized testing, the theoretical frameworks of Conley's Four Keys to College Readiness as well as QuantCrit and Critical Race Theory, as well as a review of the quantitative research on the most widely used middle school and high school indicators of college readiness and how they are grounded in the theoretical frameworks. The following chapter describes in detail the research design and methods used in the current study.

CHAPTER 3

Research Design and Methods

The purpose of this study was to assess how well college readiness, as measured by college enrollment and persistence, can be predicted by the SBAC test, taken in either eighth-grade (MS SBAC) or 11th-grade (HS SBAC), in comparison to the traditional predictors of SAT, MSGPA or HSGPA, and curricular intensity. The purpose was also to determine how these predictive relations may be confounded by the influences of school type; college aspirations; and student demographics of ethnicity, poverty, language classification, and gender. The first research question was "To what extent does the 11th grade SBAC test predict college readiness, as measured by college enrollment and persistence, in comparison to SAT; HSGPA; and curricular intensity while controlling for HS type; and college aspirations; and student demographics of ethnicity, poverty, language classification, and gender?" The second research question was "To what extent does the eighth-grade SBAC test predict college readiness, as measured by college enrollment and persistence, in comparison to MSGPA while controlling for 11th-grade SBAC test; HSGPA; SAT; curricular intensity; HS type; college aspirations; and student demographics of ethnicity, poverty, language classification, and gender?" The third research question was "To what extent does the eighth-grade SBAC test predict the 11th-grade SBAC test in comparison to MSGPA while controlling for HS type; college aspirations; curricular intensity; and student demographics of ethnicity, poverty, language classification, and gender?" The fourth research question was "To what extent do the eighth or 11th-grade SBAC test scores and their predictive validity for college readiness suffer from the same biases of school type, ethnicity, and poverty that have been shown to bias the SAT and GPA?"

This was a quantitative study with an ex post facto design since the data were numerical variables and were already been collected from school survey records (Vogt, 2005). The key variable of college readiness was represented by an ordinal variable representing college enrollment and persistence with five levels: 1) student did not immediately enroll in college, 2) student immediately enrolled in a two-year college but did not persist, 3) student immediately enrolled in a four-year university but did not persist, 4) student immediately enrolled in a two-year college and persisted, and 5) student immediately enrolled in a 4-year university and persisted. Enrollment and persistence were chosen as the primary college variable because it was grounded in Conley's framework where the definition of college readiness includes the ability to successfully complete college-level courses without remediation and persist to the next level courses (Conley, 2014, 2018).

The other variables consisted of the following: SAT ELA (SAT ELA scores, continuous variable), SAT math (SAT math scores, continuous variable), GPA (MSGPA and HSGPA, continuous on a scale of 0-4), MS SBAC ELA (numerical score, continuous variable), MS SBAC math (numerical score, continuous variable), HS SBAC ELA (numerical score, continuous variable), HS SBAC math (numerical score, continuous variable), ethnicity (coded into separate dichotomous variables of White, Black, Asian, and Latinx, while necessarily excluding the categories of "Mixed". "Native American/Alaskan Native", and "Pacific Islander" due to very small sample sizes), poverty (dichotomous variable: qualifying for free and reduced lunch yes or no), English learner (categorical variable with two levels, limited English proficient (LEP) and English proficient), gender (dichotomous variable: female or male), school type (continuous variable: school size), curricular intensity (an ordinal variable with eight levels: 1) did not complete a-g courses, 2) completed a-g with at least one or more Ds, 3) completed a-g with a C or better, 4) completed advanced math, science or LOTE courses, 5) completed at least one AP course, 6) completed advanced math, science or LOTE course plus one AP course, 7) completed two or more AP courses, 8) completed advanced math, science or LOTE course plus two or more AP courses), and college aspirations (an ordinal variable: students' expectations of highest degree earned: 1) I do not plan to complete HS, 2) complete HS, 3)technical/vocational school certificate, 4) two-year college degree, 5) four-year university degree, 6) graduate degree).

Participants

The study sample consisted of the 2019 cohort of HS graduates (n > 20,000; ages 17-21; demographically heterogeneous) who took both the SBAC examination and the SAT, and whose records were drawn from a large, urban district in California. The school district is the second largest in the nation, spanning over 700 square miles of a major metropolitan city along with all or portions of 26 additional cities and unincorporated areas with a population of approximately 4.8 million people. The district serves approximately 650,000 students in grades pre-kindergarten through high school across more than 1,000 schools.

I selected the Class of 2019 because they participated in the first administration of the SBAC examinations as eighth-graders in the spring of 2015 and were potentially currently enrolled in their second year of college. The population under investigation consists of HS graduates who enrolled in either two-year colleges or four-year universities. The sample excluded students with identified disabilities because of missing data or curricular accommodations.

The total study sample, without removing any subjects with missing data on any variables, consisted of 23,271 students, of which 12,455 students (53.5%) identified as female and 10,816 students (46.5%) identified as male, 1,831 students (8%) identified as Asian, 1,750 students (7.6%) identified as Black, 1,712 students (7.4%) identified as White, 17,712 students (77%) identified as Latinx, 2,168 students (9.3%) were English-learning according to school records of language classification, and 21,116 students (90.7%) were considered in poverty according to enrollment in the free and reduced lunch program. The reduced study sample, after removing all subjects with missing data on at least one or more variables that were needed for the analyses, consisted of approximately 9,670 students. However, the total number depended on the type of analysis and which variables were included. Of these students, 5754 students (59.5%) identified as female and 3,916 students (40.5%) identified as male, 938 students (9.7%) identified as Asian, 522 students (5.4%) identified as Black, 628 students (6.5%) identified as White, 7,581 students (78.4%) identified as Latinx, 368 students (3.8%) were English-learning according to school records of language classification, and 8,809 students (91.1%) were considered in poverty according to enrollment in the free and reduced lunch program. These descriptive statistics show that, although a large percentage of students, approximately 58.5%, in the original study sample were removed due to missing data on one or more IVs, the remaining sample without any missing data appears very similar in terms of demographic variability. This was an encouraging sign that removal of missing data probably did not substantially alter the study sample and therefore the results. Further evidence of similarities between the study samples with and without missing data are provided in the descriptive statistics section of Chapter 4.

Instruments and Protocols

The first instrument is the SBAC test, which measures ELA and math knowledge (see example test items in Appendices A-B) in an adaptive style customized to students' performance

(SBAC, 2016). Scores are continuous but usually categorized using a scale of college readiness: Level 1 (standard not met), Level 2 (standard nearly met), Level 3 (standard met), and Level 4 (standard exceeded). Colleges recognize both Level 3 and 4 as indicating college readiness. SBAC test scores and vertical scaling have strong validity and reliability due to extensive pilot testing, institutional review, and computer simulations (SBAC, 2016). For the purpose of this analysis, SBAC score variables are numerical and continuous. Therefore, there are four SBAC variables in total: MS SBAC ELA (numerical score, continuous), MS SBAC math (numerical score, continuous), HS SBAC ELA (numerical score, continuous), and HS SBAC math (numerical score, continuous).

The second instrument is the SAT, which was redesigned in 2016 to improve evidence of student ability and college readiness and contains sections on evidence-based reading, writing, and math, creating separate English, math, and writing scores each on a 200-800 scale (Westrick et al., 2019). Recent piloting of the revised SAT demonstrated improved content validity, reliability, and predictive validity for college performance and persistence (Westrick et al., 2019). For the purpose of this study, the two variables used are SAT ELA (scores, continuous variable) and SAT math (scores, continuous variable).

The third instrument is GPA which represents student academic performance in either MS or HS. Each final mark earned in each course is awarded points; A equates to 4, B equates to 3, C equates to, 2, D equates to 1, and an F equates to 0. The points are added and then divided by the number of courses and reported as a number between 0 and 4. GPA is continuous and ranges from 0 to 4.0, calculated for each student as their average grade point across all MS courses they completed for MSGPA and across all HS courses they completed for HSGPA.

The fourth instrument, curricular intensity, has been shown to have an important influence on academic performance and college access and outcomes (Allensworth & Clarke, 2020; Barrow et al., 2016; Koretz & Langi, 2018). Curricular intensity reflects the rigor or difficulty of courses taken by students in HS, and can be conceived as both the quantity (e.g., number of courses) and quality (i.e., the difficulty level) of coursework (Austin, 2020). Many previous studies have demonstrated the important influence of curricular intensity on grades and GPA, test performance, and college access and outcomes (Adelman, 2006; Austin, 2020; Byun et al., 2014; Preston et al., 2017). Curricular intensity is an ordinal variable with the following eight ordered levels: 1) did not complete a-g courses, 2) completed a-g with at least one or more Ds, 3) completed a-g with a C or better, 4) completed advanced math, science or LOTE courses, 5) completed at least 1 AP course, 6) completed advanced math, science or LOTE course plus one AP course, 7) completed 2 or more AP courses, 8) completed advanced math, science or LOTE course plus two or more AP courses.

The study adhered to the following protocol. I obtained archival data, already fully de-identified from the school district's student information system following the Institutional Review Board process and approval from the district's Office of Data and Accountability Research and Reporting Branch. I used Microsoft Excel to store the data, merge datasets using the de-identified student ID column to match records by students, recode any variables as necessary, and remove any entries for which some categories of data were missing. I used SPSS Version 26 (IBM Corp., 2019) for statistical exploration and analysis. Extreme outliers were removed in SPSS procedures based on a definition of having a z-score of 3 or greater with respect to the mean of the study sample (Lund & Lund, 2018).

Analysis Overview

First, I created initial descriptive summaries and tables for the sample demographics and all other variables. Next, I tested for demographic group differences I the academic and college variables with ANOVAs and post-hoc tests. Then, I performed a path analysis with college enrollment and persistence, the final endogenous outcome variable. Subsequently, I conducted eight additional path analyses: four separate path analyses for each of the ethnicity categories (Asian, Black, Latinx, and White), two for poverty (qualifies for free and reduced lunch meals yes or no), two for gender (male or female), and one for school type, keeping all other variables in each model. After this, I conducted additional logistic regressions and discriminant function analyses (DFA) to more rigorously check the reliability of the path analysis results and to better understand the observed patterns. In these analyses, the original five-level college variable was separated into several different dichotomous dependent variables measuring enrollment, or persistence, in two-year or four-year schools. Logistic regression and DFA are very similar in that both are used to test which IVs are most related to a nominal DV (i.e., dichotomous DV for logistic regression, dichotomous or multinomial DV for DFA) and both can be used to classify which students belong in which group. However, logistic regression is more often used for estimating ability of IVs to predict the DV, while discriminant functional analyses seem more useful for classifying outcomes based on the IVs. As both of these additional analyses are similar with complementary strengths, I decided to use both for even more rigorous checking of the reliability of results. Finally, I conducted a series of additional regressions to better understand how the predictive validity of SBAC may be influenced by the presence of other independent variables in the same regression models.

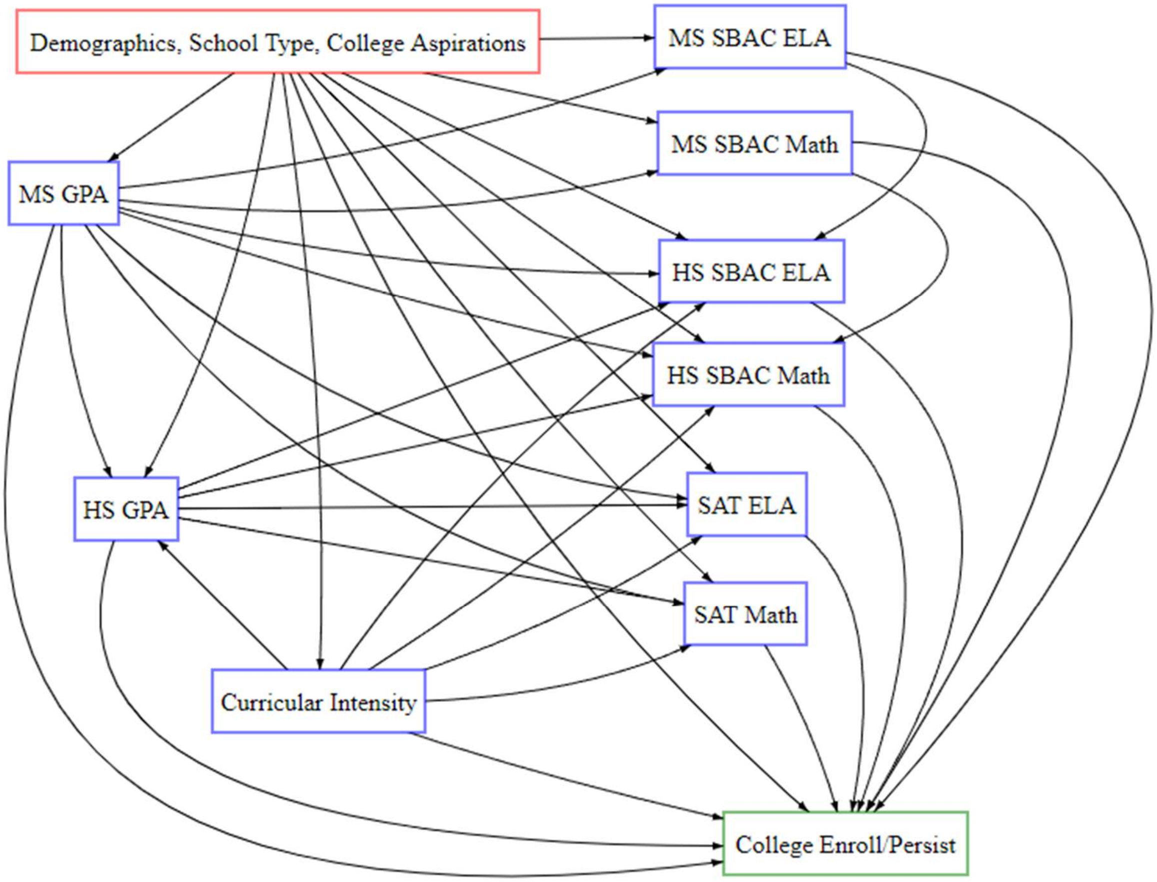
For all regression and ANOVA analyses, I used listwise deletion of missing data instead of pairwise deletion. The reason for this is because there were numerous students who were missing data points on one or more variables, usually the middle school variables (e.g., MS SBAC, MS GPA) and the SAT variables, which were needed for the analyses. Listwise deletion was used to remove these students from the analysis, instead of using pairwise deletion, in order to ensure that every student who has a data point for each IV also has a data point for every other IV and for each DV. This is especially ideal because all IVs were entered simultaneously in the models.

Path Diagrams and Analyses

Figure 2 shows a summary diagram of the "before path diagram" with all endogenous and exogenous variables and hypothesized paths. This is a conceptual model that links together the variables that either directly or indirectly affect college enrollment and persistence. There are six exogenous variables: school type; college aspirations; and the demographics of ethnicity, poverty, language classification, and gender. There are 10 endogenous variables in total: MSGPA, HSGPA, curricular intensity, MS SBAC ELA, MS SBAC math, HS SBAC ELA, HS SBAC math, SAT ELA, SAT math, and college enrollment and persistence. College readiness is measured by the final endogenous outcome variable of college enrollment and persistence.

To simplify the illustration so that all paths can be clearly observed and annotated with values, Figure 2 shows the red box as a set of different exogenous variables – demographics (ethnicity, poverty, language classification, gender), college aspirations, and school type – each of which will be considered as separate exogenous variables with identical (or nearly identical) paths in the diagram. In other words, instead of just one red box (i.e., exogenous variable), there will be six red boxes (i.e., exogenous variables), one for each of the following: college aspirations, school type, ethnicity, poverty, language classification, and gender. The first five red boxes (i.e., exogenous variables) have identical paths, whereas only school type differs by not having paths toward MSGPA, MS SBAC ELA, or MS SBAC math variables, given that school type refers only to HS and so cannot backward influence these MS variables. Appendix E shows different slices of the full path diagram in order to illustrate how these six endogenous variables and their paths will be represented and analyzed. It is important to emphasize that there is only one path model being analyzed; only the illustrations of the path diagrams are simplified in this way.

Figure 2. Main path analysis (before diagram)



Note. The "before path diagram" for the main path analysis. The five-level ordinal variable of college enrollment and persistence is the outcome variable. All variables in blue boxes are the academic measures reflected as endogenous variables. The red box contains all exogenous variables, which are shown for simplicity together in one box although each is included in the path analysis as a separate exogenous variable with the same paths as shown for the single red box above. These exogenous variables are ethnicity (separated into Asian, Black, Latinx, and White variables), poverty, gender, language classification (EL), school size for school type, and college aspirations.

The procedure for conducting path analysis was the following. In Step 1, the "before path diagram" was created as illustrated above. In Step 2, a series of regressions was conducted to estimate the standardized beta coefficients of all paths and the corresponding R^2 values for each endogenous variable. The standardized beta coefficient indicates the direction and relative strength or effect size of the link between two variables, and the R^2 value indicates the total proportion of variance in an exogenous variable that is explained by all variables pointing to it. Table 1 summarizes the dependent variable, independent variables for all 10 standard regressions in the path analysis.

Table 1. ***Main path analysis (description of regressions)***

Regression Model	Dependent Variable	Independent Variables
Regression 1 (standard regression)	DV: College enrollment/persistence (ordinal)	Independent Variables (IV): Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, HS_SBAC_ELA, HS_SBAC_Math, MS_SBAC_ELA, MS_SBAC_Math, SAT_ELA, SAT_Math, HSGPA, MSGPA, CollegeAspiration, CurricularIntensity
Regression 2 (standard regression)	DV: SAT math (continuous)	IV: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, CollegeAspiration, CurricularIntensity, MSGPA, HSGPA
Regression 3 (standard regression)	DV: SAT ELA (continuous)	IV: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, CollegeAspiration, CurricularIntensity, MSGPA, HSGPA
Regression 4 (standard regression)	DV: HS SBAC math (continuous)	IV: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, CollegeAspiration, CurricularIntensity, MSGPA, HSGPA, MS_SBAC_Math
Regression 5 (standard regression)	DV: HS SBAC ELA (continuous)	IV: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, CollegeAspiration, CurricularIntensity, MSGPA, HSGPA, MS_SBAC_ELA
Regression 6 (standard regression)	DV: MS SBAC math (continuous)	IV: Gender, Asian, Black, Latinx, EL, Poverty, CollegeAspiration, MSGPA
Regression 7 (standard regression)	DV: MS SBAC ELA (continuous)	IV: Gender, Asian, Black, Latinx, EL, Poverty, CollegeAspiration, MSGPA
Regression 8 (standard regression)	DV: Curricular intensity (ordinal)	IV: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, CollegeAspiration
Regression 9 (standard regression)	DV: HSGPA (continuous)	IV: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, CollegeAspiration, Curricular Intensity, MSGPA

Regression Model	Dependent Variable	Independent Variables
Regression 10 (standard regression)	DV: MSGPA (continuous)	IV: Gender, Asian, Black, Latinx, EL, Poverty, CollegeAspiration

Note. Table 1 summarizes the dependent variable, independent variables for all 10 regressions in the path analysis.

In Step 3, the final path analysis results were recorded in a large table instead of updating the diagram because the complexity of the model did not enable it to be easily readable. In the table, each IV effect (i.e., path) that was statistically significant (i.e., $p < 0.05$) was displayed as the corresponding path coefficient, also known as the standardized beta coefficient. Each non-significant IV effect was left empty. Therefore, this table summarized the directions and strengths of the relationships between all variables. Finally, in Step 4, a decomposition of bivariate covariation was conducted for every exogenous or endogenous predictor (i.e., all variables except college enrollment and persistence) in order to estimate the original covariation (i.e., correlation) of the predictor with the college variable, the direct influence of the predictor on the college outcome variable (i.e., the coefficient of the direct path from predictor to college variable), the indirect influence of the predictor on the college outcome variable via other predictors (i.e., multiplication of the intermediate paths from original predictor to other predictors to college outcome variable), the total causal influence of the predictor on the college outcome variable (i.e., the sum of the direct and indirect influence), and the non-causal influence of each predictor on the college outcome variable (i.e., the original covariation minus the total causal influence).

The four research questions (RQs) can be answered by different parts of the path regression results and decomposition of bivariate covariation. RQ1 asks, to what extent the 11^{th}-

grade SBAC test predicts college readiness, as measured by college enrollment and persistence, in comparison to SAT, HSGPA, and curricular intensity while controlling for HS type; and college aspirations; and student demographics of ethnicity, poverty, language classification, and gender. This question was answered in two ways. The first was by comparing between the path coefficients from HS SBAC ELA and HS SBAC math to college enrollment and persistence and the path coefficients from SAT ELA, SAT math, HSGPA, and curricular intensity to college enrollment and persistence. The other variables were controlled for by including them as additional IVs in the regression models. The second way was by comparing the total causal statistic between those variables, with the expectation that the HS SBAC variables should have a higher total causal influence than the other variables.

RQ2 asks to what extent eighth- grade SBAC test predicts college readiness, as measured by college enrollment and persistence, in comparison to MSGPA while controlling for 11th-grade SBAC test, HSGPA, SAT, curricular intensity, HS type, college aspirations, and student demographics of ethnicity, poverty, language classification, and gender? This question was answered in two ways. The first was by comparing the path coefficients from MS SBAC ELA and MS SBAC math to college enrollment and persistence and the path coefficient from MSGPA to college enrollment and persistence. The other variables were controlled for by including them as additional IVs in the regression models. The second way was by comparing the total causal statistic between those variables, with the expectation that the MS SBAC variables should have a higher total causal influence than the other variables.

RQ3 asks to what extent the eighth-grade SBAC test predicts the 11th-grade SBAC test in comparison to MSGPA while controlling for HS type; college aspirations; curricular intensity; and student demographics of ethnicity, poverty, language classification, gender? This question was answered by comparing between the path coefficients from MS SBAC ELA and MS SBAC math to HS SBAC ELA and HS SBAC math and the path coefficient from MSGPA to HS SBAC ELA and HS SBAC math. The other variables were controlled for by including them as additional IVs in the regression models.

RQ4 asks to what extent the eighth or 11^{th}-grade SBAC test scores and their predictive validity for college readiness suffer from the same biases of school type, ethnicity, and poverty that have been shown to bias the SAT and GPA. This question was answered in two different ways. The first approach assessed the degree to which poverty, ethnicity, and school type influence SBAC in comparison to their influence on SAT or GPA. The degree of influence was indicated by the path coefficients from poverty, ethnicity, and school type toward SAT math (Regression 2) and SAT ELA (Regression 3), HS SBAC math (Regression 4) and HS SBAC ELA (Regression 5), MS SBAC math (Regression 6) and MS SBAC ELA (Regression 7), and HSGPA (Regression 9) and MSGPA (Regression 10). If SBAC scores are not substantially biased by school type, ethnicity, or poverty, or less biased than SAT and GPA, then the path coefficients toward SBAC scores should be statistically non-significant or smaller than the path coefficients toward SAT and GPA. The second approach assessed the degree to which poverty, ethnicity, and school type influence the ability of SBAC scores, in comparison to SAT or GPA, to reliably predict college enrollment or persistence. This was determined in the final path results according to whether the MS SBAC or HS SBAC scores, in comparison to SAT or MSGPA or HSGPA, predicted college variables while controlling for poverty, ethnicity, and school type. If the path coefficients toward the college variables were not significant, this indicates that they did not predict college over and above the potentially confounding variables. When using the third way, I ran a separate path analysis for each ethnicity, each poverty group, each gender, and each language classification group, but not for school type because it was a continuous variable. The purpose of this third way was to determine whether, for example, the predictability of SBAC for college enrollment and persistence was qualitatively different for any of the ethnicity, poverty, gender, or language groups because I did not compare demographic groups within the path analysis model. It's important to note that any observed differences in academic measures or predictive strengths between groups does not, by itself, necessarily mean that those measures are biased since many academic measures naturally vary across different types of individuals. This is why the potential for bias was tested in this study with the three different approaches described above so that their combined results could be assessed.

Note on Types of Bias

It is important to emphasize that this study investigated two types of demographic and school bias using statistical methods. Both types of bias were addressed in the fourth research question that was previously presented. The first type of bias was bias in the academic measures themselves. As detailed in the literature review earlier, many previous studies used ANOVAs or regression analyses to demonstrate that SAT and GPA scores are often different for demographic groups of students based on ethnicity, poverty, language classification, and gender, or also based on the type of school that students go to. Usually, their results show that SAT and GPA scores are lower for certain ethnicity groups (e.g., Latinx and Black), for students in poverty, non-native or non-fluent speakers of English, or females. Scores are often lower for students who go to smaller schools with less resources, or students who go to schools with other higher-performing students. While findings of student group differences in SAT and GPA scores do not, by themselves, necessarily indicate the presence of bias in these tests or measures, when such group differences are consistently replicated in the research literature with rigorous statistics and without any alternative explanations for why such differences might exist, then the presence of such bias seems more likely and therefore important to investigate further. Given the systemic discrimination and inequity in society, it's also important to consider that if a test shows that two groups differ, it might not mean the test is biased but instead it could be reflecting how society is biased. Therefore, I operationally defined bias of scores according to the presence of significant direct paths from the demographic and school variables to the predictor variables, because that would indicate direct influence and thus group differences in those measures.

The second type of bias was bias in the ability of the academic measures to predict college. Here too, many previous studies, usually based on regression analyses, have shown that such prediction is often unequal across student groups or influenced by demographic variables. For example, SAT may predict first-year college GPA better for non-poverty students or White/Asian students (Rothstein, 2004). This type of prediction bias was tested in two different ways. The first way was whether the academic measures can predict college while controlling for the demographic or school variables in the same regression model. If they cannot, then it provides some evidence that predictive bias may exist. However, it's not conclusive evidence, because the lack of prediction from SBAC, for example, might be due to the presence of other academic IVs instead of the demographic IVs. The second way was whether the academic prediction was different for different demographic subgroups. For example, if SAT predicts college well for White students but not Black students, then one can say that SAT predictive validity interacts with, or depends on, ethnicity. However, because including interaction effects in the path analysis would have made the model far too complex, I chose an alternative strategy of repeating the path analysis model for the different demographic subgroups. Note, this is conceptually similar to testing for interaction effects, because if the direct path from SAT to college DV is significant for the White subgroup but not significant for the Black subgroup, then this finding would be consistent with the presence of an interaction. However, it’s important to note that, using this alternative method, any predictive differences between subgroups are qualitative and not quantitative because the subgroup differences are not statistically tested for significance, which would require a statistical test of interaction effect.

Because demographic and school biases were investigated in this study with statistical methods, it’s also important that there was none or minimal statistical bias affecting the results. For example, the very large sample size of the current study increased the potential for one type of statistical bias known as Type I error or false positive, because large sample sizes create high degrees of freedom which can artificially decrease the estimated p values used for determining statistical significance (Lund & Lund, 2018). This statistical bias was avoided as much as possible by also considering the effect sizes, such as the standardized beta coefficients, when interpreting the regression results. Statistical bias could also occur from violation of statistical assumptions, so it was important to carefully check and correct any such violations. There was also a risk of statistical bias in this study because of some unbalanced frequencies across categorical groups. For example, the vast majority of the study sample identified as Latinx as compared to the other ethnicities. Such unbalanced group sizes can bias the estimates and significance of differences between groups (Lund & Lund, 2018). This was discussed in Chapter 5 as one potential limitation of the study results.

Finally, it’s important to distinguish the two types of bias investigated in this study – bias on scores and bias on prediction – from measurement bias, which is another major type of bias that can influence tests like the SAT or SBAC. For example, measurement bias can refer to how well test items measure the concept, construct, or skill of interest or how well the test uses culturally or racially appropriate language, materials, or procedures. Although the issue of measurement bias was outside the scope of the present study, the subsections on SBAC and SAT test designs in Chapter 2 reported on previous literature about how the tests were designed and standardized to minimize the presence of measurement bias and problems with test validity and reliability as much as possible. However, even if a test has demonstrated minimal measurement bias for demographic issues, it's still possible for the test scores to be demographically biased (i.e., bias on scores) and still possible for the ability of those tests scores to predict college readiness to be demographically biased (i.e., bias on prediction or predictive validity). Given previous studies have demonstrated both of these types of bias for SAT and GPA, it was important to investigate these biases in SBAC as well.

Pilot Study Results and Implications for the Dissertation

Using the same research objectives, RQ, and hypotheses, I conducted an initial pilot study on a small subset of four randomly selected HSs within the school district to determine the feasibility of the proposed study. For the first objective and question, the pilot study results show that 11th-grade SBAC math test results positively predicted college enrollment over and above the effects of HSGPA and White ethnicity. However, no SBAC test results predicted college persistence, which was instead predicted by HSGPA, SAT math scores, and poverty. For the second objective and question, the pilot study results similarly indicate that eighth-grade SBAC math test results positively predicted college enrollment (over and above the effects of MSGPA, White ethnicity, and poverty) but not persistence, which was instead only predicted by MSGPA. For the third objective and question, test results for eighth-grade SBAC ELA predicted 11th-grade SBAC ELA test results, and for eighth-grade SBAC math test results predicted 11th-grade SBAC math test results. These effects in both models were over and above the significant effects of MSGPA and Black ethnicity. Finally, pilot study results for the fourth objective and question indicate mixed evidence of presence and absence of interactions between the potentially confounding variables of school type, ethnicity, and poverty with the primary variables of SBAC scores, SAT scores, and GPA.

These pilot study results demonstrate the feasibility of addressing the proposed objectives and RQ with the available data and with multiple logistic regressions for the analysis. However, a limitation of the pilot analysis was that the smaller sample size created some imbalances in subgroup samples of the categorical independent variables, so it will be necessary to conduct the analysis on the entire school district to eliminate or reduce this limitation. However, if the limitation still remains, it will be necessary to account for it in the design or analysis (e.g., by removing any variables with an extreme imbalance in subgroup sample sizes) so that the results are not biased by this limitation. The pilot analysis also indicates that the hypothesized results are mostly on-track for that subset of the school district, so it will be important to see if similar results hold in the full sample.

Finally, although regression analysis is appropriate for this type of study and consistent with previous quantitative literature on this topic, because of the multidimensional nature of college readiness and the complex interrelations between numerous academic (SBAC scores, SAT scores, GPA) and nonacademic factors (poverty, ethnicity, school type), the prediction of college enrollment and persistence could be improved by using the more statistically rigorous technique of path analysis to estimate and separate hypothesized direct and indirect effects between academic and nonacademic factors and college outcomes. Path analysis can test these complex relations between predictor variables and potentially confounding variables while also determining which of these variables are the most predictive of college readiness.

Protection of Human Subjects

All study procedures adhered to two IRB processes: the university's IRB process and the school district's internal IRB process. All student data was de-identified prior to being sent to the researcher, so that all subjects were protected by anonymity without the researcher having any access to their identifying information. In this way, the data were truly anonymous and linked to students and corresponding schools with the unique non-identifying ID number. If this dataset were not anonymized, it would be crucial to remove all potential identifiers to ensure complete confidentiality and the inability to link measures such as test scores or college enrollment to any specific students. Additionally, because this study analyzed archival data, study participants did not receive any benefits or compensation, but future students in these schools and districts may benefit from any administrative or policy changes that could result from the findings.

Researcher Positionality

As a district administrator, my researcher positionality is that all students should graduate college and career ready with access to postsecondary opportunities. As a social change agent and educational leader, I am passionate about closing opportunity and achievement gaps. One of the keys to successfully closing such gaps is finding accurate predictors of college success early enough to provide intervention and support for students to remedy any discrepancies. In my pursuit of educational equity, I must address the inequities in educational policy and practice and advocate for increased resources and opportunities that enable students to overcome barriers. This will generate equality in educational outcomes and begin to dismantle systemic inequalities within the educational system. While everyone has blind spots that may potentially influence or bias their perception, whether consciously or unconsciously, these do not influence this study's data collection since the data used is pre-existing archival data. In addition, I reduced any potential bias by adhering to rigorous analysis methods, such as carefully evaluating all model fit and effect size measures.

Key Terms

Bias: Influence from demographic or school variables on a specific variable of interest (e.g., SBAC scores), which can be called bias of the scores, or the influence on the relationship of that variable (i.e., SBAC) to another variable of interest (e.g., college enrollment), which can be called prediction bias or bias of the predictive validity.

Class of 2019: The group of students who graduated high school from one large urban district on-time (i.e., within four years), and who earned a district high school diploma.

College aspirations: A student's expectation for the highest level of education that they plan to complete, as self-reported in a survey.

College readiness: Demonstration of student academic and nonacademic knowledge and skills to successfully enroll in and complete college-level, credit-bearing courses and persist into their second year of college.

Curricular intensity: The quantity and quality of HS courses taken, which is summarized here with a composite index created from four variables: highest math course completed, number of course units in English, number of course units in core sciences, and whether an AP course was taken.

Grade point average (GPA): An indication of student academic performance in either MS or HS. Each final mark earned in each course is awarded points; A equates to 4, B equates to 3, C equates to, 2, D equates to 1, and an F equates to 0. The points are added and then divided by the number of courses and reported as a number between 0 and 4.

Scholastic Aptitude Test (SAT): A standardized assessment that is used for four-year university admissions and is designed to evaluate student math and English knowledge and skills needed for college.

School type: School type was defined with a single continuous variable called "School Size" which measured the number of enrolled students in each high school.

Smarter Balanced Assessment Consortium (SBAC): A standardized test consortium that developed tests aligned with the Common Core Standards to specifically assess college readiness.

CHAPTER 4

Results

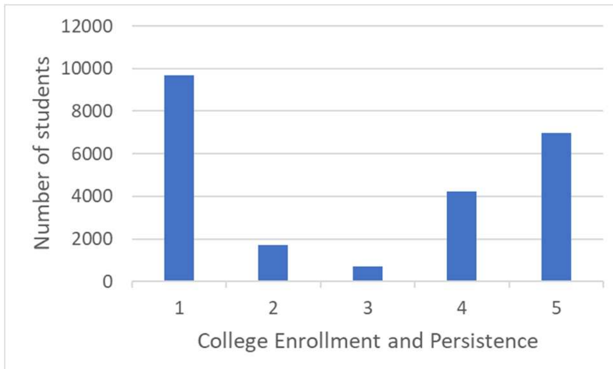
In this chapter, the results from several different statistical analyses are reported. At first, demographic differences between students subgroups were analyzed with ANOVAs and post hoc pairwise t-tests. Next, in order to address all four research questions, a large path analysis was conducted with the five-level variable of college enrollment and persistence as the primary outcome variable with hypothesized paths from the different demographic, school, and academic measures as endogenous or exogenous variables. In addition, to test the fourth research question about differences of effects across demographics, the path analysis model was repeated for each of the student subgroups of the demographic variables: four analyses for ethnicity (Asian, Black, Latinx, White), two analyses for gender (males, females), two analyses for poverty (students in poverty, students not in poverty), and two analyses for language classification (English-learning students, native English-speaking students). Finally, additional analyses of logistic regressions and discriminant function analyses were further performed. The original five-level outcome variable of college enrollment and persistence was separated into different dichotomous dependent variables measuring enrollment, or persistence, in two-year or four-year schools. In the discriminant function analyses, it was selected to predict group sizes according to prior probabilities. The purpose of this analysis was to better understand the complex patterns and dynamics seen in the results for the path analyses. Both logistic regression and DFA are useful for testing relations between IVs and a nominal DV and for classifying students in different DV groups or categories. Logistic regression seems more often used for estimating predictive effects whereas DFA seems more often used for estimating classification. Because these analyses are similar with complementary strengths, I decided to use both as additional confirmation of the results from the path analysis. Finally, additional standard regressions were conducted, using the original five-level college DV, to determine which variables were likely contributing to the lack of SBAC prediction.

Descriptive Statistics

The study sample consisted of a total of 23,271 students, of which 12,455 students (53.5%) identified as female and 10,816 students (46.5%) identified as male, 1,831 students (8%) identified as Asian, 1,750 students (7.6%) identified as Black, 1,712 students (7.4%) identified as White, 17,712 students (77%) identified as Latinx, 2,168 students (9.3%) were English-learning according to school records of language classification, and 21,116 students (90.7%) were considered in poverty according to enrollment in the free and reduced lunch program.

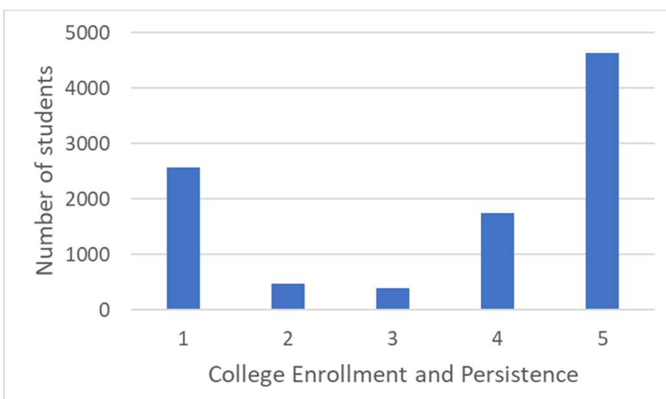
The primary variable for college readiness is college enrollment and persistence (i.e., "CollegeReady") with five levels or student subgroups: 1) student did not immediately enroll in college, 2) student immediately enrolled in a two-year college but did not persist, 3) student immediately enrolled in a four-year university but did not persist, 4) student immediately enrolled in a two-year college and persisted, and 5) student immediately enrolled in a four-year university and persisted. Figure 3 below shows the distribution of frequencies of students in these five groups, including all students in the sample size regardless of any missing data. In this overall study sample, 9,670 students did not immediately enroll in college, 1,696 enrolled in two-year college but did not persist, 708 enrolled in a four-year university but did not persist, 4,225 enrolled in a two-year college and persisted, and 6,972 enrolled in a four-year university and persisted. Figure 4 below shows the distribution of frequencies of students in these five groups, including only students with no missing data in any variables used in the main path analysis. In this study sample without missing data, 2,572 students did not immediately enroll in college, 474 enrolled in two-year college but did not persist, 394 enrolled in a four-year university but did not persist, 1,745 enrolled in a two-year college and persisted, and 4,638 enrolled in a four-year university and persisted.

Figure 3. ***Sample sizes of college enrollment and persistence groups (with missing data)***



Note. Figure 3 shows the distribution of student frequencies in each of the five student groups of college enrollment and persistence: 1) student did not immediately enroll in college, 2) student immediately enrolled in a two-year college but did not persist, 3) student immediately enrolled in a four-year university but did not persist, 4) student immediately enrolled in a two-year college and persisted, and 5) student immediately enrolled in a four-year university and persisted. These frequencies are based on the total sample size of all students regardless of any missing data (n = 23,271).

Figure 4. ***Sample sizes of college enrollment and persistence groups (no missing data)***



Note. Figure 4 shows the distribution of student frequencies in each of the five student groups of college enrollment and persistence: 1) student did not immediately enroll in college, 2) student immediately enrolled in a two-year college but did not persist, 3) student immediately enrolled in a four-year university but did not persist, 4) student immediately enrolled in a two-year college and persisted, and 5) student immediately enrolled in a four-year university and persisted. These *frequencies are based on the sample size of only those students without any missing data on variables used in the path analysis (n = 9,823).*

Table 2. ***Descriptive statistics of academic measures***

Descriptives

		N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
						Lower Bound	Upper Bound		
HS_SBAC_ELA	1	8622	2570.21	101.182	1.090	2568.08	2572.35	2299	2795
	2	1493	2558.26	92.417	2.392	2553.57	2562.96	2299	2795
	3	666	2621.58	85.834	3.326	2615.05	2628.11	2299	2795
	4	3921	2603.41	91.715	1.465	2600.54	2606.28	2299	2795
	5	6837	2663.27	83.179	1.006	2661.30	2665.24	2305	2795
	Total	21539	2606.55	101.804	.694	2605.19	2607.91	2299	2795
HS_SBAC_Math	1	8615	2528.65	103.517	1.115	2526.46	2530.83	2280	2862
	2	1484	2513.05	89.961	2.335	2508.47	2517.63	2280	2845
	3	663	2581.98	98.843	3.839	2574.45	2589.52	2280	2862
	4	3929	2555.49	97.653	1.558	2552.43	2558.54	2280	2862
	5	6829	2632.33	100.829	1.220	2629.94	2634.72	2280	2862
	Total	21520	2567.02	110.858	.756	2565.53	2568.50	2280	2862
MS_SBAC_ELA	1	7638	2523.20	79.101	.905	2521.43	2524.98	2288	2769
	2	1366	2513.53	73.505	1.989	2509.63	2517.43	2288	2752
	3	563	2550.53	75.735	3.192	2544.27	2556.80	2300	2769
	4	3490	2544.53	75.117	1.272	2542.04	2547.03	2288	2769
	5	5815	2589.71	76.968	1.009	2587.73	2591.68	2288	2769
	Total	18872	2547.75	82.677	.602	2546.57	2548.93	2288	2769
MS_SBAC_Math	1	7641	2500.16	93.868	1.074	2498.05	2502.26	2265	2802
	2	1360	2488.87	83.740	2.271	2484.42	2493.32	2265	2764
	3	553	2543.11	89.197	3.793	2535.66	2550.56	2265	2802
	4	3469	2523.44	91.124	1.547	2520.40	2526.47	2265	2802
	5	5801	2584.46	96.151	1.262	2581.98	2586.93	2265	2802
	Total	18824	2530.87	100.521	.733	2529.44	2532.31	2265	2802
SAT_ELA	1	3445	469.59	79.534	1.355	466.93	472.25	260	780
	2	622	445.24	70.479	2.826	439.69	450.79	200	770
	3	539	476.83	74.130	3.193	470.56	483.10	320	760
	4	2222	480.95	76.484	1.623	477.77	484.14	280	750
	5	5664	524.79	84.392	1.121	522.59	526.99	290	800
	Total	12492	495.74	85.143	.762	494.25	497.23	200	800
SAT_Math	1	3445	455.65	83.850	1.429	452.85	458.45	200	800
	2	622	429.36	69.330	2.780	423.90	434.82	280	770
	3	539	471.17	81.114	3.494	464.31	478.03	290	770
	4	2222	466.03	79.473	1.686	462.72	469.34	270	790
	5	5664	517.63	93.513	1.243	515.19	520.06	270	800
	Total	12492	484.96	92.169	.825	483.34	486.57	200	800
HSGPA	1	9669	2.65019	.706840	.007188	2.63610	2.66428	1.000	4.608
	2	1696	2.47969	.581845	.014128	2.45198	2.50740	1.016	4.396
	3	708	3.22869	.485460	.018245	3.19287	3.26451	1.500	4.491
	4	4223	2.90378	.658680	.010136	2.88390	2.92365	1.118	4.478
	5	6972	3.62200	.487153	.005834	3.61057	3.63344	1.677	4.742
	Total	23268	2.99258	.760916	.004988	2.98280	3.00236	1.000	4.742
MSGPA	1	7849	2.75980	.774663	.008744	2.74266	2.77694	.000	4.550
	2	1397	2.63096	.675901	.018084	2.59548	2.66643	.000	4.497
	3	574	3.11969	.712958	.029758	3.06124	3.17814	.000	4.500
	4	3541	2.98598	.725494	.012192	2.96207	3.00988	.000	4.525
	5	5891	3.54575	.672620	.008763	3.52857	3.56293	.000	4.578
	Total	19252	3.04328	.807000	.005816	3.03188	3.05468	.000	4.578

Note. Descriptive statistics are displayed for student scores on all measures of academic performance for each of the five student subgroups of college enrollment and persistence: 1) student did not immediately enroll in college, 2) student immediately enrolled in a two-year college but did not persist, 3) student immediately enrolled in a four-year university but did not persist, 4) student immediately enrolled in a two-year college and persisted, and 5) student immediately enrolled in a four-year university and persisted.

An initial 5 x 1 analysis of variance (ANOVA), with listwise deletion of missing data, with college enrollment and persistence as a five-level IV was performed for each of the academic performance measures of interest: HSGPA, MSGPA, SAT_Math, SAT_ELA, MS_SBAC_ELA, MS_SBAC_Math, HS_SBAC_ELA, HS_SBAC_Math. The descriptive statistics of these eight DVs for each level of the IV are shown in Table 2 above.

All statistical assumptions of ANOVA were checked. The only violation was the assumption of homogeneity of variance in each ANOVA, so therefore the Welch test was used to test for overall difference between means, as recommended when homogeneity is violated (Lund & Lund, 2018). The Welch test was significant for each ANOVA, all $p < 0.0001$ as shown in Table 4.

Table 3. ***ANOVA significant tests***

Robust Tests of Equality of Means

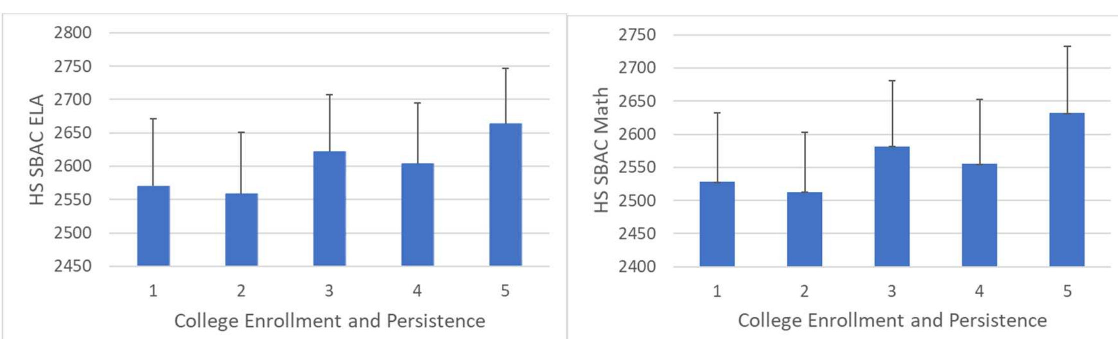
		Statistic[a]	df1	df2	Sig.
HS_SBAC_ELA	Welch	1152.317	4	3540.510	.000
HS_SBAC_Math	Welch	1162.499	4	3539.865	.000
MS_SBAC_ELA	Welch	691.154	4	3066.673	.000
MS_SBAC_Math	Welch	747.044	4	3040.525	.000
SAT_ELA	Welch	366.806	4	2229.224	.000
SAT_Math	Welch	403.282	4	2249.277	.000
HSGPA	Welch	3551.372	4	3877.640	.000
MSGPA	Welch	1210.040	4	3128.713	.000

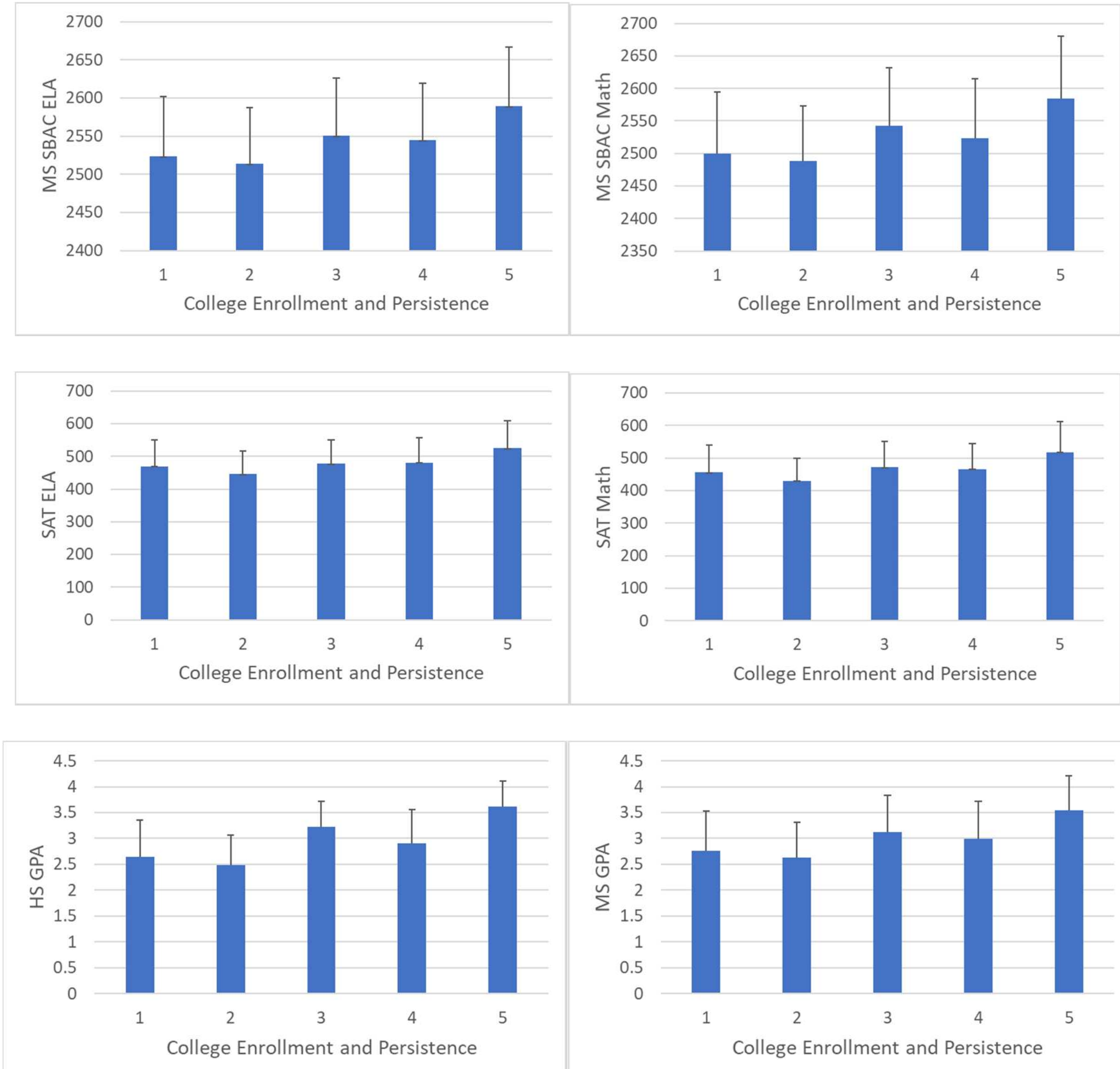
a. Asymptotically F distributed.

Note. Table 3 shows the results of the significance tests of the ANOVA for each academic variable as the DV.

Post hoc comparisons were conducted using the Games-Howell test for when homogeneity is violated (Lund & Lund, 2018). Almost all post hoc tests were significant ($p < 0.0001$ in most cases), and only a few were not significant ($p > 0.05$). The plots of means are displayed below in Figure 5. The general pattern of results for each DV is approximately the same: as the level of college enrollment and persistence increases, the measure of academic performance tends to increase as well. This indicates that, on average, students who successfully enrolled and persisted in college are more likely to have higher scores on SBAC tests, SAT tests, and MS and HS GPA. However, the first two levels of college enrollment and persistence reveal an exception to this pattern, because students who did not immediately enroll in any college (i.e., first level) have higher scores than students who immediately enrolled in a two-year college but did not persist (i.e., second level), which was statistically significant ($p < .0001$) for every measure. Similarly, students who enrolled but did not persist in a four-year college (i.e., third level) showed higher scores than students who enrolled and persisted in a two-year college (i.e., fourth level), which was statistically significant ($p < .0001$) for every measure except SAT_Math ($p = .676$), SAT_ELA ($p = .779$), and MS_SBAC_ELA ($p = .406$).

Figure 5. ***Means of academic measures for college enrollment and persistence groups***





Note. Figure 5 displays students' mean scores for the academic performance variables for each student subgroup of college enrollment and persistence: 1) student did not immediately enroll in college, 2) student immediately enrolled in a two-year college but did not persist, 3) student immediately enrolled in a four-year university but did not persist, 4) student immediately enrolled in a two-year college and persisted, and 5) student immediately enrolled in a four-year university and persisted.

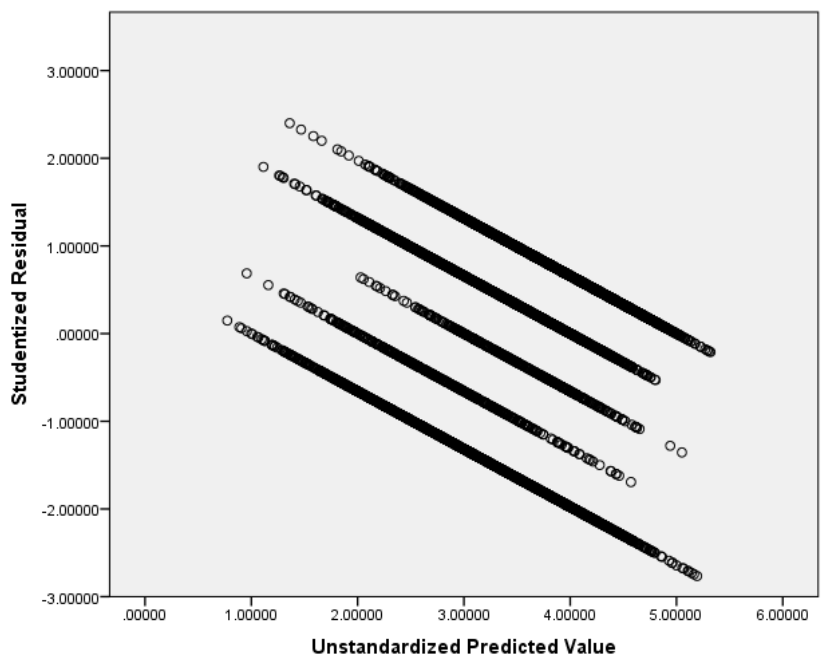
Some additional descriptive statistics and logistic regressions were conducted to take a closer look at the demographic identity of students who did not enroll or who did not persist in either two-year colleges or four-year universities. Of the students who did not enroll, 52% were female, 6.1% were Asian, 7.3% were Black, 6% were White, 80.6% were Latinx, 14.1% were

English learners, and 93% were in poverty. Of the students who enrolled in either two-year colleges or four-year universities, 42.5% were female, 9.3% were Asian, 7.8% were Black, 8.5% were White, 74.4% were Latinx, 5.9% were English learners, and 89.1% were in poverty. A logistic regression was conducted with college enrollment in either two-year colleges or four-year universities as the dichotomous DV and with gender, Asian, Black, Latinx, language classification (EL), and poverty as the IVs. The results are shown in Supplementary Table 9 of Appendix E. There was a significant effect of gender (B = -.39, $p < .0001$) such that males were less likely to enroll in college. There was a significant effect of language classification (B = -.93, $p < .0001$) such that English learners were less likely to enroll in college. There was a significant effect of poverty (B = -.33, $p < .0001$) such that students in poverty were less likely to enroll in college. There was a marginally significant effect of Asian (B = .13, $p = 0.070$) such that, relative to White students, Asian students were more likely to enroll in college. There was a significant effect of Black (B = -.31, $p < .0001$) such that, relative to White students, Black students were less likely to enroll in college. There was a significant effect of Latinx (B = -.34, $p < .0001$) such that, relative to White students, Latinx students were less likely to enroll in college.

Of the students who did not persist in any college, 55.3% were female, 4.3% were Asian, 9.4% were Black, 4.1% were White, 82.2% were Latinx, 7.7% were English learners, and 93.6% were in poverty. Of the students who persisted in either two-year colleges or four-year universities, 39.8% were female, 10.3% were Asian, 7.5% were Black, 9.4% were White, 72.7% were Latinx, 5.6% were English learners, and 88.1% were in poverty. A logistic regression was conducted with college persistence in either two-year colleges or four-year universities as the dichotomous DV and with gender, Asian, Black, Latinx, language classification (EL), and poverty as the IVs. The results are shown in Supplementary Table 10 of Appendix E. There was a significant effect of gender (B = -.68, $p < .0001$) such that males were less likely to persist in college. There was a significant effect of language classification (B = -.38, $p < .0001$) such that English learners were less likely to persist in college. There was a significant effect of poverty (B = -.40, $p < .0001$) such that students in poverty were less likely to persist in college. There was no significant effect of Asian (B = .12, $p = .422$) indicating that, relative to White students, Asian students were equally likely to persist in college. There was a significant effect of Black (B = -1.06, $p < .0001$) such that, relative to White students, Black students were less likely to persist in college. There was a significant effect of Latinx (B = -.88, $p < .0001$) such that, relative to White students, Latinx students were less likely to persist in college. The overall pattern of these results indicates that the students who did not enroll or persist in college were more likely to be male, Black, Latinx, English learner, or in poverty.

To address the three different research questions, path analyses were conducted with a separate multiple regression for each endogenous variable in each path diagram. All assumptions of multiple regression were rigorously checked. The first two assumptions were met because all dependent variables were continuous or ordinal with numerous levels and so treated as continuous, and all independent variables were continuous, nominal, or ordinal. For the ordinal variables, they were treated as continuous to satisfy SPSS requirements for multiple regression (Lund & Lund, 2018). The assumptions of independent observations, linear relations between IVs and DV (i.e., no nonlinear relations), and no high multicollinearity were all met. For some of the regressions, there were many outliers (based on Z score > 3) but these outliers resulted from the model not fitting these individual data points well and so the decision was made to not exclude them. The assumption of normally distributed residuals was violated for some of the regressions but the large sample size of this study should be robust to this violation (Lund & Lund, 2018). The assumption of homoscedasticity of residuals was also violated for some regressions. Figure 6 below shows an example for the first regression. Homoscedasticity is violated because the residuals are linearly related to the predicted values, or in other words, the variance of the residuals are not the same for all predicted values. However, alternative WLS regressions, which are designed to be robust to heteroscedasticity of residuals (Lund & Lund, 2018), showed very similar results and so the decision was made to retain the standard (OLS) regression results.

Figure 6. ***Example of violation of homoscedasticity***

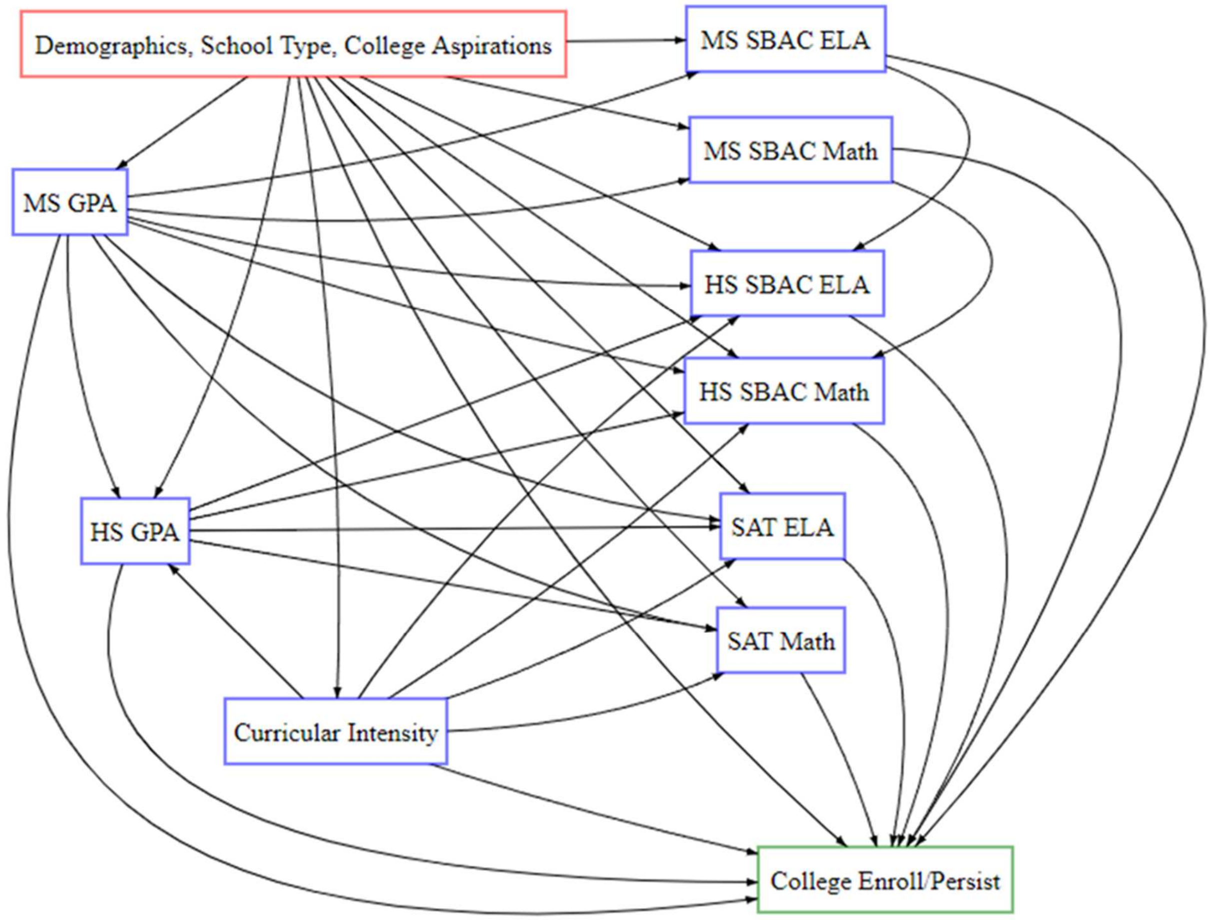


Note. Figure 6 shows an example of heteroscedasticity, or in other words a violation of homoscedasticity, in the residuals for the first regression of the path analysis.

Research Question 1 (RQ1)

The first research question asks, to what extent does the 11th-grade SBAC test (HS SBAC ELA, and HS SBAC Math) predict college readiness, as measured by college enrollment and persistence, in comparison to SAT (SAT ELA, and SAT Math), HSGPA, and curricular intensity while controlling for gender, ethnicity, poverty, language classification (EL), HS type, college aspirations, MS GPA, and 8th-grade SBAC test (MS SBAC ELA, and MS SBAC Math)? An initial path analysis was conducted to address this question, as shown again in Figure 7 below. The first way to answer RQ1 is by comparing between the path coefficients from HS SBAC ELA and HS SBAC math to college enrollment and persistence and the path coefficients from SAT ELA, SAT math, HSGPA, and curricular intensity to college enrollment and persistence. Table 4 shows the path coefficients, or in other words the standardized beta coefficients, for each regression in the path analysis. The first regression relates to RQ1. The overall model fit was significant, $F(17, 9722) = 136.82$, accounting for approximately 19% of the variance in college enrollment and persistence. The HS SBAC variables did not significantly predict the college variable, in contrast to HS GPA, SAT Math and ELA, and curricular intensity which all positively predicted college (i.e., as those scores increased, so did college enrollment and persistence). There were additional significant effects from college aspirations, gender, and ethnicity, as well as a puzzling negative prediction from MS SBAC ELA (i.e., as scores increased, enrollment and persistence decreased). It's also interesting to note that the results from MS SBAC and MS GPA are quite different, indicating that these variables are indeed measuring different aspects of academic preparation in middle school.

Figure 7. ***Main path analysis before diagram (duplicate)***



Note. The "before path diagram" for the main path analysis. The five-level ordinal variable of college enrollment and persistence is the outcome variable. All variables in blue boxes are the academic measures reflected as endogenous variables. The red box contains all exogenous variables, which are shown for simplicity together in one box although each is included in the path analysis as a separate exogenous variable with the same paths as shown for the single red box above. These exogenous variables are ethnicity (separated into Asian, Black, Latinx, and White variables), poverty, gender, language classification (EL), school size for school type, and college aspirations.

Table 4. ***Main path analysis (regression results)***

	Path Analysis Regressions (Full Model)									
	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender	-0.046	0.22	0.099	0.095	0.028	0.113	-0.012	-0.101	-0.035	-0.157
Asian	-0.047	0.043	-0.028	0.023	0.018	0.039		0.074		0.03
Black	0.037	-0.073	-0.084	-0.033	-0.044	-0.097	-0.083	-0.12	-0.065	-0.15
Latinx		-0.173	-0.21			-0.105	-0.102	-0.066	-0.085	-0.204
EL		-0.077	-0.13		-0.051	-0.177	-0.23	-0.159		-0.149
Poverty		-0.073	-0.102	-0.015		-0.049	-0.07	-0.065	-0.019	-0.101
College Aspirations	0.139	0.035	0.038	0.032	0.056	0.059	0.065	0.253	0.096	0.201
School Size					0.01			-0.142	0.024	
Curricular Intensity	0.08	0.131	0.156	0.105	0.142				0.36	
MS GPA		0.189	0.181		-0.03	0.557	0.502		0.472	
HS GPA	0.299	0.328	0.259	0.254	0.219					
MS SBAC ELA	-0.069				0.502					
MS SBAC Math				0.552						
HS SBAC ELA										
HS SBAC Math										
SAT ELA	0.059									
SAT Math	0.059									
Model R^2	0.19	0.48	0.41	0.67	0.58	0.46	0.43	0.17	0.65	0.18

Note. Table 4 summarizes the main results of all regressions, numbered #1-#10, for the path analysis. All IVs used throughout the whole path analysis are shown in the first column "IV". The DV for each regression is shown, for example, "College Enroll/Persist" is the DV for regression #1. Any IV that was not originally included in each regression model is grayed out to indicate that the path between that IV and that DV was not hypothesized in the "before path diagram". For example, in regression #2, MS SBAC Math was hypothesized to not influence SAT Math, and so no path between these variables was defined. The cell values represent the path coefficients, which are the standardized beta coefficients from the corresponding regression model. If the beta is present in this table, this indicates a significant effect between IV and DV. Non-significant effects have cells that are left blank. The bottom row shows the R^2 values for each regression, which represents the percentage of variance in the DV explained by all relevant IVs. For example, in regression #1, the IVs explain about 19% of variance in college enrollment and persistence.

The second way to answer RQ1 is by comparing the total causal statistic from the bivariate decomposition of the path analysis results, with the expectation that the HS SBAC variables should have a higher total causal influence than SAT variables, HSGPA, and curricular intensity. Table 5 shows the bivariate decomposition results. The variables are listed in order from highest total causal effect to lowest. The highest variable was HS GPA (0.33), followed by curricular intensity (0.20), college aspirations (0.19), MS GPA (0.13), and SAT ELA (0.06) and SAT Math (0.06).

Table 5. ***Main path analysis (decomposition table)***

Variable	Original Covariation	Direct	Indirect	Total Causal	Non-Causal
HS GPA	0.39	0.30	0.03	0.33	0.06
Curricular Intensity	0.29	0.08	0.12	0.20	0.08
College Aspirations	0.24	0.14	0.05	0.19	0.05
MS GPA	0.26	0.00	0.13	0.13	0.13
SAT ELA	0.26	0.06		0.06	0.20
SAT Math	0.27	0.06		0.06	0.21
Black	0.02	0.04	-0.03	0.00	0.01
MS SBAC Math	0.23	0.00	0.00	0.00	0.23
HS SBAC ELA	0.25	0.00		0.00	0.25
HS SBAC Math	0.27	0.00		0.00	0.27
School Size	0.00	0.00	0.00	0.00	0.00
EL	-0.07	0.00	-0.01	-0.01	-0.06
Poverty	-0.06	0.00	-0.02	-0.02	-0.05
Asian	0.03	-0.05	0.01	-0.04	0.07
Gender	-0.09	-0.05	0.00	-0.04	-0.04
Latinx	-0.07	0.00	-0.05	-0.05	-0.02
MS SBAC ELA	0.21	-0.07	0.00	-0.07	0.28

Note. Table 5 shows the bivariate decomposition results for the main path analysis. All IVs are shown in the "Variable" column. The "Original Covariation" column shows the correlation coefficient between each IV and the primary outcome variable of college enrollment and persistence. The "Direct" column shows the direct influence, or the standardized beta path coefficient, from each IV to the primary outcome variable. The "Indirect" column shows the indirect influence of each IV to the primary outcome variable via other IVs (i.e., multiplication of the intermediate paths from original predictor to other predictors to college outcome variable). The "Total Causal" column shows the total causal influence of the IV on the primary outcome variable (i.e., the sum of the direct and indirect influence). The "Non-causal" column shows the total non-causal influence of each IV on the primary outcome variable (i.e., the original covariation minus the total causal influence).

Research Question 2 (RQ2)

The second research question asks, to what extent does the 8th-grade SBAC test (MS SBAC ELA, and MS SBAC Math) predict college readiness, as measured by college enrollment and persistence, in comparison to MSGPA while controlling for 11th-grade SBAC test, HSGPA, SAT, curricular intensity, HS type, college aspirations, and student demographics of ethnicity, poverty, language classification, and gender? The first way to answer this question, as seen in Regression 1 in Table 4, is by comparing the path coefficients from MS SBAC ELA and MS SBAC math to college enrollment and persistence and the path coefficient from MSGPA to college enrollment and persistence. The results indicate that both MS GPA and MS SBAC Math do not significantly predict college over and above all the other variables in the model. MS SBAC ELA does significantly predict college, but the direction of the effect is negative such that students with higher test scores showed less enrollment and persistence. The second way to answer this question is by comparing the total causal statistic between those variables, with the expectation that the MS SBAC variables should have a higher total causal influence than MS GPA. The results show that while MS SBAC ELA retained some degree of total causal influence (-0.07), MS GPA showed higher total causal influence (0.13) which is due to large indirect effects of MS GPA significantly predicting SAT Math and ELA as seen in Regression 2 of Table 4, MS SBAC Math and ELA as seen in Regressions 6-7 of Table 4, and HS GPA as seen in Regression 9 of Table 4. Taking both patterns of results together, it appears that MS GPA did not show significant direct effects but did show strong indirect effects, whereas MS SBAC ELA showed a significant direct effect but not indirect effects (see Table 5, “Direct” and “Indirect” columns).

Research Question 3 (RQ3)

The third research question asks, to what extent does the 8th-grade SBAC test predict the 11th-grade SBAC test, in comparison to MSGPA, while controlling for all other variables? This question can be answered from Regressions 4-5 of Table 4 by comparing between the path coefficients from MS SBAC ELA and MS SBAC math to HS SBAC ELA and HS SBAC math and the path coefficient from MSGPA to HS SBAC ELA and HS SBAC math. The results indicate that MS SBAC Math significantly and strongly predicts HS SBAC Math (B = 0.552) whereas MS GPA shows no significant effect. Similarly, MS SBAC ELA significantly and strongly predicts HS SBAC ELA (B = 0.502) whereas MS GPA shows only a weak effect (B = -0.03) in an unexpectedly opposite direction (i.e., as MS GPA increases, HS SBAC ELA scores decrease).

Research Question 4 (RQ4)

The fourth research question asks, to what extent does the 8th or 11th-grade SBAC test scores, and their predictive validity for college enrollment and persistence, suffer from the same demographic and school biases that have been shown to bias the SAT and GPA. There are three different ways to answer this question.

The first approach assesses the degree to which poverty, ethnicity, gender, and school type influence SBAC in comparison to their influence on SAT and GPA. The degree of influence is indicated, as seen in Regressions 2-10 of Table 4, by the path coefficients from poverty, ethnicity, gender, and school type toward SAT math and SAT ELA, HS SBAC math and HS SBAC ELA, MS SBAC Math and MS SBAC ELA, and HSGPA and MSGPA. There is a generally consistent pattern of results. Gender significantly influences every variable such that males (Gender = 1) tend to score higher than females (Gender = 0) on test scores but not GPA. Asian students on average, relative to White students (the reference group for the dummy variable coding, thus not shown in the model), tend to score higher on almost all measures (i.e., positive path coefficients indicate increase relative to reference group). Black and Latinx students on average consistently underperformed on all test and GPA measures when compared to White students (i.e., negative path coefficients indicate decrease relative to reference group). Language classification (i.e., EL) shows consistent effects such that English-learning students (EL = 1) on average underperformed (i.e., negative path coefficients) when compared to their native English-speaking peers (EL = 0). Similarly, students in poverty (Poverty = 1) on average also underperformed relative to students not in poverty (Poverty = 0). Finally, school type (i.e., school size) only showed a few significant effects, such that larger schools tended to have higher HS SBAC ELA (B = 0.01) and HS GPA (B = 0.024) scores while also having lower curricular intensity (B = -0.142).

It is interesting to note that the relative effects (i.e., the path coefficients) of these demographic biases appear to be consistently stronger for SAT variables than for SBAC variables (in particular, the HS SBAC variables). For example, gender influences SAT Math (B = 0.220) and SAT ELA (B = 0.099) much more strongly than HS SBAC Math (B = 0.095) and HS SBAC ELA (B = 0.028), as well as MS SBAC Math (B = 0.113) and HS SBAC ELA (B = -0.012). Similarly, the effects of ethnicity, language classification (EL), and poverty are all stronger for SAT variables than for HS SBAC variables, but they are comparable to the effects on MS SBAC variables. This difference in degree of bias between HS and MS variables also appears for GPA such that HS GPA shows much lower effects (i.e., lower path coefficients) than

MS GPA. This pattern of results indicates that the demographic biases are stronger for SAT than for SBAC variables and also stronger for middle school than for high school variables.

The second approach for answering RQ4 assesses the degree to which poverty, ethnicity, gender, and school type influence the ability of SBAC scores to reliably predict college enrollment or persistence in comparison to SAT or GPA. This can be determined in the path analysis results according to whether the MS SBAC or HS SBAC scores, in comparison to SAT or MSGPA or HSGPA, can predict college variables while controlling for poverty, ethnicity, and school type. As shown in Regression 1 of Table 4, both HS GPA and SAT reliably predicted college over and above the confounding variables, whereas the SBAC variables did not, with the exception of MS SBAC ELA which showed an unexpected effect. However, because several other independent variables were included in these regression models (including SAT and GPA), it’s possible that their presence also contributed to the lack of SBAC predictability.

In the third approach for answering RQ4, the original path analysis was repeated separately for each student subgroup of potentially confounding variables: four analyses for ethnicity (Asian, Black, Latinx, White), two analyses for gender (males, females), two analyses for poverty (students in poverty, students not in poverty), and two analyses for language classification (English-learning students, native English-speaking students). The purpose of this approach is to determine whether the predictability of SBAC for college enrollment and persistence (in comparison to the predictability of SAT, GPA, and curricular intensity) is qualitatively different between student subgroups. Such differences would provide additional evidence of demographic bias in these measures.

The results of the path analysis regressions and bivariate decomposition are shown below for Asian students in Tables 6 and 7, Black students in Tables 8 and 9, Latinx students in Tables

10 and 11, and White students in Tables 12 and 13. For all four subgroups, in Regression 1 of each path analysis, the HS SBAC tests are not significantly predictive of college enrollment and persistence over and above the other variables. For Latinx students only, the MS SBAC ELA is significant and negatively predicts college enrollment and persistence, similar to the full model. This pattern of results indicates no substantial evidence of ethnicity bias in the HS SBAC tests, although there appears to be some ethnicity bias in the MS SBAC ELA test, which might be negatively impacting Latinx students' college-going behavior. There is also evidence of ethnicity bias in the SAT tests because they are not predictive for Black and White students, but SAT Math is strongly positively predictive for Asian students (B = 0.235) and, for Latinx students, both SAT ELA (B = 0.062) and SAT Math (B = 0.047) are positively but not as strongly predictive. For all four subgroups, HS GPA is strongly and positively predictive of college (although less so for Asian students) whereas MS GPA is not significant, thereby indicating no substantial evidence of ethnicity bias in GPA measures. For all four subgroups, college aspiration is strongly and positively predictive of college, whereas curricular intensity is strongly and positively predictive for all subgroups except for Black students who showed no effect. This pattern indicates no substantial ethnicity bias in college aspirations but some bias in curricular intensity such that the curricular rigor of Black students does not seem to impact their college-going behavior. Finally, all subgroups show that MS GPA has one of the strongest total causal influences on college enrollment and persistence, apparently driven by indirect effects on SAT, MS SBAC, and HS GPA measures (similar to the full model).

Table 6. ***Path analysis regression results (Asian students)***

	Path Analysis Regressions (Asian students)									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender		0.263	0.124	0.099	0.041	0.124		-0.114	-0.06	-0.204
EL	0.104	-0.061	-0.209	0.04		-0.157	-0.33	-0.257	0.04	-0.125
Poverty		-0.068	-0.109			-0.065	-0.097	-0.048		-0.13
College Aspirations	0.094	0.059			0.073	0.101	0.052	0.187	0.055	0.178
School Size								-0.15		
Curricular Intensity	0.103	0.147	0.133	0.113	0.14				0.364	
MS GPA		0.132	0.143	-0.052		0.589	0.493		0.49	
HS GPA	0.133	0.416	0.338	0.236	0.235					
MS SBAC ELA					0.532					
MS SBAC Math				0.645						
HS SBAC ELA										
HS SBAC Math										
SAT ELA										
SAT Math	0.235									
Model R^2	0.17	0.41	0.37	0.72	0.62	0.44	0.45	0.16	0.6	0.12

Note. Path analysis results for the student subgroup of Asian students. Total sample size of this subgroup was n = 1831, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 7. ***Path analysis decomposition table (Asian students)***

Variable	Original Covariation	Direct	Indirect	Total Causal	Non-Causal
SAT Math	0.268	0.235		0.235	0.033
HS GPA	0.394	0.133	0.09776	0.23076	0.16324
Curricular Intensity	0.286	0.103	0.082957	0.185957	0.100043
College Aspirations	0.242	0.094	0.040441	0.134441	0.107559
MS GPA	0.263	0	0.09619	0.09619	0.16681
EL	-0.07	0.104	-0.035486	0.068514	-0.138514
Gender	-0.087	0	0.042083	0.042083	-0.129083
MS SBAC ELA	0.212	0	0	0	0.212
MS SBAC Math	0.232	0	0	0	0.232
HS SBAC ELA	0.252	0		0	0.252
HS SBAC Math	0.273	0		0	0.273
SAT ELA	0.261	0		0	0.261
School Size	-0.004	0	-0.01545	-0.01545	0.01145
Poverty	-0.064	0	-0.020924	-0.020924	-0.043076

Note. Bivariate decomposition results for the student subgroup of Asian students.

Table 8. ***Path analysis regression results (Black students)***

	Path Analysis Regressions (Black students)									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender		0.141	0.081	0.055		0.103	-0.041	-0.106	-0.04	-0.157
EL					-0.052					
Poverty		-0.08	-0.102	-0.046		-0.064	-0.074	-0.099		-0.198
College Aspirations	0.128			0.079		0.049	0.054	0.238	0.05	0.218
School Size					0.05			-0.093		
Curricular Intensity		0.111	0.156	0.128	0.177				0.307	
MS GPA		0.217	0.282			0.642	0.602		0.574	
HS GPA	0.373	0.374	0.247	0.22	0.182					
MS SBAC ELA					0.459					
MS SBAC Math				0.495						
HS SBAC ELA										
HS SBAC Math										
SAT ELA										
SAT Math										
Model R^2	0.19	0.43	0.42	0.6	0.54	0.44	0.41	0.09	0.668	0.12

Note. Path analysis results for the student subgroup of Black students. Total sample size of this subgroup was n = 1750, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 9. ***Path analysis decomposition table (Black students)***

Variable	**Original Covariation**	**Direct**	**Indirect**	**Total Causal**	**Non-Causal**
HS GPA	0.392	0.373	0	0.373	0.019
MS GPA	0.299	0	0.214102	0.214102	0.084898
College Aspirations	0.23	0.128	0.01865	0.14665	0.08335
Curricular Intensity	0.225	0	0.114511	0.114511	0.110489
EL	-0.046	0	0	0	-0.046
Poverty	-0.089	0	0	0	-0.089
School Size	0.008	0	0	0	0.008
MS SBAC ELA	0.162	0	0	0	0.162
MS SBAC Math	0.17	0	0	0	0.17
HS SBAC ELA	0.227	0		0	0.227
HS SBAC Math	0.247	0		0	0.247
SAT ELA	0.247	0		0	0.247
SAT Math	0.206	0		0	0.206
Gender	-0.026	0	-0.01492	-0.01492	-0.01108

Note. Bivariate decomposition results for the student subgroup of Black students.

Table 10. ***Path analysis regression results (Latinx students)***

	Path Analysis Regressions (Latinx students)									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender	-0.056	0.238	0.106	0.105	0.028	0.116		-0.105	-0.033	-0.163
EL	-0.027	-0.088	-0.132	-0.018	-0.059	-0.2	-0.24	-0.156	-0.012	-0.161
Poverty		-0.054	-0.075			-0.031	-0.054	-0.032	-0.024	-0.056
College Aspirations	0.142	0.039	0.045	0.028	0.056	0.062	0.074	0.271	0.103	0.211
School Size								-0.148	0.029	
Curricular Intensity	0.084	0.143	0.165	0.11	0.137				0.377	
MS GPA		0.203	0.183		-0.031	0.555	0.496		0.463	
HS GPA	0.305	0.337	0.269	0.262	0.222					
MS SBAC ELA	-0.07				0.493					
MS SBAC Math				0.534						
HS SBAC ELA										
HS SBAC Math										
SAT ELA	0.062									
SAT Math	0.047									
Model R^2	0.202	0.4	0.34	0.63	0.55	0.4	0.39	0.15	0.62	0.12

Note. Path analysis results for the student subgroup of Latinx students. Total sample size of this subgroup was n = 17,712, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 11. ***Path analysis decomposition table (Latinx students)***

Variable	Original Covariation	Direct	Indirect	Total Causal	Non-Causal
HS GPA	0.407	0.305	0.032517	0.337517	0.069483
Curricular Intensity	0.295	0.084	0.131936	0.215936	0.079064
College Aspirations	0.25	0.142	0.018426	0.160426	0.089574
MS GPA	0.261	0	0.127382	0.127382	0.133618
SAT ELA	0.258	0.062		0.062	0.196
SAT Math	0.262	0.047		0.047	0.215
MS SBAC Math	0.224	0	0	0	0.224
HS SBAC ELA	0.255	0		0	0.255
HS SBAC Math	0.27	0		0	0.27
School Size	0.005	0	-0.00359	-0.00359	0.008587
Poverty	-0.021	0	-0.01342	-0.01342	-0.00758
EL	-0.092	-0.027	-0.01228	-0.03928	-0.05272
Gender	-0.104	-0.056	-0.00113	-0.05713	-0.04687
MS SBAC ELA	0.212	-0.07	0	-0.07	0.282

Note. Bivariate decomposition results for the student subgroup of Latinx students.

Table 12. ***Path analysis regression results (White students)***

	Path Analysis Regressions (White students)									
	#1	#2	#3	#4	#5	#6	#7	#8	#9	#10
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender		0.274	0.094	0.067		0.15		-0.06	-0.045	-0.118
EL		-0.107	-0.152		-0.05	-0.133	-0.252	-0.203	0.044	-0.148
Poverty	-0.095	-0.136	-0.193			-0.089	-0.082	-0.215		-0.277
College Aspirations	0.169			0.071	0.077			0.164	0.122	0.18
School Size				0.04	0.045			-0.144		
Curricular Intensity	0.093	0.155	0.207	0.087	0.19				0.31	
MS GPA		0.194	0.197	-0.059	-0.075	0.581	0.523		0.539	
HS GPA	0.221	0.302	0.172	0.238	0.175					
MS SBAC ELA					0.552					
MS SBAC Math				0.635						
HS SBAC ELA										
HS SBAC Math										
SAT ELA										
SAT Math										
Model R^2	0.17	0.46	0.39	0.7	0.58	0.44	0.44	0.16	0.65	0.17

Note. Path analysis results for the student subgroup of White students. Total sample size of this subgroup was n = 1712, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 13. ***Path analysis decomposition table (White students)***

Variable	Original Covariation	Direct	Indirect	Total Causal	Non-Causal
HS GPA	0.335	0.221	0	0.221	0.114
College Aspirations	0.237	0.169	0.042214	0.211214	0.025786
Curricular Intensity	0.234	0.093	0.06851	0.16151	0.07249
MS GPA	0.239	0	0.119119	0.119119	0.119881
MS SBAC ELA	0.156	0	0	0	0.156
MS SBAC Math	0.216	0	0	0	0.216
HS SBAC ELA	0.152	0		0	0.152
HS SBAC Math	0.222	0		0	0.222
SAT ELA	0.186	0		0	0.186
SAT Math	0.213	0		0	0.213
EL	0.003	0	-0.00916	-0.00916	0.012155
School Size	-0.051	0	-0.01339	-0.01339	-0.03761
Gender	-0.065	0	-0.01553	-0.01553	-0.04948
Poverty	-0.153	-0.095	-0.02	-0.115	-0.03801

Note. Bivariate decomposition results for the student subgroup of White students.

The results of the path analysis regressions and bivariate decomposition are shown below for English-native in Tables 14 and 15, and for English-learning students in Tables 16 and 17. For both subgroups, the HS SBAC tests are not significantly predictive of college enrollment and persistence over and above the other variables. For English-native students only, the MS SBAC ELA is significant and negatively predicts college enrollment and persistence (similar to the full model), the SAT tests are positively predictive, and curricular intensity is also positively predictive. For both subgroups, both college aspirations and HS GPA are positively predictive. Interestingly, school size is strongly and positively predictive of college for only English-learning students, which might indicate that being in larger high schools might facilitate or encourage English-learning students' college-going behavior. Similar to the full model and ethnicity subgroups, MS GPA is not directly predictive but is indirectly strongly predictive of college enrollment and persistence. Furthermore, curricular intensity has similar indirect and total causal influence, but it appears stronger for English-native students. Taken together, this pattern of results indicates that language classification does not appear to bias the predictability of HS SBAC tests, college aspirations, and HS GPA or MS GPA. However, it does appear to bias the predictability of MS SBAC ELA, both SAT tests, and curricular intensity.

Table 14. ***Path analysis regression results (English-native students)***

	Path Analysis Regressions (English-native students)									
	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender	-0.043	0.226	0.103	0.097	0.03	0.119	-0.014	-0.105	-0.036	-0.16
Asian	-0.048	0.039	-0.027	0.021	0.016	0.042	0.017	0.073		0.027
Black	0.041	-0.077	-0.088	-0.034	-0.046	-0.101	-0.091	-0.132	-0.064	-0.156
Latinx		-0.181	-0.22			-0.106	-0.113	-0.077	-0.079	-0.208
Poverty		-0.074	-0.104	-0.018		-0.052	-0.072	-0.067	-0.022	-0.107
College Aspirations	0.14	0.035	0.04	0.033	0.054	0.058	0.067	0.256	0.093	0.206
School Size								-0.145	0.023	
Curricular Intensity	0.081	0.133	0.159	0.106	0.145				0.358	
MS GPA		0.193	0.184		-0.036	0.58	0.533		0.476	
HS GPA	0.301	0.328	0.265	0.253	0.222					
MS SBAC ELA	-0.061				0.502					
MS SBAC Math				0.553						
HS SBAC ELA										
HS SBAC Math										
SAT ELA	0.063									
SAT Math	0.061									
Model R^2	0.19	0.46	0.39	0.66	0.55	0.42	0.38	0.14	0.65	0.15

Note. Path analysis results for the student subgroup of English-native students. Total sample size of this subgroup was n = 20,852, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 15. ***Path analysis decomposition table (English-native students)***

Variable	**Original Covariation**	**Direct**	**Indirect**	**Total Causal**	**Non-Causal**
HS GPA	0.388	0.301	0.036703	0.337703	0.050297
Curricular Intensity	0.279	0.081	0.125888	0.206888	0.072112
College Aspirations	0.237	0.14	0.049297	0.189297	0.047703
MS GPA	0.255	0	0.134128	0.134128	0.120872
SAT ELA	0.253	0.063		0.063	0.19
SAT Math	0.258	0.061		0.061	0.197
Black	0.015	0.041	-0.03465	0.006354	0.008646
MS SBAC Math	0.219	0	0	0	0.219
HS SBAC ELA	0.241	0		0	0.241
HS SBAC Math	0.262	0		0	0.262
School Size	-0.01	0	-0.00482	-0.00482	-0.00518
Poverty	-0.063	0	-0.01872	-0.01872	-0.04428
Gender	-0.089	-0.043	0.001788	-0.04121	-0.04779
Asian	0.026	-0.048	0.005554	-0.04245	0.068446
Latinx	-0.057	0	-0.04802	-0.04802	-0.00898
MS SBAC ELA	0.202	-0.061	0	-0.061	0.263

Note. Bivariate decomposition results for the student subgroup of English-native students.

Table 16. ***Path analysis regression results (English-learning students)***

	Path Analysis Regressions (English-learning students)									
	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender	-0.094	0.185	0.112	0.087		0.09		-0.077		-0.15
Asian		0.17		0.068	0.091			0.112		0.114
Black					-0.053					
Latinx			-0.133			-0.15			-0.18	-0.178
Poverty				0.047	0.063				0.044	0.052
College Aspirations	0.132				0.111	0.108	0.123	0.263	0.139	0.159
School Size	0.145							-0.144		
Curricular Intensity		0.114	0.155	0.099	0.146				0.39	
MS GPA		0.093	0.117			0.386	0.285		0.363	
HS GPA	0.192	0.38	0.265	0.306	0.248					
MS SBAC ELA					0.357					
MS SBAC Math				0.387						
HS SBAC ELA										
HS SBAC Math										
SAT ELA										
SAT Math										
Model R^2	0.26	0.47	0.28	0.53	0.46	0.25	0.12	0.12	0.59	0.14

Note. Path analysis results for the student subgroup of English-learning students. Total sample size of this subgroup was n = 2,153, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 17. ***Path analysis decomposition table (English-learning students)***

Variable	**Original Covariation**	**Direct**	**Indirect**	**Total Causal**	**Non-Causal**
HS GPA	0.423	0.192	0	0.192	0.231
College Aspirations	0.262	0.132	0.026688	0.158688	0.103312
School Size	0.129	0.145	0	0.145	-0.016
Curricular Intensity	0.288	0	0.07488	0.07488	0.21312
MS GPA	0.302	0	0.069696	0.069696	0.232304
Poverty	0.016	0	0.008448	0.008448	0.007552
Asian	0.229	0	0	0	0.229
Black	-0.019	0	0	0	-0.019
MS SBAC ELA	0.157	0	0	0	0.157
MS SBAC Math	0.306	0	0	0	0.306
HS SBAC ELA	0.308	0		0	0.308
HS SBAC Math	0.357	0		0	0.357
SAT ELA	0.257	0		0	0.257
SAT Math	0.346	0		0	0.346
Latinx	-0.279	0	-0.03456	-0.03456	-0.24444
Gender	-0.047	-0.094	0	-0.094	0.047

Note. Bivariate decomposition results for the student subgroup of English-learning students.

The results of the path analysis regressions and bivariate decomposition are shown below for students not in poverty in Tables 18 and 19, and for students in poverty in Tables 20 and 21. For both subgroups, the HS SBAC tests are not significantly predictive of college enrollment and persistence over and above the other variables. For only students in poverty, the MS SBAC ELA is significant and negatively predicts college enrollment and persistence (similar to the results of the full model as well as ethnicity and language subgroups), the SAT tests are positively predictive, and curricular intensity is also positively predictive. For both subgroups, both college aspirations and HS GPA are positively predictive. Interestingly, school size is strongly and negatively predictive of college for only students not in poverty, which might indicate that being in larger high schools might hinder the college-going behavior of these students. Similar to the full model and ethnicity subgroups, MS GPA is not directly predictive but has strong indirect and total causal influence of college enrollment and persistence. Furthermore, curricular intensity has similar indirect and total causal influence, but it appears much stronger for students in poverty, perhaps indicating a facilitation effect. Taken together, this pattern of results indicates that, similar to language classification, poverty does not appear to bias the predictability of HS SBAC tests, college aspirations, and HS GPA or MS GPA. However, it does appear to bias the predictability of MS SBAC ELA, SAT tests, and curricular intensity.

Table 18. ***Path analysis regression results (non-poverty students)***

	Path Analysis Regressions (Students not in poverty)									
	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender		0.268	0.109	0.102	0.044	0.144		-0.116		-0.146
Asian	-0.092		-0.075			0.057				
Black		-0.088	-0.094			-0.088	-0.069	-0.178	-0.066	-0.164
Latinx		-0.178	-0.226			-0.105	-0.074	-0.199	-0.047	-0.344
EL			-0.091	-0.034	-0.068	-0.075	-0.126	-0.134	-0.045	-0.145
College Aspirations	0.163			0.034	0.049	0.042		0.213	0.068	0.197
School Size	-0.076							-0.167		
Curricular Intensity		0.141	0.172	0.075	0.122				0.281	
MS GPA		0.213	0.245	-0.058	-0.058	0.626	0.595		0.577	
HS GPA	0.26	0.312	0.234	0.236	0.239					
MS SBAC ELA					0.542					
MS SBAC Math				0.645						
HS SBAC ELA										
HS SBAC Math										
SAT ELA										
SAT Math										
Model R^2	0.2	0.49	0.46	0.74	0.62	0.51	0.47	0.19	0.71	0.23

Note. Path analysis results for the student subgroup of non-poverty students. Total sample size of this subgroup was n = 2087, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 19. ***Path analysis decomposition table (non-poverty students)***

Variable	**Original Covariation**	**Direct**	**Indirect**	**Total Causal**	**Non-Causal**
HS GPA	0.382	0.26	0	0.26	0.122
College Aspirations	0.239	0.163	0.01768	0.18068	0.05832
MS GPA	0.316	0	0.15002	0.15002	0.16598
Curricular Intensity	0.257	0	0.07306	0.07306	0.18394
Gender	-0.06	0	0	0	-0.06
MS SBAC ELA	0.238	0	0	0	0.238
MS SBAC Math	0.28	0	0	0	0.28
HS SBAC ELA	0.273	0		0	0.273
HS SBAC Math	0.296	0		0	0.296
SAT ELA	0.295	0		0	0.295
SAT Math	0.282	0		0	0.282
School Size	0.112	-0.076	0.07306	-0.00294	0.11494
EL	0.073	0	-0.0117	-0.0117	0.0847
Latinx	-0.123	0	-0.01222	-0.01222	-0.11078
Black	0.025	0	-0.01716	-0.01716	0.04216
Asian	-0.002	-0.092	0	-0.092	0.09

Note. Bivariate decomposition results for the student subgroup of non-poverty students.

Table 2. ***Path analysis regression results (poverty students)***

	Path Analysis Regressions (Students in poverty)									
	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender	-0.047	0.222	0.102	0.095	0.026	0.112	-0.013	-0.1	-0.037	-0.161
Asian	-0.038	0.06		0.023	0.018	0.04		0.096		0.052
Black	0.042	-0.063	-0.077	-0.034	-0.049	-0.096	-0.087	-0.099	-0.07	-0.139
Latinx		-0.151	-0.189			-0.096	-0.102	-0.029	-0.09	-0.165
EL		-0.084	-0.14	-0.009	-0.052	-0.189	-0.244	-0.16		-0.153
College Aspirations	0.137	0.038	0.042	0.033	0.057	0.062	0.071	0.258	0.1	0.205
School Size					0.01			-0.141	0.025	
Curricular Intensity	0.084	0.135	0.16	0.11	0.145				0.369	
MS GPA		0.188	0.177		-0.028	0.554	0.497		0.463	
HS GPA	0.3	0.337	0.268	0.257	0.217					
MS SBAC ELA	-0.065				0.493					
MS SBAC Math				0.54						
HS SBAC ELA										
HS SBAC Math										
SAT ELA	0.055									
SAT Math	0.062									
Model R^2	0.19	0.45	0.37	0.65	0.56	0.43	0.41	0.16	0.64	0.15

Note. Path analysis results for the student subgroup of poverty students. Total sample size of this subgroup was n = 20,918, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 31. ***Path analysis decomposition table (poverty students)***

Variable	**Original Covariation**	**Direct**	**Indirect**	**Total Causal**	**Non-Causal**
HS GPA	0.39	0.3	0.035634	0.335634	0.054366
Curricular Intensity	0.284	0.084	0.12787	0.21187	0.07213
College Aspirations	0.24	0.137	0.051723	0.188723	0.051277
MS GPA	0.252	0	0.127986	0.127986	0.124014
SAT Math	0.259	0.062		0.062	0.197
SAT ELA	0.25	0.055		0.055	0.195
Black	0.014	0.042	-0.0318	0.010198	0.003802
MS SBAC Math	0.219	0	0	0	0.219
HS SBAC ELA	0.244	0		0	0.244
HS SBAC Math	0.264	0		0	0.264
School Size	0.006	0	-0.00434	-0.00434	0.010344
EL	-0.067	0	-0.01049	-0.01049	-0.05651
Asian	0.029	-0.038	0.011784	-0.02622	0.055216
Latinx	-0.042	0	-0.04256	-0.04256	0.000563
Gender	-0.093	-0.047	0.000719	-0.04628	-0.04672
MS SBAC ELA	0.201	-0.065	0	-0.065	0.266

Note. Bivariate decomposition results for the student subgroup of poverty students.

The results of the path analysis regressions and bivariate decomposition are shown below for male students in Tables 22 and 23, and for female students in Tables 24 and 25. For both subgroups, the HS SBAC tests are not significantly predictive of college enrollment and persistence, the MS SBAC ELA test is negatively predictive, and college aspirations, curricular intensity, and HS GPA are all positively predictive. An opposite pattern appears for SAT such that SAT ELA is positively predictive of college for Male students but SAT Math is positively predictive of college for Female students. MS GPA has different direct effects (i.e., negatively predictive for Females but not for Males) but very similar indirect and total causal effects. Curricular intensity has very similar direct, indirect, and total causal effects for both Male and Female students. Taken together, this pattern of results indicates that gender does not appear to substantially affect the predictability of HS SBAC tests, MS SBAC tests, college aspirations, curricular and HS GPA or MS GPA. However, it does appear to affect the predictability of the SAT tests. However, it's unclear from this result if this indicates that the SAT test is biased specifically or the observed effect is part of a more general, systemic bias from gender and other demographic variables as seen in other parts of the results.

Table 22. ***Path analysis regression results (male students)***

	Path Analysis Regressions (Male students)									
	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Asian				0.029		0.026		0.063		
Black	0.051	-0.096	-0.087	-0.033	-0.046	-0.098	-0.093	-0.128	-0.06	-0.148
Latinx		-0.182	-0.212			-0.109	-0.108	-0.093	-0.08	-0.224
EL		-0.085	-0.131	-0.014	-0.063	-0.18	-0.23	-0.151		-0.143
Poverty		-0.089	-0.103	-0.027		-0.055	-0.071	-0.062	-0.027	-0.104
College Aspirations	0.141	0.03	0.028	0.042	0.054	0.059	0.059	-0.142	0.113	0.197
School Size								0.258	0.023	
Curricular Intensity	0.092	0.144	0.172	0.115	0.147				0.367	
MS GPA		0.166	0.157	-0.027	-0.042	0.55	0.494		0.462	
HS GPA	0.307	0.34	0.259	0.257	0.244					
MS SBAC ELA	-0.07				0.468					
MS SBAC Math				0.555						
HS SBAC ELA										
HS SBAC Math										
SAT ELA	0.089									
SAT Math										
Model R^2	0.22	0.48	0.41	0.68	0.56	0.46	0.42	0.16	0.65	0.15

Note. Path analysis results for the student subgroup of male students. Total sample size of this subgroup was n = 10,683, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 23. ***Path analysis decomposition table (male students)***

Variable	**Original Covariation**	**Direct**	**Indirect**	**Total Causal**	**Non-Causal**
HS GPA	0.421	0.307	0.023051	0.330051	0.090949
Curricular Intensity	0.314	0.092	0.127977	0.219977	0.094023
College Aspirations	0.247	0.141	0.019989	0.160989	0.086011
MS GPA	0.287	0	0.121227	0.121227	0.165773
SAT ELA	0.296	0.089		0.089	0.207
School Size	-0.008	0	0.030797	0.030797	-0.0388
Black	0.032	0.051	-0.03143	0.019571	0.012429
Asian	0.062	0	0.005796	0.005796	0.056204
MS SBAC Math	0.249	0	0	0	0.249
HS SBAC ELA	0.267	0		0	0.267
HS SBAC Math	0.308	0		0	0.308
SAT Math	0.311	0		0	0.311
EL	-0.06	0	-0.00945	-0.00945	-0.05055
Poverty	-0.083	0	-0.01819	-0.01819	-0.06481
Latinx	-0.104	0	-0.04442	-0.04442	-0.05958
MS SBAC ELA	0.217	-0.07	0	-0.07	0.287

Note. Bivariate decomposition results for the student subgroup of male students.

Table 24. ***Path analysis regression results (female students)***

	Path Analysis Regressions (Female students)									
	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Asian	-0.06	0.056		0.017	0.022	0.053	0.022	0.086		0.049
Black		-0.055	-0.081	-0.035	-0.043	-0.095	-0.075	-0.112	-0.072	-0.154
Latinx		-0.165	-0.208	-0.029		-0.099	-0.098	-0.041	-0.093	-0.192
EL		-0.075	-0.129		-0.039	-0.174	-0.233	-0.169		-0.16
Poverty		-0.062	-0.101			-0.044	-0.071	-0.069		-0.101
College Aspirations	0.137	0.038	0.046	0.021	0.054	0.058	0.071	0.246	0.079	0.208
School Size					0.023			-0.145	0.025	
Curricular Intensity	0.068	0.121	0.143	0.095	0.136				0.359	
MS GPA	-0.039	0.208	0.195			0.546	0.499		0.482	
HS GPA	0.293	0.321	0.257	0.244	0.188					
MS SBAC ELA	-0.067				0.536					
MS SBAC Math				0.548						
HS SBAC ELA										
HS SBAC Math										
SAT ELA										
SAT Math	0.068									
Model R^2	0.17	0.46	0.42	0.66	0.59	0.45	0.43	0.15	0.63	0.15

Note. Path analysis results for the student subgroup of female students. Total sample size of this subgroup was n = 12,322, but sample sizes for the different regressions are different depending on which IVs are included and missing data from students.

Table 25. ***Path analysis decomposition table (female students)***

Variable	**Original Covariation**	**Direct**	**Indirect**	**Total Causal**	**Non-Causal**
HS GPA	0.363	0.293	0.021828	0.314828	0.048172
Curricular Intensity	0.255	0.068	0.113415	0.181415	0.073585
College Aspirations	0.226	0.137	0.02959	0.16659	0.05941
MS GPA	0.23	-0.039	0.121937	0.082937	0.147063
SAT Math	0.266	0.068		0.068	0.198
EL	-0.078	0	0.005259	0.005259	-0.08326
MS SBAC Math	0.23	0	0	0	0.23
HS SBAC ELA	0.239	0		0	0.239
HS SBAC Math	0.268	0		0	0.268
SAT ELA	0.242	0		0	0.242
Poverty	-0.055	0	-0.00021	-0.00021	-0.05479
School Size	-0.004	0	-0.00254	-0.00254	-0.00147
Black	0.005	0	-0.02142	-0.02142	0.026421
Latinx	-0.044	0	-0.0272	-0.0272	-0.0168
Asian	0.018	-0.06	0.006271	-0.05373	0.071729
MS SBAC ELA	0.199	-0.067	0	-0.067	0.266

Note. Bivariate decomposition results for the student subgroup of female students.

Additional Analyses

Some additional analyses were performed in order to look carefully and shed further light on the different dynamics of the patterns seen in the results of the path analyses, also because the dependent variable of college enrollment and persistence is ordinal with five levels which is less optimal for standard regression which assumes a continuous dependent variable. Both logistic regression and DFA can test the relations of IVs with a nominal DV and can test classification of students. Logistic regression seems ideal for prediction whereas DFA seems ideal for classification. The combination of these additional tests provides further clarification of the results from the path analyses.

Additional Analysis #1

The first additional analysis was a discriminant function analysis (DFA) using the original dependent variable of college enrollment and persistence (i.e., "CollegeReady") which is ordinal with five levels or student subgroups: 1) student did not immediately enroll in college, 2) student immediately enrolled in a two-year college but did not persist, 3) student immediately enrolled in a four-year university but did not persist, 4) student immediately enrolled in a two-year college and persisted, and 5) student immediately enrolled in a four-year university and persisted. The purpose of this analysis was to determine how well the different categories of college enrollment and persistence could be predicted or classified for all students based on the same set of 18 independent variables that were used in the path analyses: gender, ethnicity (Asian, Black, Latinx, White), language classification (i.e., EL), poverty, school type (i.e., school size), SBAC variables (HS_SBAC_ELA, HS_SBAC_Math, MS_SBAC_ELA, MS_SBAC_Math), SAT variables (SAT_ELA, SAT_Math), GPA variables (HS GPA, MS

GPA), college aspirations, and curricular intensity. In the discriminant functions, it was selected to predict group sizes according to prior probabilities.

In this first DFA, since there are five different levels or student groups in the dependent variable, there is a maximum of four discriminant functions (DF). Inspection of the Wilks' Lambda results, as shown in Table 26, indicates that the first three DFs were statistically significant at the $p < .0001$ level and the fourth DF was significant at the $p < 0.05$ level. All four DFs made a significant contribution, but the first DF made the largest contribution because it has the highest eigenvalue (0.366) and percentage of the variance (94.2%) explained in the dependent variable (see Table 27).

Table 26. ***Additional analysis #1 (DFA: Wilks' Lambda)***

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 4	.716	3250.527	68	.000
2 through 4	.978	217.479	48	.000
3 through 4	.990	98.887	30	.000
4	.997	28.495	14	.012

Note. Significance test of the discriminant functions for additional analysis #1.

Table 27. ***Additional analysis #1 (DFA: Eigenvalues)***

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.366[a]	94.2	94.2	.518
2	.012[a]	3.2	97.4	.110
3	.007[a]	1.9	99.2	.085
4	.003[a]	.8	100.0	.054

a. First 4 canonical discriminant functions were used in the analysis.

Note. Eigenvalues of the discriminant functions for additional analysis #1.

The discriminant functions, which are composite variables based on the independent variables, represent the best possible predictors of group membership in these data. The structure coefficient matrix, as shown in Table 28, reveals which independent variables were the most important in constructing the DFs and predicting group classification. The variables contributing the most to the first DF, which was the most important DF based on the highest variance explained, were the following in order of contribution: HS GPA, HS_SBAC_Math, curricular intensity, SAT_Math, MS GPA, SAT_ELA, HS_SBAC_ELA, MS_SBAC_Math, MS_SBAC_ELA, and college aspiration. The variables contributing the most to the second DF were college aspiration and Asian. The variables contributing the most to the third DF were gender, White, Latinx, poverty, EL, and school size. The variable contributing to the most to the fourth DF was Black.

Table 4. ***Additional analysis #1 (DFA: Structure Matrix)***

Structure Matrix

	Function			
	1	2	3	4
HSGPA	.912*	-.250	.186	.040
HS_SBAC_Math	.583*	-.192	.084	.327
CurricularIntensity	.579*	.135	-.117	-.270
SAT_Math	.560*	-.127	.012	.323
MSGPA	.550*	-.275	-.136	.300
SAT_ELA	.532*	-.241	-.239	.476
HS_SBAC_ELA	.523*	-.198	-.106	.133
MS_SBAC_Math	.480*	-.145	.001	.215
MS_SBAC_ELA	.432*	-.302	-.213	.277
CollegeAspiration	.427	.523*	-.396	.009
Asian	.094	-.441*	-.052	-.089
Gender	-.168	.372	.518*	.481
White[b]	.077	-.057	-.433*	.206
Latinx	-.113	.204	.417*	-.231
Poverty	-.109	.072	.301*	.025
EL	-.117	-.134	.137*	-.100
SchoolSize	-.006	.112	.115*	-.079
Black	-.003	.269	-.217	.312*

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.

*. Largest absolute correlation between each variable and any discriminant function

b. This variable not used in the analysis.

Note. Structure matrix of the discriminant functions for additional analysis #1. All relevant IVs are displayed in the first column and their loadings on each discriminant function are displayed in the subsequent columns. Higher loadings indicate higher importance of IV for classifying DV.

As shown in Table 29 below, 55.6% of the original cases were correctly predicted by all DFs, which is higher than 47.2% which could have been correctly predicted by chance. Chance is determined by the prior value in Table 30 below for the largest subgroup by sample size, which was group 5 or those students who immediately enrolled in a four-year college and persisted to the second year. This is a proportional reduction in error (PRE) of 15.64%, based on this formula: (55.6% - 47.2%) / (100% - 47.2%). This PRE is some improvement over chance prediction based on the prior probabilities. The combination of all four DFs correctly classified 50.4% of the first group (i.e., students did not immediately enroll in college), only 2.8% of the second group (i.e., students immediately enrolled in a two-year college but did not persist), only 0% of the third group (i.e., students immediately enrolled in a four-year university but did not persist), only 2.5% of the fourth group (i.e., students immediately enrolled and persisted in a two-year college), and 88.7% of the fifth group (i.e., students immediately enrolled and persisted in a four-year university).

Table 29. ***Additional analysis #1 (DFA: Classification)***

Classification Results[a]

		CollegeReady	Predicted Group Membership 1	2	3	4	5	Total
Original	Count	1	1282	16	0	41	1206	2545
		2	341	13	0	11	104	469
		3	123	0	0	6	263	392
		4	719	13	0	43	958	1733
		5	488	0	0	33	4080	4601
	%	1	50.4	.6	.0	1.6	47.4	100.0
		2	72.7	2.8	.0	2.3	22.2	100.0
		3	31.4	.0	.0	1.5	67.1	100.0
		4	41.5	.8	.0	2.5	55.3	100.0
		5	10.6	.0	.0	.7	88.7	100.0

a. 55.6% of original grouped cases correctly classified.

Note. DFA classification results for additional analysis #1.

Table 30. ***Additional analysis #1 (DFA: Prior probabilities)***

Prior Probabilities for Groups

CollegeReady	Prior	Cases Used in Analysis Unweighted	Weighted
1	.261	2545	2545.000
2	.048	469	469.000
3	.040	392	392.000
4	.178	1733	1733.000
5	.472	4601	4601.000
Total	1.000	9740	9740.000

Note. DFA prior probabilities of student assignment to the different subgroups of the DV, for additional analysis #1.

Additional Analysis #2

The second additional analysis was a DFA performed using a newly created dependent variable called “CollegeEnroll_binary” which was dichotomous with two levels (1 = immediately enrolled in a two-year college or four-year university, 0 = did not immediately enroll in either). Note that all student groups were included, and none were excluded, in this binary DV, because every student either did or did not enroll in any university or college. The purpose of this analysis was to determine how well college enrollment, in general, could be predicted or classified for all students based on the same set of 18 independent variables used previously. In the discriminant function, it was selected to predict group sizes according to prior probabilities.

In this second DFA, since there are only two levels or groups, there is only one DF. This DF was statistically significant at the $p < .0001$ level as shown in Table 31, had an eigenvalue of 0.103 and explained 100% of the variance in college enrollment as shown in Table 32. The structure matrix shown in Table 33 revealed that the following independent variables made the most important contributions to the prediction: HSGPA, curricular intensity, college aspiration, SAT_Math, HS_SBAC_Math, SAT_ELA, MSGPA, HS_SBAC_ELA, MS_SBAC_Math, and MS_SBAC_ELA. It is interesting to note that these important variables all represent different aspects of academic preparation, and it is also interesting that none of the demographic or school variables provided any substantial contribution.

Table 31. ***Additional analysis #2 (DFA: Wilks' Lambda)***

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.906	956.206	17	.000

Note. Significance test of the discriminant function for additional analysis #2.

Table 32. ***Additional analysis #2 (DFA: Eigenvalues)***

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.103[a]	100.0	100.0	.306

a. First 1 canonical discriminant functions were used in the analysis.

Note. Eigenvalues of the discriminant functions for additional analysis #2.

Table 5. *Additional analysis #2 (DFA: Structure Matrix)*

Structure Matrix

	Function
	1
HSGPA	.813
CurricularIntensity	.632
CollegeAspiration	.615
SAT_Math	.557
HS_SBAC_Math	.556
SAT_ELA	.538
MSGPA	.531
HS_SBAC_ELA	.514
MS_SBAC_Math	.474
MS_SBAC_ELA	.417
EL	-.175
Gender	-.139
Poverty	-.135
Latinx	-.130
White[a]	.127
Black	.094
SchoolSize	.003
Asian	.003

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.

a. This variable not used in the analysis.

Note. Structure matrix of the discriminant functions for additional analysis #2. All relevant IVs are displayed in the first column and their loadings on each discriminant function are displayed in the subsequent columns. Higher loadings indicate higher importance of that IV for explaining the DV.

As shown in Table 34 below, 74.6% of the original cases were correctly predicted by this DF, which is higher than 73.9% which could have been correctly predicted by chance. Chance is determined by the prior value in Table 35 below for the largest subgroup by sample size, which was group 1 or those students who immediately enrolled. This is a proportional reduction in error (PRE) of 2.68%, based on this formula: (74.6% - 73.9%) / (100% - 73.9%). This PRE is some improvement over chance prediction based on the prior probabilities. This DF correctly classified only 17.0% of the first group (i.e., students who did not enroll) but 95.0% of the second group (i.e., students who enrolled).

Table 6. ***Additional analysis #2 (DFA: Classification)***

Classification Results[a]

		CollegeEnroll_binary	Predicted Group Membership 0	Predicted Group Membership 1	Total
Original	Count	0	432	2113	2545
		1	360	6835	7195
	%	0	17.0	83.0	100.0
		1	5.0	95.0	100.0

a. 74.6% of original grouped cases correctly classified.

Note. DFA classification results for additional analysis #2.

Table 35. ***Additional analysis #2 (DFA: Prior probabilities)***

Prior Probabilities for Groups

CollegeEnroll_binary	Prior	Cases Used in Analysis: Unweighted	Cases Used in Analysis: Weighted
0	.261	2545	2545.000
1	.739	7195	7195.000
Total	1.000	9740	9740.000

Note. DFA prior probabilities of student assignment to the different subgroups of the DV, for additional analysis #2.

In order to further explore the pattern of results seen in the DFA above, a logistic regression was performed using the same DV and IVs. All statistical assumptions of logistic regression were checked (Lund & Lund, 2018). The assumption of a dichotomous DV was met. The assumption of continuous, ordinal, or nominal IVs was met. The assumption of independent observations was also met because each student is only measured once. The assumption of mutually exclusive and exhaustive categories of the DV and nominal IVs was also met. The assumption of minimum 15 subjects per IV was also met because the very large sample size enabled more than at least 500 subjects per IV. The assumption of no high multicollinearity was also met. The assumption of no significant outliers was violated for some regressions which had many outliers based on Z score > 3, but these outliers resulted from the model not fitting these individual data points well and so, similar to the standard regressions of the path analysis, the decision was made to not exclude them. Finally, the assumption of linear relationship between the continuous IVs and the logit transformation of the DV was also met.

The overall model was significant, χ (17) = 902.46, $p < 0.0001$, $R^2 = 0.09$. The classification results in Table 36 show that 74.6% of students overall were correctly classified, with only 14.9% correct in the first group (i.e., students who did not enroll) and 95.7% correct in the second group (i.e., students who enrolled). Table 37 shows the contribution of all the IVs in the model. The significant variables were the following: Asian, Black, MS_SBAC_ELA, SAT_ELA, SAT_Math, HSGPA, college aspiration, and curricular intensity. It is interesting to note that the classification and significant variables produced by the logistic regression are consistent with the DFA results above.

Table 36. ***Additional analysis #2 (Logistic regression: Classification)***

Classification Table[a]

Observed			Predicted CollegeEnroll_binary 0	1	Percentage Correct
Step 1	CollegeEnroll_binary	0	380	2165	14.9
		1	309	6886	95.7
	Overall Percentage				74.6

a. The cut value is .500

Note. Logistic regression classification results for additional analysis #2.

Table 37. ***Additional analysis #2 (Logistic regression: Variables)***

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B) Lower	Upper
Step 1[a]	Gender(1)	-.081	.053	2.366	1	.124	.922	.805	1.056
	Asian(1)	-.518	.131	15.577	1	.000	.596	.425	.835
	Black(1)	.418	.158	6.983	1	.008	1.520	1.011	2.285
	Latinx(1)	-.006	.114	.003	1	.958	.994	.741	1.333
	EL(1)	-.144	.124	1.357	1	.244	.866	.630	1.191
	Poverty(1)	-.070	.098	.511	1	.475	.933	.725	1.199
	SchoolSize	.000	.000	.784	1	.376	1.000	1.000	1.000
	HS_SBAC_ELA	.000	.000	.276	1	.599	1.000	.999	1.001
	HS_SBAC_Math	.000	.000	.022	1	.881	1.000	.999	1.001
	MS_SBAC_ELA	-.002	.001	11.992	1	.001	.998	.997	1.000
	MS_SBAC_Math	.000	.000	.059	1	.808	1.000	.999	1.001
	SAT_ELA	.001	.001	6.965	1	.008	1.001	1.000	1.003
	SAT_Math	.001	.001	6.948	1	.008	1.001	1.000	1.003
	HSGPA	.685	.060	130.828	1	.000	1.984	1.701	2.316
	MSGPA	-.051	.049	1.112	1	.292	.950	.838	1.077
	CollegeAspiration	.190	.016	143.426	1	.000	1.209	1.161	1.259
	CurricularIntensity	.076	.015	25.735	1	.000	1.079	1.038	1.122
	Constant	.633	1.406	.203	1	.652	1.884		

a. Variable(s) entered on step 1: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, HS_SBAC_ELA, HS_SBAC_Math, MS_SBAC_ELA, MS_SBAC_Math, SAT_ELA, SAT_Math, HSGPA, MSGPA, CollegeAspiration, CurricularIntensity.

Note. Logistic regression results of model and IVs for additional analysis #2.

Additional Analysis #3

The third additional analysis was a DFA performed using a newly created dependent variable called "CollegeEnroll_2yr" which was dichotomous with two levels where 1 = enrolled in a two-year college and 0 = did not enroll in a two-year college. Note that this DV includes all students who enrolled in a two-year college, whether or not they persisted, and it also excludes all students who enrolled in a four-year university, whether or not they persisted. The purpose of this analysis was to determine how well college enrollment in a two-year college could be predicted or classified for all students based on the same set of 18 independent variables used previously. In the discriminant function, it was selected to predict group sizes according to prior probabilities.

In this third DFA, since there are only two levels or groups, there is only one DF. This DF was statistically significant at the $p < .0001$ level as shown in Table 38, had an eigenvalue of 0.017 and explained 100% of the variance in two-year college enrollment as shown in Table 39. The structure matrix shown in Table 40 revealed that the following independent variables made the most important contributions to the prediction, in order of importance: college aspiration, Black, Asian, HS GPA, White, HS_SBAC_Math, EL, poverty, Latinx, curricular intensity, MS_SBAC_math, MS GPA, and SAT_Math, with additional but decreasing contributions from the other variables. It is interesting to note that this DF included a mix of academic preparation and demographic variables.

Table 38. ***Additional analysis #3 (DFA: Wilks' Lambda)***

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.983	79.884	17	.000

Note. Significance test of the discriminant functions for additional analysis #3.

Table 39. ***Additional analysis #3 (DFA: Eigenvalues)***

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.017[a]	100.0	100.0	.129

a. First 1 canonical discriminant functions were used in the analysis.

Note. Eigenvalues of the discriminant functions for additional analysis #3.

Table 7. *Additional analysis #3 (DFA: Structure Matrix)*

Structure Matrix

	Function
	1
CollegeAspiration	-.572
Black	-.399
Asian	.348
HSGPA	.313
White[a]	-.290
HS_SBAC_Math	.196
EL	.179
Poverty	.156
Latinx	.150
CurricularIntensity	-.115
MS_SBAC_Math	.113
MSGPA	.110
SAT_Math	.103
HS_SBAC_ELA	.085
MS_SBAC_ELA	.079
SAT_ELA	-.004
Gender	.002
SchoolSize	-.002

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.

a. This variable not used in the analysis.

Note. Structure matrix of the discriminant functions for additional analysis #3. All relevant IVs are displayed in the first column and their loadings on each discriminant function are displayed in the subsequent columns. Higher loadings indicate higher importance of that IV for explaining the DV.

As shown in Table 41 below, 56.1% of the original cases were correctly predicted by this DF, which is higher than the 46.4% which could have been correctly predicted by chance. Chance is determined by the prior value in Table 42 for the largest subgroup by sample size, which was group 1 or those students who enrolled). This is a proportional reduction in error (PRE) of 18.09%, based on this formula: (56.1% - 46.4%) / (100% - 46.4%). This PRE indicates a substantial increase in prediction strength. Finally, this DF correctly classified 77.2% of the first group (i.e., students who did not enroll) but only 31.6% of the second group (i.e., students who enrolled).

Table 41. ***Additional analysis #3 (DFA: Classification)***

Classification Results[a]

		CollegeEnroll_2yr	Predicted Group Membership 0	1	Total
Original	Count	0	1965	580	2545
		1	1506	696	2202
		Ungrouped cases	3966	1027	4993
	%	0	77.2	22.8	100.0
		1	68.4	31.6	100.0
		Ungrouped cases	79.4	20.6	100.0

a. 56.1% of original grouped cases correctly classified.

Note. DFA classification results for additional analysis #3.

Table 42. ***Additional analysis #3 (DFA: Prior probabilities)***

Prior Probabilities for Groups

CollegeEnroll_2yr	Prior	Cases Used in Analysis Unweighted	Weighted
0	.536	2545	2545.000
1	.464	2202	2202.000
Total	1.000	4747	4747.000

Note. DFA prior probabilities of student assignment to the different subgroups of the DV, for additional analysis #3.

In order to further explore the pattern of results seen in the DFA above, a logistic regression was performed using the same DV and IVs. Similar to the first logistic regression, all statistical assumptions of logistic regression were checked and confirmed. The overall model was significant, χ (17) = 80.27, $p < .0001$, $R^2 = 0.02$. The classification results shown in Table 43 show that 56.1% of students overall were correctly classified, with 77.2% correct in the first group (i.e., students who did not enroll) and only 31.7% correct in the second group (i.e., students who enrolled). Table 44 shows the contribution of all the IVs in the model. The significant variables were the following: Asian, Latinx, HS GPA, college aspiration, and curricular intensity. It is interesting to note that the classification and significant variables produced by the logistic regression are consistent with the DFA results above.

Table 43. ***Additional analysis #3 (Logistic regression: Classification)***

Classification Table[a]

	Observed		Predicted: CollegeEnroll_2yr 0	Predicted: CollegeEnroll_2yr 1	Predicted: Percentage Correct
Step 1	CollegeEnroll_2yr	0	1965	580	77.2
		1	1503	699	31.7
	Overall Percentage				56.1

a. The cut value is .500

Note. Logistic regression classification results for additional analysis #3.

Table 44. *Additional analysis #3 (Logistic regression: Variables)*

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Gender(1)	.021	.063	.114	1	.736	1.022	.868	1.203
	Asian(1)	-.618	.161	14.672	1	.000	.539	.356	.817
	Black(1)	.028	.183	.024	1	.877	1.029	.643	1.646
	Latinx(1)	-.359	.134	7.164	1	.007	.699	.495	.987
	EL(1)	-.224	.143	2.445	1	.118	.799	.552	1.156
	Poverty(1)	-.152	.118	1.655	1	.198	.859	.634	1.164
	SchoolSize	.000	.000	.070	1	.792	1.000	1.000	1.000
	HS_SBAC_ELA	.000	.001	.041	1	.840	1.000	.999	1.001
	HS_SBAC_Math	-.001	.001	.943	1	.332	.999	.998	1.001
	MS_SBAC_ELA	.000	.001	.416	1	.519	1.000	.998	1.001
	MS_SBAC_Math	.000	.001	.014	1	.906	1.000	.999	1.002
	SAT_ELA	.000	.001	.550	1	.458	1.000	.999	1.002
	SAT_Math	.000	.001	.002	1	.963	1.000	.998	1.002
	HSGPA	-.242	.071	11.706	1	.001	.785	.654	.942
	MSGPA	.032	.059	.298	1	.585	1.032	.888	1.200
	CollegeAspiration	.102	.019	29.195	1	.000	1.107	1.055	1.162
	CurricularIntensity	.046	.017	7.098	1	.008	1.047	1.002	1.095
	Constant	2.549	1.675	2.316	1	.128	12.791		

a. Variable(s) entered on step 1: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, HS_SBAC_ELA, HS_SBAC_Math, MS_SBAC_ELA, MS_SBAC_Math, SAT_ELA, SAT_Math, HSGPA, MSGPA, CollegeAspiration, CurricularIntensity.

Note. Logistic regression results of model and IVs for additional analysis #3.

Additional Analysis #4

The fourth additional analysis was a DFA performed using a newly created dependent variable called “CollegeEnroll_4yr” which was dichotomous with two levels where 1 = enrolled in a four-year university and 0 = did not enroll in a four-year university. Note that this DV includes all students who enrolled in a four-year university, whether or not they persisted, and it also excludes all students who enrolled in a two-year college, whether or not they persisted. The purpose of this analysis was to determine how well college enrollment in a four-year university could be predicted or classified for all students based on the same set of 18 independent variables used previously. In the discriminant function, it was selected to predict group sizes according to prior probabilities.

In this fourth DFA, since there are only two levels or groups, there is only one DF. This DF was statistically significant at the $p < .0001$ level as shown in Table 45 had an eigenvalue of 0.299 and explained 100% of the variance in four-year college enrollment as shown in Table 46. The structure matrix in Table 47 revealed that the following independent variables made the most important contributions to the prediction, in order of importance: HS GPA, curicular intensity, HS_SBAC_Math, SAT_Math, college aspiration, MS GPA, HS_SBAC_ELA, SAT_ELA, MS_SBAC_Math, and MS_SBAC_ELA. It is interesting to note that this DF included only academic preparation variables as the most important variables.

Table 45. ***Additional analysis #4 (DFA: Wilks' Lambda)***

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.770	1970.509	17	.000

Note. Significance test of the discriminant functions for additional analysis #4.

Table 46. ***Additional analysis #4 (DFA: Eigenvalues)***

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.299[a]	100.0	100.0	.480

a. First 1 canonical discriminant functions were used in the analysis.

Note. Eigenvalues of the discriminant functions for additional analysis #4.

Table 47. ***Additional analysis #4 (DFA: Structure Matrix)***

Structure Matrix

	Function
	1
HSGPA	.865
CurricularIntensity	.615
HS_SBAC_Math	.538
SAT_Math	.519
CollegeAspiration	.512
MSGPA	.506
HS_SBAC_ELA	.494
SAT_ELA	.494
MS_SBAC_Math	.448
MS_SBAC_ELA	.394
EL	-.143
Gender	-.127
Poverty	-.107
Latinx	-.103
White[a]	.089
Black	.048
Asian	.034
SchoolSize	.003

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.

a. This variable not used in the analysis.

Note. Structure matrix of the discriminant functions for additional analysis #4. All relevant IVs are displayed in the first column and their loadings on each discriminant function are displayed in the subsequent columns. Higher loadings indicate higher importance of that IV for explaining the DV.

As shown in Table 48 below, 76.0% of the original cases were correctly predicted by this DF, which is higher than the 66.2% which could have been correctly predicted by chance. Chance is determined by the prior value in Table 49 for the largest subgroup by sample size, which was group 1 or those students who enrolled. This is a proportional reduction in error

(PRE) of 28.99%, based on this formula: (76.0% - 66.2%) / (100% - 66.2%). This PRE indicates a substantial increase in prediction strength. Finally, this DF correctly classified 49.0% of the first group (i.e., students who did not enroll) and 89.7% of the second group (i.e., students who enrolled).

Table 48. ***Additional analysis #4 (DFA: Classification)***

Classification Results[a]

		CollegeEnroll_4yr	Predicted Group Membership 0	1	Total
Original	Count	0	1248	1297	2545
		1	512	4481	4993
		Ungrouped cases	1042	1160	2202
	%	0	49.0	51.0	100.0
		1	10.3	89.7	100.0
		Ungrouped cases	47.3	52.7	100.0

a. 76.0% of original grouped cases correctly classified.

Note. DFA classification results for additional analysis #4.

Table 49. ***Additional analysis #4 (DFA: Prior probabilities)***

Prior Probabilities for Groups

		Cases Used in Analysis	
CollegeEnroll_4yr	Prior	Unweighted	Weighted
0	.338	2545	2545.000
1	.662	4993	4993.000
Total	1.000	7538	7538.000

Note. DFA prior probabilities of student assignment to the different subgroups of the DV, for additional analysis #4.

In order to further explore the pattern of results seen in the DFA above, a logistic regression was performed using the same DV and IVs. Similar to the first logistic regression, all statistical assumptions of logistic regression were checked and confirmed. The overall model was significant, χ (17) = 1846.62, p < .0001, R^2 = 0.22. The classification results shown in Table

50 show that 76% of students overall were correctly classified, with 49% correct in the first group (i.e., students who did not enroll) and 89.7% correct in the second group (i.e., students who enrolled). Table 51 shows the contribution of all the IVs in the model. The significant variables were the following: Asian, Black, MS_SBAC_ELA, SAT_ELA, SAT_Math, HS GPA, MS GPA, college aspiration, and curricular intensity. It is interesting to note that the classification and significant variables produced by the logistic regression are very similar to the DFA results above.

Table 50. ***Additional analysis #4 (Logistic regression: Classification)***

Classification Table[a]

	Observed		Predicted		
			CollegeEnroll_4yr		Percentage Correct
			0	1	
Step 1	CollegeEnroll_4yr	0	1247	1298	49.0
		1	512	4481	89.7
	Overall Percentage				76.0

a. The cut value is .500

Note. Logistic regression classification results for additional analysis #4.

Table 8. *Additional analysis #4 (Logistic regression: Variables)*

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Gender(1)	-.152	.061	6.156	1	.013	.859	.734	1.006
	Asian(1)	-.564	.146	14.914	1	.000	.569	.390	.829
	Black(1)	.527	.180	8.578	1	.003	1.693	1.066	2.690
	Latinx(1)	.132	.129	1.049	1	.306	1.141	.819	1.590
	EL(1)	-.241	.154	2.443	1	.118	.786	.529	1.169
	Poverty(1)	-.063	.110	.326	1	.568	.939	.708	1.246
	SchoolSize	.000	.000	1.720	1	.190	1.000	1.000	1.000
	HS_SBAC_ELA	.000	.001	.451	1	.502	1.000	.999	1.002
	HS_SBAC_Math	.000	.001	.478	1	.489	1.000	.999	1.002
	MS_SBAC_ELA	-.003	.001	22.491	1	.000	.997	.995	.999
	MS_SBAC_Math	.000	.001	.133	1	.715	1.000	.998	1.001
	SAT_ELA	.001	.001	5.685	1	.017	1.001	1.000	1.003
	SAT_Math	.002	.001	9.518	1	.002	1.002	1.000	1.004
	HSGPA	1.486	.074	400.098	1	.000	4.418	3.648	5.349
	MSGPA	-.170	.057	8.981	1	.003	.844	.729	.976
	CollegeAspiration	.273	.020	183.825	1	.000	1.314	1.248	1.384
	CurricularIntensity	.138	.018	57.663	1	.000	1.148	1.096	1.204
	Constant	-1.323	1.635	.655	1	.418	.266		

a. Variable(s) entered on step 1: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, HS_SBAC_ELA, HS_SBAC_Math, MS_SBAC_ELA, MS_SBAC_Math, SAT_ELA, SAT_Math, HSGPA, MSGPA, CollegeAspiration, CurricularIntensity.

Note. Logistic regression results of model and IVs for additional analysis #4.

Additional Analysis #5

The fifth additional analysis was a DFA performed using a newly created dependent variable called "CollegePersist_binary" which was dichotomous with two levels where 1 = persisted in a two-year college or four-year university and 0 = did not persist in a two-year college or four-year university. Note that this DV includes all students who enrolled, and excludes all students who did not enroll, in either a two-year college or four-year university. The purpose of this analysis was to determine how well college persistence, in general, could be predicted or classified for all students based on the same set of 18 independent variables used previously. In the discriminant function, it was selected to predict group sizes according to prior probabilities.

In this DFA, since there are only two levels or groups, there is only one DF. This DF was statistically significant at the $p < .0001$ level as shown in Table 52, had an eigenvalue of 0.116 and explained 100% of the variance in overall college persistence as shown in Table 53. The structure matrix in Table 54 revealed that the following independent variables made the most important contributions to the prediction, in order of importance: HSGPA, MSGPA, SAT_ELA, HS_SBAC_Math, curricular intensity, HS_SBAC_ELA, SAT_Math, MS_SBAC_ELA, MS_SBAC_Math, college aspiration, and gender, with additional but decreasing contributions from the other variables. It is interesting to note that this DF included almost entirely academic preparation variables as the most important variables.

Table 52. ***Additional analysis #5 (DFA: Wilks' Lambda)***

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.896	787.310	17	.000

Note. Significance test of the discriminant functions for additional analysis #5.

Table 53 ***Additional analysis #5 (DFA: Eigenvalues)***

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.116[a]	100.0	100.0	.322

a. First 1 canonical discriminant functions were used in the analysis.

Note. Eigenvalues of the discriminant functions for additional analysis #5.

Table 9. *Additional analysis #5 (DFA: Structure Matrix)*

Structure Matrix

	Function
	1
HSGPA	.902
MSGPA	.624
SAT_ELA	.592
HS_SBAC_Math	.591
CurricularIntensity	.582
HS_SBAC_ELA	.581
SAT_Math	.548
MS_SBAC_ELA	.526
MS_SBAC_Math	.496
CollegeAspiration	.372
Gender	-.355
Asian	.220
Latinx	-.217
Poverty	-.165
White[a]	.144
EL	-.106
SchoolSize	-.051
Black	-.049

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.

a. This variable not used in the analysis.

Note. Structure matrix of the discriminant functions for additional analysis #5. All relevant IVs are displayed in the first column and their loadings on each discriminant function are displayed in the subsequent columns. Higher loadings indicate higher importance of that IV for explaining the DV.

As shown in Table 55 below, 87.8% of the original cases were correctly predicted by this DF. However, this is not higher than 88.0% which could have been correctly predicted by chance. Chance was determined by the prior value in Table 56 for the largest subgroup by sample size, which was group 1 or those students who persisted. This is a proportional reduction in error (PRE) of -1.67%, based on this formula: (87.8% - 88.0%) / (100% - 88.0%). This PRE which has a negative value indicates that there was no improvement over chance prediction, or in fact an increase in error, based on the prior probabilities. Finally, this DF correctly classified only 9.2% of the first group (i.e., students who did not persist) but 98.5% of the second group (i.e., students who persisted).

Table 55. ***Additional analysis #5 (DFA: Classification)***

Classification Results[a]

		CollegePersist_2yr4yr	Predicted Group Membership 0	Predicted Group Membership 1	Total
Original	Count	0	79	782	861
		1	98	6236	6334
		Ungrouped cases	224	2321	2545
	%	0	9.2	90.8	100.0
		1	1.5	98.5	100.0
		Ungrouped cases	8.8	91.2	100.0

a. 87.8% of original grouped cases correctly classified.

Note. DFA classification results for additional analysis #5.

Table 56. ***Additional analysis #5 (DFA: Prior probabilities)***

Prior Probabilities for Groups

CollegePersist_2yr4yr	Prior	Cases Used in Analysis: Unweighted	Cases Used in Analysis: Weighted
0	.120	861	861.000
1	.880	6334	6334.000
Total	1.000	7195	7195.000

Note. DFA prior probabilities of student assignment to the different subgroups of the DV, for additional analysis #5.

In order to further explore the pattern of results seen in the DFA above, a logistic regression was performed using the same DV and IVs. Similar to the first logistic regression, all statistical assumptions of logistic regression were checked and confirmed. The overall model was significant, χ (17) = 736.59, $p < .0001$, $R^2 = 0.10$. The classification results in Table 57 show that 88.0% of students overall were correctly classified, with only 5.5% correct in the first group (i.e., students who did not persist) and 99.2% correct in the second group (i.e., students who persisted). Table 58 shows the contribution of all the IVs in the model. The significant variables were the following: gender, SAT_ELA, HS GPA, and college aspiration.

Table 10. ***Additional analysis #5 (Logistic regression: Classification)***

Classification Table[a]

	Observed		Predicted		
			CollegePersist_2yr4yr		Percentage Correct
			0	1	
Step 1	CollegePersist_2yr4yr	0	47	814	5.5
		1	50	6284	99.2
	Overall Percentage				88.0

a. The cut value is .500

Note. Logistic regression classification results for additional analysis #5.

Table 118. *Additional analysis #5 (Logistic regression: Variables)*

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Gender(1)	-.674	.082	67.038	1	.000	.510	.412	.630
	Asian(1)	.229	.267	.736	1	.391	1.258	.632	2.505
	Black(1)	-.151	.248	.367	1	.544	.860	.454	1.631
	Latinx(1)	-.212	.202	1.105	1	.293	.809	.480	1.361
	EL(1)	.119	.200	.358	1	.550	1.127	.674	1.885
	Poverty(1)	-.125	.176	.505	1	.477	.883	.561	1.388
	SchoolSize	.000	.000	.891	1	.345	1.000	1.000	1.000
	HS_SBAC_ELA	.000	.001	.304	1	.581	1.000	.999	1.002
	HS_SBAC_Math	.001	.001	3.374	1	.066	1.001	.999	1.003
	MS_SBAC_ELA	-.001	.001	.516	1	.473	.999	.997	1.002
	MS_SBAC_Math	-.001	.001	3.595	1	.058	.999	.997	1.001
	SAT_ELA	.003	.001	14.335	1	.000	1.003	1.001	1.005
	SAT_Math	.001	.001	.883	1	.347	1.001	.999	1.003
	HSGPA	1.038	.094	121.257	1	.000	2.822	2.214	3.598
	MSGPA	.041	.075	.299	1	.585	1.042	.859	1.263
	CollegeAspiration	.110	.026	17.571	1	.000	1.116	1.043	1.194
	CurricularIntensity	.015	.023	.413	1	.521	1.015	.956	1.078
	Constant	-2.742	2.193	1.564	1	.211	.064		

a. Variable(s) entered on step 1: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, HS_SBAC_ELA, HS_SBAC_Math, MS_SBAC_ELA, MS_SBAC_Math, SAT_ELA, SAT_Math, HSGPA, MSGPA, CollegeAspiration, CurricularIntensity.

Note. Logistic regression results of model and IVs for additional analysis #5.

Additional Analysis #6

The sixth additional analysis was a DFA performed using a newly created dependent variable called "CollegePersist_2yr" which was dichotomous with two levels where 1 = persisted in a two-year college and 0 = did not persist in a two-year college. Note that this DV includes all students who enrolled in a two-year college, and excludes all students who enrolled in a four-year university or who did not enroll in two-year college or four-year university. The purpose of this analysis was to determine how well college persistence in a two-year college could be predicted or classified for all students based on the same set of 18 independent variables used previously. In the discriminant function, it was selected to predict group sizes according to prior probabilities.

In this DFA, since there are only two levels or groups, there is only one DF. This DF was statistically significant at the $p < .0001$ level as shown in Table 59 and had an eigenvalue of 0.123 and explained 100% of the variance in two-year college persistence as shown in Table 60. The structure matrix in Table 61 revealed that the following independent variables made the most important contributions to the prediction, in order of importance: HSGPA, MSGPA, SAT_Math, curricular intensity, SAT_ELA, HS_SBAC_ELA, HS_SBAC_Math, gender, MS_SBAC_ELA, MS_SBAC_Math, college aspiration, Asian, poverty, and Latinx, with additional but decreasing contributions from the other variables. It is interesting to note that this DF included a mix of mostly academic preparation variables as well some demographic variables.

Table 59. ***Additional analysis #6 (DFA: Wilks' Lambda)***

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.891	253.714	17	.000

Note. Significance test of the discriminant function for additional analysis #6.

Table 60. ***Additional analysis #6 (DFA: Eigenvalues)***

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.123[a]	100.0	100.0	.331

a. First 1 canonical discriminant functions were used in the analysis.

Note. Eigenvalues of the discriminant functions for additional analysis #6.

Table 12. *Additional analysis #6 (DFA: Structure Matrix)*

Structure Matrix

	Function
	1
HSGPA	.803
MSGPA	.555
SAT_Math	.533
CurricularIntensity	.532
SAT_ELA	.532
HS_SBAC_ELA	.521
HS_SBAC_Math	.517
Gender	-.485
MS_SBAC_ELA	.462
MS_SBAC_Math	.456
CollegeAspiration	.362
Asian	.252
Poverty	-.211
Latinx	-.199
White[a]	.139
EL	-.083
Black	-.078
SchoolSize	-.039

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.

a. This variable not used in the analysis.

Note. Structure matrix of the discriminant functions for additional analysis #6. All relevant IVs are displayed in the first column and their loadings on each discriminant function are displayed in the subsequent columns. Higher loadings indicate higher importance of that IV for explaining the DV.

As shown in Table 62 below, 78.6% of the original cases were correctly predicted by this DF. However, this is not higher than 78.7% which could have been correctly predicted by chance. Chance was determined by the prior value in Table 63 for the largest subgroup by sample size, which was group 1 or those students who persisted. This is a proportional reduction in error (PRE) of -.47%, based on this formula: (78.6% - 78.7%) / (100% - 78.7%). This PRE which has a negative value indicates that there was no improvement over chance prediction, or in fact an increase in error, based on the prior probabilities. Finally, this DF correctly classified only 10.7% of the first group (i.e., students who did not persist) but 96.9% of the second group (i.e., students who persisted).

Table 13. ***Additional analysis #6 (DFA: Classification)***

Classification Results[a]

		CollegePersist_2yr	Predicted Group Membership 0	1	Total
Original	Count	0	50	419	469
		1	53	1680	1733
		Ungrouped cases	144	7394	7538
	%	0	10.7	89.3	100.0
		1	3.1	96.9	100.0
		Ungrouped cases	1.9	98.1	100.0

a. 78.6% of original grouped cases correctly classified.

Note. DFA classification results for additional analysis #6.

Table 14. ***Additional analysis #6 (DFA: Prior probabilities)***

Prior Probabilities for Groups

CollegePersist_2yr	Prior	Cases Used in Analysis Unweighted	Weighted
0	.213	469	469.000
1	.787	1733	1733.000
Total	1.000	2202	2202.000

Note. DFA prior probabilities of student assignment to the different subgroups of the DV, for additional analysis #6.

In order to further explore the pattern of results seen in the DFA above, a logistic regression was performed using the same DV and IVs. Similar to the first logistic regression, all statistical assumptions of logistic regression were checked and confirmed. The overall model was significant, χ (17) = 257.94, $p < .0001$, $R^2 = 0.11$. The classification results in Table 64 show that 78.5% of students overall were correctly classified, with only 10.4% correct in the first group (i.e., students who did not persist) and 96.9% correct in the second group (i.e., students who persisted). Table 65 shows the contribution of all the IVs in the model. The significant variables were the following: gender, HSGPA, and college aspiration. It is interesting to note that the classification and significant variables produced by the logistic regression are very similar to the DFA results above.

Table 15. ***Additional analysis #6 (Logistic regression: Classification)***

Classification Table[a]

Observed			Predicted: CollegePersist_2yr 0	Predicted: CollegePersist_2yr 1	Predicted: Percentage Correct
Step 1	CollegePersist_2yr	0	49	420	10.4
		1	53	1680	96.9
	Overall Percentage				78.5

a. The cut value is .500

Note. Logistic regression classification results for additional analysis #6.

Table 16. *Additional analysis #6 (Logistic regression: Variables)*

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Gender(1)	-.803	.118	46.652	1	.000	.448	.331	.606
	Asian(1)	.656	.395	2.759	1	.097	1.926	.697	5.324
	Black(1)	.116	.334	.120	1	.729	1.123	.474	2.657
	Latinx(1)	.133	.269	.245	1	.621	1.142	.572	2.283
	EL(1)	.183	.262	.486	1	.486	1.201	.611	2.360
	Poverty(1)	-.439	.268	2.697	1	.101	.644	.324	1.284
	SchoolSize	.000	.000	.133	1	.715	1.000	1.000	1.000
	HS_SBAC_ELA	.001	.001	.835	1	.361	1.001	.998	1.003
	HS_SBAC_Math	.000	.001	.092	1	.762	1.000	.998	1.003
	MS_SBAC_ELA	-.001	.001	.672	1	.412	.999	.996	1.002
	MS_SBAC_Math	-.001	.001	.395	1	.530	.999	.997	1.002
	SAT_ELA	.002	.001	3.471	1	.062	1.002	.999	1.005
	SAT_Math	.002	.001	3.491	1	.062	1.002	.999	1.006
	HSGPA	.802	.136	34.669	1	.000	2.231	1.570	3.169
	MSGPA	-.008	.113	.005	1	.944	.992	.742	1.326
	CollegeAspiration	.116	.034	11.529	1	.001	1.123	1.028	1.226
	CurricularIntensity	.017	.030	.326	1	.568	1.018	.941	1.101
	Constant	-1.899	3.095	.376	1	.540	.150		

a. Variable(s) entered on step 1: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, HS_SBAC_ELA, HS_SBAC_Math, MS_SBAC_ELA, MS_SBAC_Math, SAT_ELA, SAT_Math, HSGPA, MSGPA, CollegeAspiration, CurricularIntensity.

Note. Logistic regression results of model and IVs for additional analysis #6.

Additional Analysis #7

The seventh additional analysis was a DFA performed using a newly created dependent variable called "CollegePersist_4yr" which was dichotomous with two levels where 1 = persisted in a four-year university and 0 = did not persist in a four-year university. Note that this DV includes all students who enrolled in a four-year university, and excludes all students who enrolled in a two-year college or who did not enroll in two-year college or four-year university. The purpose of this analysis was to determine how well college persistence in a four-year university could be predicted or classified for all students based on the same set of 18 independent variables used previously. In the discriminant function, it was selected to predict group sizes according to prior probabilities.

In this DFA, since there are only two levels or groups, there is only one DF. This DF was statistically significant at the $p < .0001$ level as shown in Table 66, and had an eigenvalue of 0.057 and explained 100% of the variance in two-year college persistence as shown in Table 67. The structure matrix in Table 68 revealed that the following independent variables made the most important contributions to the prediction, in order of importance: HSGPA, MSGPA, SAT_ELA, HS_SBAC_Math, HS_SBAC_ELA, MS_SBAC_ELA, SAT_Math, MS_SBAC_Math, curricular intensity, gender, Latinx, college aspiration, Asian, and White, with additional but decreasing contributions from the other variables. It is interesting that this DF included a mix of mostly academic preparation variables as well some demographic variables.

Table 66. ***Additional analysis #7 (DFA: Wilks' Lambda)***

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.946	276.540	17	.000

Note. Significance test of the discriminant functions for additional analysis #7.

Table 67. ***Additional analysis #7 (DFA: Eigenvalues)***

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.057[a]	100.0	100.0	.232

a. First 1 canonical discriminant functions were used in the analysis.

Note. Eigenvalues of the discriminant functions for additional analysis #7.

Table 17. *Additional analysis #7 (DFA: Structure Matrix)*

Structure Matrix

	Function
	1
HSGPA	.892
MSGPA	.639
SAT_ELA	.627
HS_SBAC_Math	.574
HS_SBAC_ELA	.563
MS_SBAC_ELA	.560
SAT_Math	.508
MS_SBAC_Math	.464
CurricularIntensity	.458
Gender	-.304
Latinx	-.293
CollegeAspiration	.244
Asian	.237
White[a]	.202
Poverty	-.160
EL	-.100
SchoolSize	-.089
Black	-.009

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.

a. This variable not used in the analysis.

Note. Structure matrix of the discriminant functions for additional analysis #7. All relevant IVs are displayed in the first column and their loadings on each discriminant function are displayed in the subsequent columns. Higher loadings indicate higher importance of that IV for explaining the DV.

As shown in Table 69 below, 92.1% of the original cases were correctly predicted by this DF, which is identical to the 92.1% which could have been correctly predicted by chance, where chance was determined by the prior value in Table 70 for the largest subgroup by sample size, which was group 1 or those students who persisted. This is a proportional reduction in error (PRE) of 0.0%, based on this formula: (92.1% - 92.1%) / (100% - 92.1%). In other words, there was no improvement over chance prediction. Finally, this DF correctly classified only 0.3% of the first group (i.e., students who did not persist) but 99.9% of the second group (i.e., students who persisted).

Table 18. ***Additional analysis #7 (DFA: Classification)***

Classification Results[a]

			Predicted Group Membership		
		CollegePersist_4yr	0	1	Total
Original	Count	0	1	391	392
		1	5	4596	4601
		Ungrouped cases	279	4468	4747
	%	0	.3	99.7	100.0
		1	.1	99.9	100.0
		Ungrouped cases	5.9	94.1	100.0

a. 92.1% of original grouped cases correctly classified.

Note. DFA classification results for additional analysis #7.

Table 70. ***Additional analysis #7 (DFA: Prior probabilities)***

Prior Probabilities for Groups

		Cases Used in Analysis	
CollegePersist_4yr	Prior	Unweighted	Weighted
0	.079	392	392.000
1	.921	4601	4601.000
Total	1.000	4993	4993.000

Note. DFA prior probabilities of student assignment to the different subgroups of the DV, for additional analysis #7.

In order to further explore the pattern of results seen in the DFA above, a logistic regression was performed using the same DV and IVs. Similar to the first logistic regression, all statistical assumptions of logistic regression were checked and confirmed. The overall model was significant, χ (17) = 267.01, $p < .0001$, $R^2 = 0.05$. The classification results in Table 71 show that 92.1% of students overall were correctly classified, with only 0.0% correct in the first group (i.e., students who did not persist) and 100% correct in the second group (i.e., students who persisted). Table 72 shows the contribution of all the IVs in the model. The significant variables were the following: gender, Latinx, HS_SBAC_Math, MS_SBAC_Math, SAT_ELA, and HSGPA. It is interesting to note that the classification and significant variables produced by the logistic regression are very similar to the DFA results above.

Table 19. ***Additional analysis #7 (Logistic regression: Classification)***

Classification Table[a]

Observed			Predicted		
			CollegePersist_4yr		Percentage Correct
			0	1	
Step 1	CollegePersist_4yr	0	0	392	.0
		1	1	4600	100.0
	Overall Percentage				92.1

a. The cut value is .500

Note. Logistic regression classification results for additional analysis #7.

Table 72. ***Additional analysis #7 (Logistic regression: Variables)***

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Gender(1)	-.530	.117	20.591	1	.000	.588	.436	.795
	Asian(1)	-.228	.386	.350	1	.554	.796	.294	2.152
	Black(1)	-.563	.386	2.122	1	.145	.570	.211	1.541
	Latinx(1)	-.706	.320	4.876	1	.027	.493	.216	1.125
	EL(1)	.002	.308	.000	1	.995	1.002	.453	2.217
	Poverty(1)	.172	.233	.548	1	.459	1.188	.652	2.166
	SchoolSize	.000	.000	.751	1	.386	1.000	1.000	1.000
	HS_SBAC_ELA	.000	.001	.080	1	.777	1.000	.997	1.002
	HS_SBAC_Math	.002	.001	4.610	1	.032	1.002	1.000	1.005
	MS_SBAC_ELA	.000	.001	.019	1	.890	1.000	.997	1.003
	MS_SBAC_Math	-.002	.001	4.391	1	.036	.998	.995	1.001
	SAT_ELA	.004	.001	11.553	1	.001	1.004	1.001	1.007
	SAT_Math	-.001	.001	.414	1	.520	.999	.996	1.002
	HSGPA	1.082	.148	53.601	1	.000	2.950	2.016	4.316
	MSGPA	.103	.100	1.059	1	.303	1.109	.856	1.436
	CollegeAspiration	.064	.043	2.223	1	.136	1.066	.954	1.192
	CurricularIntensity	.001	.037	.000	1	.985	1.001	.910	1.100
	Constant	-2.744	3.146	.761	1	.383	.064		

a. Variable(s) entered on step 1: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, HS_SBAC_ELA, HS_SBAC_Math, MS_SBAC_ELA, MS_SBAC_Math, SAT_ELA, SAT_Math, HSGPA, MSGPA, CollegeAspiration, CurricularIntensity.

Note. Logistic regression results of model and IVs for additional analysis #7.

Additional Analysis #8

The final additional analysis was a DFA performed using a newly created dependent variable called “CollegeEnroll_2yr_vs_4yr” which was dichotomous with two levels where 1 = enrolled in a four-year university and 0 = enrolled in a two-year college. The purpose of this analysis was to determine how well differences in enrollment between two-year college and four-year university could be predicted or classified for all students based on the same set of 18 independent variables used previously. In the discriminant function, it was selected to predict group sizes according to prior probabilities.

In this DFA, since there are only two levels or groups, there is only one DF. This DF was statistically significant at the $p < .0001$ level as shown in Table 73, had an eigenvalue of 0.315 and explained 100% of the variance as shown in Table 74. The structure matrix shown in Table 75 revealed that the following independent variables made the most important contributions to the prediction, in order of importance: HSGPA, HS_SBAC_Math, curricular intensity, MSGPA, SAT_Math, HS_SBAC_ELA, SAT_ELA, MS_SBAC_Math, MS_SBAC_ELA, and college aspirations. It is interesting to note that this DF included only academic preparation variables as most important.

Table 20. ***Additional analysis #8 (DFA: Wilks' Lambda)***

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.761	1966.775	17	.000

Note. Significance test of the discriminant functions for additional analysis #8.

Table 74. ***Additional analysis #8 (DFA: Eigenvalues)***

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.315[a]	100.0	100.0	.489

a. First 1 canonical discriminant functions were used in the analysis.

Note. Eigenvalues of the discriminant functions for additional analysis #8.

Table 21. *Additional analysis #8 (DFA: Structure Matrix)*

Structure Matrix

	Function
	1
HSGPA	.923
HS_SBAC_Math	.568
CurricularIntensity	.565
MSGPA	.520
SAT_Math	.518
HS_SBAC_ELA	.499
SAT_ELA	.473
MS_SBAC_Math	.456
MS_SBAC_ELA	.395
CollegeAspiration	.370
Gender	-.121
Asian	.104
EL	-.096
Poverty	-.070
Latinx[a]	-.067
Black	-.040
White	.025
SchoolSize	.002

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions
Variables ordered by absolute size of correlation within function.

a. This variable not used in the analysis.

Note. Structure matrix of the discriminant functions for additional analysis #8. All relevant IVs are displayed in the first column and their loadings on each discriminant function are displayed in the subsequent columns. Higher loadings indicate higher importance of that IV for explaining the DV.

As shown in Table 76 below, 77.1% of the original cases were correctly predicted by this DF, which is higher than the 69.4% which could have been correctly predicted by chance. Chance is determined by the prior value in Table 77 for the largest subgroup by sample size, which was group 1 or those students who enrolled). This is a proportional reduction in error (PRE) of 25.16%, based on this formula: (77.1% - 69.4%) / (100% - 69.4%). This PRE indicates a substantial increase in prediction strength. Finally, this DF correctly classified 47.1% of the first group (i.e., students who enrolled in two-year college) and 90.3% of the second group (i.e., students who enrolled in four-year university).

Table 76. ***Additional analysis #8 (DFA: Classification)***

Classification Results[a]

		CollegeEnroll_2yr_vs_4yr	Predicted Group Membership 0	1	Total
Original	Count	0	1037	1165	2202
		1	482	4511	4993
		Ungrouped cases	1187	1358	2545
	%	0	47.1	52.9	100.0
		1	9.7	90.3	100.0
		Ungrouped cases	46.6	53.4	100.0

a. 77.1% of original grouped cases correctly classified.

Note. DFA classification results for additional analysis #8.

Table 77. ***Additional analysis #8 (DFA: Prior probabilities)***

Prior Probabilities for Groups

CollegeEnroll_2yr_vs_4yr	Prior	Cases Used in Analysis Unweighted	Weighted
0	.306	2202	2202.000
1	.694	4993	4993.000
Total	1.000	7195	7195.000

Note. DFA prior probabilities of student assignment to the different subgroups of the DV, for additional analysis #8.

In order to further explore the pattern of results seen in the DFA above, a logistic regression was performed using the same DV and IVs. Similar to the first logistic regression, all statistical assumptions of logistic regression were checked and confirmed. The overall model was significant, χ (17) = 1819.77, $p < .0001$, $R^2 = 0.32$. The classification results shown in Table 78 show that 77.2% of students overall were correctly classified, with 90.8% correct in the first group (i.e., students who enrolled in four-year university) and only 46.2% correct in the second group (i.e., students who enrolled in two-year college). Table 79 shows the contribution of all the IVs in the model. The significant variables were the following: gender, Black, Latinx, HS_SBAC_Math, MS_SBAC_ELA, SAT_Math, HSGPA, MSGPA, college aspirations, and curricular intensity. It is interesting to note that the classification and significant variables produced by the logistic regression are consistent with the DFA results above.

Table 78. ***Additional analysis #8 (Logistic regression: Classification)***

Classification Table[a]

	Observed		Predicted		
			CollegeEnroll_2yr_vs_4yr		Percentage Correct
			0	1	
Step 1	CollegeEnroll_2yr_vs_4yr	0	1017	1185	46.2
		1	457	4536	90.8
	Overall Percentage				77.2

a. The cut value is .500

Note. Logistic regression classification results for additional analysis #8.

Table 79. ***Additional analysis #8 (Logistic regression: Variables)***

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)	99% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	Gender(1)	-.141	.064	4.833	1	.028	.868	.736	1.025
	Asian(1)	.072	.150	.231	1	.631	1.075	.730	1.584
	Black(1)	.683	.170	16.208	1	.000	1.980	1.279	3.065
	Latinx(1)	.530	.125	18.119	1	.000	1.699	1.233	2.342
	EL(1)	.041	.171	.059	1	.808	1.042	.671	1.618
	Poverty(1)	.161	.111	2.098	1	.148	1.175	.882	1.565
	SchoolSize	.000	.000	2.598	1	.107	1.000	1.000	1.000
	HS_SBAC_ELA	.001	.001	2.605	1	.107	1.001	.999	1.002
	HS_SBAC_Math	.001	.001	4.400	1	.036	1.001	1.000	1.003
	MS_SBAC_ELA	-.003	.001	16.314	1	.000	.997	.996	.999
	MS_SBAC_Math	-.001	.001	.816	1	.366	.999	.998	1.001
	SAT_ELA	.001	.001	2.304	1	.129	1.001	.999	1.003
	SAT_Math	.002	.001	7.627	1	.006	1.002	1.000	1.004
	HSGPA	1.788	.079	518.569	1	.000	5.980	4.885	7.321
	MSGPA	-.186	.061	9.455	1	.002	.830	.710	.970
	CollegeAspiration	.208	.023	85.611	1	.000	1.232	1.162	1.305
	CurricularIntensity	.094	.019	24.262	1	.000	1.099	1.046	1.154
	Constant	-5.488	1.715	10.234	1	.001	.004		

a. Variable(s) entered on step 1: Gender, Asian, Black, Latinx, EL, Poverty, SchoolSize, HS_SBAC_ELA, HS_SBAC_Math, MS_SBAC_ELA, MS_SBAC_Math, SAT_ELA, SAT_Math, HSGPA, MSGPA, CollegeAspiration, CurricularIntensity.

Note. Logistic regression results of model and IVs for additional analysis #8.

Additional Analysis #9

In order to better understand which of these other independent variables were responsible for the lack of SBAC effect, some follow-up regression analyses were conducted with the same five-level variable of college enrollment and persistence as the DV (see Supplemental Materials). In the first regression model, the IVs included only HS SBAC Math and HS SBAC ELA, both of which significantly predicted college. In the second regression model, the IVs included only HS SBAC Math, HS SBAC ELA, and HSGPA, all of which significantly predicted college, indicating HSGPA was not responsible by itself. In the third regression model, the IVs included only HS SBAC Math, HS SBAC ELA, college aspiration, and curricular intensity, all of which significantly predicted college, indicating that college aspiration and curricular intensity were not responsible by themselves. In the fourth regression model, the IVs included only HS SBAC Math, HS SBAC ELA, SAT Math, and SAT ELA, all of which significantly predicted college, indicating that SAT scores were not responsible by themselves. In the fifth regression model, the IVs included all six academic predictors - HS SBAC Math, HS SBAC ELA, SAT Math, SAT ELA, curricular intensity, and college aspirations – and all predictors *except* the HS SBAC scores were significant. In other words, the initial relation between HS SBAC tests and college readiness disappeared only when controlling for the *combined* effects, not the individual effects, of the other four academic predictors.

It is important to note, however, that the other variables in the model included not only the demographic and school variables but also all the other academic variables, so it's difficult to know which variables contributed to the lack of SBAC predictive effects. Some follow-up regression analyses were conducted to probe this issue further. In a first regression model with only HS SBAC Math and HS SBAC ELA as the IVs, each HS SBAC test significantly and positively predicted college enrollment and persistence. In a second regression model which added the demographic and school variables as additional IVs, the HS SBAC predictive effects remained significant. This procedure was repeated for the MS SBAC tests and the results were the same. These follow-up findings suggest that the lack of SBAC effects seen in the first regression of the main path analysis are probably not due to the demographic and school variables, because if they were, then the SBAC effects would have disappeared with the inclusion of those demographic and school variables.

Summary Tables of Main Results

The three tables below summarize and simplify the various results that were obtained for the main path analysis, the logistic regressions, and the discriminant function analyses in order to enable easier detection of overall patterns of which variables were most relevant for prediction or classification. In Table 80 and Table 81, for example, there are three variables which were always, or almost always, significant and positively predictive: HS GPA, college aspirations, and curricular intensity. In Table 82, the academic variables almost always had high importance for classification, whereas the demographic and school variables almost always had low importance. These various results and patterns are further discussed in the next chapter.

Table 80. ***Summary results of main path analysis***

	Path Analysis Regressions									
	#1	**#2**	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**	**#9**	**#10**
IV	College Enroll/Persist	SAT Math	SAT ELA	HS SBAC Math	HS SBAC ELA	MS SBAC Math	MS SBAC ELA	Curricular Intensity	HS GPA	MS GPA
Gender	-	+	+	+	+	+	-	-	-	-
Asian	-	+	-	+	+	+	ns	+	ns	+
Black	+	-	-	-	-	-	-	-	-	-
Latinx	ns	-	-	ns	ns	-	-	-	-	-
EL	ns	-	-	ns	-	-	-	-	ns	-
Poverty	ns	-	-	-	ns	-	-	-	-	-
College Aspirations	+	+	+	+	+	+	+	+	+	+
School Size	ns	ns	ns	ns	+			-	+	
Curricular Intensity	+	+	+	+	+				+	
MS GPA	ns	+	+	ns	-	+	+		+	
HS GPA	+	+	+	+	+					
MS SBAC ELA	-				+					
MS SBAC Math	ns			+						
HS SBAC ELA	ns									
HS SBAC Math	ns									
SAT ELA	+									
SAT Math	+									
Model R^2	0.19	0.48	0.41	0.67	0.58	0.46	0.43	0.17	0.65	0.18

Note. Significant positive relations are shown with "+", significant negative relations are shown with "-", and non-significant relations are shown with "ns". Gray boxes indicate that the IV did not enter into that specific model because there was no hypothesized path in the diagram.

Table 81. Summary results of logistic regressions

	Logistic Regressions						
	#2	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**
	DV	**DV**	**DV**	**DV**	**DV**	**DV**	**DV**
IV	College Enroll (2yr and 4yr)	College Enroll (2yr)	College Enroll (4yr)	College Persist (2yr and 4yr)	College Persist (2yr)	College Persist (4yr)	College Enroll (2yr vs 4yr)
Gender	ns	ns	-	-	-	-	-
Asian	-	-	-	ns	ns	ns	ns
Black	+	ns	+	ns	ns	ns	+
Latinx	ns	-	ns	ns	ns	-	+
EL	ns	ns	ns	ns	ns	ns	ns
Poverty	ns	ns	ns	ns	ns	ns	ns
School Size	ns	ns	ns	ns	ns	ns	ns
HS SBAC ELA	ns	ns	ns	ns	ns	ns	ns
HS SBAC Math	ns	ns	ns	ns	ns	+	+
MS SBAC ELA	-	ns	-	ns	ns	ns	-
MS SBAC Math	ns	ns	ns	ns	ns	-	ns
SAT ELA	+	ns	+	+	ns	+	ns
SAT Math	+	ns	+	ns	ns	ns	+
HS GPA	+	-	+	+	+	+	+
MS GPA	ns	ns	-	ns	ns	ns	-
College Aspirations	+	+	+	+	+	ns	+
Curricular Intensity	+	+	+	ns	ns	ns	+
Model R^2	0.13	0.02	0.31	0.19	0.17	0.12	0.32

Note. Significant positive relations are shown with "+", significant negative relations are shown with "-", and non-significant relations are shown with "ns".

Table 82. ***Summary results of DFAs***

	Discriminant Function Analyses						
	#2	**#3**	**#4**	**#5**	**#6**	**#7**	**#8**
	DV	**DV**	**DV**	**DV**	**DV**	**DV**	**DV**
IV	College Enroll (2yr and 4yr)	College Enroll (2yr)	College Enroll (4yr)	College Persist (2yr and 4yr)	College Persist (2yr)	College Persist (4yr)	College Enroll (2yr vs 4yr)
Gender	low	low	low	high	high	high	low
Asian	low	high	low	low	low	low	low
Black	low	high	low	low	low	low	low
Latinx	low	low	low	low	low	low	low
White	low	high	low	low	low	low	low
EL	low	high	low	low	low	low	low
Poverty	low	low	low	low	low	low	low
School Size	low	low	low	low	low	low	low
HS SBAC ELA	high	low	high	high	high	high	high
HS SBAC Math	high	low	high	high	high	high	high
MS SBAC ELA	high	low	high	high	high	high	high
MS SBAC Math	high	low	high	high	high	high	high
SAT ELA	high	low	high	high	high	high	high
SAT Math	high	low	high	high	high	high	high
HS GPA	high	high	high	high	high	high	high
MS GPA	high	low	high	high	high	high	high
College Aspirations	high	high	high	high	high	high	high
Curricular Intensity	high	low	high	high	high	high	high

Note. "High" indicates the IV had a high loading on the DFA structure matrix such that it was important in classifying the DV. "Low" indicates a low loading and relative lack of importance. A cutoff threshold of 0.30 was chosen to separate high and low loadings based on the observation that the loadings tended to cluster around this value for most of the structure matrices.

CHAPTER 5

Discussion

The research problem of the present study was the gap in knowledge about the predictive validity and potential demographic and school biases of the middle and high school SBAC tests for college readiness in comparison to GPA, SAT, curricular intensity, and college aspirations. The purpose was to conduct a quantitative study using statistical analysis to investigate the degree to which college readiness, as measured by college enrollment and persistence, can be predicted by the SBAC tests in comparison to GPA, SAT, curricular intensity, and college aspirations while accounting for potential biases of school type (i.e., school size) and student demographics of ethnicity, poverty, language classification (i.e., EL), and gender. This study is theoretically grounded in Conley's multidimensional definition of college readiness (Conley, 2014, 2017) as well as the QuanCrit framework (Garcia et al., 2018; Gilbourn et al., 2018) for guiding the use of quantitative research on racial and socioeconomic issues in education. This study investigated these topics with several research questions which are discussed below in light of the observed findings, interpretations, and potential limitations.

Research Question 1

The first research question asked, to what extent do the 11th-grade SBAC tests in Math and ELA predict college readiness as measured by enrollment and persistence, in comparison to SAT tests in Math and ELA, high school GPA, and curricular intensity, while controlling for middle school GPA, middle school SBAC tests in Math and ELA, college aspirations, school size, and student demographics? The overall pattern was that HSGPA, SAT tests, curricular intensity, and college aspirations each uniquely and positively predicted college readiness, which was consistently observed in the path analysis and less consistently so in the logistic regressions and DFAs, whereas the SBAC tests in general did not show any predictive validity. This pattern consisted of several important findings which are described below for all academic indicators, followed by separate discussions for each indicator.

All academic indicators

Before controlling for any other variables, the high school SBAC tests initially showed some positive correlation with college readiness, such that increasing test scores were associated with increasing levels of enrollment and persistence, as indicated by the original covariation values in Table 3. Similarly, the other predictors of interest – HSGPA, MSGPA, curricular intensity, college aspirations, and SAT tests – also showed similar positive association with college readiness when considered independently. But when controlling for other variables, the results varied depending on the statistical analysis. According to the path analysis, the high school SBAC tests did not uniquely predict college or show any total causal influence, while the variables of GPA, SAT tests, curricular intensity, and college aspirations each uniquely and positively predicted college with substantial total causal influence.

In the additional analyses with logistic regressions, which were conducted with different dichotomous dependent variables of enrollment or persistence that were considered overall or for separate two-year college or four-year universities, the results closely resembled the path analysis. HSGPA was the strongest and most reliable positive predictor. College aspirations positively predicted all except four-year persistence. Curricular intensity positively predicted only enrollment but not persistence variables. The HS SBAC tests were almost not significant predictors except for when HS SBAC Math positively predicted four-year persistence and whether or not a student went to a four-year university or two-year college. However, the size of the effect as determined by the odds ratio (i.e., Exp(B) in the results tables) was very small, in both cases under 1.003, which means that the odds of a student enrolling in a four-year university versus a two-year college or the odds of a student persistence versus not persisting in a four-year university were about the same. Given the very low effect size, the highly significant result is likely a false positive result due to having a very large sample size (Lund & Lund, 2018).

The additional analyses with DFA, with separate models conducted for the original five-level college variable as well as the dichotomous enrollment or persistence variables used in the logistic regressions, showed a mixed pattern of results. Significant discriminant function (DF) variables were always found and showed high levels of contribution or importance from HSGPA, college aspiration, and curricular intensity in all models, as well as SAT and SBAC tests in all models except for two-year college enrollment. Interestingly, none of the demographic or school variables provided any strong contribution to the DFs, indicating that the academic variables were most useful for classifying students' college-going behavior. The average classification accuracy of these DFs was almost always higher than chance for enrollment but consistently less than chance for persistence. However, in all models except for the model of four-year college enrollment, the subgroup that did not enroll, or did not persist, was poorly classified. The poor classification of students who did not enroll, in particular, might be partially explained by the findings in the descriptive statistics that students who did not immediately enroll, or who did not persist, tended to have similar or often higher scores on many of the academic variables. In other words, many students appear college-ready according to the typical academic metrics, but for some reason they are rejected from college admissions or they decide not to go. Finally, the exclusion of students from the sample who did not have complete data might help to explain why the noncollege students scored higher than the college students on several of the key academic measures. These noncollege students are not a random sample of students who did not go to college but rather they are non-attenders who still prepared for college by taking the SAT and SBAC tests. Future research should focus on these particular students to better understand these paradoxical results and why they did not go to college.

SBAC

Despite some differences, the combination of results from path analysis, logistic regression, and DFA provides mostly consistent evidence that the high school SBAC tests do not reliably or uniquely predict college enrollment and persistence when controlling for other measures of academic preparation, school, and demographics. In contrast, the traditional indicators of college readiness such as HSGPA and SAT, as well as curricular intensity and college aspirations, do tend to be reliable and unique predictors. The lack of predictive validity for high school SBAC tests, in contrast to SAT, may seem surprising to many educators given that it was designed to be much more closely aligned to the Common Core Standards and K-12 curricula and so therefore it was intended to be a more reliable and accurate assessment of student preparation for college (SBAC, 2020a). It was also designed with the latest technologies in standardized testing in order to enhance testing efficiency and validity (Moncaleano & Russell, 2018). At least 20 states have adopted SBAC assessments (Gewertz, 2017) and over 200 higher education institutions, including the UC system in California, are using SBAC scores for deciding course placement (Smarter Balanced, 2016) and are now considering SBAC scores for deciding admissions (Burke, 2021; Gordon, 2020). Indeed, both the UC and CSU systems in California recently removed the SAT and ACT from their admission procedures (Douglass, 2020). SBAC's lack of predictability is also surprising because the SBAC test, which measures the accumulation of student ability and knowledge in core subject areas, seems to be well-grounded in the first three factors of Conley's theoretical framework (i.e., cognitive ability, content knowledge, and academic skills) as well as Conley's definition of college readiness as "the content knowledge, strategies, skills, and techniques necessary to be successful in any of a range of postsecondary settings" (p. 15), where success necessarily includes both college enrollment and persistence. Despite the many advantages of SBAC, it is surprising that there remains a large gap in knowledge about the relation between SBAC tests and college outcomes because there has been very little empirical research on SBAC, or other state-based assessments, in comparison to SAT or GPA (Michelau, 2015). The few published studies on this topic have painted a mixed picture of both present or absent predictive links between college variables and SBAC or similar state-based tests (Cimetta et al., 2010; D'Agostino & Bonner, 2009; Dam, 2019; Kingston & Anderson, 2013; Kurlaender & Cohen, 2019).

Given the various advantages of SBAC mentioned above, why do SBAC test scores not predict college readiness, as measured by college enrollment and persistence, in this study? One likely explanation is that the SBAC cannot uniquely predict college readiness when controlling for the effects of other strong predictors such as GPA, SAT, curricular intensity, and college aspirations. It is important to emphasize that, without considering any other variables, there were indeed significant and positive correlations between college readiness and both HS SBAC Math and HS SBAC ELA, as shown in the "original covariation" column of the bivariation decomposition table of the first path analysis. This indicates an initial association such that as HS SBAC scores increased, so did college enrollment and persistence. However, this association between HS SBAC and college disappeared in the full regression model with the inclusion of all other independent variables that accounted for even more variance in the dependent variable. In other words, the SBAC relation to college readiness was overshadowed by the effects of other predictors. For years it has been shown that GPA is a stronger predictor of college outcomes than

SAT; but SAT does contribute additional predictive power above and beyond GPA. My results appear to indicate that the SBAC results are less predictive than either GPA or SAT scores; furthermore, they do not contribute additional predictive power above and beyond GPA and SAT scores.

In order to better understand which of these other independent variables were responsible for the lack of SBAC effect, some follow-up regression analyses were conducted with the same five-level variable of college enrollment and persistence as the DV (see Additional Analysis #9 in Chapter 4). The findings were that the initial relation between HS SBAC tests and college readiness disappeared only when controlling for the combined effects, not the individual effects, of the other four academic predictors. These additional regression results are consistent with the predictive validities of HSGPA, SAT, curricular intensity, and college aspirations that were found in the path analyses, which leads to the implication that using them all together to predict college-going behavior should be more useful than considering SBAC scores alone. This implication is consistent with the multidimensional definition of college readiness used by Conley (2014, 2018) and other conceptual frameworks (Bryan et al., 2015; Mattern et al., 2014; Perusse et al., 2015; Westrick et al., 2017), and it’s also supported by some empirical studies demonstrating that college enrollment or persistence can be better predicted by a combination of factors that usually includes GPA and test scores (Kobrin et al., 2008; Woodruff & Ziomek, 2004).

Another possible reason for the lack of HS SBAC effects could be that, at least currently, HSGPA and SAT scores are still the dominant indicators that most colleges use for admission decisions, with SBAC almost entirely used so far as an indicator for course placement. It seems probable that most high students in the local site under investigation were aware of this distinction when they took the 11th-grade SBAC tests. So perhaps they did not take the SBAC tests as seriously, or consider them as important, as the SAT tests. If so, this may have reduced their individual SBAC scores or increased the variability of SBAC scores in the study sample, potentially contributing to decrease ability of SBAC to predict college. Still another possible reason for why SBAC scores don't predict college enrollment could be if college admission officers have not sufficiently embraced the Common Core standards in their practice even if high schools and districts have already done so.

GPA

The observed importance of HSGPA for predicting college in this study could be considered surprising because some have argued that grades can be confounded and inequitable (Bowers, 2011; Brookhart et al., 2016; Gershenson, 2018; Hurwitz & Lee, 2018; Kelly, 2008). However, it could also be considered not surprising for the following reasons. It replicates numerous empirical studies showing HSGPA as the strongest predictor of college success even when controlling for standardized tests and school or demographic variables (Allensworth & Clark, 2020; Balfanz et al., 2016; Fonteyne et al., 2017; Giersch, 2016; Hodara, & Lewis, 2017; Koretz & Langi, 2018; Mattern et al., 2018; Morgan et al., 2018; Westrick et al., 2015). HSGPA is a multidimensional measure that captures both cognitive and noncognitive aspects of college readiness (Mattern & Patterson, 2014; Conley, 2014). HSGPA is an essential factor in most frameworks of college readiness (Bryan et al., 2015; Conley, 2014, 2017; Hatch, 2013; Nagaoka et al., 2013; Perusse et al., 2015). Finally, most universities include HSGPA for admission decision (Westrick, 2017).

Curricular Intensity

The observed importance of curricular intensity for predicting college in this study is also not surprising for several reasons. Taking advanced courses in high school has been recommended for decades (Adelman, 1999, 2006; Austin, 2020). Increasing the vertical alignment between HS and college curricula was also an essential part of the national reform efforts to adopt the Common Core Standards (Conley, 2008; Jimenez & Sargrad, 2018). For example, the a-g course sequence was recently mandated as a requirement for HS graduation in several California school districts, including the school district under investigation in the current study, and several states across the country (Buddin & Croft, 2014; Jimenez & Sargrad, 2018; Martinez et al., 2012). In the present study, the ordinal curricular intensity variable includes a-g course taking as one of the higher levels, and the study sample consisted of students who were among the first to graduate under the new a-g policy. So it is encouraging to find here that curricular intensity, which includes a-g course taking in the study sample, very reliably and strongly predicts college-going behavior. This result is interesting especially because of the ongoing debate surrounding curricular intensity in the empirical research literature due to mixed evidence of both positive and negative outcomes which were discussed in the previous literature review (Buddin & Croft, 2014; Byun et al., 2014; Howard et al., 2015; Kim et al., 2015; Long et al., 2012; Mazzeo, 2010; Preston et al., 2017; Rivkin & Schiman, 2015; Royster et al., 2015). The present study contributes to this ongoing debate by providing key evidence that curricular intensity can uniquely, strongly, consistently, and positively predict college enrollment and persistence.

However, for the current study, it is interesting to note that, in the path analysis, curricular intensity significantly predicted the five-level ordinal variable that combines both college enrollment and persistence, although in the logistic regressions curricular intensity was a significant predictor for only the college enrollment variables and not the college persistence variables. The reason for this pattern seems unclear. Perhaps taking advanced courses boosted the students' knowledge and skills to make them competitive for college admission decisions but the courses were not advanced or aligned enough with the college-level curricula to enable them to succeed in the second-year of college, where courses should be increasingly harder. Or perhaps their curricular intensity in high school was sufficiently aligned with college-level classes but other factors, perhaps nonacademic or personal, interfered with their college persistence. Although this intriguing issue cannot be adequately investigated in the current study, future research could selectively focus on this question such as, for example, a qualitative study on student perspectives of why they did or did not persist into the second year.

College Aspirations

The observed positive role of college aspirations for predicting college in this study is also expected for several reasons. Students' aspiration or expectations to go to college has been considered to be as equally important as academic planning for college readiness (College Board, 2010). Many other educators and researchers have also highlighted the idea that a college-oriented mindset is necessary for students to prepare for and go to college (Conley and French, 2014; Bryan et al., 2015; Perusse et al., 2015). Both Royster et al. (2015) and Jacob et al. (2016) stated have proposed a positive association between college aspirations and taking advanced courses, which supports the hypothesized link between college aspirations and curricular intensity that was included in the present study's path analysis diagrams. Royster et al. also reported that students' college aspirations continue to increase as they realize the importance of earning a degree for employment. College aspirations aligns with the first (Key 1: "think") and second (Key 2: "know") components of Conley's college readiness framework because a college-going mindset can motivate students to not only enroll but also persist throughout college. College aspirations can also inspire students to learn more and hone their critical thinking skills (Gaertner & McClarty, 2015; Perusse et al., 2015) and take ownership and accountability of their learning (Conley & French, 2014). Similar to SBAC tests, despite the strong reasons for the importance of college aspirations, there has been a knowledge gap in the literature, although some empirical studies have validated the positive effects of college aspirations for college readiness (Cabrera & La Nasa, 2001; Perusse et al., 2015; Royster et al., 2015). The present study helps to reduce this knowledge gap by providing valuable evidence that college aspirations can uniquely, strongly, consistently, and positively predict college enrollment and persistence.

SAT

The observed predictive validity of SAT Math and ELA for college readiness in the present study is consistent with numerous previous empirical studies, as discussed in the previous literature review, demonstrating that SAT can reliably predict different measures of college success, such as college GPA, persistence, and degree completion, even when controlling for student demographics or other measures of academic preparation such as GPA (College Board, 2021; Huh & Huang, 2016; Mattern & Patterson, 2011; Mattern et al., 2013; Radunzel & Noble, 2012; Shaw, 2015; Westrick et al., 2019; Zwick, 2017, 2019). The present finding of significant prediction from SAT and GPA combined is also consistent with many published reports of the importance of combining effects (Huh & Huang, 2016; Krompecher, 2020; Mattern & Patterson, 2011; Mattern et al., 2013; Randunzel & Mattern, 2015; Roszkowski & Speat, 2016; Sackett & Kuncel, 2018; Westrick et al., 2019; Woodruff & Ziomek, 2004; Zwick, 2019). Although, many other studies have demonstrated that HSGPA is usually a stronger predictor of college performance than standardized tests (Hiss & Franks, 2014; Hodara & Cox, 2016; Hodara, & Lewis, 2017; Westrick et al., 2015), which was also found in the present study. This might be because standardized tests like SAT do not capture other noncognitive factors like student interest or aspirations which GPA does (Conley, 2012). This possibility further justifies the inclusion of both GPA and college aspiration in the current study.

Research Questions 2 and 3

The SBAC test was designed to be aligned with Common Core Standards and K-12 curricula and to be used as a monitoring system to hold school districts accountable for students' academic progress and college readiness (Gonzalez-Canché, 2019; SBAC, 2016). Although the 11^{th}-grade SBAC test can help to identify students at risk of not graduating, it is usually too late to help improve these students' chance of getting into college (Gaertner & McClarety, 2015; Gonzalez-Canché, 2019; Mattern et al., 2016). Therefore, the 8^{th}-grade SBAC test provides a crucial opportunity for early evaluation in middle school and so it is important to assess its predictive validity for high school and college variables in comparison to the traditional measure of MSGPA.

The second research question asked how the 8^{th}-grade SBAC tests predict college readiness, as measured by college enrollment and persistence, in comparison to MSGPA while controlling for all other variables. The overall pattern of results was such that MSGPA tended to be a much stronger predictor than the MS SBAC tests. In the path analysis, MSGPA had high total causal influence due to high indirect influence of SAT and HSGPA. In other words, MSGPA has an important role for predicting college because it influences SAT and HSGPA which are important predictors of college. Unfortunately, in contrast to MSGPA, the MS SBAC tests were either not predictive of college or negatively predictive such that increasing test scores were associated with decreasing enrollment and persistence. The reasons for these absent or negative findings for MS SBAC are not at all clear and will require future quantitative or qualitative research to further investigate.

The observed predictive validity of MSGPA, although indirectly via SAT and HSGPA, provides valuable evidence for a major knowledge gap in the research literature due to relatively few studies that have investigated how middle school variables relate to future academic success (Casillas et al., 2012; Mattern et al., 2016). This finding also supports many researchers who have emphasized the importance of considering middle school indicators for predicting college readiness (Allensworth, 2013; Allensworth et al., 2014; Allensworth & Easton, 2005; Balfanz et al., 2007; Casillas et al., 2012; Lee, 2012) as well as the advantages of early assessments and interventions in middle school to help identify and redirect students who are falling behind (Hollman et al., 2019; Nemelka, 2018; Radcliffe & Bos, 2013). It is interesting that, in the current study, the observed effect of MSGPA on college readiness was not direct but rather indirect via SAT and HSGPA and to a lesser extent the MS SBAC tests, which makes sense because middle school occurs before high school which occurs before college so the influence of middle school variables on college would seem likely to be intermediate through high school.

This indirect influence of MSGPA is possibly a novel finding which does not seem to have been reported in previous studies and so it would be worth exploring more closely in future research. For example, future studies should try to replicate this result with different samples of students, schools, and other districts to increase the generalizability of findings. Also, MS GPA should be more closely monitored by school districts as part of an early warning indicator system. It would also be important to investigate whether the indirect influence of MS GPA on college via HS GPA, SAT, and MS SBAC tests that was observed in this study was specific to those variables or a more general effect involving any other academic indicators, such as ACT or PSAT tests, or other college outcome variables such as college GPA, degree completion, or college course-taking.

The third research question asked how the 8th-grade SBAC tests predict the 11th-grade SBAC tests, in comparison to MSGPA, while controlling for all other variables. There was a consistent pattern of results. MS SBAC Math strongly and positively predicts HS SBAC Math whereas MSGPA shows no effect. MS SBAC ELA strongly and positively predicts HS SBAC ELA whereas MSGPA only shows a weak effect. Therefore, the results are clear that 8th-grade SBAC tests can indeed predict 11th-grade SBAC tests such that increasing MS scores are associated with increasing HS scores. This is consistent with several studies that have assessed MS achievement and how it predicts HS tests in order to develop early warning indicators (Allensworth, 2013; Allensworth et al., 2014; Allensworth & Easton, 2005; Balfanz et al., 2007). These results also show high internal consistency in the SBAC assessment where it should be expected that that it closely tracks similar performance in the same students across time.

Research Question 4

The fourth research question asked, to what extent does the 8th or 11th-grade SBAC test scores, and their predictive validity for college enrollment and persistence, suffer from the same demographic and school biases that have been shown to bias the SAT and GPA. This question distinguishes between two different types of bias. The first is bias on the academic measures themselves, as determined by the presence of significant paths from the demographic and school variables towards the academic predictors. The second is bias on the ability of the academic measures to predict college enrollment and persistence, as determined by whether or not the academic measures can significantly predict college variables while controlling for the demographic and school variables. The findings were reported in detail in the Results section above, so the overall summaries for each of the academic predictors are discussed below.

SAT

For the SAT tests, each of the demographic variables, but not school size, significantly predicted both SAT Math and SAT ELA, which indicates the presence of demographic but not school bias on SAT scores. Males scored higher than females on both tests. Relative to White students, Asian students scored higher on SAT Math but lower on SAT ELA, whereas Black and Latinx students scored lower on both tests. English learners and students in poverty scored lower on both tests. The observed demographic bias on SAT scores is consistent with previous findings that SAT performance can be biased by race and ethnicity and socioeconomic factors (College Board, 2019; Dixon et al, 2013; Geiser, 2015; Gonzales Canché, 2018). However, it's unclear from this result if this indicates that the SAT test is biased specifically or the observed effect is part of a more general, systemic bias from gender and other demographic variables as seen in other parts of the results. The lack of bias from school size is not consistent with previous findings that SAT scores can vary depending on the type of school (Gonzalez Canche, 2018), although school size probably does not fully capture the distinctions between different types of school.

The predictive validity of SAT tests for college enrollment and persistence was found to be partially but not completely biased. In the first regression of the main path analysis controlling for all other variables, both SAT tests significantly predicted the five-level variable of college enrollment and persistence. In the additional logistic regressions controlling for all other variables, both SAT tests predicted overall enrollment and four-year but not two-year enrollment, while only SAT ELA predicted overall persistence and four-year but not two-year enrollment, and only SAT_Math predicted whether a student enrolled in a four-year university or a two-year college. These results indicate that, in general but not always, the SAT tests can predict college variables over and above the influence of demographic or school variables. In the additional path analyses, which used the original five-level college enrollment and persistence variable and was conducted separately for each student subgroup of the demographic variables, there was evidence of bias such that the predictive effects were significant for some but not all subgroups. The SAT tests were predictive of college enrollment and persistence for Asian and Latinx students but not for Black and White students, for English-native but not English-learning students, and for students in poverty but not students out of poverty. There were also different predictive effects for different genders. Taken together, this pattern of results indicates a general pattern of demographic bias in SAT predictive validity, because although the SAT tests can often predict college over and above demographic and school variables, the prediction differs for different student subgroups. These findings are consistent with previous reports of demographic bias in the ability of SAT scores to predict college variables (Gonzalez Canche, 2019; Linn, 1990; Rothstein, 2004).

GPA

There was evidence of bias in both HSGPA and MSGPA scores. Males scored lower than females on both HSGPA and MSGPA. Relative to White students, both Black and Latinx students scored lower on both HSGPA and MSGPA, while Asian students scored higher on MSGPA with no difference in HSGPA. English learners scored lower than English-native students on MSGPA only. Students in poverty scored lower than students not in poverty on both HSGPA and MSGPA. Finally, school size biased HSGPA such that students in larger schools had higher HSGPA. Note, school size was a measure specific to only high school, so the effect on middle school could not be tested. This pattern of results indicates substantial evidence of demographic and school bias in HSGPA scores and evidence of demographic bias in MSGPA scores. The observed biases in HSGPA scores are consistent with numerous previous studies showing that grades and GPA scores can show inequity for students of different race and ethnicity, socioeconomic status, and school context (Allensworth & Clarke, 2020; Betts et al., 2016; Koretz & Langi, 2018; Preston et al., 2017; Zwick, 2013; Zwick & Himelfarb, 2011). The observed demographic bias in MSGPA is consistent with some previous studies. For example, Black and Latinx have consistently been found to underperform in middle school relative to their White or Asian peers (Johnson et al., 2021; Lee, 2012; Quintana & Correnti, 2020). Similarly, other studies have found that the growth of learning in middle school can be biased by race and ethnicity or gender (Downey et al., 2020; Kuhfeld et al., 2019; Reardon et al., 2015).

The predictive validity for college enrollment and persistence was found to be biased for only MSGPA but not HSGPA. In the first regression of the main path analysis controlling for all other variables, only HSGPA significantly and positively predicted the five-level variable of college enrollment and persistence. In the additional logistic regressions controlling for all other variables, HSGPA was always a significant and positive predictor, but MSGPA was almost always not significant. These results indicate that only HSGPA, and not MSGPA, can reliably predict college variables over and above the influence of demographic or school variables. In the additional path analyses, which used the original five-level college enrollment and persistence variable and was conducted separately for each student subgroup of the demographic variables, HSGPA remained a consistent positive predictor for all student subgroups but MSGPA was never significant except for female students. Taken together, this pattern of results indicates that the predictive validity of MSGPA, but not HSGPA, is biased by student demographics. The lack of bias in HSGPA predicting college in this study sample is encouraging and consistent with many previous studies showing that HSGPA can predict college variables while controlling for demographic or school variables or their interaction effects (Allensworth & Clarke, 2020; Hiss & Franks, 2014; Hodara & Cox, 2016; Hodara, & Lewis, 2017; Westrick et al., 2015). The observed bias in predictive validity of MSGPA for college appears to be a relatively novel result that has not been sufficiently studied in the research literature. Future research could investigate what factors might be contributing to this bias in prediction.

SBAC

There was evidence of demographic bias in both HS SBAC and MS SBAC test scores. Females almost always scored lower than males. Relative to White students, Asian students almost always scored higher, Black students always scored lower, and Latinx students scored lower for only the MS SBAC tests. English-learning students scored lower than English-native students on almost all tests. Students in poverty scored lower than students not in poverty on almost all tests. School size did not bias HS SBAC Math but it did bias HS SBAC ELA such that students in larger schools had higher scores. The effect of school size on MS SBAC could not be tested because school size is specific to high school. This pattern of results indicates that indeed the SBAC tests do suffer from the same biases that affect SAT and GPA. This result is consistent with the relatively few studies that have addressed this issue which have found similar biases of race and ethnicity, poverty, and school type in SBAC scores (Locke, 2019; Merkel, 2019; Reed et al., 2019; Warren, 2018). However, it is interesting to emphasize, as was reported in the Results section, that the degree or strength of these demographic biases appear to be consistently stronger for SAT variables than for SBAC variables (in particular, the HS SBAC variables), while the degree of bias in SBAC appears more similar to the degree of bias in HSGPA. This finding is encouraging for SBAC because it was explicitly designed to reduce the problems of racial and socioeconomic inequity that affect SAT and GPA. So although enough demographic bias in SBAC scores remains to warrant further efforts to fix this problem, the decrease level of bias relative to SAT is a partial success and supports the use of SBAC for monitoring student academic progress. However, it is ineffective predictability of enrollment and persistence limits its ability to be considered as a replacement for the SAT.

The predictive validity of SBAC for college enrollment and persistence was found to be mostly not biased by demographics or school variables. There was a generally consistent pattern such that none of the SBAC tests, except for MS SBAC ELA which had an unexpected negative influence, were able to significantly predict college variables while controlling for all other variables. It is important to note, however, that the other variables in the model included not only the demographic and school variables but also all the other academic variables, so it’s difficult to know which variables contributed to the lack of SBAC predictive effects. Some follow-up regression analyses were conducted to probe this issue further (see Additional Analysis #9 in Chapter 4). These follow-up findings suggest that the lack of SBAC effects seen in the first regression of the main path analysis are probably not due to the demographic and school variables, because if they were, then the SBAC effects would have disappeared with the inclusion of those demographic and school variables. In other words, the lack of SBAC effects does not appear to arise from demographic or school bias.

The predictive validity of SBAC was also assessed in the additional path analyses, which used the original five-level college enrollment and persistence variable and was conducted separately for each student subgroup of the demographic variables. Similar to the results of the first regression in the main path analysis, none of the SBAC tests, except for MS SBAC ELA, were significant predictors. Because this general lack of SBAC prediction was consistent for each student subgroup, this indicates no substantial demographic bias for most SBAC tests. The exception was MS SBAC ELA, which significantly and negatively predicted college enrollment and persistence for only the Latinx students, for only the English-native students, and for only the students in poverty. This unexpected pattern of results seems to indicate that taking the MS SBAC ELA test might be somehow detrimental or negatively impacting these students' chance for success in college, although there is no apparent reason for why and so future research focusing on the MS SBAC may help to clarify. In sum, it appears that the predictive validity of MS SBAC ELA was biased by ethnicity, language classification, and poverty.

The general lack of demographic or school biases in the predictive validity of most SBAC tests, except for MS SBAC ELA, is encouraging and supports the notion that the SBAC test was designed to be a more equitable assessment of college readiness. However, it's possible that the lack of biases in prediction may be due to the lack of prediction effects in general. The results of this study are valuable given the huge knowledge gap about the predictive nature of SBAC for college. In the literature review of the current study, only two previous studies were found to investigate the SBAC relation to college variables and they showed conflicting results (Dam, 2019; Kurlaender & Cohen, 2019). Only one of these studies (Kurlaender & Cohen, 2019) tested for biases in prediction and they found that lower-income students, relative to higher-income students, showed lower correlations between SBAC test scores and first-year college GPA. Thus, it seems that the present study could be the first to rigorously test not only the predictive power of SBAC for college but also the potential biases in prediction. Future research is necessary to replicate the present findings.

Curricular Intensity

There was evidence that curricular intensity was also biased by demographic and school variables. Relative to White students, curricular intensity was higher for Asian students but lower for Black and Latinx students. Advanced course-taking was also higher for female students, English-native students, students' without poverty, students with higher college aspirations, and students who went to smaller schools. Curricular intensity was one of the strongest predictors of college enrollment and persistence while controlling for other variables, indicating that its effect was unique and greater than the confounding effects of demographics and school size. However, the effect of curricular intensity on college was not necessarily independent of school size given that larger schools tended to have lower curricular intensity. This is a surprising result given that larger schools in this district typically have more resources for curricular rigor, but perhaps these larger schools were in poorer neighborhoods or enrolled more students in poverty than the smaller schools and so had less resources available. Although this might be inconsistent with other findings that larger schools also tended to have higher HS SBAC and GPA scores, which would be a strange outcome for schools with less resources. Or perhaps, larger schools make it more difficult for students to compete with each other for enrollment in the advanced courses. Future research could try to clarify this issue by using more than one measure of school type, such as comparing between private versus public schools, or affiliated versus nonaffiliated.

In the separate path analyses by demographic subgroups, curricular intensity was positively predictive of college enrollment and persistence for all ethnicities except Black students, for only English-native students, and for only students not in poverty, while it was similarly predictive for both males and females. These results indicate that ethnicity, language classification, and poverty biased the predictive validity of curricular intensity which is consistent with previous studies showing curricular intensity was biased by ethnicity and socioeconomic status (Betts et al., 2016; Byun et al., 2014; Plunk et al., 2014; Preston et al., 2017). It's important to note that the lack of effect of curricular intensity for only the Black students was surprising and could be related to potential bias in how individual teachers adhere to the Common Core standards in their course instruction or relations with different student subgroups, given that this form of racial inequity has been previously reported for specifically Black students (Hambacher, 2018).

Bias in College Enrollment and Persistence

The last important issue to discuss is the degree to which college enrollment and persistence, as measures of college readiness, can be biased by student demographics or school-related variables. The theoretical frameworks of CRT and QuantCrit are based on the fundamental idea that racism is deeply embedded in the history and foundation of American society and its educational system, thereby creating systemic problems of social and educational inequality which also overlap with issues of gender and class (Ladson-Billings, 1998; Gilbourn et al., 2018). Because of this, higher education has become a primary vehicle for racial inequity and other forms of demographic inequality due to racially biased admissions policies, curricular content, test-taking practices, school funding, geographical segregation, academic assessment, and teaching practices (Patton, 2015). These frameworks are supported by decades of qualitative and quantitative evidence of biases, usually based on White privilege as well as socioeconomic status that persist in admission decisions of many colleges and universities (Ladson-Billings, 1998; Gilbourn et al., 2018).

The current study is firmly grounded in these theories and explicitly tests for such biases in order to help raise awareness of problems which could be improved by more progressive educational policies. Similar to the demographic biases that were reported in the previous sections for academic indicators, there also appears to be some biases affecting the measures of college enrollment and persistence. There was an overall pattern of bias in the results of the different path analyses and logistic regressions such that college enrollment or persistence was almost always influenced by ethnicity, often influenced by gender, language classification, and poverty, but only rarely influenced by school size.

These various biases might have also influenced the surprising results from the descriptive statistics of the study sample. As seen in Figures 3 and 4 previously, a large percentage of students did not immediately enroll in college and many of these students had similar or higher scores on the academic indicators compared to students who immediately enrolled. These findings raise an important question: why do so many students not enroll or drop out of college even though they appear to be highly qualified and college ready? A possible factor might be socioeconomic if the students are required to work instead to support themselves or their family. It's also possible that their college applications were denied due to their race or ethnicity, their language skills, their gender, or their socioeconomic status. Or it's possible that any of these demographic issues of identity might have negatively impacted their college experience and influenced them to drop out. Or perhaps they simply decided not to go or changed their mind for any number of reasons. These possible explanations cannot be confirmed because the school district does not acquire data on why students do not immediately enroll or why they do not persist.

However, in the results reported in Chapter 4, some additional descriptive statistics and logistic regressions were conducted to take a closer look at the demographic identity of these students. The overall pattern of these results indicates that the students who did not enroll or persist in college were more likely to be male, Black, Latinx, English learner, or in poverty.

These findings are consistent with previous research documenting similar demographic biases in college-going behavior (Lemann, 2000; Plunk et al., 2014; NCES, 2020b), highlighting the persistent difficulty in college access that faces many students. However, it's still uncertain whether or not these observed demographic biases influenced individual students' college-going behavior. Future research using qualitative methods could interview these students who did not enroll or dropped out of college in order to better understand their reasons for doing so. Finally, one limitation related to this issue is that many of these students who did not immediately enroll in college may have eventually enrolled in college, and many of the students who dropped out may have later re-enrolled. These data are not collected by the school district but future research could attempt to follow-up with these students.

Limitations and Future Directions

Limitations

This study has certain limitations. First, although multiple regressions and path analysis are often used to assess the predictive power of indicator variables (e.g., Mattern et al., 2016; Westrick et al., 2019; Zwick, 2019), these findings do not imply a cause-effect relation because a truly experimental design is not being used (Barnighausen et al., 2017). Future research could test the causal role of tests such as the SBAC examinations or SAT in predicting college readiness by, for example, randomizing the administration of the tests across students or schools. A second limitation relates to generalizability. Because students with disabilities were excluded, the results of this study do not generalize to that specific population of students, which is an issue that future studies could address. It's also important to note that the generalizability of these study findings is limited to other large, urban school districts with similarly diversity in student demographics. A third potential limitation is that violations of statistical assumptions may have occurred and biased the estimated means, path coefficients, R^2 values, or significance tests. However, this limitation was minimized by using appropriate statistical procedures in multiple regression analyses and path analysis to find and correct any violations (Lund & Lund, 2018).

A fourth limitation is that the race and ethnicity categories or labels used in this study overly simplify the complexity of racial or ethnic identity or experiences. For example, the Asian category lumps together students from many different countries in Asia, each of which have their own cultures, languages, and other aspects that contribute widely diverse experiences for any individual student. This same limitation applies to all other categories of ethnicity, gender, language classification, and poverty that were used in this study. Indeed, the QuantCrit framework emphasizes that labels matter, both for their usefulness in explicitly addressing issues of bias and also for their tendency to perpetuate such bias if used irresponsibly (Gilbourn et al., 2018). So despite the potential risk of perpetuating further bias, for the purpose of this analysis, it was necessary to use these demographic categories as responsibly as possible, which is standard practice in this school district and most others, in order to sufficiently ground the study in the QuantCrit theoretical framework and explicitly test for demographic biases (Gilbourn et al., 2018).

A fifth limitation is that language classification was operationally defined as a nominal variable with only two levels, English-learner or English-native, instead of being defined as an ordinal variable with multiple levels that are provided in the school district database. These levels are English learner, initially fluent English learner, and long-term English learner, English only, and reclassified. The decision to change language classification from ordinal to dichotomous was based on the fact that the distribution of student frequencies across ordinal levels was far too imbalanced for statistical reliability as well as the fact that it's very difficult if not impossible to reliably order the different categories of language classification. For example, just because a student speaks English natively does not necessarily make them better at English than someone who was reclassified, initially fluent, or bilingual.

A sixth limitation is that differences between the effects observed in the different path analyses for the demographic subgroups are qualitative because they can be described but they are not quantitative because they were not statistically tested. For example, curricular intensity did not significantly predict college enrollment and persistence in the path analysis for the Black subgroup but it was a significant predictor for the Asian, Latinx, and White subgroups. However, there was no quantitative (i.e., statistical) test of this difference in predictive validity, for example, by testing an interaction effect between ethnicity and curricular intensity as an additional higher-order IV in the regression model so that the effect of curricular intensity on college enrollment and persistence (i.e., the path coefficients, which are the standardized beta coefficients) could be statistically tested between the different ethnicity groups. Testing for interactions between ethnicity and academic indicator variables would have been ideal for addressing the issue of bias in the fourth research question, but this was not possible in this study. The next best alternative was to conduct separate path analyses for individual demographic subgroups so that differences in predictive validity of academic indicator variables could at least be observed. Therefore, while these findings do provide some initial evidence of demographic bias in this study sample and for the generalizable population, for example that curricular intensity may be less predictive for Black students, the evidence cannot be interpreted as conclusive because the differences were only observed qualitatively and not tested quantitatively.

A seventh potential limitation is the imbalance of student frequencies across demographic subgroups, specifically, for ethnicity, language classification, and poverty subgroups. These imbalances are simply a description of the data and so not inherently a problem. However, imbalanced groups can be a problem for generalizability because if other schools or districts do not have similar demographic distributions then these results may not apply as well to them. Imbalanced groups can also decrease the statistical reliability of any effects or results involving those categorical variables (Lund & Lund, 2018). For example, this study found evidence of ethnicity bias in SAT test because they are not predictive for Black and White students but they are for Asian and Latinx students. While ethnicity bias in SAT tests is not necessarily surprising, the result that SAT was not predictive for White students in particular is surprising because of the White privilege and advantages for SAT that have been discussed before (College Board, 2019; Linn, 1990; Zwick, 1999). Similarly, the imbalanced groups' sizes of the five-level ordinal variable of college enrollment and persistence (i.e., CollegeReady) might also be contributing some statistical problems, such as the very low classification accuracies observed for some groups in the DFA results.

These imbalances can also help to explain patterns of effects that are observed in the full sample. For example, because the vast majority (77%) of students in this sample are Latinx, any effects within the Latinx subgroup may likely be driving overall effects. In the main path analysis with all subgroups combined, there was an unexpected result that MS SBAC ELA negatively predicted college enrollment and persistence. The separate path analyses for ethnicity subgroups indicated that this negative prediction was present only in the Latinx subgroup, although it's unclear why this would be the case. Therefore, it's possible that the Latinx subgroup was driving the overall effect. However, given that this negative prediction was also found in the separate path analyses for English-native subgroup and poverty subgroup, those groups could also be contributing to the overall effect, especially since these demographic subgroups are overlapping and many Latinx students are also English-native and in poverty. It's interesting to see which effects are being driven by specific subgroups and future studies could investigate these specific effects in more detail.

A final potential limitation is the COVID-19 pandemic which may have influenced the college-going decisions of students in this sample. Specifically, these students graduated high school in the spring of 2019 and started first year of college in the fall of 2019 before the pandemic started, which meant that these students were still in their first year of college when the pandemic started. It's possible that the pandemic influenced some students to drop-out during their first year or drop-out before starting their second year, although these data were not available. Therefore, it's possible that the pandemic partially confounded the measure of college persistence and thereby also any tests of academic prediction of college persistence. This limitation would be especially problematic if the confounding effect of the pandemic was demographically uneven, such as having stronger effects for students in poverty or students of color for whom the pandemic may have presented more challenges for these students to persist in college. This is an important possibility that will need to be addressed by future research, especially when attempting to replicate in later cohorts of HS graduates given that the pandemic also created a two-year disruption in the normal SBAC testing procedure which may influence their college applications.

Future Research Directions

Compared to SAT or GPA, hardly any quantitative research and even less, if any, qualitative research has been conducted on the SBAC assessment and its relation to college. The present quantitative dissertation has helped to narrow this drastic knowledge gap with key findings about predictive validities and biases of SBAC, SAT, GPA, curricular intensity, and college aspirations. For example, the analyses reported in this study indicate that the predictive effects of the other academic indicators overshadow the SBAC effect. Given that the current study adds to the mixed evidence in the research literature about the relation between SBAC and college (Dam, 2019; Kurlaender & Cohen, 2019), it will be necessary for future quantitative studies with similarly rigorous methods to try to replicate these findings, in other student populations and school districts, and also expand on this research. For example, future studies could include other relevant variables from middle school or high school which may influence student academic performance, such as study habits, student-teacher relations, relations with high school counselors, or social influence of student peers. There is also a need for future research to more rigorously test the potential causal links between academic predictors and college outcomes with causal designs such as randomized controlled trials. For example, a study could randomly assign some students to a treatment group taking the SBAC test and other students to a control group taking some control task or test, perhaps an IQ test, and then compare these groups on their rates of college enrollment and persistence or compare the predictive validities of SBAC, SAT, GPA, and other variables between these randomized groups.

The uncertainty of SBAC prediction could also be investigated further with qualitative research. For example, a qualitative study could conduct interviews with middle or high school students to reveal how these students perceive the SBAC test's design, scores, and importance for their college applications. A qualitative study could also interview teachers to understand how they view the SBAC test's design or importance, how they help or do not help students prepare for the tests, how they adhere to Common Core standards in their teaching practice, or how they deal with potential demographic or socioeconomic bias. Future qualitative studies should also further investigate the predictive power of students' aspirations for higher education which was demonstrated here to have consistently positive and strong effects. For example, other questions could be asked of each student to develop a more fine-grained understanding of their aspirations and how they are related to their college-going behavior. It might be important to ask students not just *if* they plan to go to college but also *why* they plan to go, since their rationale or motivation could help inform research and practice. It might also be useful to ask students about aspirations for educational opportunities beyond college, such as graduate or medical school, which might help to increase the prediction accuracy especially for estimating differences between students who are already high performing on academic measures. Also, acquiring information on not just educational aspirations but also career aspirations would be well grounded in Conley's framework which emphasized readiness for not just college but also careers. It would also add valuable information for understanding all students, especially those who score highly on academic measures but who do not go to college, as was demonstrated in this study. This unexpected finding was not the focus of this study but it could be considered a major finding in itself, to be more fully investigated by future research, because of the implications it has for how to interpret academic measures of college readiness and their relationships with both college and career outcomes.

These types of future research are an imperative for me for the following reasons. Replication of research findings, especially across different types of student samples, schools and districts, and other variables, is essential for demonstrating reliable effects, and reliable effects are ideal for informing policy changes. As a researcher and practitioner, I strive to practice methods that are informed and validated by sufficient research that is rigorous and unbiased as much as possible. I also strive to increase social justice by trying to eliminate the systemic problems that afflict our education system, which is why I grounded this research in QuantCrit and CRT theories and why I included many analyses on the potential demographic biases of SBAC and other academic variables.

Overall Summary and Recommendations for Policy

Several research questions were answered in this study which investigated the predictive validities and potential biases of academic indicators from middle and high school in relation to college readiness as measured by college enrollment and persistence. For the first and second research questions, both the middle school and high school SBAC tests were not reliable predictors of college readiness, despite their intended design to be used as such, in contrast to high school GPA, SAT, curricular intensity, and college aspirations which tended to strongly and reliably predict college readiness either directly or indirectly via their positive effects on other predictors. For the third research question, the middle school SBAC tests reliably and positively predicted the high school SBAC tests, even when controlling for middle school GPA, which indicates high internal consistency within SBAC assessments and suggests that these tests can accurately and reliably track students' academic progress between middle and high school. For the fourth research question, there was evidence of demographic or school bias in the scores of all academic indicators as well as some bias in their predictive validity for college enrollment and persistence, which is generally consistent with previous reports in the research literature on this topic. Importantly, the observed biases for SBAC tests tended to be less than the biases for SAT tests but similar for GPA measures.

The overall conclusion and recommendation for educational policy is that the SBAC tests seem ideal for monitoring students' academic progress, instruction, and needs throughout middle and high school but less ideal for predicting college enrollment and persistence. The findings of this study support the intended use of SBAC as a monitoring system of academic progress throughout middle and high school for the following reasons. First, the MS SBAC tests strongly and positively predicted HS SBAC tests, indicating the SBAC test is internally consistent and can track chronological progress in academic performance. If it did not do this, that would be a major limitation for the consistency and reliability of the test. Second, MS GPA strongly and positive predicts MS SBAC tests. In other words, MS SBAC tests are highly associated with middle school grades, which is essential evidence for the claim that the MS SBAC test is tracking student academic progress in middle school. Third, HS GPA does positively predict the HS SBAC tests, although the relation is not as strong as the relation between MS GPA and MS SBAC. So in other words, HS SBAC tests are associated with high school grades, which is essential evidence for the claim that the HS SBAC test is tracking student academic progress in high school. Based on these various results, the school district should continue using MS and HS SBAC tests for tracking student academic progress in MS and HS, respectively. The district can also use MS SBAC test results to try to predict HS SBAC results for individual or groups of students. Given that the SBAC system also provides abundant support an online repository for teachers and schools to enhance their instruction methods for stronger adherence to Common Core and more vertical alignment with college readiness, these resources should be taken advantage of, especially given the present evidence that SBAC has high utility for tracking academic progress. But it’s also recommended that school districts need to scrutinize the use of SBAC to make sure that teachers are appropriately adjusting their teaching practices to align with SBAC to ensure optimal results.

Because of SBAC adherence to Common Core and vertical alignment, SBAC was also designed to be a better indicator of college readiness. Itt is already being used by many colleges in their decisions about course placement and remediation, and it is being considered by many colleges to be used for admission decision as well, possibly to replace the SAT. However, the findings of this study fail to support the intended use of SBAC as an academic indicator of college readiness. It was discovered here that neither MS SBAC nor HS SBAC tests can reliably predict college enrollment and persistence when controlling for other stronger predictors of HS GPA, curricular intensity, college aspirations, and SAT tests. MS SBAC showed some evidence of prediction but it was an unexpected finding in the opposite direction because higher scores were associated with lower enrollment and persistence. This finding was possibly a false positive since the effect size (i.e., standardized beta coefficient) was very small. Even if the result turns out to be reliable if it is replicated in other studies, the negative prediction further provides evidence that the MS SBAC tests are not associated with increased college readiness. In the additional logistic regressions, it's curious to note that for analyses #7 and #8 (see Tables 81 and 82), HS SBAC Math showed positive predictions of four-year college persistence as well as enrollment in two-year college vs four-year university. Although these results are initially encouraging for use of SBAC to predict college, the betas for these effects are very small (e.g., 0.001) despite their statistical significance, so here again these results seem likely to be false positive effects driven by high sample size and artificially low p-values. Or even if these results are reliable and not the result of statistical bias, the very small effect sizes indicate very low practical importance, especially given that the classification accuracies for those two models are very low as well.

Based on these various results, it is currently suggested that MS or HS SBAC tests should not be used for enrollment decisions. However, it is important to note some caveats to this recommendation. These results have not yet been replicated and there still is hardly any research on SBAC tests, so replication of these findings will be necessary before making any changes to educational policy. For example, the current study sample included only the first wave of high school graduates from the school district to have taken the SBAC tests. Because it will take time for school districts and teachers to modify their teaching practices to align well with the SBAC system, and it can also take time for college admissions to more adequately adopt the Common Core standards which anchors the SBAC, it will be necessary to replicate this study with future cohorts of students. The current study only tested enrollment and persistence as the college variables being predicted, but it will be important to test whether SBAC and other academic variables can predict other college variables such as college GPA, college course placement, college course remediation, and degree completion because these variables are also important for providing a more complete picture of college readiness. In particular, it would be important to test the degree to which SBAC tests can reliably predict college course placement and remediation given that, currently, colleges and universities are primarily using SBAC tests to inform their decisions about which college classes students should take if they are accepted. The current study did not test for prediction of course placement or remediation. However, with the assumption that if students fail college courses they will likely not persist, the observed inability of SBAC tests to reliably predict persistence provides at least partial or indirect evidence that SBAC tests may not be so useful for this purpose. Despite these negative results, it is still recommended that colleges and universities continue using SBAC tests for deciding course placement and remediation until there is sufficient research in the near future to support or not support this use. There is also an equity argument for continuing the use of SBAC, because SBAC tests are often tied to scholarships and many private universities and other state universities still require SBAC tests as part of their applications, so discontinuing SBAC will remove these opportunities for many students.

Importantly, it is recommended that SBAC should be part of an early indicator system involving multiple variables such as MS and HS GPA, curricular intensity, college aspirations, SAT tests, and any others that may show reliable positive prediction of academic progress. Regarding SAT tests in particular, although there is currently a policy shift towards removing SAT as a testing requirement for college applications, it is not recommended to eliminate the SAT from admission decisions based on the present findings that both SAT tests, but not the SBAC tests, provided unique prediction of college enrollment and persistence. Regarding curricular intensity, the positive evidence of predictive validity for college enrollment and persistence supports the idea that school districts should increase high school graduation requirements so that as many students as possible are ready for advanced college curricula. For example, the A-G course sequence was recently mandated by the school district investigated in this study. Because A-G course-taking was included as one of the levels in the curricular intensity variable used in this study, A-G course-taking contributed to the positive findings of curricular intensity. However, given the ongoing debate surrounding the mixed evidence of positive and negative effects of increasing graduation requirements, it will be important to replicate these findings in future studies. Finally, is advised that college admissions continue to adopt a more complex picture of college readiness as a multidimensional construct requiring multiple variables, given that the complexity of college readiness is supported by key theoretical frameworks (Conley, 2018) and the quantitative research literature.

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Appendix A: 8th-Grade SBAC

Math (Concepts and Procedures), example item

Determine for each number whether it is a rational or irrational number.

	Rational	Irrational
$-\sqrt{36}$		
$\frac{1}{\pi}$		
$4.\overline{3}$		
$1\frac{3}{17}$		
$\sqrt{\frac{1}{4}}$		

English (Reading), example item

A Story of the Oregon Trail (by James Otis)

Susan rode with me, as she had from the beginning of the journey. Nothing of note happened to us, unless I should set down that this day was stormy, and on that day the sun shone, until we came into the valley of the North Fork of the Platte, through a pass which is known as Ash Hollow. There we drove down a dry ravine on our winding way to the river bottoms, stopping now and then to gather a store of wild currants and gooseberries which grew in abundance. Near the mouth of the ravine we came upon a small log cabin, which had evidently been built by trappers, but the emigrants on their way into the Oregon country had converted it into a post office, by sticking here and there, in the crevices of the logs, letters to be forwarded to their friends in the States. Hung on the wall where all might see it, was a general notice requesting any who passed on their way to the Missouri River to take these missives, and deposit them in the nearest regular post office. The little cabin had an odd appearance, and Susan confessed that, almost for the first time since leaving Independence, she was growing homesick, solely because of seeing this post office. After crossing the stream we came upon a party of emigrants from Ohio, having only four wagons drawn by ten yoke of oxen, and driving six cows. Truly it was a small company to set out on so long a march, and when the leader begged that they be allowed to join us, I could not object, understanding that unless the strangers had someone of experience to guide them, the chances were strongly against their arriving at the Columbia River. There was in the company a girl of about Susan's age, whose name was Mary Parker, and from that time I had two companions as I rode in advance of the train. I could have found no fault with these new members of our company, for they obeyed my orders without question from the oldest man to the youngest child. Mary Parker was a companionable girl, and she and Susan often cheered me on the long way, for even when the rain was coming down in torrents, drenching them to the skin, they rode by my side, laughing and singing. On the twenty-fourth day of June we arrived at Fort Laramie, in the midst of a heavy storm. We had traveled six hundred sixty-seven miles since leaving Independence, if our course had been the most direct; but allowing for the distances some of us had ridden in search of cattle or here and there off the trail looking for a camping place it must have been that we made at least a hundred miles more. Fort Laramie is on the west side of a stream known as Laramie's Fork and about two miles from the Platte River. It is a trading post belonging to the North American Fur Company, and built of adobe, by which I mean sun dried bricks, with walls not less than two feet thick and twelve or fourteen feet high. This fort, if it can be called such, is simply a wall enclosing an open square of twenty-five yards each way, along the sides of which are the dwellings, storerooms, blacksmith shops, carpenter shops, and offices all fronting inside, while from the outside can be seen only two gates, one of which faces the north and the other the south. Just south of the fort is a wall enclosing about an acre of land, which is used as a stable or corral, while a short distance farther on is a cultivated field, the scanty crops of which give good evidence that the soil is not suitable for farming. About a mile below Fort Laramie, and having much the same appearance as that fortification, although not so large, is Fort John, which is in possession of the St. Louis Fur Company. We were given quarters inside Fort Laramie, which was much to our liking. Then, when we set off once more, it was with greater cheerfulness and increased hope, for the way could not have been improved nor made more pleasant. Ten days after we celebrated the independence of this country we encamped near the Narrows, within sight of the snow-capped Wind River Mountains, and then it was that our company got some idea of what a herd of buffaloes looked like. When we broke camp in the morning it seemed as if the entire land was covered with the animals. They were in such throngs that the sound of their hoofs was like the rumbling of distant thunder. One could compare the scene to nothing more than to an ocean of dark water surrounding us on every side, pitching and tossing as if under the influence of a strong wind. It was such a sight as I had seen more than once, but to my companions it was terrifying at the same time that it commanded their closest attention.

The reader can infer that the narrator is in charge of the group. Which sentence from the text **best** supports this inference?

a) There we drove down a dry ravine on our winding way to the river bottoms, stopping now and then to gather a store of wild currants and gooseberries which grew in abundance.

b) There was in the company a girl of about Susan's age, whose name was Mary Parker, and from that time I had two companions as I rode in advance of the train.

c) I could have found no fault with these new members of our company, for they obeyed my orders without questions from the oldest man to the youngest child.

d) It was such a sight as I had seen more than once, but to my companions it was terrifying at the same time that it commanded their closest attention.

Appendix B: 11th-Grade SBAC

Math (Concepts and Procedures), example item

Select an expression that is equivalent to $\sqrt{3^8}$.

A. $3^{\frac{1}{4}}$

B. 3^3

C. 3^4

D. 3^6

English (Reading), example item

Moving to the Back of Beyond

When my parents said the three of us were moving out to California, to a place just north of Los Angeles, my mind immediately went to thoughts of Disneyland and Hollywood, glitz and glamour. I imagined a Rodeo Drive shopping spree to pick out a bikini for the endless days I would be spending on the beach. However, I'd forgotten about my parents' penchant for the unconventional; they're definitely "the road less traveled" kind of people. Mom had a gopher snake for a pet when she was younger, and Dad was never happier than when he was climbing near-vertical cliffs that only mountain goats could love. These are not city folk. They had chosen to buy a 900-square-foot cabin under a 250-year-old oak tree in the high chaparral[1] forest out in the back of beyond—so far away from Los Angeles that you couldn't even see the glow of the lights at night. When I first saw where we were going to live, I vacillated between feeling terrified and excited. This would be an adventure, for sure. But this was no camping trip where you could go home to civilization after a few days of roughing it; this *was* home, and roughing it was the new normal.

On move-in day, we drove fifteen miles out from Antelope Valley—where the nearest grocery store was located—on a two-lane road past llamas, cattle, and horses. Up and up we went, until finally we turned down a dirt road and headed into a canyon full of towering Coulter pines, blue-green sagebrush, and ancient canyon live oaks. I didn't know the names of these plants then, of course; I learned them later. That first day all I saw then was a million shades of green. We parked under an oak tree that shaded our cabin and a front yard of rock, sand, and sagebrush twice as large as the cabin itself. On the stone staircase that led to the front door, black lizards interrupted their push-ups to twist their heads and eye us as we passed. Scrub jays squawked and hummingbirds zoomed past the eaves, scolding us with their territorial calls. No cars roared past. No radios blared from a neighbor's house. There were no neighbors—no human neighbors, anyway.

Our new home consisted of one bedroom, one bathroom, and one big room for everything else. A fireplace in the corner of the big room would be our sole source of heat in the winter. A swamp box (cooler) would blow a breeze over a big damp pad to keep us cool all summer, or so my father said. But it was early autumn that day, and the temperature was perfect in the shade of the oak tree. *Our* oak tree, I thought; I was settling in. Mom wiped a layer of grime off the kitchen counter and muttered about getting a bottle of bleach on our next trip into town. That was the beginning of an important lesson about living in the back of beyond: you don't just zip over to the local convenience store anytime you need something out here. You have to make a careful list and check it twice so that you don't forget anything, because anywhere is a long way from here. On my first walk around the property, I saw two horned toads, a red-tailed hawk, and some deer tracks. I wondered what else I might find deeper and higher in the canyon. Dad told me the real estate agent had mentioned that coyotes, bobcats, mountain lions, rattlesnakes, and even bears roamed these hills. To my surprise, I found I couldn’t wait to see them. All of them. I felt my feet taking root in the earth, claiming this place as home.

With no street lamps timed to turn on at sunset, when night came it was darker than anything I had ever experienced. Mom and I went out to look at the stars while Dad tried to unplug the ancient toilet. In the city, or even in the suburbs where I had lived before, you could see only the brightest stars in the sky. But out here, it was like being in a planetarium, except there were no labels typed onto our sky. The sheer number and spread of stars was awe-inspiring. That first night, we slept on air mattresses on the living room floor because the movers had not yet arrived. There were no curtains on the windows, so when the moon rose, it shone in as if moonbeams were an integral part of the cabin.

Eventually, I moved into the bedroom and Mom and Dad got a foldout bed for the living room. Over the next few months, I began to count the passage of time in full moons rather than by the pages of a calendar, and for the first time I really noticed the days growing shorter in winter and longer in summer. It’s hard to believe, but we’ve been here for six years now. I’ve been going to school in the valley, but I feel most at home up here with my wild fellow canyon dwellers. Soon, I will have to leave home for college, and I’m a little afraid of the culture shock I’m sure I will feel when I move back to civilization. Soon I’ll be walking on pavement and well-mowed grass again, rooming with strangers, and eating meals in a cafeteria crowded with more people than live within twenty miles of this house. But I know I will come back. The back of beyond is home now.

The narrator implies that living at the "back of beyond" helps her to connect to the natural world. Which detail from the text **best** supports this idea?

- (A) "But this was no camping trip where you could go home to civilization after a few days of roughing it; this was home…"
- (B) "Dad told me the real estate agent had mentioned that coyotes, bobcats, mountain lions, rattlesnakes, and even bears roamed these hills."
- (C) "Over the next few months, I began to count the passage of time in full moons rather than by the pages of a calendar…"
- (D) "Soon, I will have to leave home for college, and I'm a little afraid of the culture shock I'm sure I will feel when I move back to civilization."

Appendix C: Data Use Agreement

DATA USE AGREEMENT
BETWEEN

THE LOS ANGELES UNIFIED SCHOOL DISTRICT

AND

[Carol Alexander]

FOR

DATA SHARING [STUDIES/ RESEARCH]

1. PARTIES

1.1 The Los Angeles Unified School District (the District) is a public school district organized and existing under and pursuant to the constitution and laws of the State of California and with a primary business address at 333 S. Beaudry Avenue, Los Angeles, California 90017.

1.2 Carol Alexander (Researcher) is located at Claremont Graduate University at 150 East 10th Street, Claremont, California 917011

2. PURPOSE

2.1 The purpose of this Data Use Agreement ("Agreement) is to provide the District with **data in order to conduct a dissertation study evaluating the utility of SBAC for college readiness within an urban school district.** This Agreement is meant to ensure that Researcher adheres to the District's requirements concerning use of student information and applies to studies/research conducted by District schools.

2.2 The disclosure of personally identifiable information from student education records is for, or on behalf of District, in order to: Develop, validate, or administer predictive tests; Administer student aid programs; or Improve instruction.

2.3 Explain the purpose of/legitimate interest for the study/research. **The specific aims are to assess (1) the degree to which 11th-grade SBAC scores predict college readiness over and above GPA, SAT, and advanced course completion (2) the degree to which 8th-grade SBAC scores can be used as an early indicator for predicting high school SBAC score and college success over and above GPA, SAT, advanced course completion (3) how SBAC effects may vary by student aspiration, ethnicity, school type, and poverty. College readiness is measured with college persistence, defined as second-year enrollment, an important but understudied measure (Seidman, 2019).**

3. DISTRICT DUTIES

The District will provide data in compliance with the Family Educational Rights and Privacy Act ("FERPA"), 20 U.S.C. section 1232g and 34 C.F.R. 99, and California Education Code sections 49060-49085.

4. RESEARCHER DUTIES

4.1 The Researcher will perform the following duties and comply with all FERPA and California Education Code provisions, including the following:

4.1.1 Use the data shared under this Agreement for no purpose other than the work stated in this Agreement and in Requestor's agreements with District schools and authorized under Section 99.31(a)(6) of Title 34 of the Code of Federal Regulations. Researcher further agrees not to share data received under this Agreement with any other entity. Researcher agrees to allow LAUSD access to any relevant Researcher records for purposes of completing authorized audits.

4.1.2 Require all employees, contractors and agents of any kind to comply with all applicable provisions of FERPA and other federal and California laws with respect to the data shared under this Agreement.

4.1.3 Maintain all data obtained pursuant to this Agreement in a secure computer environment and not copy, reproduce or transmit data obtained pursuant to this Agreement except as necessary to fulfill the purpose of the original request. All copies of data of any type, including any modifications or additions to data from any source that contains information regarding students, are subject to the provisions of this Agreement in the same manner as the original data. The ability to access or maintain data under this Agreement shall not under any circumstances transfer from Researcher to any other institution or entity.

4.1.4 Not disclose any data obtained under this Agreement in a manner that could identify an individual (e.g. student or parent) to any other entity in published results of studies as authorized by this Agreement.

4.1.5 Destroy all personally identifiable data obtained under this Agreement within three (3) years after receipt of data. **DATA DESTRUCTION DEADLINE:** June 30, 2024 .[1] Nothing in this Agreement authorizes Researcher to maintain personally identifiable data beyond this specified date. If personally identifiable data provided by the District is required ***beyond*** this specified date, a formal request (in writing) must be submitted by the Researcher to the Executive Director of the Office of Data and Accountability for

[1] Note: If the terms of the Data Use Agreement require the provision of data over the course of multiple years, then an amendment to the original Agreement must be submitted for approval ***before*** subsequent transfers of data will be authorized. Each amendment must include the proposed new Data Destruction Deadline so that a record is maintained to document when data is required to be destroyed.

approval. This request must include a detailed justification for the deadline extension request along with a proposed new deadline for data destruction. Unless approval for the extension is granted, all personally identifiable data shall be destroyed in compliance with 34 CFR Section 99.31(a)(6) by the specified date. Researcher agrees to require all employees, contractors, or agents of any kind to comply with this provision.

4.2 If Researcher is an operator of an Internet website, online service, online application, or mobile application, Researcher shall comply with the requirements of California Business and Professions Code section 22584 and District policy as follows:

4.2.1 Researcher shall not (i) knowingly engage in targeted advertising on the Researcher's site, service or application to District students or their parents or legal guardians; (ii) use PII to amass a profile about a District student; (iii) sell information, including PII; or (iv) disclose PII without the District's written permission.

4.2.2 Researcher will store and process District Data in accordance with commercial best practices, including appropriate administrative, physical, and technical safeguards, to secure such data from unauthorized access, disclosure, alteration, and use. Such measures will be no less protective than those used to secure Researcher's own data of a similar type, and in no event less than reasonable in view of the type and nature of the data involved. Without limiting the foregoing, Researcher warrants that all electronic District Data will be encrypted in transmission using SSL [(Secure Sockets Layer)] [or insert other encrypting mechanism] (including via web interface) [and stored at no less than 128-bit level encryption].

4.2.3 Researcher shall delete a student's covered information upon request of the District.

4.2.4 District Data will not be stored outside the United States without prior written consent from the District.

4.3 Researcher shall comply with the District's information security specifications prior to receiving any electronic transfers of pupil record information. District may require Researcher to provide documentation of compliance prior to any transmittal.

4.4 If the Researcher will provide cloud-based services which will involve digital storage, management and retrieval of pupil records or will provide digital educational software to access, store and use pupil records, the following requirements in compliance with California Education Code section 49073.1 pertain:

4.4.1 The pupil records continue to be the property of and under the control of the District;

4.4.2 Researcher will not use any information in the pupil record for any purpose other than those required or specifically permitted by this Agreement.

4.4.3 In order for a parent, legal guardian or eligible pupil to review personally identifiable information in the pupil's records and correct erroneous information, Researcher shall contact the school of enrollment so that information can be corrected.

4.4.4 Researcher shall take the following actions, including the designation and training of responsible individuals, to ensure the security and confidentiality of pupil records:

All student data from the district's archive will be deidentified and assigned pseudo IDs by the district, so that the identity of each student remains completely anonymous and there will not be any personally identifiable information collected that would need to be kept confidential. Before conducting the study, I will clear all study procedures with the Claremont Graduate University professor, who is the Chair of my dissertation committee. I will make sure to strictly follow all District protocols (e.g., for data use and analysis). In addition, I will adhere to the data use agreement and all district requirements for use of their de-identified data using the procedures described above.

4.4.5 Researcher shall use the following procedure for notifying the affected parent, legal guardian, or eligible pupil in the event of an unauthorized disclosure of the pupil's records:

Although very unlikely, if this occurs, I will first take action to notify the school district of the unauthorized disclosure and apprise them of my second action, which will be to contact the affected person/s and let them know of the unauthorized disclosure.

4.4.6 Researcher certifies that he/she/it will not retain the pupil records upon completion of the services. Researcher will take the following actions to enforce this certification:

Upon completion, I will destroy (permanently delete) any digital or hard copy of the records. Morever, throughout the study, I will only ever keep one digital copy of the records, to avoid the possibility of duplicate copies accidentally not getting deleted after completion.

4.4.7 Researcher shall not use personally identifiable information in pupil records to engage in targeted advertising.

4.5 Pre-Publication Review. Upon notice, District may request and Researcher agrees to timely provide, prior to publication or re-publication, access to any report, memorandum, article, thesis or any other writing that includes Student Record Information provided under this Agreement and links District to any outcome or enables District to be linked to any outcome. District reserves the right to withdraw consent to the publication of any such writing if the District determines that the privacy rights of its students or interests of the District are jeopardized, or such writing contains statements that the District considers unacceptable for publication due to, but not limited to, sampling error, flaws in analysis, or misrepresentation of findings.

5. NO WARRANTY CONCERNING DATA

Researcher agrees that District makes no warranty concerning the accuracy of the student data provided.

6. DATA AUTHORIZED FOR TRANSFER

The data listed in Attachment A is authorized for transfer. Due to the substantial time and effort required for staff to provide requested data with the appropriate selection and matching of records and concealment of personal identities etc., there may be costs associated with data extracts. If applicable, a time estimate and dollar amount will be provided to the Researcher prior to the transfer of data and the Researcher agrees to pay the District the amount requested prior to receiving the data authorized by this Agreement.

7. TERM

This Agreement shall be effective for three years from the date the last party signs. Either party may terminate this Agreement for any reason at any time upon reasonable notice to the other party.

8. GENERAL PROVISIONS

8.1 INDEPENDENT CONTRACTOR While engaged in performance of this Agreement the Researcher is an independent contractor and is not an officer, agent, or employee of the District. Researcher is not entitled to benefits of any kind to which District's employees are entitled, including but not limited to unemployment compensation, workers' compensation, health insurance, and retirement benefits. Researcher assumes full responsibility for the acts and/or omissions of Researcher's employees or agents as they relate to performance of this Agreement. Researcher assumes full responsibility for workers' compensation insurance, and payment of all federal, state and local taxes or contributions, including but not limited to unemployment insurance, social security, Medicare, and income taxes with respect to Researcher and Researcher's employees. Researcher warrants its compliance with the criteria established by the U.S. Internal Revenue Service (I.R.S.) for qualification as an independent contractor, including but not limited to being hired on a temporary basis, having some discretion in scheduling time to complete contract work, working for more than one employer at a time, and acquiring and maintaining its own office space and equipment. Researcher agrees to indemnify District for all costs and any penalties arising from audits by state and/or federal tax entities related to services provided by Researcher's employees and agents under this Agreement.

8.2 CONFLICT OF INTEREST Researcher represents that Researcher has no existing financial interest and will not acquire any such interest, direct or indirect, which could conflict in any manner or degree with the performance of services required under this Agreement and that no person having any such interest shall be subcontracted in connection with this Agreement, or employed by Researcher. Researcher shall not conduct or solicit any non-District business while on District property or time.

8.2.1 Researcher will also take all necessary steps to avoid the appearance of a conflict of interest and shall have a duty to disclose to the District prior to entering into this Agreement any and all circumstances existing at such time which pose a potential conflict of interest.

8.2.2 Researcher warrants that he/she/it has not directly or indirectly offered or given, and will not directly or indirectly offer or give, to any employee, agent, or representative of District any cash or noncash gratuity or payment with view toward securing any business from District or influencing such person with respect to the conditions, or performance of any contracts with or orders from District, including without limitation this Agreement. Any breach of this warranty shall be a material breach of each and every contract between District and Requestor.

8.2.3 The following shall be considered a part of and required under this Agreement:

- **The District's Contractor Code of Conduct** (http://achieve.lausd.net/cms/lib08/CA01000043/Centricity/Domain/218/5.%20%20CODE%20OF%20CONDUCT%20irfp.pdf)
- **SB 1177 Student Online Personal Information Protection Act (SOPIPA)** (https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201320140SB1177).

8.2.4 Should a conflict of interest issue arise, Requestor agrees to fully cooperate in any inquiry and to provide the District with all documents or other information reasonably necessary to enable the District to determine whether or not a conflict of interest existed or exists.

8.2.5 Failure to comply with the provisions of this section shall constitute grounds for immediate termination of this Agreement, in addition to whatever other remedies the District may have.

8.3 EQUAL EMPLOYMENT OPPORTUNITY It is the policy of the District that, in connection with all work performed under District agreements, there shall be no discrimination against any employee or applicant for employment because of race, color, religious creed, national origin, ancestry, marital status, sex, sexual orientation, age, disability or medical condition and therefore the Requestor agrees to comply with applicable federal and state laws. In addition, the Requestor agrees to require like compliance by all subcontractors employed on the work.

8.4 GOVERNING LAW The validity, interpretation and performance of this Agreement shall be determined according to the laws of the State of California.

8.5 INDEMNIFICATION Requestor shall indemnify and hold the District and its Board Members, administrators, employees, agents, attorneys, and contractors ("Indemnitees") harmless against all liability, loss, damage and expense (including reasonable attorneys' fees) resulting from or arising out of this Agreement or its performance, whether such loss, expense, damage or liability was proximately caused in whole or in part by the negligent or willful act or omission of Requestor, including, without limitation, its agents, employees, subcontractors or anyone employed directly or indirectly by it.

8.6 WARRANTY Researcher shall not have contact with any District student in furtherance of this Agreement.

8.7 NOTICES All notices required or permitted by this Agreement shall be in writing and shall be either personally delivered or sent by nationally-recognized overnight courier, facsimile or by registered or certified U.S. mail, postage prepaid, addressed as set forth below (except that a party may from time to time give notice changing the address for this purpose). A notice shall be effective on the date personally delivered, on the date delivered by a nationally-recognized overnight courier, on the date set forth on the receipt of a telecopy or facsimile, or upon the earlier of the date set forth on the receipt of registered or certified mail or on the fifth day after mailing.

DISTRICT:	RESEARCHER:
Attention: Oscar Lafarga, Executive Director Office of Data and Accountability	**Attention:** Carol Alexander 644 South Parish Place Burbank, CA 91506
333 South Beaudry Avenue, 16th Floor Los Angeles, CA 90017 TEL: (213) 241-2460 FAX: (213) 241-8462	TEL: **818-631-0101** FAX: ______________

IN WITNESS WHEREOF, the parties have executed this Agreement as of the last day noted below.

LOS ANGELES UNIFIED SCHOOL DISTRICT

By: Kevon R. Tucker-Seeley Date: 5/24/21

Name, Title/Position: Kevon Tucker-Seeley, Director, Office of Data and Accountability

RESEARCHER

By: Carol Alexander Date:

(sign here)

Name, Title/Position: Director A-G

Doc# 3445357

DATA USE AGREEMENT
ATTACHMENT A: DATA AUTHORIZED FOR TRANSFER

The data use agreement between the District and the Researcher covers the data listed below:

RESEARCHER TO LIST ALL DATA ELEMENTS BEING REQUESTED FROM THE DISTRICT.

The data I will need will need to be de-identified for the study. The following is the list of data needed:

- Class of 2019 LAUSD Graduates from all LA Unified high schools
- Data will exclude all students with IEPs and those that earned a GED or certificate instead of an LAUSD diploma)
- Demographic data will include (Race/ethnicity) (2018-19 SY)
- English learner (yes/no) (2018-19 SY)
- Cumulative Attendance Rate in HS (2018-19 SY)
- Cumulative Attendance Rate in MS (2014/15 SY)
- Poverty indicator (yes/no) (2018-19 SY)
- A-G completion with a D or better (yes/no) (2018-19 SY)
- A-G completion with a C or better (yes/no) (2018-19 SY)
- SBAC ELA level and score for their 8th grade (2014-15 SY) and 11th grade year (2017-18 SY)
- SBAC Math level and score for their 8th grade (2014-15 SY) and 11th grade year (2017-18 SY)
- SAT student overall score for Class of 2019 (last SAT score)
- SAT English "Evidence-Based Reading & Writing" score for Class of 2019 (last SAT score)
- SAT Math score for Class of 2019 (last SAT score)
- Number of ELA AP Courses completed
    1. AP English Language and Composition B
    2. AP English Literature and Composition B
- Number of History AP Courses completed
    1. AP Comparative Government
    2. AP European History B
    3. AP Human Geography B
    4. AP Macroeconomics
    5. AP Microeconomics
    6. AP Psychology B
    7. AP US Government and Politics
    8. AP US History B
    9. AP World History: Modern B
- Number of Math AP Courses completed
    1. AP Calculus A
    2. AP Calculus B
    3. AP Calculus C
    4. AP Computer Science A
    5. AP Computer Science Principles
    6. AP Statistics B
- Number of Science AP Courses completed

1. AP Biology B
2. AP Chemistry B
3. AP Environmental Science B
4. AP Physics 1 B
5. AP Physics 2 B
6. AP Physics C: Electricity and Magnetism
7. AP Physics C: Mechanics

- Number of "Advanced" Math courses above Algebra 2
    1. Precalculus B
    2. Statistics and Probability B
    3. Transition to College Mathematics and Statistics B
    4. Honors Advanced Mathematics B
    5. Discrete Mathematics B
    6. Quantitative Reasoning B
- Number of IB courses completed
- Number of community college semester courses completed (concurrent or dual enrollment)
- Number of "Advanced" LOTE courses completed
    1. LOTE 3A
    2. LOTE 3B
    3. LOTE 4A
    4. LOTE 4B
- LAUSD Cumulative GPA at end of MS (2014-15 SY)
- LAUSD Cumulative GPA at end of HS (Class of 2019)
- 2 year college immediately enrolled (yes/no) (from Clearinghouse) (Class of 2019)
- 4 year college immediately enrolled (yes/no) (from Clearinghouse) (Class of 2019)
- College persistence into 2nd year at either a 2 year or 4 year college (from Clearinghouse) (Class of 2019)
- School type flag (magnet, comprehensive, pilot, partnership etc.) (Class of 2019)
- Affiliated Charter flag (Class of 2019)
- School site cohort grad rate (2018-19 SY)
- School site % on free and reduced lunch (Title 1 rate 2018-19 SY)
- School site student enrollment (2018-19 SY)
- 2018-19 College Readiness Survey Responses
- 2018-19 School Experience Survey Responses

Appendix D: District Approval to Conduct the Study

Los Angeles Unified School District

Office of Data and Accountability
333 South Beaudry Avenue, 16th Floor, Los Angeles, California 90017
Telephone: (213) 241-2460 Fax: (213) 241-8462

Austin Beutner
Superintendent of Schools

Veronica Arreguin
Chief Strategy Officer

Oscar Lafarga
Executive Director

May 24, 2021

Dr. Carol Alexander
644 S. Parish Place
Burbank, CA 91506

Re: Proposal # 894

Dear Researcher:

The LAUSD Committee for External Research Review has approved your request to initiate the research study entitled "Examining the Smarter Balanced Assessment Consortium Exams, Scholastic Aptitude Test, and High School Grade Point Average as Predictors of College Readiness." This action by the committee is an approval to conduct your study in LAUSD schools. In addition, the terms presented in the Statement of Agreement for External Researchers and signed on May 12, 2021 apply. This letter does not:

- Create any obligation for district personnel, students, or parents to participate. All participation must be completely voluntary, and the confidentiality of all sources must be maintained.
- Permit the administrators or staff to engage in this study during paid work time nor any students to engage in this study during instructional time.

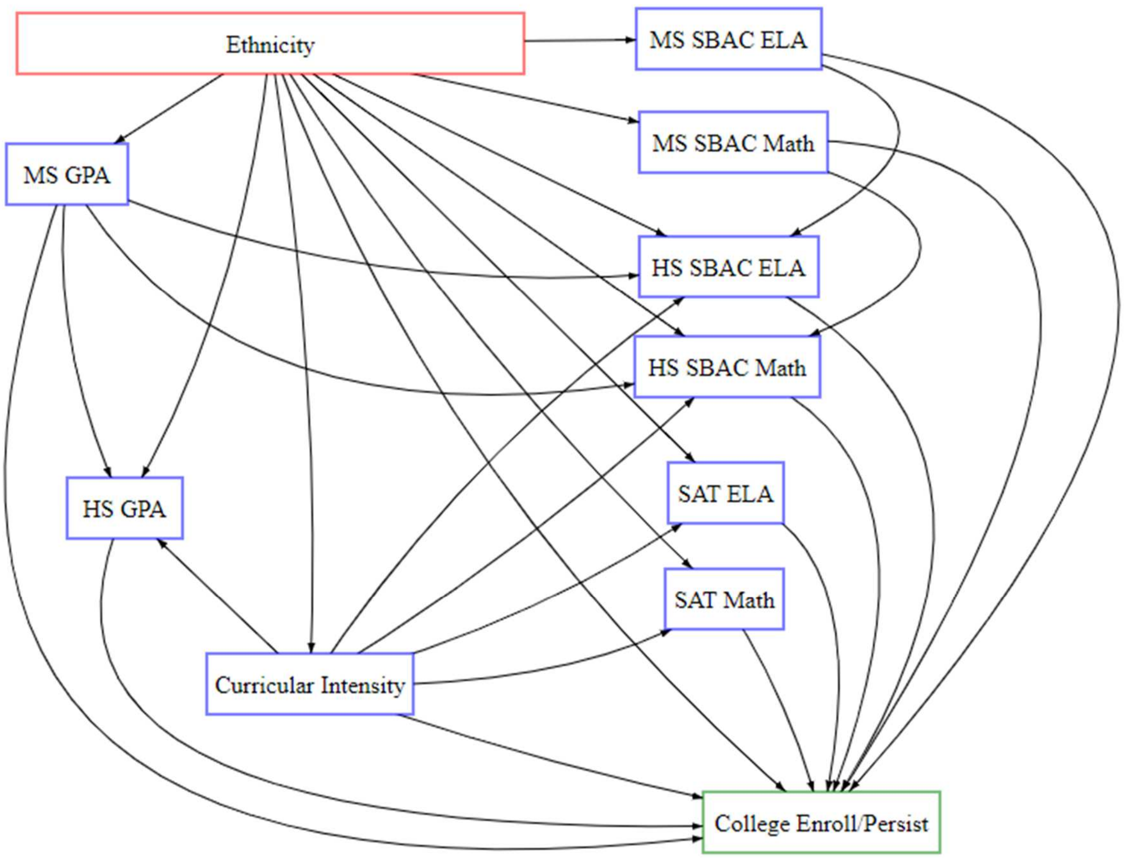
This letter provides approval for you to conduct your research in LAUSD schools. Please ensure that neither the District nor the schools will be identified in any communications or reports. The approval is valid until May 24, 2022. At that time or at the conclusion of your study, whichever comes first, please send a practitioner-friendly summary (Power Point presentation, infographic, research brief, etc.) of your findings and copies of any reports to my attention. I wish you the best of luck in your research endeavors.

Sincerely,

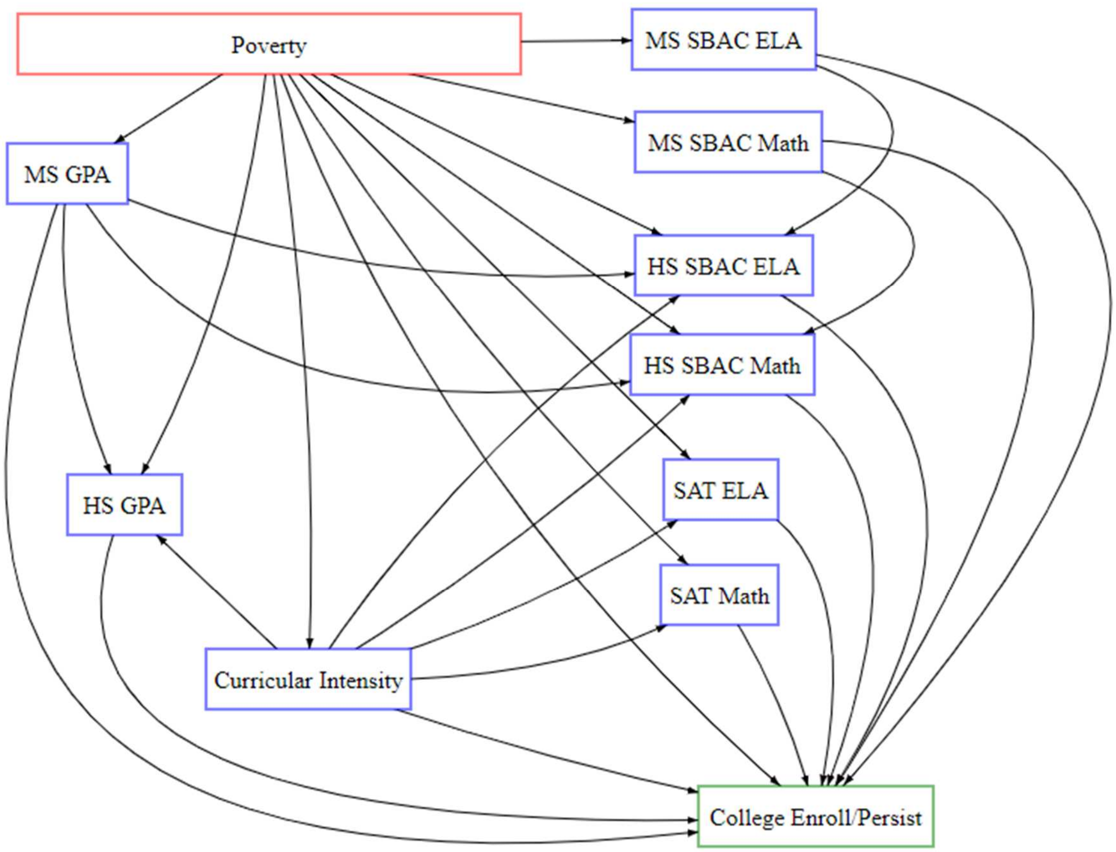
Katherine Hayes, Ph.D.
Coordinator CERR, School Experience Survey
Research and Reporting Branch
Office of Data and Accountability
Los Angeles Unified School District

Appendix E: Path Analysis Diagrams

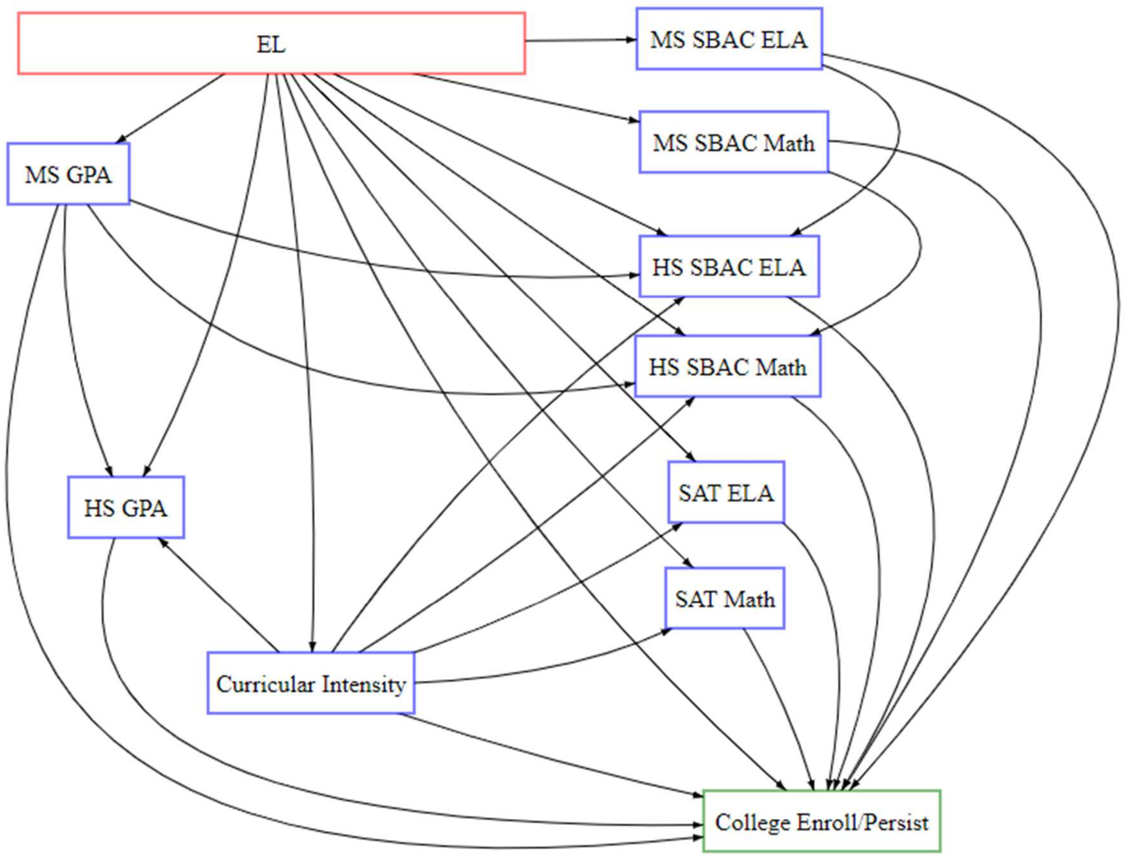
Ethnicity as exogenous variable (subset of full path diagram model)



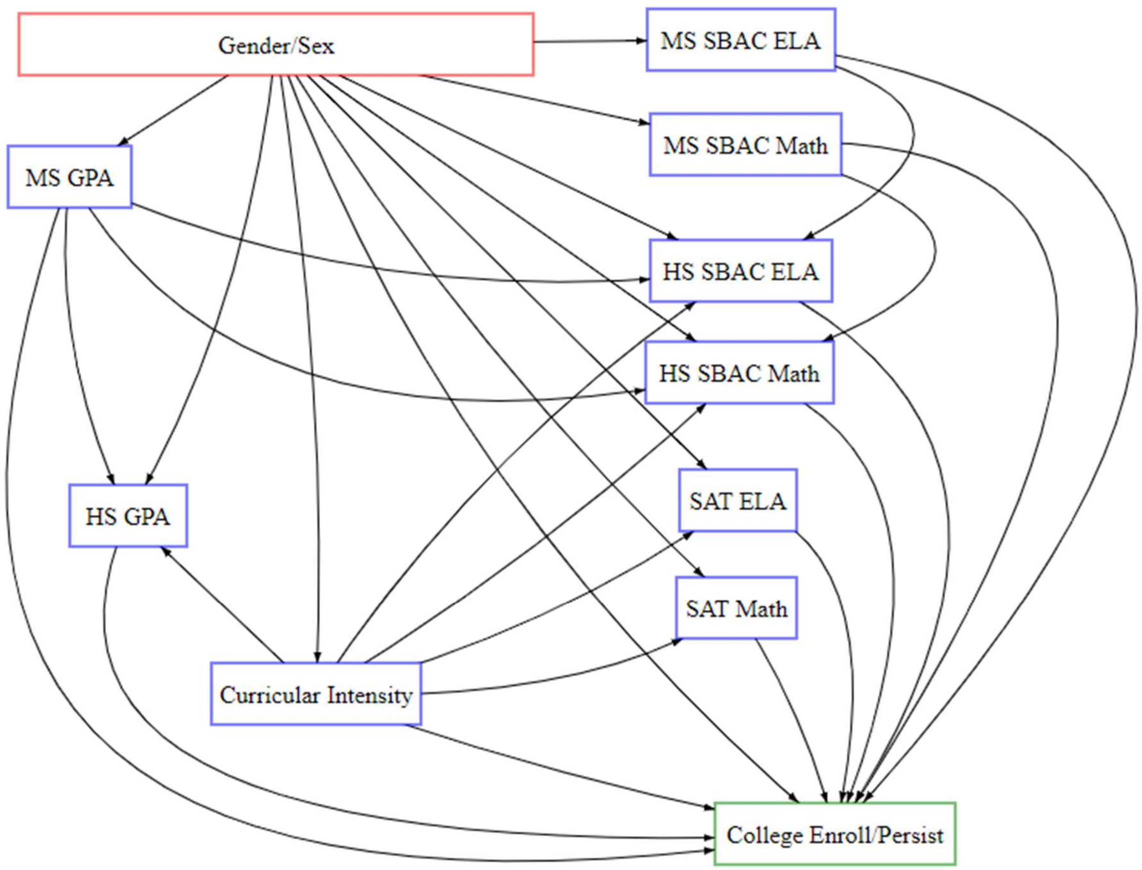
Poverty as exogenous variable (subset of full path diagram model)



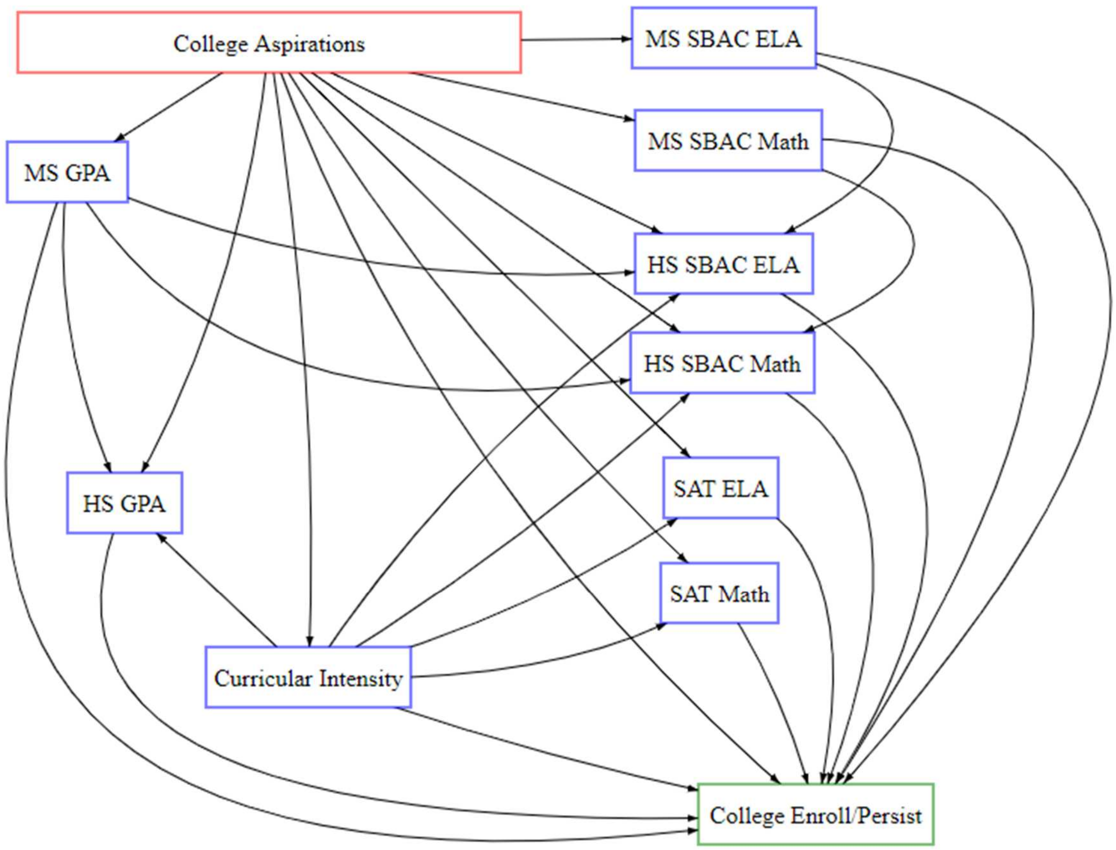
English Learner (EL) as exogenous variable (subset of full path diagram model)



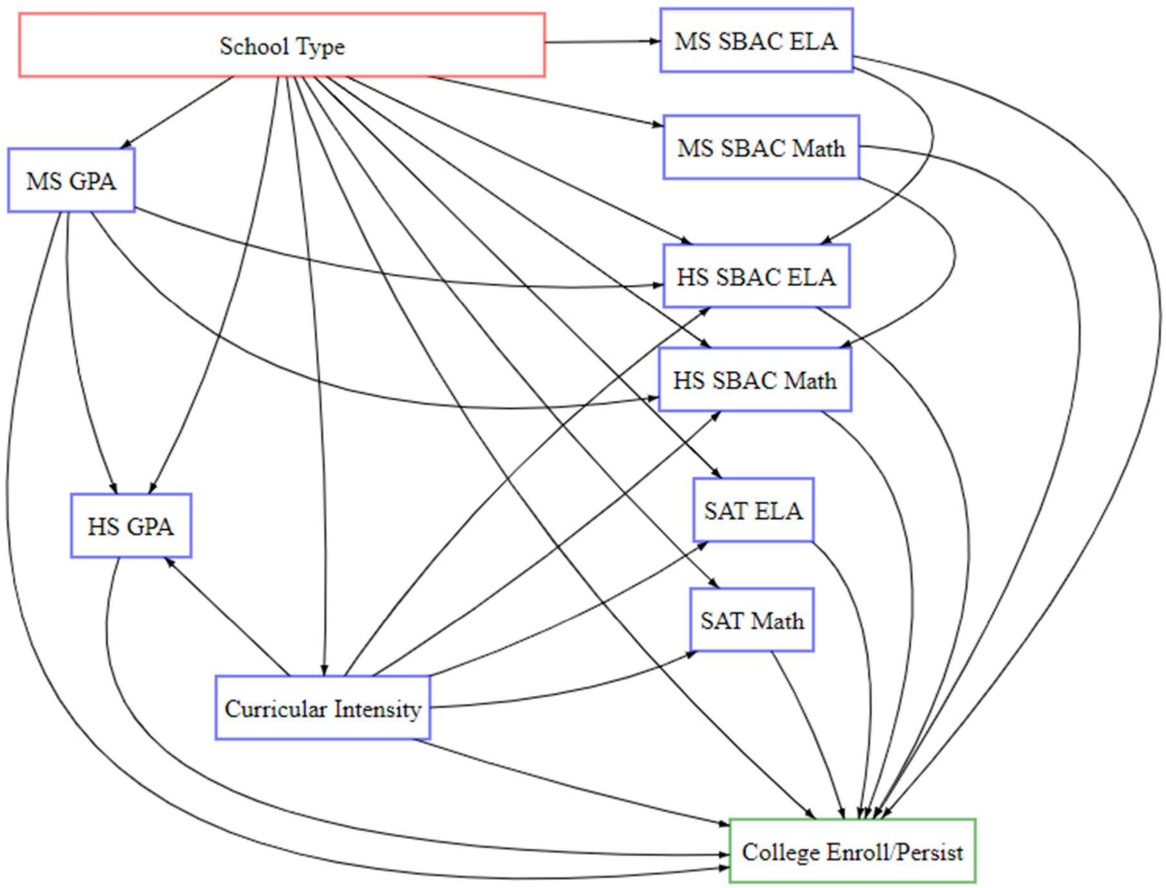
Gender/Sex as exogenous variable (subset of full path diagram model)



College Aspirations as exogenous variable (subset of full path diagram model)



School Type as exogenous variable (subset of full path diagram model)



Appendix F: Supplementary Analyses

Supplementary Table 1

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.407[a]	.166	.165	1.614

a. Predictors: (Constant), HS_SBAC_Math, HS_SBAC_ELA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	11083.344	2	5541.672	2128.140	.000[b]
	Residual	55884.404	21461	2.604		
	Total	66967.748	21463			

a. Dependent Variable: CollegeReady

b. Predictors: (Constant), HS_SBAC_Math, HS_SBAC_ELA

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-15.974	.292		-54.637	.000
	HS_SBAC_ELA	.004	.000	.222	24.760	.000
	HS_SBAC_Math	.003	.000	.217	24.265	.000

a. Dependent Variable: CollegeReady

Supplementary Table 2

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.514[a]	.264	.264	1.515

a. Predictors: (Constant), HSGPA, HS_SBAC_ELA, HS_SBAC_Math

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17688.520	3	5896.173	2567.651	.000[b]
	Residual	49279.228	21460	2.296		
	Total	66967.748	21463			

a. Dependent Variable: CollegeReady

b. Predictors: (Constant), HSGPA, HS_SBAC_ELA, HS_SBAC_Math

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-6.199	.330		-18.809	.000
	HS_SBAC_ELA	.002	.000	.109	12.610	.000
	HS_SBAC_Math	.000	.000	.028	3.019	.003
	HSGPA	1.009	.019	.422	53.632	.000

a. Dependent Variable: CollegeReady

Supplementary Table 3

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.506[a]	.256	.256	1.524

a. Predictors: (Constant), CurricularIntensity, CollegeAspiration, HS_SBAC_Math, HS_SBAC_ELA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	17151.756	4	4287.939	1847.379	.000[b]
	Residual	49792.085	21452	2.321		
	Total	66943.841	21456			

a. Dependent Variable: CollegeReady

b. Predictors: (Constant), CurricularIntensity, CollegeAspiration, HS_SBAC_Math, HS_SBAC_ELA

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-8.630	.320		-26.947	.000
	HS_SBAC_ELA	.002	.000	.106	12.032	.000
	HS_SBAC_Math	.002	.000	.117	13.369	.000
	CollegeAspiration	.202	.006	.199	31.866	.000
	CurricularIntensity	.192	.006	.250	34.262	.000

a. Dependent Variable: CollegeReady

Supplementary Table 4

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.312[a]	.097	.097	1.617

a. Predictors: (Constant), SAT_Math, HS_SBAC_ELA, SAT_ELA, HS_SBAC_Math

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3383.329	4	845.832	323.595	.000[b]
	Residual	31415.976	12019	2.614		
	Total	34799.305	12023			

a. Dependent Variable: CollegeReady

b. Predictors: (Constant), SAT_Math, HS_SBAC_ELA, SAT_ELA, HS_SBAC_Math

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-6.450	.621		-10.393	.000
	HS_SBAC_ELA	.002	.000	.098	7.225	.000
	HS_SBAC_Math	.001	.000	.084	5.191	.000
	SAT_ELA	.002	.000	.077	5.110	.000
	SAT_Math	.002	.000	.095	5.649	.000

a. Dependent Variable: CollegeReady

Supplementary Table 5

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.436[a]	.190	.190	1.531

a. Predictors: (Constant), CollegeAspiration, SAT_Math, CurricularIntensity, HS_SBAC_ELA, HSGPA, SAT_ELA, HS_SBAC_Math

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	6615.078	7	945.011	402.921	.000[b]
	Residual	28177.667	12014	2.345		
	Total	34792.745	12021			

a. Dependent Variable: CollegeReady

b. Predictors: (Constant), CollegeAspiration, SAT_Math, CurricularIntensity, HS_SBAC_ELA, HSGPA, SAT_ELA, HS_SBAC_Math

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.999	.612		-1.633	.103
	HS_SBAC_ELA	.000	.000	.017	1.279	.201
	HS_SBAC_Math	.000	.000	-.021	-1.340	.180
	HSGPA	.749	.031	.273	23.928	.000
	SAT_ELA	.001	.000	.036	2.502	.012
	SAT_Math	.001	.000	.043	2.657	.008
	CurricularIntensity	.078	.009	.087	8.640	.000
	CollegeAspiration	.172	.010	.148	17.379	.000

a. Dependent Variable: CollegeReady

Supplementary Table 6

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.428[a]	.183	.183	1.597

a. Predictors: (Constant), SchoolSize, Gender, Asian, EL, Black, Poverty, HS_SBAC_Math, HS_SBAC_ELA, Latinx

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	12115.087	9	1346.121	527.917	.000[b]
	Residual	54105.785	21219	2.550		
	Total	66220.872	21228			

a. Dependent Variable: CollegeReady

b. Predictors: (Constant), SchoolSize, Gender, Asian, EL, Black, Poverty, HS_SBAC_Math, HS_SBAC_ELA, Latinx

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-15.151	.337		-44.908	.000
	HS_SBAC_ELA	.003	.000	.189	20.281	.000
	HS_SBAC_Math	.004	.000	.243	26.406	.000
	Gender	-.432	.022	-.122	-19.323	.000
	Asian	-.050	.056	-.008	-.902	.367
	Black	.184	.059	.027	3.128	.002
	Latinx	-.059	.044	-.014	-1.344	.179
	EL	-.056	.042	-.009	-1.337	.181
	Poverty	-.064	.040	-.010	-1.581	.114
	SchoolSize	-8.172E-5	.000	-.029	-4.620	.000

a. Dependent Variable: CollegeReady

Supplementary Table 7

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.355[a]	.126	.126	1.647

a. Predictors: (Constant), MS_SBAC_Math, MS_SBAC_ELA

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	7288.488	2	3644.244	1343.503	.000[b]
	Residual	50460.511	18603	2.712		
	Total	57748.999	18605			

a. Dependent Variable: CollegeReady

b. Predictors: (Constant), MS_SBAC_Math, MS_SBAC_ELA

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-15.808	.376		-42.080	.000
	MS_SBAC_ELA	.004	.000	.178	17.635	.000
	MS_SBAC_Math	.004	.000	.203	20.085	.000

a. Dependent Variable: CollegeReady

Supplementary Table 8

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.376[a]	.141	.141	1.633

a. Predictors: (Constant), SchoolSize, Gender, Poverty, EL, Black, Asian, MS_SBAC_Math, MS_SBAC_ELA, Latinx

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	8076.831	9	897.426	336.520	.000[b]
	Residual	49114.125	18417	2.667		
	Total	57190.956	18426			

a. Dependent Variable: CollegeReady

b. Predictors: (Constant), SchoolSize, Gender, Poverty, EL, Black, Asian, MS_SBAC_Math, MS_SBAC_ELA, Latinx

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-14.445	.442		-32.699	.000
	MS_SBAC_ELA	.003	.000	.144	13.754	.000
	MS_SBAC_Math	.004	.000	.223	21.614	.000
	Gender	-.415	.025	-.118	-16.927	.000
	Asian	.021	.063	.003	.335	.737
	Black	.042	.070	.005	.600	.548
	Latinx	-.071	.051	-.016	-1.410	.159
	EL	.050	.056	.007	.897	.369
	Poverty	-.081	.046	-.013	-1.764	.078
	SchoolSize	-8.346E-5	.000	-.030	-4.354	.000

a. Dependent Variable: CollegeReady

Supplementary Table 9

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	30404.317[a]	.035	.047

a. Estimation terminated at iteration number 4 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Gender	-.391	.027	205.215	1	.000	.676
	Asian	.133	.073	3.274	1	.070	1.142
	Black	-.308	.073	17.907	1	.000	.735
	Latinx	-.337	.056	35.664	1	.000	.714
	EL	-.932	.047	386.578	1	.000	.394
	Poverty	-.328	.052	39.085	1	.000	.721
	Constant	1.190	.065	337.577	1	.000	3.288

a. Variable(s) entered on step 1: Gender, Asian, Black, Latinx, EL, Poverty.

Supplementary Table 10

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	12091.232[a]	.034	.055

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Gender	-.684	.046	219.812	1	.000	.505
	Asian	.120	.149	.645	1	.422	1.127
	Black	-1.063	.132	64.414	1	.000	.346
	Latinx	-.879	.113	60.854	1	.000	.415
	EL	-.384	.090	18.410	1	.000	.681
	Poverty	-.401	.094	18.028	1	.000	.670
	Constant	3.023	.128	558.174	1	.000	20.562

a. Variable(s) entered on step 1: Gender, Asian, Black, Latinx, EL, Poverty.