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Predicting Student Success in Co-remediated General Education Mathematics Courses at a Large Urban Public University

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Abstract

Placement and support of students in first-year mathematics courses at institutions of higher education has long been a consequential issue. In a bid to address it, many systems and institutions of higher learning have elected to implement a co-remediation framework in place of pre-remediation, due in large part to the prohibitive cost of the latter, both in terms of financial resource, as well as student academic progress. Accompanying this evolution has been the expansion of the introductory mathematics curriculum beyond algebra to include statistics and quantitative reasoning. The present study discusses three distinct introductory mathematics courses at a large urban public M.S. granting institution in the U.S., with the goal of identifying the characteristics that correlate with success in each. Conditional probability and non-completion rate analyses were implemented to compare student performance in each course. Predictive models were then trained and validated, building insight concerning the differential relationships of demographic and academic covariates with course completion.

Introduction

Remedial courses have long been included in the course catalogs of post-secondary, degree-granting institutions in the United States (U.S.) with data from the early 1990s indicating approximately 90% of community colleges and 91% of public colleges or universities nationwide offered remedial courses (Mansfield et al., 1991). Over two decades later, remedial courses were still in high demand on college campuses with roughly 60% of community college students nationally (Bailey, 2009; Chen, 2016) and about 85% of community college students in California (California Community Colleges Chancellor's Office, 2011) placing into remedial mathematics. While the figures were considerably lower at four-year institutions, they were still notable with approximately one-third of freshmen testing into remedial mathematics (Chen, 2016).

Remedial coursework was intended to bridge the preparation gap present among incoming college freshmen; however, a strong body of literate exists indicating remedial courses failed to achieve that objective and in fact, were associated with undesirable outcomes. It has been estimated that approximately 30% of students referred to remedial mathematics do not even attempt to make progress toward satisfying their mathematics requirement

(Bailey et al., 2010; Logue et al., 2017). For those who enroll in prerequisite remediation, the narrative is still dismal. While figures vary, the literature suggests only a minority share of students placed in remedial mathematics successfully complete a college level mathematics course (Bailey et al., 2010; Fong et al., 2013; Logue et al., 2017).

A notable proportion of students placed in remedial courses not only fail to complete course sequences, but unfortunately, they fail to complete their degree. Research has found a correlation between the number of remedial courses required for community college students and attrition rates (Bahr, 2010; Hawley & Harris, 2005; Hoyt, 1999). It has been stated that students placed in remedial education, particularly those placed in remedial math, have a very low probability of completing an associate degree or transferring to a four-year institution (Bailey et al., 2010; Calcagno et al., 2007; Fong et al., 2015; Melguizo et al., 2008) with figures as low as 10% of students obtaining an associate degree in 3 years (Logue et al., 2017). Given these outcomes, it is clear that as a whole, prerequisite remediation has not bridged the preparation gap, but has served as a roadblock or obstacle for students seeking higher education (Hawley & Harris, 2005; Horn & Nevill, 2006; Hoyt, 1999; Scott-Clayton & Rodriguez, 2012). It has also raised an equity issue in education, for multiple studies have found that student groups historically underrepresented on college campuses are overrepresented in remedial courses. That is, remedial classrooms are largely comprised of students who identify as female, members of racial/ethnic minority groups, low income, or first-generation college students (Attewell et al., 2006; Chen, 2005; Crisp & Delgado, 2013; Grimes & David, 1999; Hagedorn et al., 1999; Logue et al., 2017; Perry et al., 2010).

Given the evidence indicating prerequisite remediation was at best unsuccessful and at worst hindered student progress toward a degree and educational equity, the past two decades have seen a shift away from the prerequisite remediation model, toward corequisite support. In the late 1990s, the City University of New York (CUNY) and California State University (CSU) systems announced policies to begin limiting and eliminating prerequisite remediation. In January 2000, CUNY began to phase out remedial coursework (Hebel, 1999) while the CSUs imposed a one-year time limit on students for the completion of prerequisite remedial course sequences (Weiss, 1999). While these policies were considered controversial at the time (Hagedorn et al., 2000), other states, including Florida, Georgia, Massachusetts, Texas, and Virginia, implemented similar policies intended to reduce the presence of remedial courses in community college catalogs (Shaw, 1997).

Effective Fall 2014, remedial education became optional for a large proportion of college students in the state of Florida, and the 28 colleges in the Florida College System (FCS) were required to redesign their developmental math structure to offer academic support in at least two of the four approved forms: modularized, compressed, contextualized, and corequisite courses (Park et al., 2018). Following the policy changes, a higher percentage of first-time freshmen enrolled in and passed Intermediate Algebra, a college level course (Park et al., 2018). Notably, students who took advantage of the optional compressed or corequisite support were more likely to pass Intermediate Algebra than students who did not enroll in a support course (Park et al., 2018).

Corequisite support has emerged as the leading alternative to prerequisite remediation due to correlations with various measures of academic success. Studies have linked corequisite support to greater proportions of students passing college level mathematics courses across multiple achievement levels, students attempting and completing more college level courses, and greater retention rates from one semester to the next (Cho et al., 2012; Denley, 2015; Hayward & Willett, 2014). For these reasons, Colorado, Connecticut, and Indiana have implemented statewide policies to support the implementation of corequisite support at their community colleges (Jones, 2015; Vandal, 2016). The state of Tennessee also saw great success in Fall 2015 when 13 community colleges implemented corequisite support at scale, and 51% of students placed in a college-level mathematics course with corequisite support passed the college-level course in one semester (Belfield et al., 2016). This was a 39-percentage point increase from the 12% of students placed in prerequisite remedial math who passed a college level math course in one academic year (Belfield et al., 2016).

Along with a shift toward corequisite support, another trend that emerged with the elimination of prerequisite remediation was an exploration of course options other than algebra to satisfy general education (GE) math requirements. A randomized controlled trial was conducted at 3 community colleges at CUNY in fall 2013 assigning students who placed into remedial mathematics to one of three course designs. Results indicated students assigned to a college level statistics course with a two-hour weekly workshop had a pass rate of 56%, compared to 45% for students in remedial algebra with weekly workshops, and 39% for students in remedial algebra without weekly workshops, leading to the conclusion that given proper support, students traditionally assigned to remedial algebra courses can pass college-level, credit-bearing quantitative courses in their first semester (Logue et al., 2017).

On a broader scale, a new model of math education, commonly referred to as math pathways, emerged in 2011 – 2012 with the goal of aligning math curriculum with students' academic and career goals (Ganga & Mazzariello, 2018). Pathways were implemented in both community colleges and state universities with the list of participating states including Arkansas, California, New York, and Texas. Each state adapted the model appropriately, but common course offerings included a statistics path, a quantitative reasoning path, and a path through calculus with a strong recommendation for corequisite support regardless of path (Ganga & Mazzariello, 2018). Studies conducted on implementations in California, New York, and Texas all found students participating in math pathways were far more likely to complete a college level mathematics/quantitative reasoning course than their peers enrolled in traditional remedial mathematics (Ganga & Mazzariello, 2018).

Falling in line with the movement toward corequisite support and expansion of course options, CSU Chancellor, Timothy P. White, issued two Executive Orders (EO) effective Fall 2018 for all 23 CSU campuses — EO 1100 and EO 1110. EO 1110 eliminated prerequisite remedial mathematics courses by mandating all freshmen who had not yet satisfied the CSU category B4: Mathematics/Quantitative Reasoning GE requirement enroll in a category B4 course during their first academic year. Under EO 1110, students who demonstrated a need for additional academic support were required to participate in support course models such as corequisite support, supplemental instruction, or "stretch" course formats which extended a course beyond one academic term (CSU, 2017a). EO 1100 allowed students to satisfy the category B4 GE requirement with courses other than traditional mathematics, adding to the list of approved courses "computer science, personal finance, statistics or discipline-based mathematics or quantitative reasoning courses" (CSU, 2017b), courses which would align with students' academic and career goals. The policies implemented by EO 1100 and EO 1110 prompted both the redesign and creation of entry level mathematics courses at all 23 CSU campuses. This study focuses on the resulting GE mathematics experience at one specific campus: California State University, Long Beach (CSULB).

Background

Prior to the Fall 2018 semester, CSULB students who did not demonstrate preparation for college level mathematics through SAT/ACT Mathematics exam scores, Advanced Placement (AP) exam scores, Early Assessment Program (EAP) scores, or transfer credit were required to take the Entry Level Mathematics (ELM) exam, a test comprised of topics from Algebra I, Algebra II, and Geometry (CSU, 2010). Students who scored less than 50 on the ELM — just under 20% of students each year in the 5-year period from 2012 to 2017 — were placed in remedial mathematics (CSULB Institutional Research & Analytics, n.d.).

The remedial mathematics pipeline at CSULB started with Mathematics Prebaccalaureate (MAPB) 1: Elementary Algebra and Geometry, a 4-unit course required for students scoring in the lowest category on the ELM. After demonstrating competency in MAPB 1 topics, students enrolled in MAPB 7: Basic Intermediate Algebra, if their intended major did not require calculus, or MAPB 11: Enhanced Intermediate Algebra if they were following the calculus track. Unfortunately, the MAPB sequence echoed the national trend in which prerequisite remedial courses served as a roadblock to students with failure rates that averaged between 30% and 40% (CSULB Institutional Research & Analytics, n.d.).

In Fall 2018, EO 1100 and EO 1110 took effect, prompting a redesign of the course placement process and the entry level mathematics experience for students at all 23 CSU campuses. EO 1110 eliminated the Entry Level Mathematics exam, replacing it with a multiple measures approach to mathematics placement which considered the following at CSULB: students' high school grade point averages (GPA), 12th grade mathematics experiences, Mathematics SAT/ACT scores, and Advanced Placement (AP), International Baccalaureate (IB) and College-Level Examination Program (CLEP) exam scores (CSULB College of Natural Sciences and Mathematics, 2019). This transition allowed students at all levels of academic preparation, not just those at the top, to benefit from a more holistic approach to mathematics placement.

In addition to banning the ELM, EO 1110 eliminated the MAPB sequence by mandating all freshmen who had not yet satisfied the Mathematics/Quantitative Reasoning GE requirement enroll in a GE category B4 course during their first academic year. Under EO 1110, students whose multiple measures for mathematics placement demonstrate a need for additional academic support must participate in "supportive course models [which] may include, among others, corequisite approaches, supplemental instruction, or 'stretch' formats that extend a course beyond one academic term" (CSU, 2017a).

EO 1100 affected the entry level mathematics experience by allowing students to satisfy the B4 GE requirement with courses other than traditional mathematics. Added to the list of approved courses were "computer science, personal finance, statistics or discipline-based mathematics or quantitative reasoning courses" (CSU, 2017b). This aligned with the national movement to provide students with quantitative course options that complimented their degree and career aspirations.

In response to the changes ushered in by EO 1100 and EO 1110, CSULB created MATH 112A: Essential Algebra A and MATH 112B: Essential Algebra B, a "stretched" version of MATH 113: Precalculus Algebra, with corequisite support course MATH 92: Foundations for Essential Algebra. STAT 90: Foundations for Statistics was also created to serve as a corequisite for STAT 108: Statistics for Everyday Life and major specific introductory statistics courses offered by the College of Liberal Arts (CLA). Along with the described modifications to previously offered courses, CSULB created a new course, MATH 104: The Power of Mathematics with corequisite support course MATH 94: Foundations for Quantitative Reasoning.

This study focused on MATH 104, MATH 112A, and STAT 108, aiming to identify the profile — including both academic and demographic variables — of a student who has the greatest chance of success in each course.

MATH 104: The Power of Mathematics

MATH 104: The Power of Mathematics is a 3-unit course featuring two 50-minute large lecture meetings and a weekly 2-hour break-out activity section. The course covers "topics that demonstrate the power and art of mathematical thinking; development of quantitative and financial literacy; number sense and computational skills; mathematical habits of mind; communication skills across various mathematical forms; and ability to analyze realistic problems with mathematical tools" (CSULB University Catalog, 2018). This course was designed to satisfy the Mathematics/Quantitative Reasoning GE requirement for students whose major does not require mathematics, thus advisors encourage that population of students to enroll in MATH 104.

MATH 112A: Essential Algebra A

MATH 112A: Essential Algebra A is a 3-unit course featuring the same structure as MATH 104, two 50-minute large lectures and a weekly break-out 2-hour activity section. Topics covered in MATH 112A include "recognizing, relating, describing, manipulating, and applying functions and equations that are linear, piecewise, quadratic and polynomial; communicating quantitative ideas both orally and in writing" (CSULB University Catalog, 2018).

MATH 112A was designed to serve two different subpopulations within the population of students who demonstrate a need for additional academic support: students who intend to pursue math-intensive majors requiring calculus, many of whom come from the College of Engineering (COE), College of Natural Sciences & Mathematics (CNSM), or College of Business Administration (CBA), and students from the College of Health & Human Services (CHHS) who need MATH 112A as a prerequisite for their general chemistry requirement. Students outside of these two groups however may choose to enroll in this course to satisfy their Mathematics/Quantitative Reasoning GE requirement. MATH 112A differs from the other two courses of interest in that it is a "stretched" course, meaning it is taught at a slower pace. It has the lowest average SAT Math score of any mathematics course at CSULB with mean SAT scores averaging about 75 points lower than the mean SAT scores in MATH 113, the traditional one-semester precalculus algebra course offered by CSULB.

STAT 108: Statistics for Everyday Life

STAT 108: Statistics for Everyday Life is a 3-unit course featuring two one hour and fifteen-minute large lecture meetings per week. Statistics for Everyday Life covers "exploratory data analysis, methods of visualizing data, descriptive statistics, misuse and manipulation of data in statistical analysis, probability, binomial and normal distributions, hypothesis testing, correlation and regression, and contingency tables" (CSULB University Catalog, 2018). Instructors encourage students to use graphing calculators for topics such as probability, hypothesis testing, correlation, and regression to shift the focus away from algebraic manipulations and maintain an emphasis on statistical concepts and ideas. Advisors encourage students whose majors require an "approved statistics course," many of whom come from the CHHS, to enroll in STAT 108. Students whose majors do not explicitly require statistics however may enroll in the course for Mathematics/Quantitative Reasoning GE credit due to EO 1100.

Corequisite Support and Growth Mindset

As previously stated, all three courses of interest — MATH 104, MATH 112A, and STAT 108 — feature a corequisite support course for students whose multiple measures indicate a need for additional academic support. Like many other colleges and universities piloting corequisite support models, CSULB observed positive results in the first year of implementation. During the Fall 2018 – Spring 2019 academic year, 64% of the 745 students demonstrating a need for corequisite support passed a Mathematics/Quantitative Reasoning course that satisfied their B4 GE requirement (Chang, 2019). This marked a 28-percentage point increase from the previous academic year in which only 36% of the 744 students assigned to prerequisite remedial mathematics passed a B4 GE course by the end of their first year (Chang, 2019), supporting the transition to the corequisite support model.

In addition to offering corequisite support courses, CSULB implemented growth mindset in entry level mathematics courses to close the opportunity and achievement gap present among first-time freshmen. Growth mindset "endorse[s] the idea that ability is malleable and can be developed through persistence, good strategies, and quality mentoring" (Canning et al., 2019). A study involving 150 STEM (science, technology, engineering, and mathematics) professors and over 15,000 undergraduate students indicated on average, students achieved greater academic success in STEM courses taught by faculty who endorsed more growth, rather than fixed, mindset beliefs (Canning et al., 2019). Not only did students perform better overall, but the racial achievement gap also narrowed under the instruction of growth mindset faculty from 0.19 grade points in courses taught by fixed mindset faculty to 0.10 grade points in courses taught by more growth mindset faculty (Canning et al., 2019), a phenomenon that if replicated, would greatly benefit the diverse student population at CSULB.

All three courses implemented growth mindset in a different manner. MATH 104 explicitly introduces the concept to students in the first week of the semester and consistently encourages students and instructors to use verbiage that aligns with growth mindset. MATH 112A allows students to revisit topics for which they failed to demonstrate proficiency on an exam and complete similar problems for exam credit up to 70% with the intention of placing emphasis on teaching students how to study rather than holding them accountable to a strict timeline (F. Newberger, personal communication, January 28, 2020). STAT 108 includes a "Maintenance or Improvement" component in the grading scheme, worth 6% of the final course grade. Students who score 70% or better on a quiz or exam automatically earn 10 Maintenance points, while students who do not earn a passing grade on an assessment can earn 10 Improvement points by attending two 1-hour tutoring, office hour, or supplemental instruction sessions before the next assessment.

Methods

Data

This observational study was approved by the CSULB Institutional Review Board (IRB), and data was obtained from CSULB Institutional Research & Analytics (IR&A). Students included in the data set were First Time Freshmen in the Fall 2018, Spring 2019, or Fall 2019 cohort who took one of three courses of interest — MATH 104, MATH 112A, or STAT 108 — in the Fall 2018, Spring 2019, or Fall 2019 semester. Given the goal of the entry level mathematics redesign was to give students an opportunity to satisfy their B4 General Education requirement during their first enrollment in a mathematics or quantitative reasoning course, this study only examined academic records for a student's first enrollment in a B4 course of interest.

If a student repeated the same course or took a different B4 course in a subsequent semester, those academic records were removed from the data set. Most of the analyses performed in this study involved students' high school GPA's and SAT or ACT scores; therefore, the 16 students who did not have a recorded high school GPA and the 41 students who did not have a recorded ACT or SAT score were removed from the data set. The resulting data set included 1,433 MATH 104 students, 1,052 MATH 112A students, and 1,383 STAT 108 students, for a total sample size of n = 3,868 students.

Descriptive Statistics – Academic Variables

This study aimed to identify the profile of a student who has the greatest probability of success in MATH 104, MATH 112A, and STAT 108 with the profile including both academic and demographic variables. The academic variables used as model inputs were comprised of two components: CSULB enrollment information and measures of academic performance in high school.

CSULB Enrollment Information

CSULB has 7 colleges from which students can graduate. First-time freshmen can belong to any one of those seven colleges or University Programs if they enter as an undeclared major. Table 1 presents information regarding the composition of each B4 course of interest based on the college to which students belong. Note, undeclared majors comprised nearly one-third of the respective sample in both MATH 112A and STAT 108.

Outside of undeclared majors, the population of students served by STAT 108 was fairly homogenous with about 55% of students coming from the CHHS. MATH 104 and MATH 112A however served a more diverse sampling of majors. Colleges with the greatest representation in MATH 104 included the College of the Arts (COTA), the CLA, and the CHHS while MATH 112A students came from the CHHS, CBA, and CNSM, aligning with expectations given the population of students MATH 112A was designed to serve.

Table 1. College to which B4 Course Students Belong

Student College	Percentage of MATH 104 Students	Percentage of MATH 112A Students	Percentage of STAT 108 Students
College of the Arts	37.54%	8.46%	7.74%
College of Business Administration	0.42%	17.59%	1.08%
College of Education	0.07%	0.10%	0.14%
College of Engineering	0.14%	5.99%	0.29%
College of Health & Human Services	24.15%	22.91%	55.46%
College of Liberal Arts	27.36%	1.90%	1.08%
College of Natural Sciences & Mathematics	0.42%	9.79%	2.10%
University Programs	9.91%	33.27%	32.10%

With the implementation of EO 1110 came a general education student classification system based upon the multiple measures for mathematics placement. Under this system, students placed in Categories I & II may enroll in a B4 course without additional academic support while students placed in Categories III & IV must enroll in corequisite support. Additionally, students placed in Category IV must enroll in the Early Start Mathematics (ESM) program (CSU, 2017a). In addition to the four categories mentioned, Table 2 includes a Category IIC which is reserved for students who may be classified as Category II pending verification of high school transcripts. Elements of the multiple measures that may be affected include completion of a 12th grade mathematics course with a passing grade or a change in high school grade point average (GPA) resulting from grades earned in the final academic term (J.-M. Chang, personal communication, April 16, 2020).

Table 2. General Education Mathematics Category for B4 Course Students

General Education Category	Percentage of MATH 104 Students	Percentage of MATH 112A Students	Percentage of STAT 108 Students
I	0.07%	0.19%	9.69%
II	71.74%	56.56%	71.73%
IIC	0.84%	5.70%	1.95%
III	19.19%	22.15%	11.42%
IV	8.16%	15.40%	5.21%

STAT 108 had the smallest proportion of students demonstrating a need for corequisite support at about 17% and MATH 112A had the greatest proportion — more than double that of STAT 108 — at approximately 38%. While Category III & IV students are required to enroll in corequisite support, and given priority in doing so, Category I & II students may also choose to enroll in MATH 94, MATH 92, or STAT 90 which explains the discrepancies in required enrollment figures and actual enrollment figures presented in Table 3.

Table 3. Corequisite Support Course Enrollment

Support Course Enrolment Status	Percentage of MATH 104 Students	Percentage of MATH 112A Students	Percentage of STAT 108 Students
Enrolled in Corequisite Support	28.82% (27.35%)	47.34% (37.55%)	18.80% (16.63%)

Note: The values presented in the table correspond to actual corequisite course enrollments while the values to the right, in parenthesis, represent the percentage of students required to enroll in corequisite support due to their multiple measures for mathematics placement.

Measures of High School Academic Performance

For students in the Fall 2018, Spring 2019, and Fall 2019 cohorts, both high school GPA and SAT Mathematics scores were taken into consideration in admissions and the multiple measures for mathematics placement. While SAT evidence-based reading and writing (ERW) scores were not a component of the multiple measures, they were used in the admissions process and provided a measure of critical reading skills which can be called upon in mathematics and quantitative reasoning courses.

For this study, ACT mathematics and ERW scores were converted to their SAT equivalents using concordance tables published by the College Board and ACT (College Board, 2018). For students who took both the ACT and SAT, the maximum of the SAT and the converted ACT score was used.

The Eligibility Index (EI) was a linear combination of a student's college preparatory GPA, SAT math score, and SAT ERW score, used to establish basic eligibility for admission. It was calculated as follows:

$$Eligibility\ Index = 800 * CollegePrepGPA + SAT_E + SAT_M$$

The eligibility index is relevant to the present study due to its overlap with the multiple measures for mathematics placement. The multiple measures considered high school GPA and SAT/ACT math scores, both of which were used to calculate EI scores. AP, IB, and CLEP exam scores were also considered under the multiple measures, but students with passing scores would have already satisfied their B4 requirement and thus would be classified as Category I. The proportion of Category I students present in the sample is very small: 0.07% of MATH 104 students, 0.19% of MATH 112A students, and 9.69% of STAT 108 students. Therefore, for a majority of students in the sample, high school GPA and SAT math scores were the two main elements considered when making placement decisions.

Figures presented in Table 4 repeatedly communicate the same information: on average, students in MATH 112A demonstrated the lowest level of academic preparation with the lowest mean and median high school GPA, SAT math score, SAT ERW score, and Eligibility Index while on average, students in STAT 108 were the most prepared with the highest mean and median scores in the aforementioned categories. STAT 108 classrooms however had the highest level of academic diversity with the greatest standard deviations and interquartile ranges (IQR) in high school GPA, SAT math score, SAT ERW score, and Eligibility Index while MATH 112A classrooms were the most homogenous, academically, with the smallest measures of variability.

Table 4. Measures of Academic Performance in High School

	Mean			Median			Standard Deviation			Interquartile Range		
	MATH 104	MATH 112A	STAT 108	MATH 104	MATH 112A	STAT 108	MATH 104	MATH 112A	STAT 108	MATH 104	MATH 112A	STAT 108
HS GPA	3.51	3.33	3.64	3.53	3.29	3.69	0.37	0.34	0.38	0.58	0.49	0.60
SAT Math Score	531.41	500.45	564.27	530	500	560	74.28	58.49	85.26	100	70	120
SAT ERW Score	558.39	517.22	569.06	560	510	570	76.22	64.03	76.82	100	90	120
EI Score	3,899.9	3,682.9	4,041.8	3,904	3,642	4,088	365.96	313.95	393.62	576	426.5	663

Dependent Variable

All models built in this study used course completion status as the dependent variable with course completion defined as earning a final grade of A, B, C, or CR (credit) and course non-completion defined as earning a final grade of D, F, W, WU (unauthorized withdrawal), WE (catastrophic withdrawal), or I (incomplete). Of the 3 courses of interest, MATH 104 had the greatest completion rate at 84.51%, followed by MATH 112A at 78.43%, then STAT 108 at 75.70%. It should be noted, in all 3 courses, at least three-fourths of the students passed their respective course on their first attempt, satisfying their B4 GE requirement.

Descriptive Statistics – Demographic Variables

Along with academic variables, demographic variables were taken into consideration when building the profile of a student with the greatest probability of success in MATH 104, MATH 112A, and STAT 108. CSULB is committed to serving its local community; therefore, students who graduated from a high school classified as "local" are guaranteed admission to CSULB if they meet the minimum eligibility requirements. The figures in Table 5 indicate a majority of students in all 3 samples enjoyed the privilege of priority admission with 57.15% of MATH 104 students, 81.47% of MATH 112A students, and 54.23% of STAT 108 students graduating from a local high school.

A majority of students in all 3 courses identified as female. In MATH 104 approximately two-thirds of students were female, and in STAT 108, the proportion exceeded three-fourths at approximately 77%. It should be noted, as of Fall 2018, the overall undergraduate population at CSULB was 57% female, thus a heavier female presence is reasonable. Pell Grant eligibility was used as a proxy for socioeconomic status in this study as students must have a total family income of $50,000 a year or less to qualify. Almost equal proportions of MATH 104 and STAT 108 students qualified for the Pell Grant at around 53%, while the proportion of MATH 112A students who were Pell eligible was larger by about 11 percentage points at 64%.

Multiclass demographic variables were collapsed into binary variables to prevent models from being saturated with indicator variables. Students were classified as members of a racial/ethnic minority if they self-identified as Hispanic/Latino, Black or African American, or American Indian or Alaskan Native. Students who identified as a racial/ethnic non-minority — White, Asian, Native Hawaiian or Other Pacific Islander, or Two or More Races — Visa non-U.S., or unknown, less than 1.5% in each course, were categorized as "not a minority." In both MATH 104 and MATH 112A, a majority of students were considered members of a racial/ethnic minority group; however, in STAT 108, only a minority share of students were classified as such.

Students who identified as first generation to attend college were flagged as "first generation," whereas students whose parent(s) attended some college, graduated from college, or whose status was unknown, 10% or less in each course, were classified as "not first generation." MATH 104 and STAT 108 had a fairly even proportion of first-generation students; however, the proportion in MATH 112A was higher by about 8 percentage points.
In summary, MATH 104, MATH 112A, and STAT 108 primarily serve students who have been historically underrepresented on college campuses as they belong to one or more of the following groups: female, socioeconomically disadvantaged, member of a racial/ethnic minority group, or a first-generation college student.

Table 5. Demographic Variables

Demographic Variable	Percentage of MATH 104 Students	Percentage of MATH 112A Students	Percentage of STAT 108 Students
Last School Attended – Local	57.15%	81.47%	54.23%
Gender – Male	33.91%	43.44%	22.85%
Pell Grant Eligible	53.38%	63.78%	53.43%
Racial/Ethnic Minority	58.34%	68.73%	47.79%
First Generation to Attend College	28.82%	38.12%	30.30%

Findings and Discussion

Exploratory Data Analysis

Given that a goal of the present study was to identify demographic variables associated with the greatest probability of success in MATH 104, MATH 112A, and STAT 108, an important component of exploratory data analysis (EDA) was testing for statistically significant differences in course completion rates for groups determined by various demographic variables, including racial/ethnic minority status, gender, first generation classification, Pell grant eligibility, and local student status.

For each course of interest, contingency tables were constructed using demographic variables and course completion status. The chi-square test for homogeneity of proportions was used to test the following hypotheses:

H_0: The proportions of students who completed their respective B4 course were the same for both classes of a given demographic variable

H_1: The proportions of students who completed their respective B4 course were different for the two classes of a given demographic variable

The resulting p-values are given in Table 6. P-values less than 0.05 indicate a statistically significant difference in the proportion of students who completed their respective B4 course.

Table 6. P-Values for Achievement Gap Analysis and Completion Rates Among Demographic Groups

Demographic Variable	Variable Value	MATH 104		MATH 112A		STAT 108	
		P-Value	Completion Rate	P-Value	Completion Rate	P-Value	Completion Rate
Racial/Ethnic Identity	Minority	$p < 0.0001$	79.78%*	$p = 0.258$	77.46%	$p < 0.0001$	65.05%*
	Not Minority		91.12%*		80.55%		85.46%*
Gender	Male	$p = 0.508$	85.39%	$p = 0.264$	76.81%	$p = 0.630$	74.68%
	Female		84.05%		79.66%		76.01%
Generation in Higher Education	First Generation to Attend College	$p = 0.0001$	78.69%*	$p = 0.942$	78.30%	$p < 0.0001$	66.83%*
	Not First Generation		86.86%*		78.49%		79.56%*
Pell Grant Eligibility	Eligible	$p < 0.0001$	80.92%*	$p = 0.018$	76.15%*	$p < 0.0001$	69.82%*
	Not Eligible		88.62%*		82.41%*		82.45%*
Local Student Status	Local	$p < 0.0001$	79.98%*	$p = 0.033$	77.13%*	$p < 0.0001$	65.47%*
	Not Local		90.55%*		84.10%*		87.84%*

Note: An asterisk to the right of the completion rate denotes the chi-square test for homogeneity of proportions indicated a statistically significant difference (at the $\alpha = 0.05$ level) in completion rates among classes of a given demographic variable.

The values in Table 6 indicate there was no evidence of a statistically significant gender gap in course completion rates for any of the three courses of interest. There was however sufficient evidence to support a significant achievement gap, in all three courses, among students who are Pell grant eligible and students who are not. The chi-square test for homogeneity of proportions was a two-tailed test, so the direction of the difference in proportions cannot be stated definitively. The values in Table 6 however indicate completion rates were lower for Pell eligible students in all three courses which suggests, but cannot confirm in the context of statistical significance, socioeconomically disadvantaged students completed all three courses of interest at lower rates. For both MATH 104 and STAT 108, results indicate significant achievement gaps among students who identify as a racial/ethnic minority and those who do not as well as students who identify as first generation to attend college and those who do not. Again, the directions of the differences in proportions cannot be stated based on the results of two-tailed hypothesis tests, but directionality may be suggested by the completion rates in Table 6.

Conditional Probability and Non-Completion Rate Analysis

It is reasonable to assume that as students' levels of academic preparation, measured by Eligibility Index (EI) scores, increase, their probability of not completing their respective B4 course would decrease. It is however imprudent to operate on assumptions when working with empirical data; therefore, a conditional probability analysis was conducted on EI scores to verify the stated assumption. The Freedman-Diaconis rule, typically used to calculate optimal bin widths for histograms, was applied to determine an appropriate set of pivot scores for the EI score analyses. Using the formula

$$Score\ Range = 2\left(\frac{IQR(x)}{\sqrt[3]{n}}\right)$$

and rounding to the nearest ten, it was determined that pivot scores should be separated by 80 units. The initial pivot score was determined by finding the lowest EI score in the data set and rounding down to the nearest ten. To test the assumption that the probability of students not completing their respective B4 course would decrease as their levels of academic preparation increased a conditional probability analysis was conducted using

$$P(B4\ Course\ Non-Completion \mid EI\ Score < Pivot) = \frac{P(Non-Completion \cap EI\ Score<Pivot)}{P(EI\ Score<Pivot)}$$

Very few students had an eligibility index score less than 3,210; therefore, when determining the overall trend in the data, conditional probabilities for pivot scores of 3,210 or less were not taken into consideration. For all three courses, the data supports the statement that the probability of a student not completing a B4 course given his/her EI score is below a particular pivot decreases as the pivot score increases. This can be observed in the decreasing shape of the curves shown in Figure 1 and values in Table 7. Overall, the conditional probabilities of non-completion for STAT 108 were consistently higher than those for MATH 104 and MATH 112A. Notably, at a pivot score of 3,690 the conditional probabilities of not completing MATH 104 and MATH 112A were about 30%, but the same conditional probability was almost 60% for STAT 108. This observation prompted further exploration through a non-completion rate analysis in eligibility index score ranges.

Table 7. Conditional Probability of Course Non-Completion Given EI Score Below a Pivot

	MATH 104		MATH 112A		STAT 108	
EI Pivot Score	Probability	Sample Size	Probability	Sample Size	Probability	Sample Size
3290	0.4918	61	0.4731	93	0.7838	37
3690	0.3387	437	0.2980	594	0.5826	321
4090	0.2200	932	0.2402	916	0.4239	696
4490	0.1625	1366	0.2174	1044	0.2765	1208

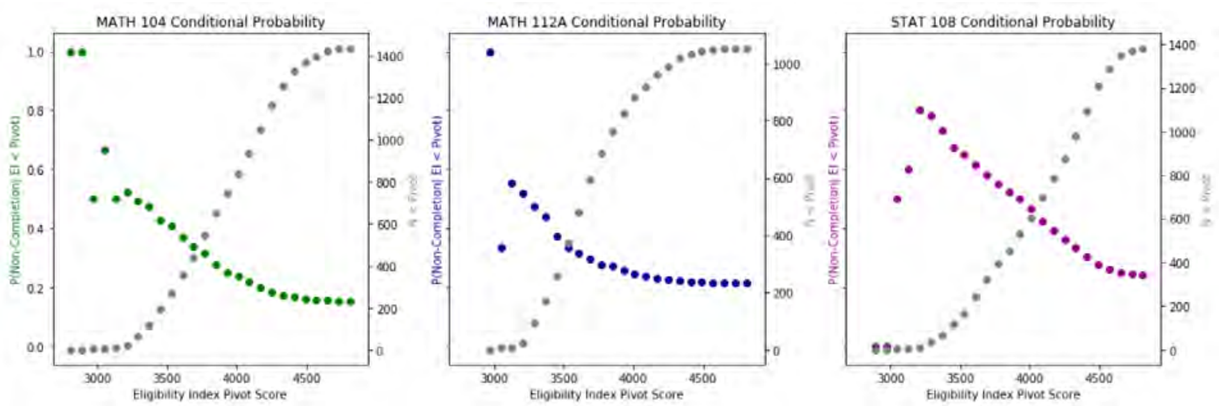

Figure 1. Conditional Probability of Course Non-Completion Given Eligibility Index Scores. The Sample Size Used in the Calculation of Each Conditional Probability is given in Grey

Bar graphs in Figure 2 and values in Table 8 indicate, for all three courses, non-completion rates in EI score ranges decrease as EI score ranges increase. With a few exceptions, MATH 104 and MATH 112A displayed comparable course non-completion rates; however, STAT 108 consistently displayed considerably higher non-completion rates. Notably, in the 3610 – 3690 EI score range, a score range that communicates a decent level of academic preparation, the non-completion rates for STAT 108 were more than double rates for MATH 104 and MATH 112A at 48.05% compared to 21.43% and 21.74%, respectively.

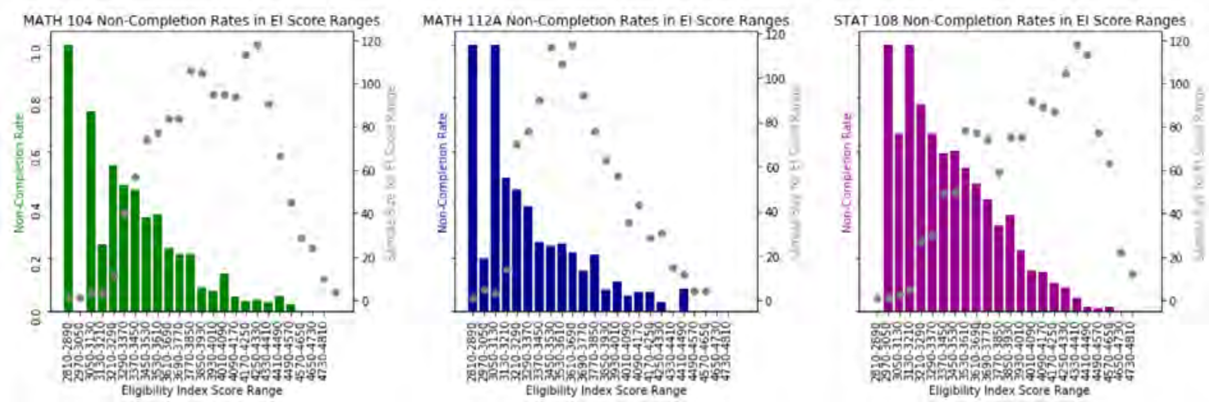

Figure 2. Course Non-completion Rates in Eligibility Index Score Ranges

Table 8. Non-Completion Rates in EI Score Ranges

	MATH 104		MATH 112A		STAT 108	
EI Score Range	Non-Completion Rate	Sample Size	Non-Completion Rate	Sample Size	Non-Completion Rate	Sample Size
3290-3370	0.4561	57	0.3947	76	0.6667	30
3690-3770	0.2170	106	0.1522	92	0.4189	74
4090-4170	0.0354	113	0.0698	43	0.1461	89
4490-4570	0	29	0	4	0.0130	77

Data Modelling

Binary Logistic Regression

Binary logistic regression was implemented in the SAS language to model course completion. Three separate models were built, one for each of the GE math courses: MATH 104, MATH 112A, and STAT 108. One of the strengths of this modelling framework is the ability to interpret parameter estimates and derive insight concerning the relationship between explanatory variables and the categorical response (Kutner et al., 2005). This classical method also serves as an effective baseline for classification problems and has been used extensively to model student success (Aulck et al., 2017; Gramling, 2013; Kim et al., 2019).

Before modeling, explanatory variables were tested for evidence of multicollinearity using variance inflation factor (VIF). Eligibility Index was not considered as a model input because it was a linear combination of three other inputs — high school GPA, SAT math score, and SAT ERW score —and thus would inflate VIF values. It was found that the VIF for support course enrollment was relatively high when an indicator variable for Category III-IV students was included which was expected as Category III-IV student are required to enroll in corequisite support. Thus, indicator variables for GE math classification were removed, resulting in VIF values less than 2 for every model input.

The following explanatory variables were used to model course completion in each course: semester unit count, SAT math score, SAT ERW score, high school GPA as well as indicator variables for undeclared major, support course enrollment, male, racial/ethnic minority, first generation to attend college, Pell grant eligibility, and priority in admissions due to local student status or military service.

To reduce model complexity and the chances of over-fitting, backward elimination with a stopping criterion of 0.10 was used to produce a reduced model. As a result, the reduced models for MATH 104, MATH 112A, and STAT 108 utilize different sets of independent variables. The resulting models are as follows:

$$\pi_{104} = P(Completing\ MATH\ 104)$$
$$logit(\hat{\pi}_{104}) = -13.0380 + 0.0118 * SAT_M + 0.00316 * SAT_E + 2.0343 * HSGPA$$

$$\pi_{112A} = P(Completing\ MATH\ 112A)$$
$$logit(\hat{\pi}_{112A}) = -9.3970 + 0.00834 * SAT_M + 2.0156 * HSGPA$$

$$\pi_{108} = P(Completing\ STAT\ 108)$$
$$logit(\hat{\pi}_{108}) = -14.6441 + 0.1370 * Units + 0.00993 * SAT_M + 2.4695 * HSGPA - 0.5459 * Minority$$

Only two of the eleven independent variables considered tested as significant at the 0.10 level for all three models: high school GPA and SAT math score, reflecting a result often observed in the literature (Hass, 2020; Jackson & Kurlaender, 2014; Komarraju et al., 2013). The odds ratios corresponding to the estimated coefficients are listed in Table 9.

An interesting result was support course enrollment appeared statistically significant, at the 0.10 level of significance, for MATH 104 only. Support course enrollment had a positive effect on the overall model with the estimated odds in favor of completing MATH 104 for a student enrolled in MATH 94 equivalent to $(e^{0.4000}) * 100 = 149.18\%$ the estimated odds for a student not enrolled in MATH 94. That is, a MATH 94 student was almost 50% more likely to complete MATH 104 than a student not enrolled in MATH 94. This is remarkable because students required to enroll in MATH 94 are those deemed underprepared for college level mathematics by the multiple measures for math placement.

A notable result was the significant, negative effect of the racial/ethnic minority indicator variable in the STAT 108 model. Interpreting the estimated coefficient leads to the conclusion that the estimated odds in favor of completing STAT 108 for a student who identifies as a racial/ethnic minority are $(e^{-0.5459}) * 100 = 57.93\%$ the estimated odds for a student who does not identify as a racial/ethnic minority. That is, students who self-identify as members of a racial/ethnic minority group are a little over 40% less likely to complete STAT 108 than their peers who identify as a racial/ethnic non-minority, visa non-U.S., or whose racial/ethnic identity is unknown.

Table 9. Odds Ratios

	MATH 104		MATH 112A		STAT 108	
	Odds Ratio	P-Value	Odds Ratio	P-Value	Odds Ratio	P-Value
Semester Unit Count 1-unit change	---	---	---	---	0.1468	0.0088
SAT Math Score 10-point change	0.1252	< 0.0001	0.0870	< 0.0001	0.1044	< 0.0001
SAT ERW Score 10-point change	0.0321	0.0385	---	---	---	---
High School GPA 0.10-point change	0.2256	< 0.0001	0.2233	< 0.0001	0.2801	< 0.0001
Support Course	1.4918	0.0542	---	---	---	---
Racial/Ethnic Minority	---	---	---	---	0.5793	0.0006

Note: Odds ratios are given for a 1 unit change in semester unit count, 10 point change in SAT math and SAT ERW scores, and a 0.10 point change in high school GPA.

The area under the receiver operating characteristics curve (AUC ROC) was used to evaluate model performance (see Figure 3). It should be noted, SAS uses the full data set to generate the ROC curve.

The AUC for the ROC curves for MATH 104 and STAT 108 indicate good model performance, with an 80.50% and 84.75% chance, respectively, the models will be able to distinguish between course completion and non-completion. These values allow for confidence in the models without raising concerns about over-fitting. Performance of the MATH 112A model however leaves room for improvement with an AUC of 0.7097.

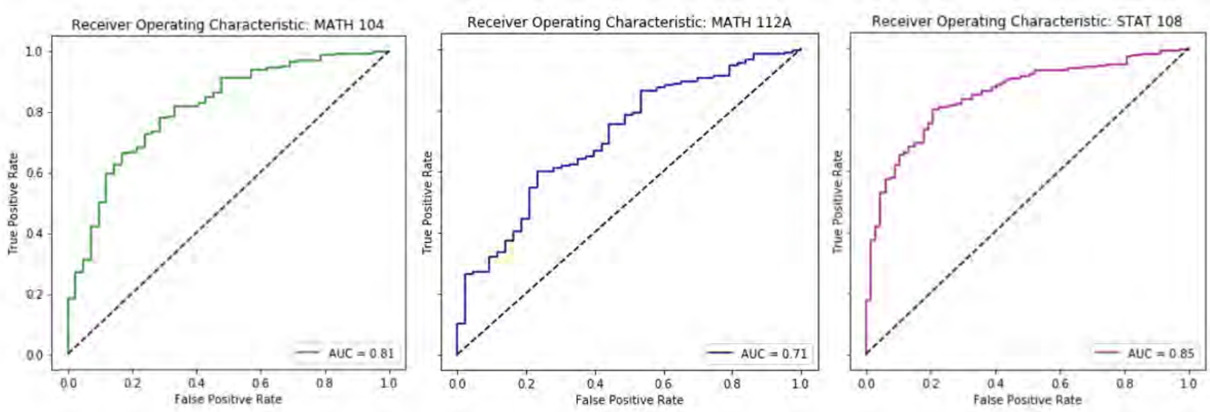

Figure 3. AUC-ROC Curves for Binary Logistic Regression

Stacked Classification and Course Completion

Classical statistical methods have been reliably effective in the tasks of description, inference, and prediction for data generated in the context of student success in higher education. Of late, machine learning algorithms have provided powerful tools for generating high performance predictive models in the educational context (Aulck et al., 2017; Kilian et al., 2020). In particular, the supervised learning construct dovetails naturally with higher educational philosophy, in which specific factors are known or assumed to be predictive of success for the majority of students. This work employed the multi-step stacking process to generate a competitive model for classification of course completion. Stacking (Breiman, 1996; Wolpert, 1992) is an example of ensemble learning that utilizes the "wisdom of the crowd" to generate estimates with better metrics than the constituent models.

For each course, the following algorithm (illustrated in Figure 4) was implemented using the ensemble module of the scikit-learn library in Python:

Step 1: Select $\ell = 3$ base model classifiers that predict successful course completion. Decision tree, Random Forest, and Regularized Logistic Regression were selected due to low correlation between predictions.

Step 2: Split the data; here the selected split was 80% training data and 20% testing data. Use the training data set to build and tune the ℓ base models using the selected algorithms and 5-fold cross validation.

Step 3: Use the ℓ base models to predict the outcomes for the observations in the test data set. The predictions of the ℓ base learners become the input for the logistic regression meta learner.

Step 4: Use 5-fold cross-validation to train the meta learner.

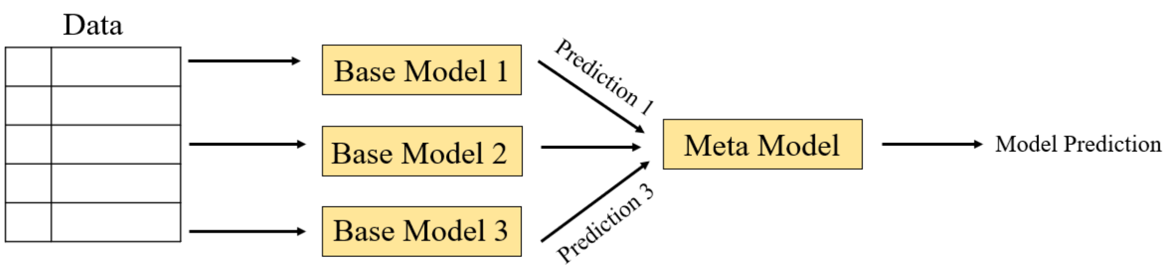

Figure 4. Stacking Algorithm

It should be noted, in the larger study from which this work was derived, a total of 6 models were implemented for the classification problem: binary logistic regression, regularized logistic regression with LASSO, regularized logistic regression with ridge, regularized logistic regression with elastic net, decision tree classifier, and random forest classifier. Before stacking models, the base models under consideration were evaluated for correlation in classifications. For all three courses, the regularized logistic regression models — LASSO, ridge, and elastic net — produced results that were highly correlated (see Table 10). Because the meta learner selected for the stacking algorithm was logistic regression, concerns arose regarding collinearity among inputs to the meta learner. Therefore, the base models used in the stacking algorithm were the decision tree classifier, random forest classifier, and the regularized logistic regression model with the best performance as measured by AUC-ROC, sensitivity, and specificity. Using these criteria, elastic net was selected for MATH 104 and MATH 112A, and ridge regression was selected for STAT 108.

Table 10. Correlation Matrix for Base Models

		Lasso	Ridge	Elastic Net	Decision Tree	Random Forest
MATH 104	Lasso	1.0	0.9781	0.9892	0.6387	0.6937
	Ridge		1.0	0.9674	0.6193	0.6725
	Elastic Net			1.0	0.6291	0.6846
	Decision Tree				1.0	0.6114
	Random Forest					1.0
MATH 112A	Lasso	1.0	0.9361	0.9227	0.5493	0.8177
	Ridge		1.0	0.9050	0.5667	0.8235
	Elastic Net			1.0	0.6154	0.8112
	Decision Tree				1.0	0.5571
	Random Forest					1.0
STAT 108	Lasso	1.0	0.9839	0.9919	0.6942	0.7975
	Ridge		1.0	0.9919	0.6767	0.7978
	Elastic Net			1.0	0.6854	0.8055
	Decision Tree				1.0	0.7659
	Random Forest					1.0

As expected, for all three courses, the meta model performance proved superior to the base models with regards to the AUC, sensitivity, specificity, and precision metrics as seen in Figure 5 and Figure 6. While this improvement was between 0.01 and 0.03 units across metrics for MATH 104 and STAT 108, the benefits of stacking were much more pronounced for MATH 112A. In MATH 112A, the AUC of the meta model was 0.76, about 0.08 units better than the best (elastic net) base model, and about 0.05 units better than the stand-alone logistic regression model discussed above. The stacked model accurately classified about 85% of course completions and about 54% of course non-completions, and while 54% is not a great value for specificity, it is about 10 percentage points higher than the specificity of the elastic net model (see Table 11). Therefore, while model stacking was beneficial, but not necessary in MATH 104 and STAT 108, it was crucial to improve results in MATH 112A.

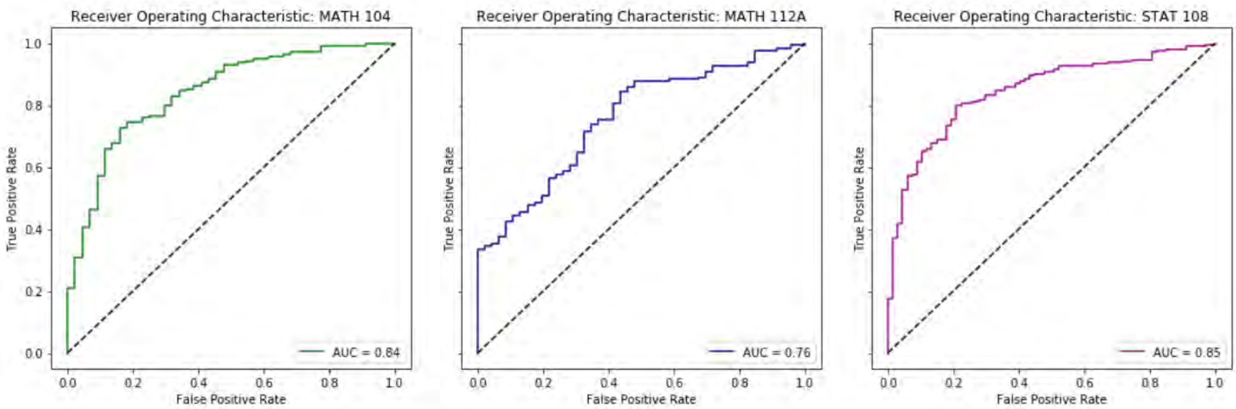

Figure 5. AUC-ROC Curves for Stacked Classification Models

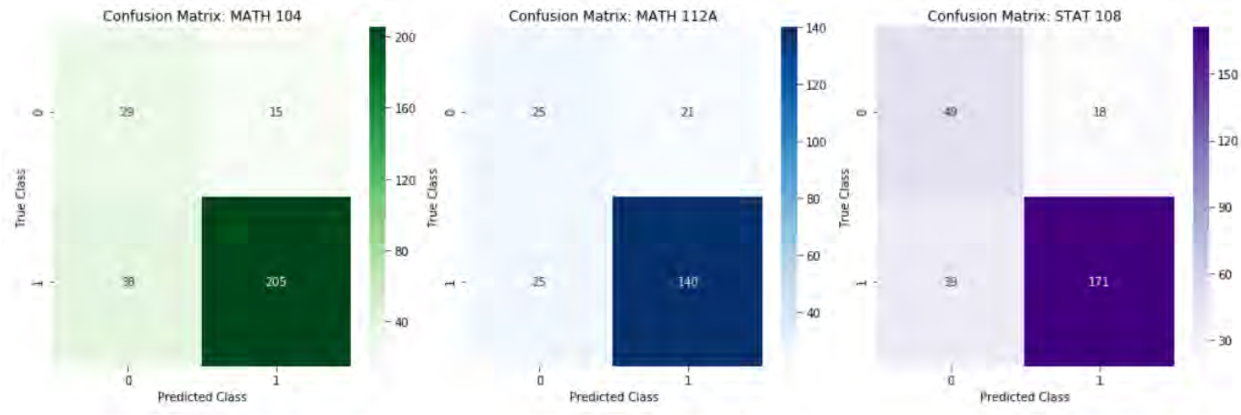

Figure 6. Confusion Matrices for Stacked Classification Models

Table 11. Stacked Classification Model Performance

Course	Sensitivity	Precision	Specificity	False Positive Rate
MATH 104	0.8436	0.9318	0.6591	0.3409
MATH 112A	0.8485	0.8696	0.5435	0.4565
STAT 108	0.8143	0.9048	0.7313	0.2687

Conclusion

Exploratory data analysis revealed STAT 108 was not the best option for students displaying relatively low levels of academic preparation. Despite having the highest average high school GPA, SAT math score, SAT ERW score, and eligibility index score, STAT 108 had the lowest completion rate at 75.70%, compared to 84.51% and 78.42% for MATH 104 and MATH 112A, respectively. At lower eligibility index scores, scores below 3450, MATH 104 and MATH 112A displayed comparable conditional probabilities of non-completion given an EI score below a selected pivot whereas STAT 108 displayed considerably higher — by at least 25 percentage points — conditional probabilities. Similarly, in lower EI score ranges, 3210 – 3370, MATH 104 and MATH 112A displayed comparable course non-completion rates, but STAT 108 non-completion rates were at least 20 percentage points higher. Thus, MATH 104 and MATH 112A may serve as better alternatives for students whose measures of high school academic performance indicate a need for additional support.

Further evidence of MATH 104 being a promising option for students in need of additional support was provided by the relationship between MATH 94 enrollment and course completion. The binary logistic regression model indicated MATH 94 had a significant, positive effect with the estimated odds in favor of completing MATH 104 for a student enrolled in MATH 94 about 50% greater than the estimated odds for a student not enrolled in MATH 94. Therefore, combining the information provided by the conditional probability analysis, non-completion rate analysis, and logistic regression model, it seems reasonable to conclude MATH 104 may serve as a good option for GE math category III and IV students, the population of students required to enroll in corequisite support.

Of the three courses considered, MATH 112A was the only course that did not demonstrate a negative relationship between racial/ethnic minority status and course completion as well as first-generation status and course completion. That is, hypothesis testing for both MATH 104 and STAT 108 indicated statistically significant differences in the proportions of students who completed their respective B4 course along racial/ethnic identity and first-generation status. While the two-tailed hypothesis tests could not be used to indicate the direction of the relationships, the coefficients for racial/ethnic minority and first-generation were negative in the binary logistic regression model for both MATH 104 and STAT 108. This result held in the three regularized logistic regression models — LASSO, ridge, and elastic net — implemented in the larger study from which this work was derived.

When all other academic and demographic variables were taken into consideration using binary logistic regression, first-generation status did not prove to be statistically significant, at the 0.10 level of significance, for either course, nor was racial/ethnic minority status significant for MATH 104, but STAT 108 still demonstrated a significant, negative relationship between racial/ethnic minority status and course completion. Thus, STAT 108 may be underserving students who identify as members of a racial/ethnic minority group.

To summarize, for the population of students without major-specific mathematics requirements, MATH 104 may be the best option for those with less developed academic backgrounds followed by MATH 112A. It is recommended that STAT 108 is reserved for the population of students whose major indicates a need for an approved statistics course or students seeking an academic challenge or alternative to traditional mathematics when satisfying their B4 course requirement. Additionally, in comparison to STAT 108, students who identify as a racial/ethnic minority tend to perform better in MATH 104 and MATH 112A, and first-generation college students tend to perform better in MATH 112A.

Further Implications

This study started as a quest to identify profiles of students that correlate with success in GE mathematics courses using machine learning models. Given three courses were compared in this observational study, it is reasonable to also mine the results to glean information concerning variables that can be controlled, namely, the characteristics of GE mathematics courses that promote student success. Looking at the results from this lens can empower educators to critically assess the role that course design plays in creating an atmosphere conducive to student engagement and achievement. It has been noted that when the course in which a student is enrolled has a large impact on student performance, it may be communicating more about the courses than the students enrolled in them (Gašević et al., 2016; O'Connell et al., 2018).

It is notable that although the STAT 108 cohort would be considered the best prepared at time of admission by all academic indicators, performance in that course was the worst. These results indicate there may be best practices for course design that can maximize success given a student's level of preparation while simultaneously providing opportunities for academic success to first generation and underrepresented students in general education mathematics courses. Based on direct input from course creators and coordinators, the three courses were filtered through the lens of the *Seven Principles for Good Practice in Undergraduate Education* (Chickering & Gamson, 1987). Please see table 12 for results.

Table 12. CSULB GE Mathematics and the Seven Principles

Model	MATH 104	MATH 112A	STAT 108
Encourages contact between students and faculty	X	X	
Develops reciprocity and cooperation among students.	X	X	
Encourages active learning	X	X	
Gives prompt feedback	X	X	X
Emphasizes time on task	X	X	X
Communicates high expectations	X	X	X
Respects diverse talents and ways of learning	X	X	

Though causality may not be asserted, the absence of some of these key qualities in STAT 108 may be related to the worse than expected performance of students in that course. In particular, it should be noted that STAT 108 was the only course that did not have a weekly 2-hour activity section to supplement the traditional large lectures. This mode of course delivery tends to correlate with significantly reduced contact time between students and instructional staff, and all but eliminates the possibility of supervised group work, two factors that are associated with student success (Goedhart et al., 2019; McKeachie & Svinivki, 2013; Shinaberger, 2017). In addition, for STAT 108 the incentive to reflect on or redo exams — an implementation of growth mindset — was not explicitly built into the grading scheme, as was the case in the other two courses.

In addition, STAT 108 differed from MATH 104 and MATH 112A in that the course was not coordinated, meaning professors used different course materials and gave different exams. In MATH 104 and MATH 112A, all students were given versions of the same exam regardless of the section in which they were enrolled. The variation of pedagogical approaches meant in any given semester, one section of STAT 108 required students to derive complex algebraic formulas and code in R, while another section expected mastery of a TI-83 calculator and emphasized statistical thinking. This disparity led to pass rates as low as 45.6% for one instructor and as high as 78.8% for another in one semester of the data used for this study.

Directions for Future Research

As previously mentioned, STAT 108 was uncoordinated and did not include the 2-hour activity session built into the MATH 104 and MATH 112A course structures. Thus, students did not receive guided practice with course material unless they took advantage of tutoring or office hours. Starting in the Fall 2020 semester, STAT 108 implemented a uniform set of course materials across all sections and the course transitioned from two one hour and fifteen-minute large lecture meetings to two 50-minute large lecture meetings and a weekly 2-hour break-out activity section. For the semesters in which STAT 108 was offered in-person, post COVID shutdown, the analyses presented in this study should be repeated to determine whether STAT 108 improved in serving the student population at CSULB.

In May of 2020, the University of California (UC) Board of Regents unanimously voted to suspend the use of SAT and ACT test scores in the admissions process through 2024. This decision supports an effort to increase socioeconomic diversity and inclusion on UC campuses as standardized tests tend to favor more affluent students who can afford preparation courses and tutoring (Gordon, 2020). UC president, Janet Napolitano, anticipates CSU cooperation in this effort (Gordon, 2020). Therefore, in preparation for anticipated changes, it would be of great interest to reconstruct the models presented in this study, excluding SAT scores as input features.

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