Tutor or Not Tutor, That Is the Question

An Analysis of the Tutoring Program at Cerritos College

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Contents

Abstract

The Student Success Center (SSC) at Cerritos College offers tutoring for students in embedded courses and students taking regular courses (general courses). The aim of this report is to analyze the impact of these tutoring programs on student outcomes (success, persistence, and retention). This is achieved by comparing the outcomes of students that utilized the tutoring services with the outcomes of students that did not utilize these tutoring services. Aggregated data and semester data were used to analyze this effect. For the semester data, the outcomes of students that were taking mathematics and chemistry courses were analyzed. Linear and Logistic models showed that the amount of times a student goes to tutoring (their session count) has a positive effect on their success. For example, in the semester data, students that did not go to tutoring had a lower probability of passing their course compared to students that went to tutoring 2 times in one semester. The models presented similar results for persistence and retention with the caveat that students at Cerritos already exhbit high persistence rates. In terms of retention, session count was not always a significant predictor.

The report also analyzes the effect of embedded tutoring and general tutoring by ethnicity. All ethnic groups in embedded courses had higher probabilities of success when compared to their general course counterparts. In addition, logistic model presented that the effect of the embedded tutor is more present in the mathematics embedded students than the chemistry embedded students. We find that students in general chemistry courses had higher probabilities of success as they went to more tutoring sessions when compared to embedded chemistry students.

1 Introduction

Cerritos College, located in Norwalk, California, is one of the seven largest community colleges in Los Angeles County. The mission of the college, as stated in the website, is to provide its "diverse student population with high-quality, comprehensive instructional programs and support services through clear, equity-minded pathways to their educational goals." Community colleges have traditionally catered to non-traditional college students with low-cost tuition and open enrollment; the majority of the student population at Cerritos, for example, are first generation college students. As such, it is generally necessary for these schools to emphasize support services in order to engage students and ensure academic success. One such support service is tutoring.

Several modalities of tutoring are conducted at Cerritos College. The Student Success Center (SSC), open throughout the week, offers general and discipline-specific tutoring. General tutoring, which comprises of mathematics, English, and ESL, is available as long as the SSC is open. Discipline-specific tutoring, covering such subjects as chemistry and physics, is limited to the availability of specific tutors. Tutoring is administered in-person, by appointment or drop-in, and online. A more recent innovation is embedded tutoring (ET), whereby former students are placed in certain course sections to facilitate learning; the instructors make use of these tutors however they choose. Embedded tutors may also opt to hold additional hours for course-specific tutoring outside of class time, and these hours are optional for students to attend.

It is necessary in the context of the client's query to discuss AB 705. AB 705 is a bill passed by the state legislature in late 2017, the goal of which is to ensure that college students are able to complete transfer level mathematics and English courses in a timely manner (one year for math, three for English)(Hope & Stanskas, 2018). AB 705 represents a policy shift from simply providing students with access to higher education to promoting program completion and transfer. The bill necessitated the removal of many remedial courses, and compelled colleges to innovate in preparing students for transfer-level coursework. One such innovation is embedded tutoring. AB 705 has made support services, such as tutoring, even more vital. The effectiveness of the tutoring program at Cerritos is, therefore, of particular interest, as resources are limited.

1.1 Goals and Objectives

The client seeks to answer the following question: Does attending tutoring through the Cerritos College Student Success Center increase the outcomes of students when compared to students who did not attend tutoring? The student outcomes of interest are success rate, retention, and persistence. Success rate is defined as the percentage of enrolled students that received a passing grade. The client is interested in whether students that go to tutoring complete and pass the course for which they received the tutoring. Concurrently, are students that go to tutoring more likely to return to Cerritos within the next school-year (retention) or term (persistence). Retention is defined as the percentage of enrolled students who re-enrolled the following year. Persistence is defined as the percentage of enrolled students who re-enrolled the following term. The client is interested in the latter two outcomes since the vision of the college is to maintain students at Cerritos College. The programs of interest at the SSC are embedded tutoring and general tutoring. It is also important to note that the client is interested in whether the ethnicity of the student and the number of times the student went to tutoring has an impact in their outcomes.

To achieve the said goal, the outcomes of students that utilize the tutoring services will compared with the outcomes of students that do not utilize the tutoring services. Specifically, outcomes of students in embedded courses that go to the tutoring sessions at the SSC will be compared to the outcomes of their embedded peers that did not go to the tutoring. In the case of students that are not in embedded courses, the outcomes of students that utilized the general tutoring services at the SSC are compared with students that did not[1]. The comparison group for general tutoring was determined using propensity score matching. Finally, the client is interested in determining if there is a difference in student outcomes between the tutoring programs. Specifically, is one program meeting the student outcomes more efficiently. This is done by comparing the logistic model results between embedded and general models. Disciplines of focus for this analysis are mathematics and chemistry courses.

The results of this report will potentially help the client justify the costs of these tutoring programs and to determine if these programs are meeting the college goal of fall to spring persistence and fall to fall retention. Additionally, we aim to help the client make informed decisions about how to fund these tutoring programs given that mathematics tutoring at the SSC is most popular, chemistry tutoring is more costly, and instructors prefer embedded tutors.

1.2 Literature Review

Community college is essential to the fabric of post secondary education. Students enrolled in community college account for 35% of all undergraduate enrollment in the US (Butcher, 2013). However, less than half of these students will earn a credential, associates degree, or transfer to a university. Remedial students are less likely to earn a credential. In fact, it is estimated that 30-40% of community college students are considered remedial or lacking sufficient preparation. Buell argues that tutoring services are a promising practice to foster course completion, retention and graduation (Buell, 2020). Tutoring even on a small, ephemeral scale, has been shown to improve course performance and GPA. Investigating tutoring centers allows for analysis on a deeper level that can provide insight into enrollment behavior.

Remedial math students complete their remediation at rates far less than those who attend community college with sufficient preparation. Curiously, remedial math students remain enrolled in the college years after their last math class (Bahr, 2013). AB 705 is a bill that passed in 2017 that eliminated remedial coursework from community colleges. The

[1]To analyze embedded and general tutoring, semester data was utilized. Specifically, only the fall semesters were analyzed. This changes the outcomes from rates to binary outcomes. The student either did or did not pass their course, enroll in the next spring semester, and enroll in the next fall semester.

goal of this bill was to alleviate the coursework burden on students to increase completion of college level math. Full implementation of this bill did not occur until 2020, so it is relatively new. It is hypothesized that students will likely struggle to complete or pass courses post-AB 705. This underscores the significance of tutoring programs in California community colleges. Regardless of a student's preparation for college-level coursework, if they make an active effort to participate with their peers and professors on campus, they are more likely to learn more (Sullivan, 2015). This demonstrates the need for permanent learning centers for colleges. In fact, it has been written that a permanent, college-supported learning space where all students can come to study, congregate, collaborate, and learn in a social, academic-oriented, and 'un-lectured' learning environment improves the satisfaction and retention of students across community colleges (Aschenbach, Blake, Gavaskar, Sanchez, & Whetzel, 2022).

It has been shown that tutoring is an essential service to be provided at community college campuses in order to increase student success and continued enrollment. It is important to study the many covariates of student success to leverage resources to enable student success. Some of these covariates, beyond college-level preparation, remediation, and tutoring accessibility are the socioeconomic data. A student's financial status, marital status, parental education status, and race/ethnicity (Goldrick-Rab, 2010). Next, it will be important to review methods essential to analyzing student success and persistence/retention data.

2 Data Structure

The client has currently provided fourteen data tables pertaining to tutoring logs, student body information, student academics, and time at Cerritos College. Some data sets are exhaustive in the information they contain, it will be the case that not all columns will be utilized for the purpose of the project. A brief summary of the information that each dataset contains along with the columns of interest will be presented in this section.

2.1 Tutoring logs

The `SSC` data table is a vital table that includes logs of students that visit the success center. Each row corresponds to a single visit; many students visit multiple times. Important columns are log-in time, log-out time, task description (embedded, general, etc.), and subtask, which may contain additional course information. At the moment, there are many task descriptions that need to be rationalized in order to investigate math and chemistry tutoring in particular. The embedded-tutoring data table is a subset of the `SSC` table, and includes logs of students who visit their embedded tutors outside of class time; this table will be vital in investigating the effectiveness of additional embedded tutoring hours. In addition to this data, the client has provided us information on embedded assignments from Fall 2019 to Spring 2023.

2.2 Student body information

The `demographics`, `student groups`, `financial aid` and `application` data sets provide insight on the type of student enrolled at Cerritos College. The `demographics` data table is pertinent to the clients interest in determining whether success is affected by ethnicity; this table provides information on ethnicity (White, Hispanic/Latino or Black to name a few), citizenship status, whether a student is first-generation, and gender (male or female).

The `student-groups-term` data table displays student affiliation with programs such as CalWORKS, SAS (Student Accessibility Services), EOPS (Extended Opportunity Program and Services), and CARE (Cooperative Agencies Resources for Education program).

The `financial-aid` table shows whether students are eligible for financial aid by year. Relevant columns are `FAFSA`, `PELL-OFFERED`, and `CCPG-OFFERED` (California Promise Grant). The entries are binary, 1 indicating that the student submitted a FAFSA and was offered grants, 0 indicating otherwise.

The `Application` data table displays each students most recent college application along with some demographic information, including birth date, marital status, highest education achieved (in years), high school GPA, and high school graduation date.

2.3 Student Academics

The academic career, awards, education plan (`edu-plan`), enrollment, and transfer math/english (`transfer-mtheng`) data sets provide extensive information regarding student enrollment, course history and awards they have received at Cerritos College.

The `academic-career` table details the academic progress of students at Cerritos. The table contains 1421145 rows and 33 columns. Each row corresponds to a student during a particular term. Columns of interest to us in this data set are `UNT-TAKEN-PRGRSS`, a count of the units a student has taken, `UNT-PASSD-PRGRSS`, a count of the units that a student has passed `CUR-GPA`, a student's term GPA, and `CUM-GPA`, a student's cumulative GPA. Additionally, a column labelled `STRM` provides term information via a code, which we describe here: 800 represents the first time a student is entered into the system, and the final digit represents the term; 3 for spring, 6 for summer, and 9 for fall. The two preceding digits represent the year (e.g. 20 for 2020). The `STRM` column is present in many of the provided data tables.

The awards data table contains information on conferred awards and certificates. Three columns, `ACAD-PLAN`, `ACAD-PLAN-DESCR`, and `DIPLOMA-DESCR`, relate to the student's major and display the same information. `COMPLETION-TERM` shows the term in which the degree or certificate was completed via the same code as `STRM` in the other data sets. `DEGR-CONFER-DT` displays the last day of the completion term.

The ed-plans data table describes the education plans that students developed with the aid of counseling. Plans can be abbreviated or comprehensive, comprehensive being more complete. Some important columns are `SAVE-STSUS-DESCR`, `ACAD-PLAN`, and `LR-SEP-PLNR-SEQ`.

If the value in SAVE-STSUS-DESCR is "Finalized", the ed-plan is complete and the student knows what courses to take, otherwise the student has only visited counseling. The ACAD-PLAN column displays the student's chosen major. The LR-SEP-PLNR-SEQ column displays the number of times a student visited counseling. It is important to note that students are informed about tutoring by counselors, so these students may be more likely to visit the SSC.

The enrollment data table is a massive table that details all the courses students enroll in throughout their academic careers at Cerritos. Some information provided by this table includes the date the student enrolled in a course, whether they dropped or completed the course, and with what grade. This will be a vital table in determining completion and success (a passing grade). The table will, furthermore, enable us to group students by course section to investigate outcomes at the course level.

The transfer-mtheng data table tracks student attempts at transfer level math and English courses. Important columns include course number course grade, number of attempts, and pass (a boolean flag). This table will help us determine whether tutoring is aiding students in passing transfer level math and English courses in a timely manner, which is the goal of AB 705.

2.4 Time at Cerritos

The persistence-retention data table displays enrollment data that can be used to calculate persistence from term to term, or retention from year to year. Some relevant columns are ENROLLED-CREDIT, ENROLLED-THIS-TERM,ENROLLED-NEXT-SPRING, and ENROLLED-NEXT-FALL. The data are boolean flags.

The sessions data table specifies the weeks of instruction for each term, including start dates, end dates, enrollment dates, and drop dates. The client specified that this table may be useful to determine at what point in the session did a student go to tutoring. The terms data table gives information on the terms, including begin dates, end dates, weeks of instruction, academic year, and category (spring, summer, and fall). This table may be useful to provide some additional information on the ever-present STRM column.

3 Data Wrangling

Achieving the client's research objectives with the data provided required extensive data cleaning. We used used several libraries, including dplyr and tidyverse especially, to extract relevant information from the provided tables and compile this data into master tables that could be used for visualization and analysis. We began at a small scale, so focused on filtering our data by the Fall 2019 term for embedded and general tutoring. A data set containing aggregated student data from fall 2015 to spring 2024 was created to answer the main research question. Particularly, this allows for an analysis of persistence and retention over several semesters. To analyze embedded and general tutoring semester data sets were formed. For the semester data, only fall semester from 2019-2023 were utilized.

The success center dataset was vital in identifying the students that attended general and embedded tutoring. Particularly, the `subtask` column provided information on the course for which the student went to the student success center for tutoring. Identifying the students that went to general tutoring, like Chemistry, required simple wrangling. First, we filtered the `ssc_tutor` dataset to contain fall 2019 log-in information and selected the students with `subtask` information containing some variation of "chemistry"[2]. In conjunction, the students taking a chemistry course in the fall 2019 were also filtered from the `enrollment` data set. Of these chemistry students, those that went to the student success center for tutoring were identified via their `Student_ID` in the filtered `ssc_tutor` log-in dataset. A column titled `tutor`, with `tutor` and `no tutor` levels was created to identify whether a student did or did not go to tutoring. Subsequently, variables of interest from other data sets such as `ethnicity` from the `demographics` data set were added to this data frame. Figure 1 illustrates the data wrangling design for obtaining this data frame. Finally, session counts and cumulative GPA from the previous semester for each student were categorized in order to facilitate visualization.

The real challenge was identifying the students with embedded courses. The `subtask` column provided instructor information which was matched with two other datasets (`instructor` and `Embedded_Schedule` as shown in the top left of Figure 1) to locate the class number. With the class number, all the students enrolled in a math embedded course in the fall 2019 were placed in a master dataset. As was done in the general tutoring case, a column titled `tutor` was formed to identify the students that did and did not go to tutoring. Variables of interest such as ethnicity were then added to this data frame.

ID	Term	Sessions	Session.Cat	Enroll	Pass	GPA	Reten.	Persist.	Tutor	Class#	Ethn.
0170412	1999	1	Rare	1	0	High	1	0	1	29373	Hispanic/Latino
0289312	1999	20	Frequently	1	1	Mid	1	1	1	22255	Hispanic/Latino

Table 1: Data Format for Embedded Tutoring

Table 1 presents a snapshot of the data frame created to answer the client's question for Embedded tutoring. For each unique student ID, term information is provided, as well as tutoring session count, time spent in tutoring, number of courses enrolled, number of courses passed, cumulative GPA, retention rate, persistence rate, whether the students attended tutoring, and ethnicity. This table also contains the course number for the embedded course. The general data frame was formatted similarly but without the course number.

Now we discuss wrangling for students across years and disciplines. We received 14 data files from the client linked together through Student ID. The issue with this is that not all of the rows in each data file are unique. That means, there are multiple entries for a student in some files, but not the others. The database diagram below shows the wrangling required to create a "master" data frame that includes one student observation per row with aggregated statistics regarding their enrollment and academic performance.

We want to get an idea of the general relationship between tutoring, success rate, retention, persistence, and GPA. Having a general trend for these relationships allows us to more

[2]Chemistry courses were identified in the following variations: `Chemistry110`, `Chem`, `CHEM`

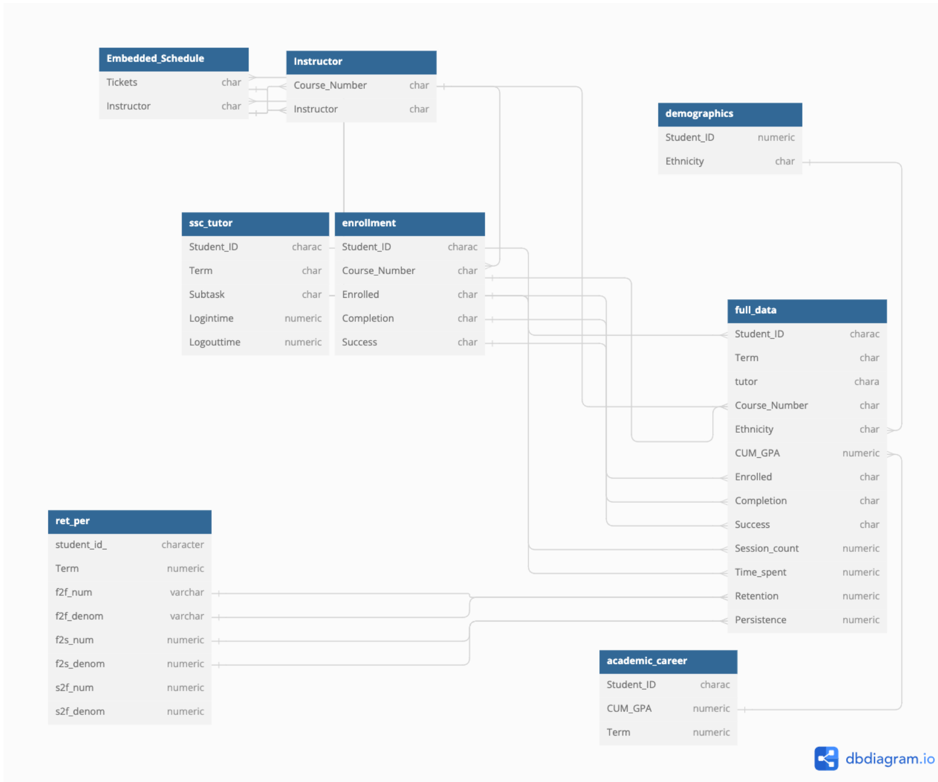

Figure 1: Semester Data File Design

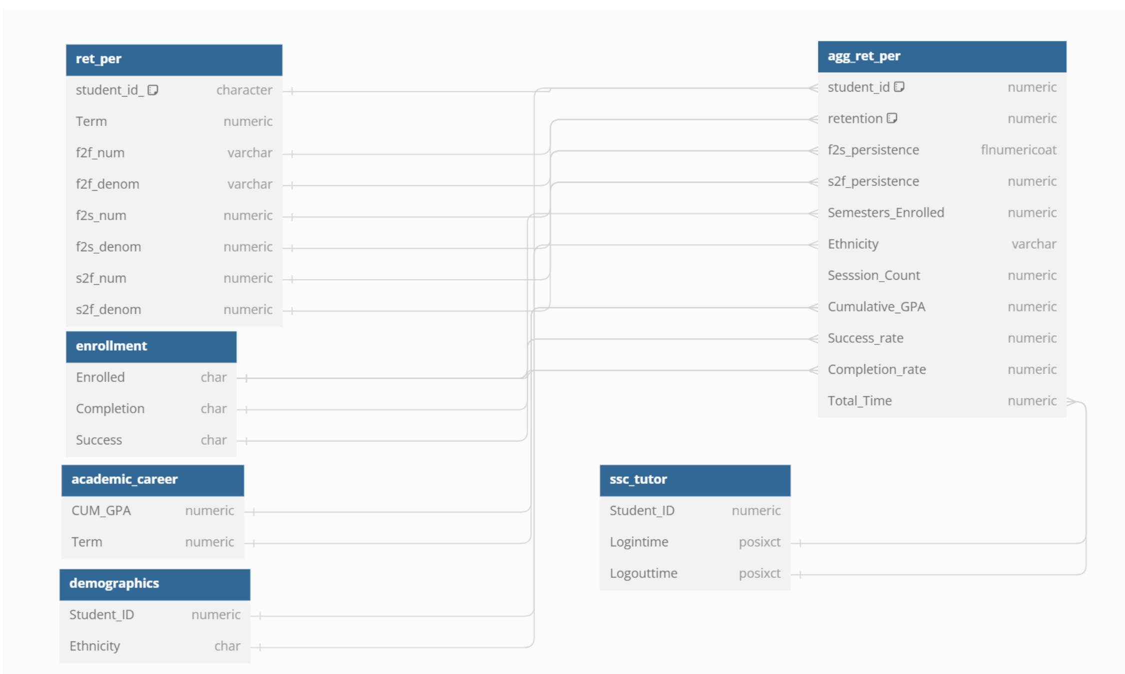

Figure 2: Aggregated Data File Design

carefully investigate discipline-specific effects. The database diagram above shows how we aggregated our metrics into the `agg_ret_per` data frame on the right. Most of our metrics are proportions which are related to how often a student is enrolled at the College. Of course retention and persistence use this criterion, however, take for example, `success_rate`. This metric is the sum of the number of courses that a student has passed divided by the number of total courses enrolled. So, `success_rate` is essentially a "pass rate." The success rate is a metric developed by the client. All this is to say, The `agg_ret_per` table is an aggregate table with proportion metrics such as completion rate, success rate, retention, and persistence.

Retention is calculated over the entire enrollment career for a student in the 'enrollment' data file; It calculates all of the times they were retained from one fall to the next and divides by their total time of their enrollment by term. Retention in our master data frame is a value between 0 and 1, as mentioned above. Similarly, `f2s_pers` and `s2f_pers` are the persistence values for Fall to Spring and Spring to Fall, respectively. The calculation is the same, but we are instead looking at continuous semester-to-semester enrollment.

The total time for students who attended tutoring (including general and embedded) is calculated by aggregated the sum of the difference between their login and logout time. This data is provided in the `scc_tutor file`. Table 2 presents snippet of what the master data file looks like.

ID	f2f ret.	f2s pers.	s2f pers.	Sem.Enroll	Time	sessions	Ethn.
0000701	0.8	0.8	1	9	164.40	9	Asian
0001212	0.66	0.33	1	4	628.48	8	Hisp./Lat.

Table 2: Data Format for Persistence and Retention

The persistence and retention table has a broad scope, encompassing the academic careers of all students. As such, though it contains some of the same variables as the tutoring tables, typical values will be significantly different. For each unique student ID in this table, retention rate is provided, as well as persistence rate, number of semesters enrolled, time spent in tutoring, number of tutoring sessions attended, and ethnicity.

4 Data Summarization

4.1 Aggregated Data

Session	Never(0)	Rare(1-2)	Occasionally(3-10)	Frequently(12)	Very Frequently(151)
Count	29,505	5,717	3,910	3,605	4,150

Table 3: Session Count Categories of Aggregated Data

Table 3 presents how session count was categorized for the aggregated data. The groups were classified based on quantiles. For instance, occasionally represents the 50th percentile.

Note that this is the number of sessions over a student's total enrollment. Time spent was categorized in a similar fashion.

GPA	Low (0.0-1.99)	Mid (2.0-3.0)	High (3.0+)
Count	13,091	14,049	19,737

Table 4: GPA Categories

Table 4 presents the categories for GPA of Cerritos College students along with the count associated for each category. GPA was categorized to help analyze trends in the data. We find that there are more students that have a GPA greater than a 3.0. Next are students in the mid category followed by students in the low category.

4.2 Fall 2019 Math Embedded Tutoring

Asian	Black/AA	Hispanic/Latino	Native American/Pacific Islander	Two/More Races	White
7.38%	7.07%	78.46%	1.23%	1.53%	4.31%

Table 5: Ethnicity Percentages Among Math Embedded Students

Among the students that took a math embedded course in fall 2019, 88 or 27% of these students went to tutoring at the student success center. The remaining 237 or 73% of students did not go to tutoring. Table 5 illustrates that a vast majority of the math embedded students are Hispanic/Latino, the second largest groups are Asians and Black/African Americans. The ethnic break down for the remaining semesters for embedded and general students is similar.

rare	occasionally	frequently	very frequently
43	6	26	13

Table 6: Session Count: rare: 1-2 visits, occasionally: 3-4 visits, frequently: 5-14 visits and very frequently: 15-26

Table 6 illustrates the number of times students went to tutoring throughout the fall 2019 semester. Most students fall in the rare category wherein they went to tutoring 1-2 times a semester. The second largest group falls in the frequently category where students visited the success center for tutoring between 5-14 times a semester. Fewer students are found in the occasionally and very frequently category. Session count trends for the remaining semesters are similar wherein the vast majority of embedded students did not attend tutoring. Similarly, the majority of general students do no attend tutoring.

5 Data Visualization

5.1 Aggregated Data

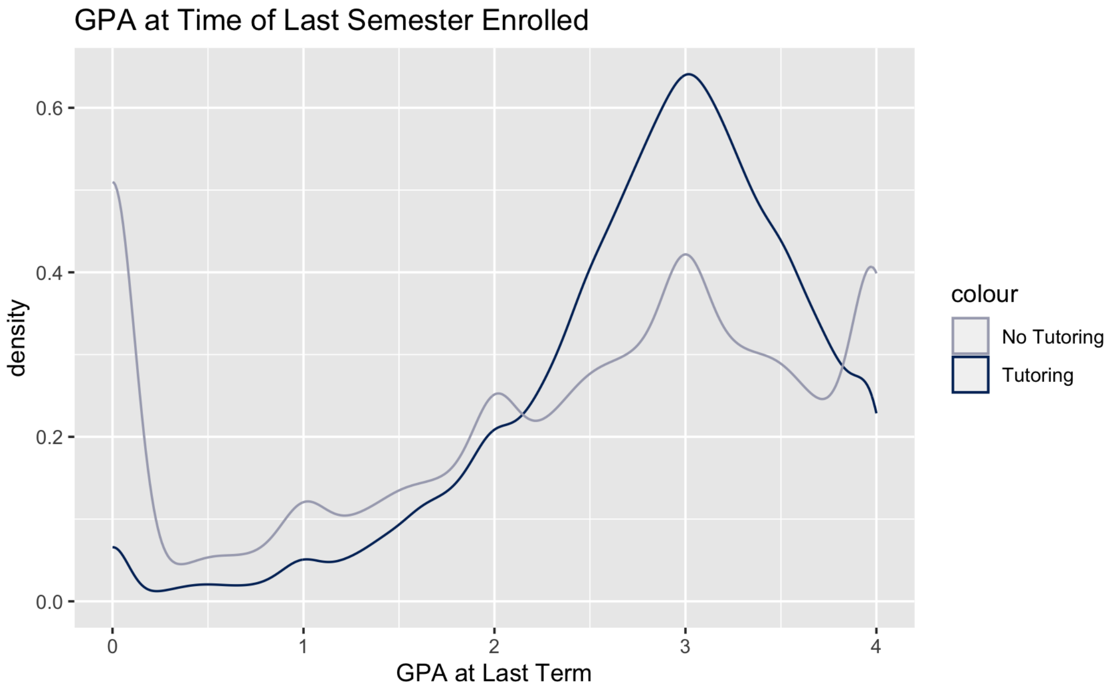

Figure 3: Fall 2015-Fall 2023 GPA At Last Term

Figure 3 shows that students who went to tutoring typically had a GPA higher than non-tutoring groups around the 3.0 GPA mark. On the x-axis, we have the GPA at the last term enrolled for each student. The data frame that I am working with here is from 2017 to 2024. So, there will be variance between at which point the GPA was recorded for this plot. That being said, students who didn't go to tutoring had lower GPAs than those who went to tutoring. However, students that did not go to tutoring were much more likely to have a 0 GPA than those who went to tutoring. So, we see that tutoring has more of a "stabilizing" effect on GPA. We see the issue that students who never go to tutoring have higher rates of 0 GPA and 4 GPA compared to students. For this reason, in section 8, we propose propensity score matching to create a "fairness" assessment of students.

Success rate is defined as the sum of number of courses passed divided by the number of courses taken. So the success rate is a number between 0 and 1. In which 0 represents the case where a student takes some number of classes but passes none of them. Conversely, 1 represents the case where a student has passed all the courses they have taken. In figure 4 students that never went to tutoring, had the lowest success rate compared to students who went rarely. From rarely, success rate marginally, but steadily increases as attendance increases. This ascending trend tells us tutoring is valuable to students, and thankfully does not result in diminishing returns.

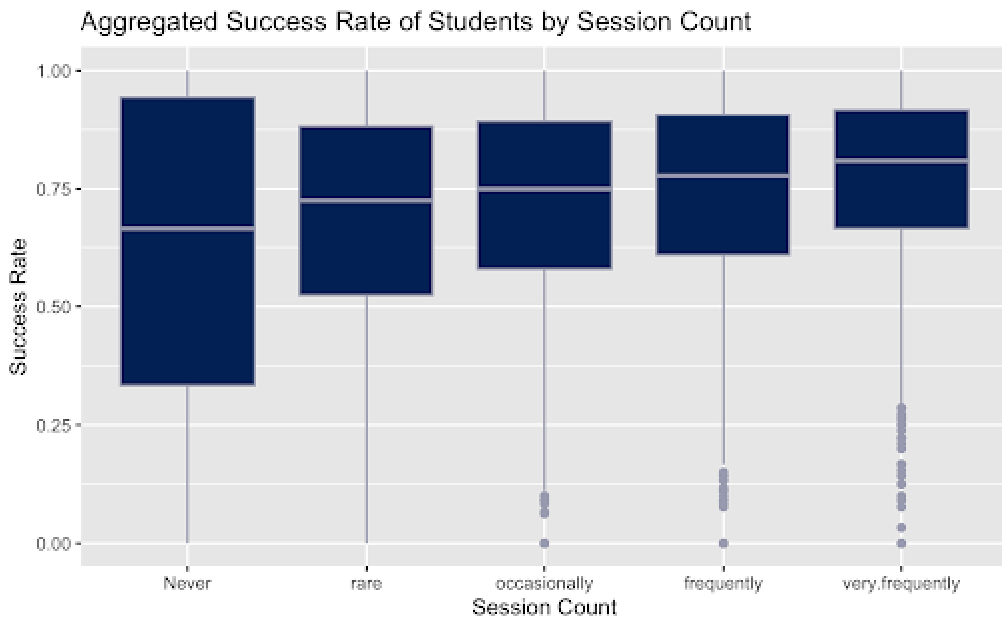

Figure 4: Success Rate Box Plot

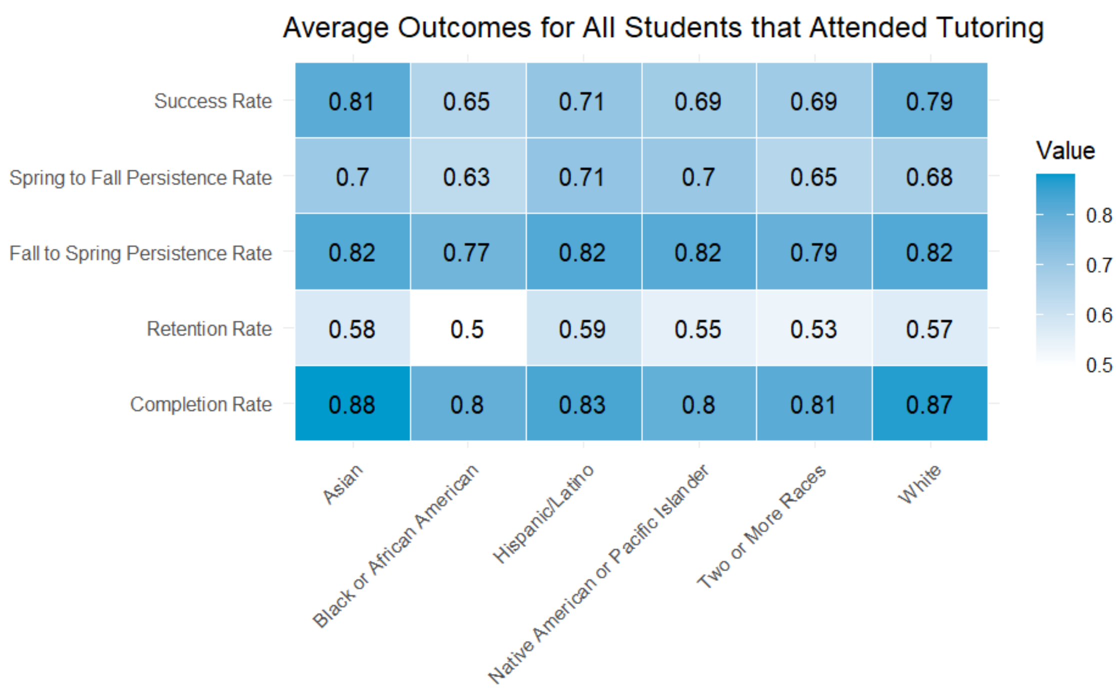

Figure 5: Treatment Heat map

Figure 5 shows a heat map of the different values for the average values of the different metrics of interest. For example, the success rate row in the figure above demonstrates the average value for that specific ethnicity. Asian's that attended tutoring have an average success rate of 0.81 compared to 0.65 for Black or African American students that also attended tutoring. We can think of success rate as a proxy for GPA. Typically, this means that a higher success rate is linked to a higher GPA when comparing two success rates.

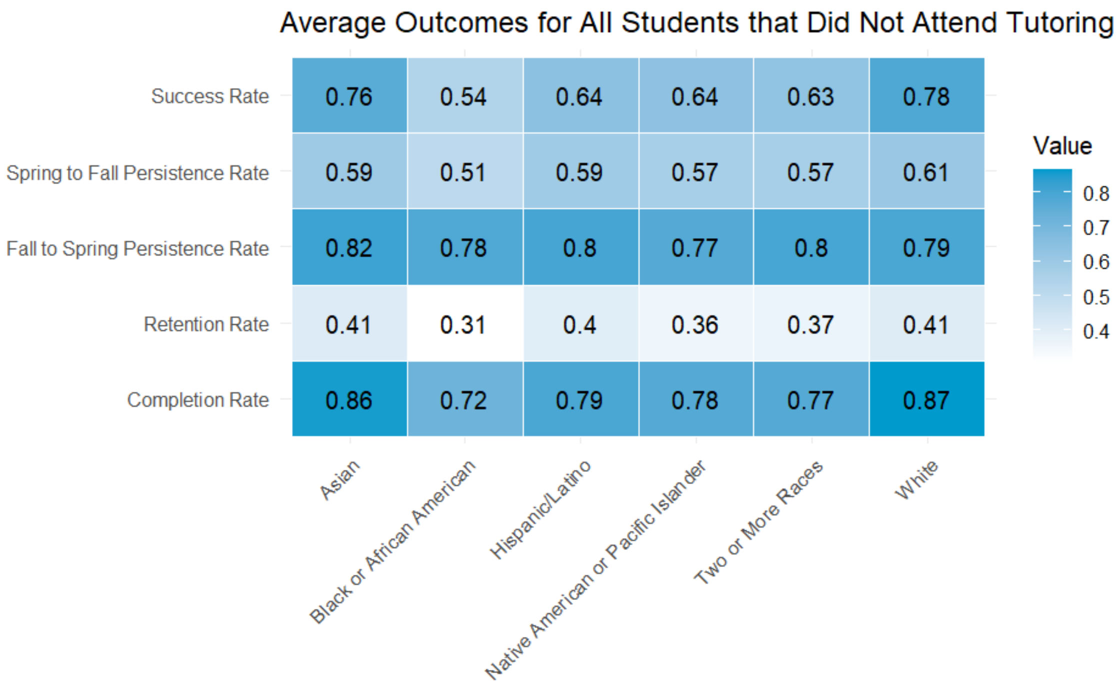

Figure 6: Control Heat map

In figure 6 we have the same outcomes in the previous figure, but for students that did not attend tutoring. As we can see, there are drastic differences between the retention rates of students that did not go to tutoring and those that did. There is a low retention value of 0.31 for Black or African American students. This suggests that of all the semesters that they were enrolled, Black students were only retained for 30% of their time at Cerritos college. On the other hand, Asian and White students had high retention and success rates regardless of tutoring status.

Figure 7 presents students across ethnicity and tutoring groups had strong persistence rates, but low retention rates. This may be due to the heavy imbalance of students that fully persisted versus those that had 0 retention. The graph below demonstrates this, where there is a significant amount of "No Retention".

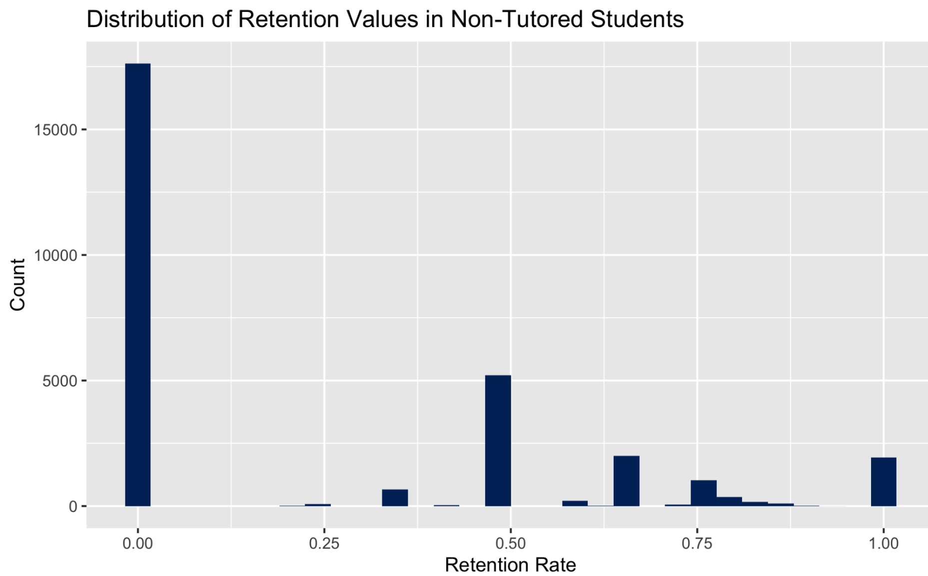

Figure 7: Retention among students that did not Attend Tutoring

5.2 Math Embedded Students

We are interested in evaluating the effectiveness of tutoring at the success center, particularly in relation to mathematics and chemistry. We have begun by examining students enrolled in mathematics and chemistry courses in the fall of 2019. The outcomes of interest to us are success, persistence, and retention rates.

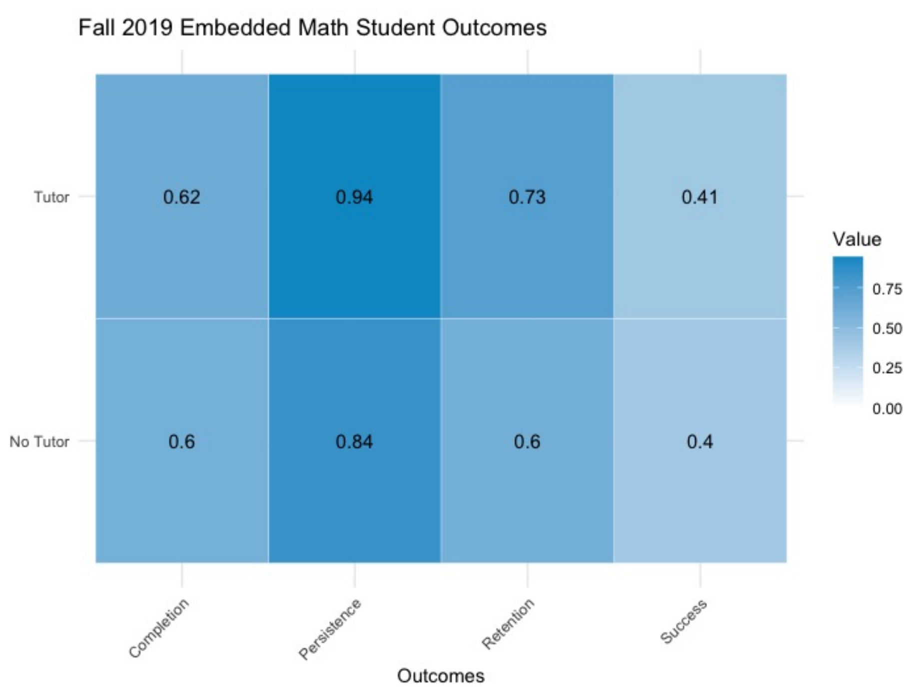

Figure 8: Outcomes for Fall 2019 Math Students

Figure 8 presents the outcomes of interest among students that did attend embedded tutoring and students that did not attend tutoring. The top row of the figure presents the outcomes among students that did go to tutoring and the bottom row presents the results of students that did go to tutoring. The darker colors in the figure represent higher numbers and such colors are found among the students that did go to tutoring. For instance, a greater percentage, 95% ,of embedded students that went to tutoring enrolled in the next semester compared to 84% of embedded students that did not go to tutoring. Across all outcomes of interest, success, persistence, and retention, there is a greater proportion of that outcome when compared to embedded students that did not go to tutoring. Hence, we observe that students that go to tutoring have greater outcomes than students that did not go to tutoring.

The outcome results across ethnicity are present in the appendix in figures 29,31, 32. The success rate by sessions plot, figure 30, also present in the appendix, illustrates that students that a higher proportion of students that rarely went to the student success center did not pass the math embedded course. We observed that a greater proportion of students that attended more sessions at the student success center passed their math embedded course.

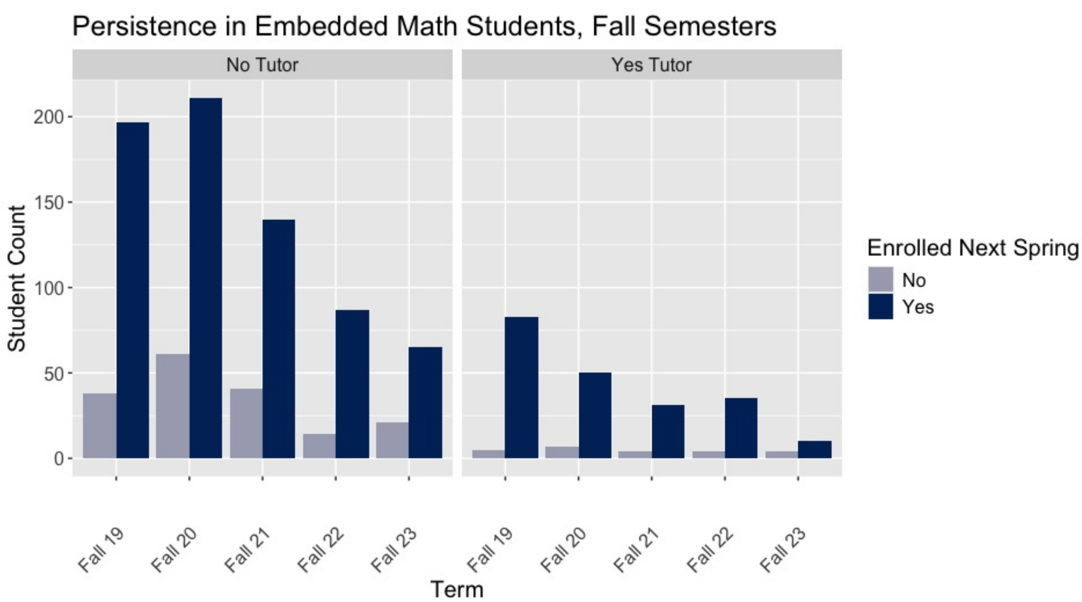

Figure 9: Persistence of embedded math students in the fall 2019, 2020, 2021, 2022 ,and 2023

Figure 9 shows that regardless of whether students attended the extra tutoring sessions at the SSC, they are still enrolling in the next spring semester. Arguably, more students in the tutoring category are enrolling in the next spring semester. Figure 10 presents retention for these same students. In this plot a greater number of students that did not got to the tutoring sessions are not enrolling in the next fall semester compared to the students that did go to tutoring.

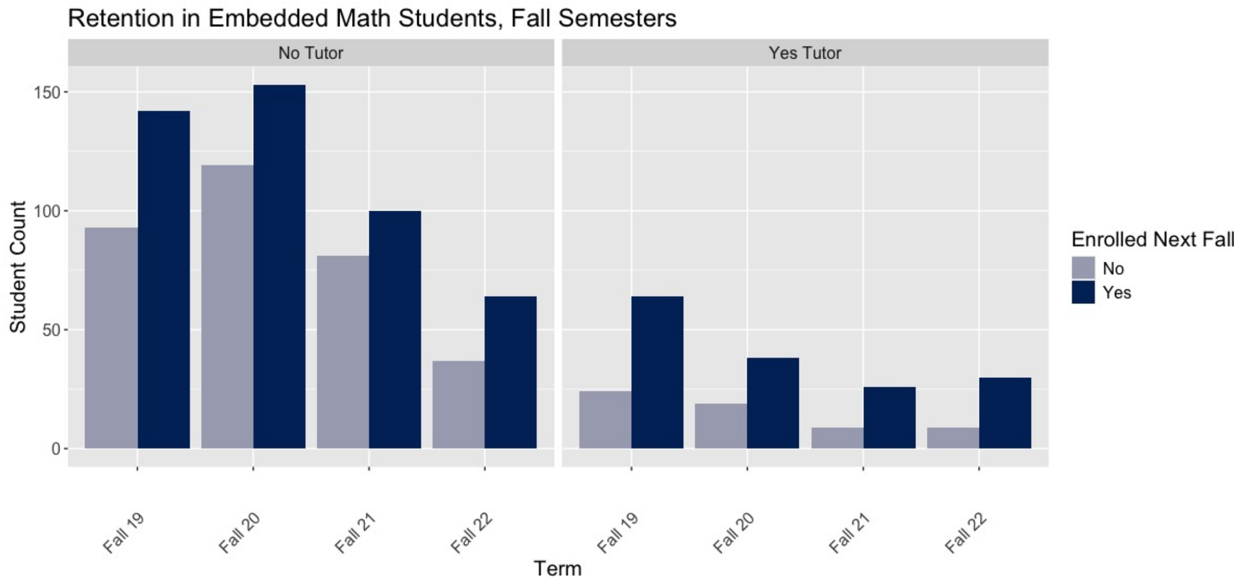

Figure 10: Retention of embedded math students in the fall 2019, 2020, 2021 and 2022

5.3 Chemistry Tutoring at the Success Center

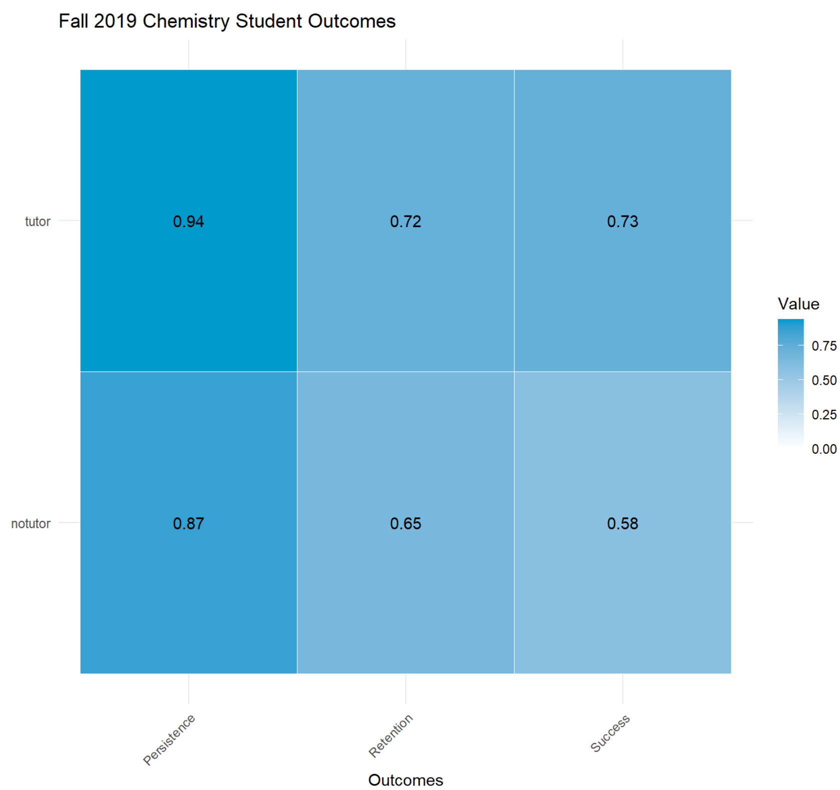

Figure 11: Outcomes between tutored and non-tutored chemistry students

The heatmap shown in figure 11 illustrates the relationship between tutoring and each of these outcomes. In general, tutoring is associated with improved outcomes. This relationship is most pronounced in relation to success rates, whereby 58% of non-tutored students pass their courses, and seventy-three percent of tutored students pass their courses.

Figure 33 [3] illustrates the relationship between the number of tutoring sessions attended and success rate. It is clear from this data that students attending tutoring more frequently are more successful; the success rate increases at each category, from a sixty-eight percent pass rate for those attending rarely, to an eighty-nine percent pass rate for those attending very frequently. Figure 34 displays success rates by ethnicity, with and without tutoring. Patterns are less evident than in the prior plot. For the most part, students who attend tutoring exhibit higher success rates, with the exception of students in the "two or more races" category. Of students in the "Native American or Pacific Islander" category, one-hundred percent who attended tutoring succeeded, and one-hundred percent who did not attend tutoring failed. We believe that more data (additional semesters) would rectify such odd results.

Next, we will examine persistence rates, defined as fall-to-spring enrollment, by ethnicity. Figure 12 illustrates persistence rates among fall 2019 chemistry students broken down by ethnicity. With the exception of "Native American or Pacific Islander" and "White" students, all students who attend tutoring exhibit higher persistence rates.

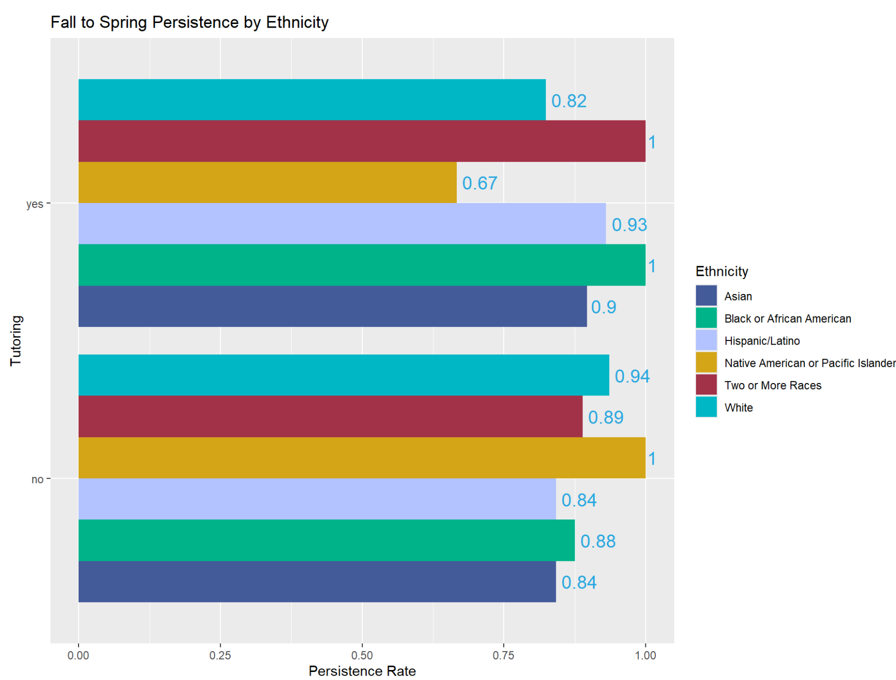

Figure 12: Persistence by ethnicity among general chemistry students

Finally, we will examine retention rates, defined as fall-to-fall enrollment, by ethnicity

[3] Figures in this paragraph are present in the appendix section: Fall 2019 Chemistry Plots

shown in figure 13. With the exception of "Native American or Pacific Islander", "two or more races", and "Black or African American" students, all students who attend tutoring exhibit higher retention rates. We expect that with more data, differences between tutored and non-tutored students would become more clear.

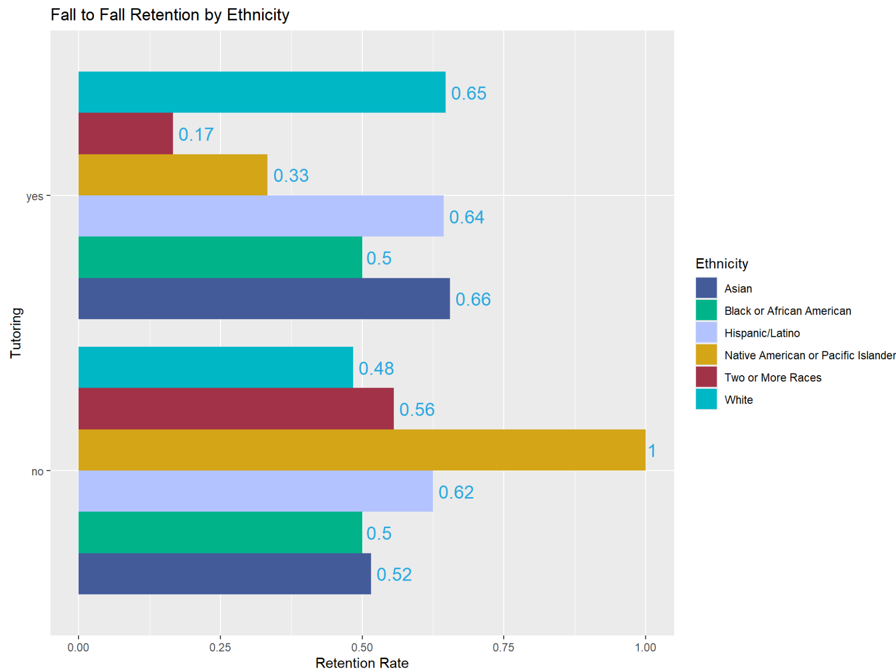

Figure 13: Retention by ethnicity among general chemistry students

6 Aggregated Data Linear Models

6.1 Methods

The aggregated data model looks at a few predictors of interest, which include: GPA, time spent in tutoring, session count, completion rate, ethnicity, gender, and first generation status. This data is agnostic to discipline and tutoring modality. Meaning that we cannot make claims about the effectiveness of any particular type of tutoring or subject. Here, we seek to investigate the effect of tutoring on student outcomes. Before we begin modeling, we want to consider correlations or colinearity of the predictor space. As such, we implemented an eXtreme Gradient Boosted Machine algorithm and LASSO regression to perform variable selection for each model with different response variables corresponding to the student outcomes[4]. For clarity, as we mention "tutored" as a variable, we refer to whether or not students ever attended tutoring during their enrollment.

For the success rate model, we have the following variables: GPA, tutored, time spent, session count, completion rate, first gen status, and gender. For the retention model we

[4]XGBoosting results for success rate are present in the aggregated data section of the appendix.

have: GPA, tutored, time spent, completion rate, gender, and ethnicity. For the persistence model we have: GPA, tutored, time spent, gender, and ethnicity. We used these variables and fit them to a linear model for each metric of student outcomes.

6.2 Results

Table 7 summarizes the information from the three linear models, including the predictors used, their coefficients, and standard error.

Beginning with model 1, we seek to predict the success rate of students. GPA and completion rate have the strongest relationship with success rate. For every 1-unit increase in GPA, students had a 16% increase in success rate. Meaning that students with higher GPAs had higher success rates. This, of course, is not particularly insightful due to the definition of success rate. Completion rate on the other hand, reveals something interesting: Students who completed their course had an increase of 50% in their success rates compared to those that did not finish a course. This suggests to us that students who completed courses were much more likely to pass them than those who have a habit of dropping courses.

Model 2 seeks to predict retention rate of students. Students that went to tutoring see a 34.6% increase in their retention rates compared to those who did not attend tutoring. This tells us that tutoring is an important factor in retaining students, but there is an important caveat that may ruin the interpretation of these results. That is: students who are enrolled (aka students that go to tutoring) are already coming back compared to those who were enrolled at the college, but never went to tutoring. This largely depends on how the data was collected and inputted into the files we were given. Regardless, we can see that students who went to tutoring had higher retention rates. Students with higher GPAs had a 6.5% increase in their retention rate, which is great. It shows that higher performing students were retained more than students that performed worse. Ethnicity did not have a large impact on retention rates. Latino's had a 7.8% increase in their retention rates over Asians. This was about the largest increase over Asians for retention according to the Table. Students who completed their courses had a 17% increase in their retention rate compared to those who did not complete their courses.

Lastly, we have model 3, which seeks to study the relationship between persistence and the same predictors as aforementioned. We see that GPA had a slight bump when compared to retention. That is, students with 1-point higher GPAs had a persistence rate increase of 9.7%. Attending tutoring demonstrated an increase of 27% compared to students that did not go. Much like retention, Latinos had the single most increase over Asians at 7.7%.

Across all models, we obtained a mean-squared error of 0.0017. This tells us that our predictions of success rate, retention, and persistence were off by 1.7%. We believe this is an acceptable MSE for these models.

6.3 Discussion

Table 7 demonstrates that model one had a particularly low Pearson's r. This is interesting because it says that a student's attendance to tutoring does not play a significant role in increasing their success rate. This tells us that on its own, tutoring overall is not important, however, we later learned that it is in fact highly dependent on which subject the student is receiving tutoring for. Students who received math tutoring for example, were much more likely to pass their courses than those who did not receive tutoring. This tells us that discipline specific tutoring may help those more than others. Due to time constraints, we could not investigate the embedded tutoring data beyond math courses; however, we posit that tutoring in subjects such as English or political science (i.e., untechnical classes) will have less of an impact on student success than math or physics classes.
Students who complete their courses are much more likely to have higher success rates than those who do not complete their courses. This suggests to us that students who habitually drop courses, fail the ones that they do complete. Completion rate is a complex phenomena on it's own that may have deeper implications for student outcomes. For this reason we digress, yet suggest further research on completion rate.

Across the retention and persistence models, we notice that tutoring provided the highest increase to these re-enrollment rate metrics. Interestingly, the amount of time spent in tutoring for this category did not significantly impact the rates of retention and persistence. This tells us the simple act of going to tutoring is important in determining whether a student will continue enrolling at the college. Demographic information such as gender, first generation status, and ethnicity did not play a big role in predicting any of the response variables for this data. At most, we noticed a slight difference in retention and persistence between Asians and Latinos. This difference may be due to the fact that Latinos comprise a significant portion of the enrollment total at Cerritos College. This may impact how much a particular set of Latino students affect the overall retention and persistence rates for their ethnic category.

Overall, we feel uncomfortable making any salient claims using aggregated data. In fact, if further research continues, we suggest evaluating student outcomes with higher granularity.

In regards to the modeling, if aggregated data needs to be analyzed for any reason, we suggest beta or Poisson regression as opposed to linear models. Student outcomes will more than likely be proportions in aggregated data, so beta or Poisson regression is better suited for response variables bounded between 0 and 1.

We suspect that there are discipline-specific effects to tutoring. We suspect that English or Political Science tutoring is less effective than math or physics tutoring. Essentially, objective, rigorous courses such as math and physics likely have a stronger measurable tutoring effect compared to language or other such writing classes within such a short time.

This leads us to the next sections where we evaluate the math and chemistry tutoring at a semester level. This provide the opportunity for better analysis, which can be used for adequate decision making.

Table 7: Success Rate Retention and 2 Rate Regression Coefficients

	DV: Success Rate (Fall 2015-Spring 2024)		
	Success Rate	Retention	Persistence
	(Fall 2019, Fall 2020, Fall 2021 Fall 2022, Fall 2023)		
	(1)	(2)	(3)
GPA	0.161***	0.065***	0.097***
	(0.001)	(0.002)	(0.002)
Tutored	0.008***	0.346***	0.274***
	(0.002)	(0.006)	(0.007)
Very Low Time Spent	−0.012**	−0.126***	−0.061***
	(0.006)	(0.008)	(0.009)
Low Time Spent	−0.009	−0.095***	−0.042***
	(0.005)	(0.008)	(0.009)
Average Time Spent	−0.008*	−0.068***	−0.025***
	(0.005)	(0.008)	(0.010)
Above Average Time Spent	0.001	−0.045***	−0.010
	(0.006)	(0.014)	(0.017)
Substantial Time Spent			
Completion Rate	0.516***	0.171***	
	(0.003)	(0.008)	
First Gen	−0.0004		
	(0.001)		
First Gen Unknown	0.012***		
	(0.002)		
Gender Unknown	−0.004	−0.015	−0.014
	(0.005)	(0.013)	(0.016)
Female	−0.006***	0.008**	−0.004
	(0.001)	(0.003)	(0.004)
Rare Attendance	−0.003		
	(0.006)		
Occasional Attendance	0.001		
	(0.005)		
Frequent Attendance	0.001		
	(0.004)		
Very Frequent Attendance			
Black or African American	−0.023***	0.024***	0.041***
	(0.003)	(0.008)	(0.009)
Hispanic/Latino	−0.015***	0.078***	0.077***
	(0.002)	(0.006)	(0.007)
Native American or Pacific Islander	−0.009	0.029	0.025
	(0.008)	(0.020)	(0.025)
Two or More Races	−0.015***	0.031***	0.044***
	(0.004)	(0.011)	(0.013)
White	0.005*	0.014*	−0.008
	(0.003)	(0.007)	(0.009)
Constant	−0.148***	−0.084***	0.243***
	(0.003)	(0.008)	(0.008)
Observations	38,108	38,108	38,108
R^2	0.853	0.274	0.184
Adjusted R^2	0.853	0.274	0.184
Residual Std. Error	0.122 (df = 38088)	0.317 (df = 38093)	0.383 (df = 38094)
F Statistic	11,650.930*** (df = 19; 38088)	1,028.309*** (df = 14; 38093)	660.664*** (df = 13; 38094)
Significance Levels			*p<0.1; **p<0.05; ***p<0.01

7 Preliminary Modeling, Semester Data

To begin, we want to select features that contribute to an accurate model. There are many other interesting potential features in our data, however, we want to limit our focus to those that contribute meaningfully to success, retention, and persistence.

Random Forests are a common machine learning technique used in classification in education data (Injadat, Moubayed, Nassif, & Shami, 2020). We cross-validated a saturated Random Forest model using the `rfcv` function from the `RandomForest` library, and this function revealed that the accuracy of the Random Forest model was not significantly affected by the number of features selected [5]. Therefore, we discarded features we knew to be highly correlated, and kept features of particular interest to us and to the client. Figures 39 and 40 in the appendix visualize our feature selection method. The Random Forest helped provide insight into how the predictors interacted with the response variables of interest.

The features selected are GPA, ethnicity, session count, time spent, first gen, and gender. GPA is a three factor variable; "low" represents a GPA below 2.0, "mid" represents a gpa between 2.0 and 3.0, and "high" represents a GPA above 3.0. Session count is a five factor variable; "none" represents no tutoring sessions attended during a semester, "rare" represents between 0 and 3 tutoring sessions attended, "occasionally" represents between 3 and 4 tutoring sessions attended, "frequently" represents between 4 and 14 sessions attended, and "very frequently" represents more than 14 sessions attended. Time spent is a six factor variable representing the time spent in tutoring. first gen is a three factor variable that describe a student's first-generation status; "first gen", "not first gen", or "unknown". Gender is a three factor variable that describes a student's gender; "male", "female", or "unknown". The following plots produced by the Random Forest (RF) function in R demonstrates the relative importance of our features; note that it ignores factor levels.

7.1 Embedded Math Tutoring

Figures 14, 35, and 36 illustrate the importance plots for each outcome: success, persistence, and retention[6]. Across all three models GPA, Session count, and ethnicity were among the top three important predictors. This suggests that a student's past academic history, their ethnicity, and the amount of embedded tutoring sessions they attended were essential in determining their outcomes.

[5] This was done for general math data.

[6] Figures not present here are in the importance plot section for embedded math.

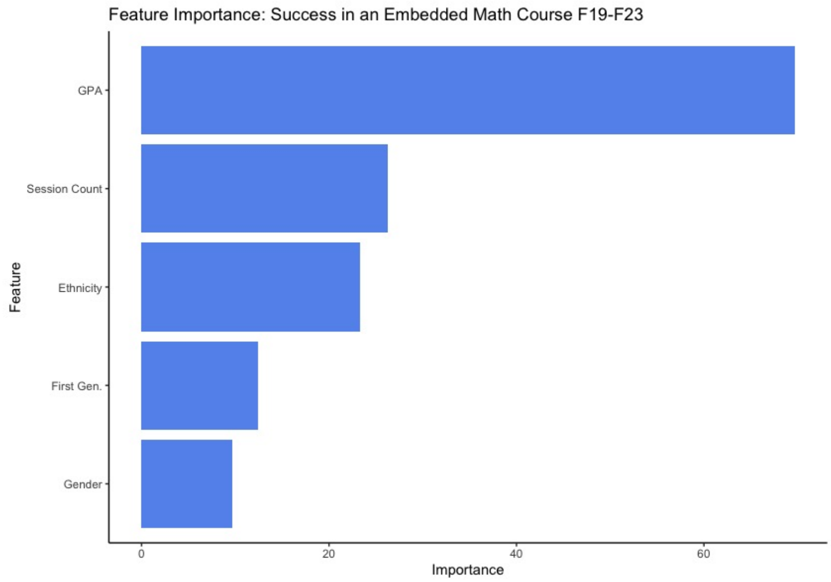

Figure 14: Importance of Success predictors among Embedded Students

In figure 14, GPA is by far the most important predictor in determining the success of a math student in an embedded course. The subsequent important variable is session count, indicating the amount of embedded tutoring sessions that a student spent at the SSC, or lack their of, is important in determining their success in an embedded math course. The RF deemed ethnicity, first generation, and gender as "less important" when compared to GPA and session count.

In figure 35 presents the importance ranking of the variables, gpa, session count, ethnicity, gender, and first generation in predicting the persistence. A student's past academic performance is essential in determining whether they enroll in the next spring semester. The subsequent important predictor is ethnicity. Indicating that a student's ethnicity plays a role in whether they enroll in the next spring semester. Ethnicity is followed closely by session count, gender and first generation.

Figure 36 illustrates the importance predictors for retention. Session count was by far the most important predictor in determining whether a student enrolls in the next fall term. This is followed by ethnicity, GPA, gender, and first generation which had similar mean decrease gini values. Interestingly enough, this was the only model where GPA was not an important predictor, in other words, a student's past academic standing does not play such a significant role in determining whether they enroll in the next fall semester.

7.1.1 Logistic Regression

	IV: Session Count (Fall 2019 - Fall 2023)		
	1.Success	2.Persistence	3.Retention
Rare	54.03%	63.53 %*	66.16%**
Occasionally	75.41%*	49.81%	63.02%
Frequently	66.25%*	72.33%*	54.07%
Very Frequently	71.78%	82.57%	75.12%*

Table 8: Probabilities of Session Count Categories for all Outcomes: Coefficients of the session count predictors in table 9 were converted into probabilities using $\frac{e^{x_i}}{1+e^{x_i}}$. Values with an asterisk indicate significant predictors in the logistic model. See the preliminary models section of the appendix for the probabilities calculated for the remaining predictors.

Following the RF models, three logistic regression models were run using each of the outcomes as the response variable. A logistic regression model classifies each student into either of the two outcomes. The logistic regression model also allows for a probability analysis of the coefficients. Since the predictors used to fit the model are categorical, this allows for a comparison of students that are found in each of the categories. Table 9 presents the coefficient results of the three logistic regression models where each column presents the coefficients of each model.

As previously mentioned, the variables used to fit the model were all categorical. The GPA variable was split into three categories: low, mid, and high. In the logistic model students in the low category were the reference; model coefficients for GPA will be comparable to students in the low category. For the session count variable, students in the none category were the reference, this allows for a comparison between students that did and did not attend the embedded tutoring sessions at the SSC. For ethnicity, Asians were set as the reference since these students perform the best. Students that were not first generation were set as the reference and female students were set as the reference.

In our first model in table 9, both GPA categories were the most significant predictors. There is an increase in log odds of 1.75 and 2.61 for students with mid and high GPAs compared to students with low GPAs. In other words, students with mid and high GPAs have an 85.23% and 93.16% chance of passing their embedded course compared to students with low GPAs. The probabilities for the other variables are shown in the appendix in table 15. In the first column of table 8 we find the probabilities of each of the session count categories. Since each of the coefficients are positive we find an increase in probability that a student passes their course if they attend the student success center rarely, occasionally, frequently, and very frequently [7] compared to embedded math students that did not go to the SSC across the fall semesters.

[7] Recall that students who rarely went to the SSC attended 1-2 times, students that occasionally went attended 3-4 times, students that frequently went attended 5-14 times and students that went very frequently attended 15-26 times.

Table 9: Outcomes Logistics Regression Coefficients

	DV: Outcomes (Fall 2019 - Fall 2023)		
	1.Success	2.Persistence	3.Retention
GPA: Mid	1.75***	1.11***	0.739***
	(0.216)	(0.197)	(0.164)
GPA: High	2.61***	1.25***	0.658***
	(0.219)	(0.204)	(0.165)
Session: Rare	0.162	0.555*	0.670**
	(0.209)	(0.293)	(0.204)
Session: Occasionally	1.12*	-0.007	0.533
	(0.499)	(0.560)	(0.436)
Session: Frequently	0.674*	0.961*	0.163
	(0.332)	(0.538)	(0.292)
Session: Very Frequently	0.933*	1.55	1.10*
	(0.517)	(1.03)	(0.511)
Black/AA	-1.67***	-0.153	-0.298
	(0.377)	(0.400)	(0.327)
Hispanic/Latino	-0.705*	0.306	-0.04
	(0.267)	(0.297)	(0.235)
Native American or Pacific Islander	-16.10	0.606	-0.221
	(449.40)	(1.13)	(0.751)
Two or More Races	-0.650	-0.261	-0.013
	(0.508)	(0.578)	(0.483)
White	-0.516	0.962*	-0.123
	(0.379)	(0.494)	(0.335)
First Gen.	-0.438**	-0.07	-0.129
	(0.154)	(0.185)	(0.140)
First Gen.: Unknown	-0.494*	0.041	-0.275
	(0.018)	(0.250)	(0.193)
Male	-0.006	0.163	0.06
	(0.138)	(0.165)	(0.126)
Gender: Unknown	0.160	0.3334	0.559
	(0.05)	(0.539)	(0.452)
Intercept	-1.03**	0.257	-0.307
	(0.318)	(0.320)	(0.265)
Observations	1,111		
Null deviance	1535.6	1047.50	1525.6 on 1110 df
Residual deviance	1261	977.57	1475.1 on 1095 df
Significance Levels			*p<0.1; **p<0.05; ***p<0.01

In our second model we find similar results to that of the previous model, students with mid and high GPAs have a higher probability of enrolling in the next spring semester. Likewise, students that attended the extra tutoring sessions at the SSC have an increased probability of enrolling in the next spring semester compared to students that did not attend the extra tutoring sessions. However, as seen in figure 9, we find that regardless of whether the math embedded student went to the SSC, they are still enrolling in the subsequent spring semester. Regardless, these results indicate that there is a high probability of this results for students that attended the tutoring sessions at the SSC.

The final model revealed again that students with high GPAs have a greater probability of enrolling in the next fall semester. The session count categories rare and occasionally were the most significant predictors in this model. This suggests that students attending tutoring for 1-2 times a semester can have a positive impact on their retention. Likewise for student that attend tutoring for 3-4 times a semester.

In terms of the ethnicity, in all three models African Americans had a decreased log odds of passing their course, enrolling in the next spring, and enrolling in the next fall semester compared to Asian math embedded students. Hispanic students like-wise had a decreased in log odds of passing their embedded math course and enrolling in the next fall semester.

Across all three models first generation students had a decrease in log odds in outcomes when compared to non-first generation students. Males had a decease in log odds of passing their embedded math course but an increase in log odds of enrolling in the next spring semester and fall semester when compared to females.

7.1.2 Embedded Math Summary

Students taking a math embedded course in the fall semesters between 2019 and 2023 that went to tutoring sessions did attain an increase in outcomes compared to students that did not attend tutoring. The results from the logistic regression model produced positive log odds for our categorical session count variable. Particularly, rare and very frequently session counts were among the most significant predictors across all outcomes.

7.2 General Math Tutoring

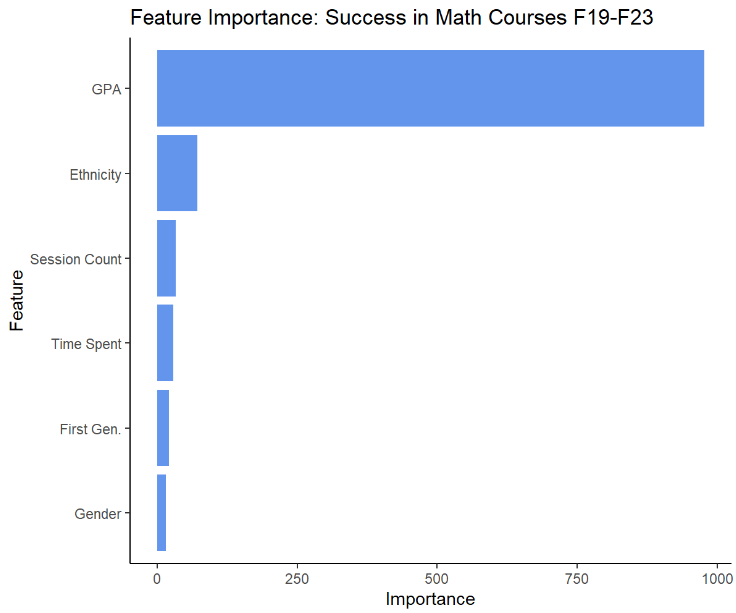

Figure 15: Importance of Success Predictors Among General Math Students

As expected, in figure 15 a student's cumulative GPA is the most important predictor of success; students with higher GPAs tend to perform well in their courses. All of the other predictors contribute to some degree, and will be included in our final models. Session count and time spent, however, are highly correlated and would produce confusing results if included together. We will include session count, rather than time spent, in our models as the client is particularly interested in this.

Figure 37 [8] tells a similar story as the previous plot. GPA is by far the most significant predictor of persistence, though it is followed by session count, indicating that students attending tutoring may be more persistent than those that do not. In figure 38, GPA is the most significant predictor here; Students with high GPAs tend to persist in their education. Session count and ethnicity are about equally significant here, so we may see some interesting trends in the persistence of students grouped by ethnicity.

7.2.1 Linear Models for Success Rate

Success rate is this dataset is not binary. Many students take more than one math class in a semester and do not pass all of them; success, then, takes a value between zero and one. Therefore, we cannot use logistic regression, as logistic regression requires a binary response. We are choosing to model success with simple linear models, as the results are easily interpretible, and linear models work with numeric responses. Furthermore, we will apply these models on a semester-to-semester basis. Further justification for the use of linear models in this context can be found in (Theobald & Freeman, 2014).

[8] Figures not present in this section are in the appendix section for general math importance plots.

Table 10: Success Rate Linear Regression Coefficients

	DV: Success Rate (Fall 2019 - Fall 2023)				
	Fall 2019	Fall 2020	Fall 2021	Fall 2022	Fall 2023
GPA: mid	0.289*** (0.016)	0.353*** (0.016)	0.332*** (0.017)	0.311*** (0.016)	0.269*** (0.029)
GPA: high	0.505*** (0.016)	0.601*** (0.016)	0.584*** (0.017)	0.571*** (0.016)	0.567*** (0.029)
Session: Rare	0.023 (0.017)	-0.091* (0.054)	-0.046 (0.046)	0.01 (0.032)	0.042 (0.043)
Session: Occasionally	0.123* (0.144)	0.176 (0.144)	0.121 (0.151)	-0.074 (0.126)	-0.024 (0.142)
Session: Frequently	0.091*** (0.022)	0.167* (0.089)	-0.082 (0.081)	0.182** (0.064)	0.015 (0.085)
Session: Very Frequently	0.237*** (0.033)	0.173 (0.112)	0.412*** (0.11)	0.165* (0.089)	0.187* (0.113)
Ethnicity: Black or African American	-0.196*** (0.033)	-0.167*** (0.034)	-0.18*** (0.036)	-0.169*** (0.033)	-0.175** (0.054)
Ethnicity: Hispanic/Latino	-0.108*** (0.021)	-0.102*** (0.024)	-0.09*** (0.024)	-0.104*** (0.024)	-0.096** (0.035)
Ethnicity: Native American or Pacific Islander	-0.192* (0.094)	-0.065 (0.083)	-0.131 (0.09)	-0.287** (0.107)	0.09 (0.186)
Ethnicity: Two or More Races	-0.105* (0.041)	-0.121* (0.047)	-0.032 (0.052)	-0.095* (0.049)	-0.14* (0.072)
Ethnicity: White	-0.065* (0.033)	-0.104** (0.035)	-0.038 (0.036)	-0.072* (0.036)	-0.072 (0.051)
First Gen.: First Gen.	0.02 (0.013)	-0.019 (0.014)	0.001 (0.015)	-0.049*** (0.015)	0.002 (0.023)
First Gen.: Unknown	0.007 (0.018)	-0.034* (0.019)	-0.014 (0.021)	-0.055** (0.019)	-0.019 (0.03)
Gender: Male	-0.017 (0.012)	0 (0.012)	-0.022* (0.013)	-0.025* (0.013)	0.026 (0.02)
Gender: Unknown	-0.006 (0.05)	0.002 (0.016)	-0.101 (0.063)	0 (0.016)	0.096 (0.097)
Significance Levels	*p<0.1; **p<0.05; ***p<0.01				

Table 10 displays the coefficients produced by linear models for each semester, from fall 2019 to fall 2023. The baseline categories are as follows: "low" for GPA, "none" for sessions, "Asian" for ethnicity, "not first-gen" for first-gen, and "Female" for gender.

The coefficients here represent the average contribution to success given that a student falls into a particular category. For example, a student with a high GPA in fall of 2019 can expect a success rate .505 higher than a student with a low GPA, holding all else constant. Similarly, a black student in 2021 can expect a success rate 0.18 lower than an Asian student, holding all else constant.

The coefficients for GPA are consistently statistically significant and contribute strongly to success; they are strongly positive as the baseline factor is "low" GPA. The coefficients associates with session count are generally positive and occasionally statistically significant. The strong effect of "very frequent" tutoring attendance indicates that even students with low GPAs may succeed if they attend tutoring about once a week, a reasonable proposition. Black or African American students consistently perform the worst of all the ethnicities, though tutoring may help offset this. All of the ethnicities exhibit lower performance than Asian students, the baseline ethnicity. First-gen students occasionally demonstrate performance slightly lower than non-first-gen students, and male students tend to perform about as well as females. In summary, the most significant positive predictors of success are GPA and very frequent, frequent, or occasional tutoring attendance, and the most significant negative predictor is black or African American ethnicity.

7.2.2 Logistic Regression for Persistence and Retention

Unlike success rates, persistence and retention are binary responses in the general math dataset. Therefore, we are choosing to model persistence and retention using logistic regression. Table 11 displays the coefficients produced by a logistic regression modeling persistence for each semester, from fall 2019 to fall 2023.

The coefficients in table 11 represent the average change in log-odds for each variable, and exponentiated represent the average change in odds. For example, a student with a high GPA in 2019 can expect to persist with $e^{1.048}$, or 2.85 times the odds of a student with a low GPA, holding all else constant. A black student in 2020 can expect to persist with $e^{-0.479}$, or 0.62 times the odds of an Asian student, holding all else constant.

Table 11: Persistence Logistic Regression Coefficients

	DV: Perisitence (Fall 2019 - Fall 2023)				
	Fall 2019	Fall 2020	Fall 2021	Fall 2022	Fall 2023
GPA: mid	0.75***	1.178***	1.074***	0.813***	0.662***
	(0.084)	(0.084)	(0.09)	(0.089)	(0.144)
GPA: high	1.048***	1.582***	1.47***	1.109***	0.946***
	(0.09)	(0.09)	(0.097)	(0.096)	(0.149)
Session: Rare	0.0462***	1.203*	0.462	0.313	0.123
	(0.11)	(0.524)	(0.32)	(0.213)	(0.248)
Session: Occasionally	0.808*	-0.035	0.21	0.819	-0.529
	(0.358)	(0.841)	(1.07)	(1.058)	(0.702)
Session: Frequently	0.723***	0.211	0.392	-0.389	0.533
	(0.159)	(0.167)	(0.557)	(0.356)	(0.547)
Session: Very Frequently	0.549*	0.157	-0.197	-0.048	-0.281
	(0.228)	(0.766)	(0.651)	(0.558)	(0.586)
Ethnicity: Black or African American	-0.254	-0.479*	-0.026	0.152	-0.703*
	(0.181)	(0.204)	(0.202)	(0.192)	(0.284)
Ethnicity: Hispanic/Latino	0.177	-0.263*	0.144	0.224	-0.136
	(0.127)	(0.157)	(0.139)	(0.139)	(0.205)
Ethnicity: Native American or Pacific Islander	0.035	-0.576	-0.496	-0.346	13.034
	(0.533)	(0.475)	(0.468)	(0.572)	(358.854)
Ethnicity: Two or More Races	0.066	-0.343	0.059	0.316	0.122
	(0.242)	(0.285)	(0.303)	(0.297)	(0.42)
Ethnicity: White	-0.186	-0.445*	0.123	-0.368*	-0.315
	(0.188)	(0.214)	(0.215)	(0.199)	(0.288)
First Gen.: First Gen.	-0.164*	-0.11	-0.02	-0.167*	-0.188
	(0.078)	(0.08)	(0.086)	(0.087)	(0.126)
First Gen.: Unknown	-0.182*	-0.131	-0.098	-0.057	-0.173
	(0.104)	(0.108)	(0.116)	(0.11)	(0.161)
Gender: Male	-0.029	-0.097	-0.098	-0.063	0.319**
	(0.07)	(0.072)	(0.077)	(0.302)	(0.111)
Gender: Unknown	0.465	-0.331	-0.704*	-0.135	0.256
	(0.324)	(0.32)	(0.319)	(0.302)	(0.524)
Significance Levels	*p<0.1; **p<0.05; ***p<0.01				

As in the linear models used to model success rates, GPA dominates these logistic regression models. All of the coefficients associated with GPA are strongly positive and statistically significant. Session count is not consistently beneficial here and is rarely statistically significant. Tutoring does, however, demonstrate a significant beneficial effect in the year 2019. Patterns among ethnicties are more sporadic than those seen in the success rate models, but black or African American students consistently demonstrate the lowest outcomes again. First-gen students demonstrate lower persistence than non-first-gen students, but the results are mostly not statistically significant.

Now we will model retention using logistic regression. Table 12 displays the coefficients produced by a logistic regression modeling retention for each semester, from fall 2019 to fall 2023. Similar to the persistence models, GPA is the dominating variable; a higher GPA tends to correlate with greater retention. Most of the other predictors are seen in 2019; these include rare and frequent tutoring attendance. Most of the coefficients associated with tutoring are positive, indicating a positive effect on retention, but many are not statistically significant. Among the ethnicities, many coefficients are positive, indicating that Asian students are not retained more consistently than other ethnicities. First-gen students tend to be retained less than non-first-gen students

7.2.3 General Math Summary

Our models produce the most interesting results for the year 2019, when the most data was available. In fall of this year, 1,481 math students attended tutoring, and 4,005 did not. The following fall, only 114 students attended tutoring, while 4,818 did not. Tutoring numbers have not recovered as of fall 2023. As a result, our models produce inconsistent results, particularly with respect to retention and persistence. While tutoring seems to contribute meaningfully to success, it's relation to retention and persistence is less apparent. It may be that there are other factors contributing more significantly to retention and persistence. That said, success rate models do demonstrate that tutoring contributes to success, and that success scales with the number of tutoring sessions attended. The success rate models also demonstrate an achievement gap particularly pronounced for black students.

Table 12: Retention Logistic Regression Coefficients

	DV: Perisitence (Fall 2019 - Fall 2023)			
	Fall 2019	Fall 2020	Fall 2021	Fall 2022
GPA: mid	0.803***	1.151***	1.069***	0.909***
	(0.075)	(0.079)	(0.084)	(0.079)
GPA: high	0.991***	1.411***	1.381***	0.853***
	(0.077)	(0.08)	(0.085)	(0.08)
Session: Rare	0.186*	0.356	0.085	0.107
	(0.082)	(0.269)	(0.226)	(0.16)
Session: Occasionally	0.434*	0.072	0.458	0.565
	(0.237)	(0.698)	(0.821)	(0.685)
Session: Frequently	0.451***	-0.136	0.042	-0.376
	(0.108)	(0.418)	(0.4)	(0.31)
Session: Very Frequently	0.205	0.562	-0.336	0.047
	(0.156)	(0.591)	(0.523)	(0.447)
Ethnicity: Black or African American	0.076	-0.372*	-0.116	-0.14
	(0.076)	(0.167)	(0.176)	(0.162)
Ethnicity: Hispanic/Latino	0.257**	-0.255*	0.195*	0.222*
	(0.099)	(0.117)	(0.116)	(0.116)
Ethnicity: Native American or Pacific Islander	0.427	-0.179	-0.303	-0.138
	(0.448)	(0.403)	(0.437)	(0.524)
Ethnicity: Two or More Races	0.09	-0.588*	-0.243	0.192
	(0.192)	(0.229)	(0.25)	(0.242)
Ethnicity: White	0.081	-0.639***	-0.127	0.011
	(0.154)	(0.169)	(0.074)	(0.176)
First Gen.: First Gen.	-0.121*	-0.096	-0.207**	-0.161*
	(0.063)	(0.067)	(0.074)	(0.074)
First Gen.: Unknown	-0.238**	-0.066	-0.046	-0.021
	(0.085)	(0.092)	(0.102)	(0.094)
Gender: Male	-0.119*	-0.08	0.026	-0.144*
	(0.056)	(0.06)	(0.066)	(0.065)
Gender: Unknown	0.452*	-0.4	-0.417	-0.196
	(0.245)	(0.279)	(0.311)	(0.265)
Significance Levels	*p<0.1; **p<0.05; ***p<0.01			

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7.3 Preliminary Model Summary

The embedded data, examined across all terms, shows that among the ethnicities, “Black and African American” students consistently perform the worst with respect to all student outcomes, while “Asian” students generally perform the best. “White” students, “Native American or Pacific Islander” students, and “Hispanic/Latino” students outperform “Asian” students with respect to retention by various degrees, however; it may be the case that persistence rates are weakly correlated with ethnicity. a similar pattern is seen for retention; although all ethnicities perform worse than “Asian” students, the difference is not very significant. Gender does not appear to affect outcomes very strongly, and first-gen students tend to perform worse than non-first-gen students. The effect of tutoring is most significant for “frequent” and “very frequent” tutoring attendance and, as expected, students with high GPAs experience significantly better outcomes.

The general data, examined on a semester-to semester basis, exhibits similar patterns as the embedded data. Results tend to be similar across semesters, which would justify modeling across semesters rather than by semester. With respect to success, “Asian” students outperform all other ethnic groups, while “Black and African American” students consistently perform the worst. There is not much of a difference in performance within the “first-gen” and “gender” categories. Success tends to scale with tutoring attendance; the strongest positive effect is seen with “very frequent” tutoring. Persistence demonstrates inconsistent results. Tutoring attendance does not demonstrate consistent positive effect, and coefficients by ethnicity appear almost random; these inconsistent results are similar to those observed in the embedded analysis. Results are somewhat inconsistent with respect to retention as well, though “Hispanic/Latino” students generally perform the best of the ethnicities. Tutoring generally has a positive effect. In short, results are very consistent across semesters with respect to success, but tend to be sporadic with respect to retention and persistence, indicating that retention and persistence are not strongly affected by tutoring or student ethnicity. In both embedded and general data, the vast majority of students did not attend tutoring; this disparity is most pronounced beyond the 2019 term.

8 Final Modeling

8.1 Collapsing Variables

Some data sparsity necessitates combining some of our groups. In sections 4.2 and 4.3, we demonstrate that relatively few students identify as Native American/Pacific Islander or Two or More Races. Furthermore, our preliminary analyses indicate that students who Identify as Native American/Pacific Islander or Black or African American tend to under-perform with respect to our outcomes of interest, while students who identify as Two or More Races tend to perform about as well as white students. Therefore, we have chosen to combine white students with students of two or more races, and black or African American students with Native American/Pacific Islander students. Given that gender does not generally have a significant effect on students outcomes, we removed the "unknown" gender category by randomly assigning students of unknown gender to either male or female. Finally, we collapsed the session count categories by combining "frequently" with "very frequently", which we now call "frequently", a category encompassing students who go to tutoring more than four times during a semester. We also combine "rare" and "occasionally" into a category called "occasionally", which includes students who attend tutoring one to four times during a semester.

8.2 Propensity Score Matching

There are some issues with our data that necessitate additional preparation prior to final modeling. One issue, demonstrated in our EDA, is a significant imbalance in the number of tutored vs. non-tutored students. Another issue that we deduced is a potential imbalance in the types of students in the tutored vs. non-tutored groups; we would expect high-performing students to be more likely to attend tutoring, and low-performing students to be less likely to attend. Therefore, if we were to simply compare compared tutored students as our "treatment" group to non-tutored students as our "control" group, our models may exaggerate the effect of tutoring on student outcomes. In order to rectify this issue, we have examined, and decided to implement, propensity score matching. Propensity score matching "is a technique that attempts to estimate the effect of a treatment (exposure) by accounting for the covariates that predict receiving the treatment (exposure)" (Valojerdi & Janani, 2018). Tutored students are matched to non-tutored students based on propensity scores, which are predicted probabilities that a student will seek tutoring based on a range of covariates. Propensity score matching has the dual effect of reducing the size of the non-tutored group to that of the tutored group, and ensuring that each group is composed of similar students. If the correct covariates are chosen, a causal relationship between tutoring and student outcomes might be inferred.

To implement propensity score matching, we have to choose covariates that would predict a student's inclination to attend tutoring. As stated before, we would expect GPA to play a significant role, and many other variables in our datasets (gender, first-gen status, ethnicity, term) could reasonably be expected to contribute as well. we are using the `matchit` function from the `MatchIt` library to apply propensity score matching to our data. This function uses logistic regression by default to calculate propensity scores, and pairs non-tutored students to tutored students with similar propensity scores. Furthermore, the function produces diagnostic plots that allow us to see the effects of our selected covariates. A handy `matchit` tutorial can be found on the R-Bloggers website (R-Bloggers, 2022). We used the following regression formula in the `matchit` function to perform propensity score matching.

$$\text{tutored} \sim \text{prior term GPA} + \text{ethnicity} + \text{first-gen status} + \text{term}$$

Where "Tutored" is a binary response variable that indicates whether a student ever attended tutoring during a semester, and the predictors are categorical variables that we had previously added to our data sets. Figure 16 presents a "love plot", produced by the `matchit` function on our general math data, shows the effects of our predictors on the likelihood of a tutor attending tutoring.

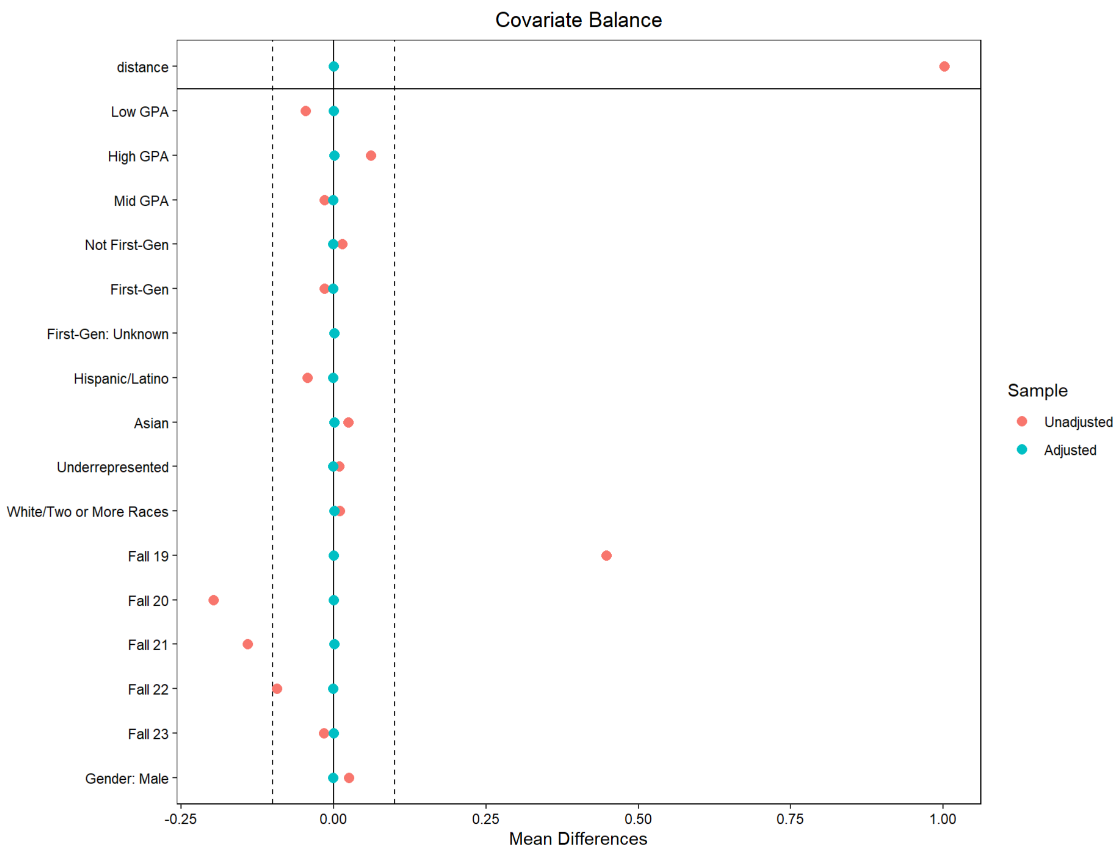

Figure 16: "Love plot": Covariate Balance among General Math Students

There are some interesting patterns in the covariates before matching, as demonstrated by the red dots. As we expected, students with higher GPAs tend to have have higher propensities to attend tutoring, while students with lower GPAs have lower propensities to attend tutoring. Hispanic/Latino students also tend to be less likely to attend tutoring. Students in the Fall of 2019 were significantly more inclined to go to tutoring than students in subsequent terms, certainly an effect of COVID. The blue dots represent covariate trends after matching, and demonstrate almost perfect matching by the `matchit` function.

In the general math data, 1,770 students attended tutoring, while 16,480 did not. The `matchit` function matched each tutored student to a similar non-tutored student. Tables 13 and 14 demonstrate the demographic composition of general math students before and after matching.

Asian	Underrepresented	Hispanic/Latino	White/Two or More Races
10.25%	6.86%	85.16%	8.47%

Table 13: Ethnic Composition of General Math Students Before Matching

Asian	Underrepresented	Hispanic/Latino	White/Two or More Races
11.38%	7.03%	73.08%	8.5%

Table 14: Ethnic Composition of General Math Students After Matching

Matching did not change the ethnic composition of our data very much, except with respect to Hispanic/Latino students, who comprise the largest group by far. Matching does, however, dramatically reduce our sample size, from 16,480 students down to 3,540. This sample size reduction is acceptable to us, however, as we can be more confident about the conclusions we draw from well-matched students. We will used matched data for our final models in the following section.

8.3 Logistic Regression Models

Given that our responses (success, persistence, and retention) are binary, We will model using logistic regression. Since we matched tutored and non-tutored students by a number of covariates in the previous section, we will use only two covariates in our logistic regression models: ethnicity and tutoring session count. Two logistic models were run with the data[9]. The first model contains session count as a categorical variable and the second model contains session count as a numerical variable[10]. The coefficents of the first model are present in the appendix of the paper beginning at table 16. These results have been converted to probabilities. The results of the second model are present in the next section via prediction curves which demonstrate how the probabilities of success, persistence, and retention scale by the number of tutoring sessions that students attend by ethnicity. We will display and discuss these curves in the following section.

8.3.1 Math Embedded and General

Figure 17 presents the results of embedded math students. In general, as session count increases the logistic model predicts that there will be an increase in probability of success across all ethnicities[11]. Asian students out perform all ethnic groups at zero session counts.

[9]We find that the coefficients for both models are similar.

[10]Recall the session count categories: None, Ocassionally, Frequently. Modeling session count as a numerical variable allows for the creation of prediction curves

[11]In table 16, session count frequently was a significant predictor

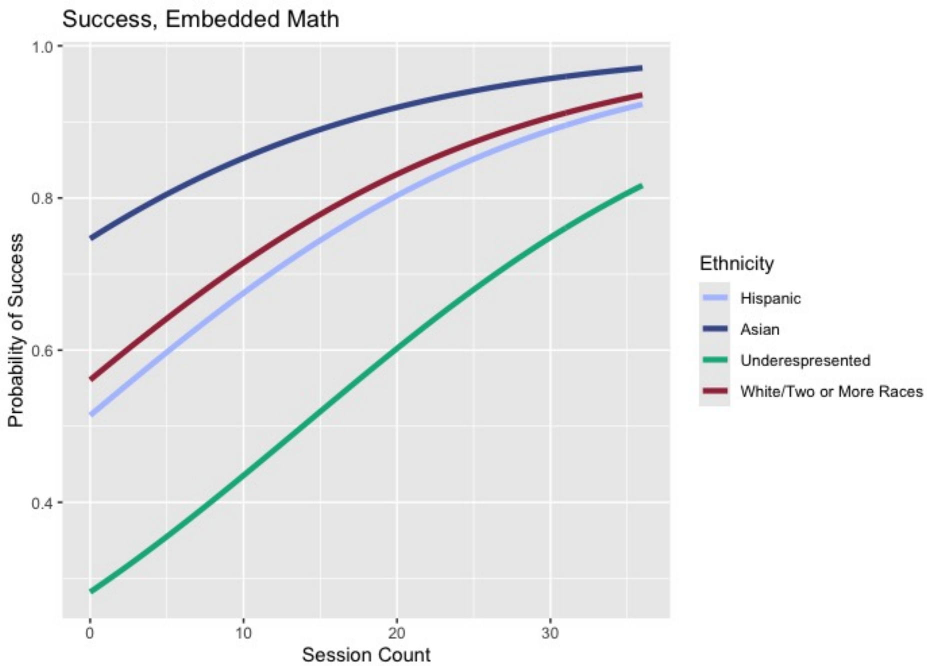

Figure 17: Predicted Probability of Success among Embedded Math Students by Ethnicity

As session count increases, White/Two or more races and Hispanic/Latino students are performing similarly. The model projects that these two groups are reaching the probability of success of Asian students. The Underrepresented group is under performing when compared to the other groups as session count increases. Figure 15 presents the results for general math students. Like in the embedded math student model, as session count increases there is an increase in probability of success[12]. Unlike the math embedded student model, the gaps between the ethnic groups remain marginally constant with Asian students performing the best followed by White/two or more races, Hispanic/Latino students and the underrepresented group.

[12] In table 17, session count occasionally and frequently were significant predictors

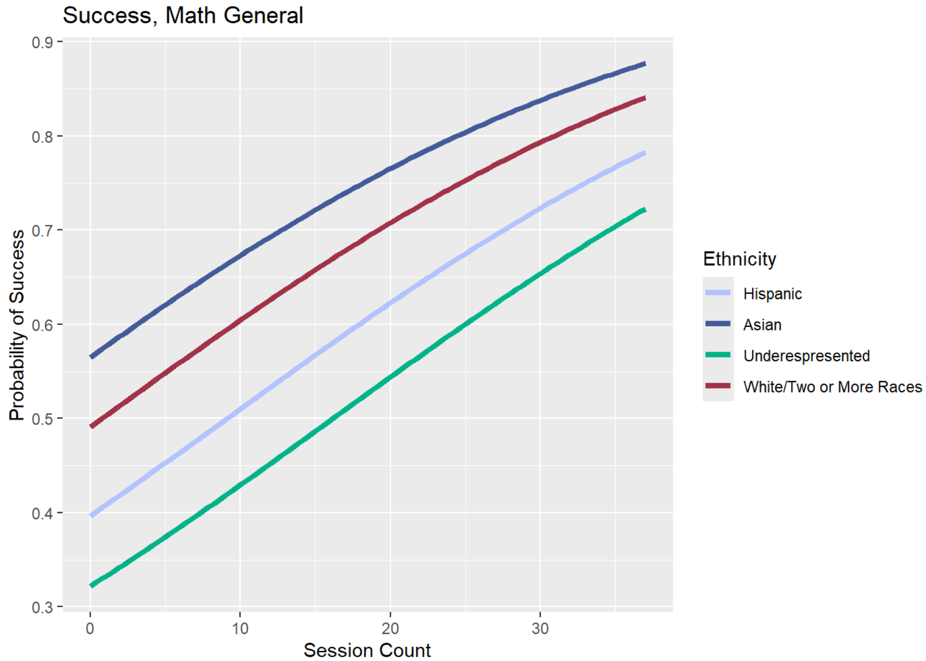

Figure 18: Predicted Probability of Success among General Math Students, by Ethnicity

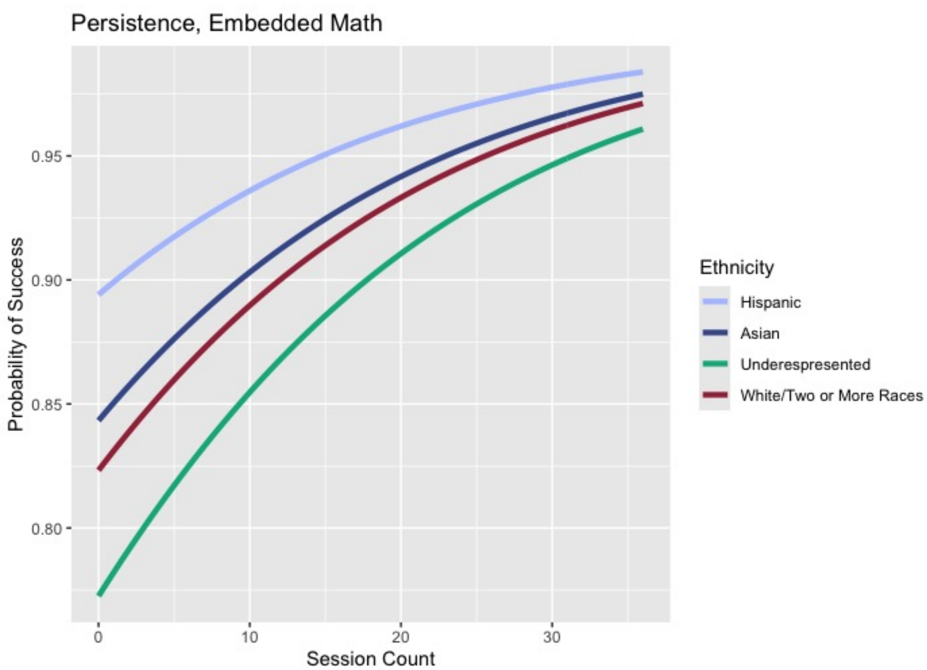

Figure 19: Predicted Probability of Fall to Spring Persistence among Embedded Math Students by Ethnicity

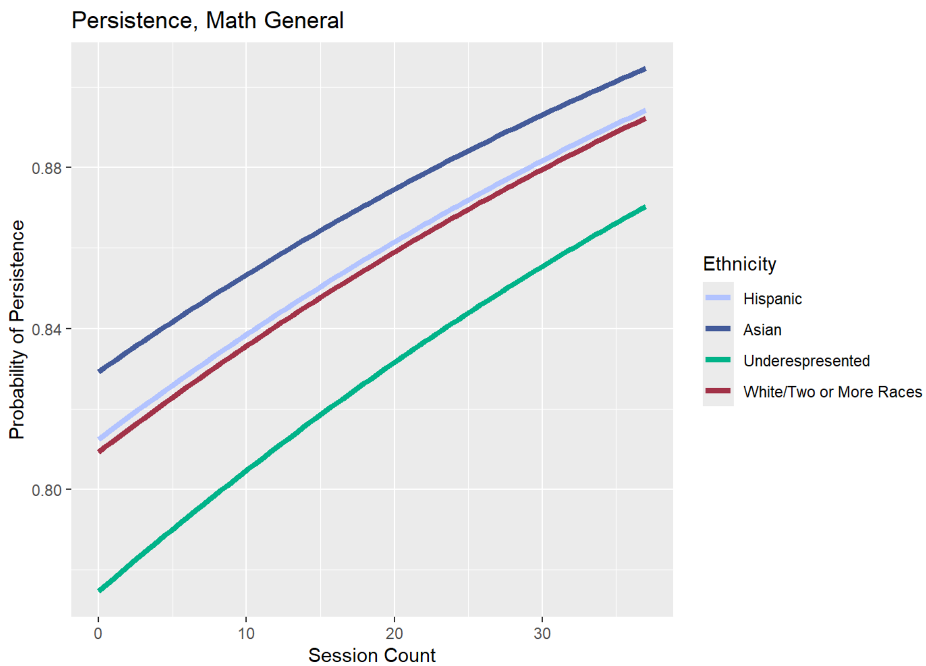

Figure 20: Predicted Probability of Fall to Spring Persistence among General Math Students, by Ethnicity

The persistence results for embedded and general math students are present in figures 19,20 respectively. These results are consistent with figure 9 where students are highly persistent regardless of their tutoring status. In figure 19, Hispanic/Latino students are the most persistent group. In addition, Asian and White/two or more races are predicted to have similar persistence rates.Underrepresented students have a consistently lower rate of persistence , however, they are closely behind the white/two or more group. In figure 20, Asian students are more persistent, followed by Hispanic/Latino students, White/Two or more races and Underrepresented students[13].

[13]In the first model, session count was not significant for math embedded students. Occasionally and frequently were significant for general math students in predicting their probability of persistence

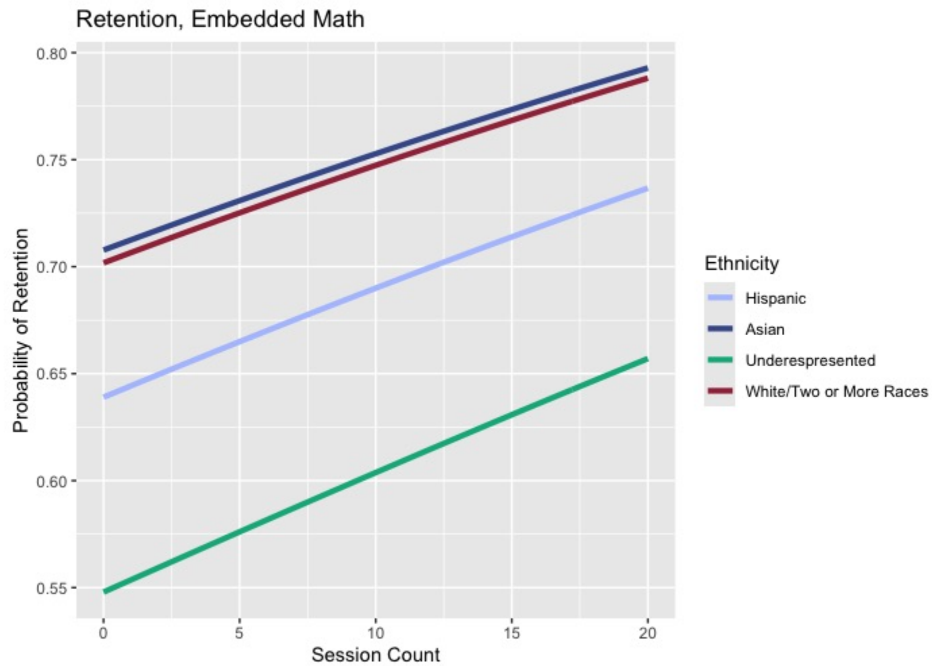

Figure 21: Predicted Probability of Fall to Fall Retention among Embedded Math Students by Ethnicity

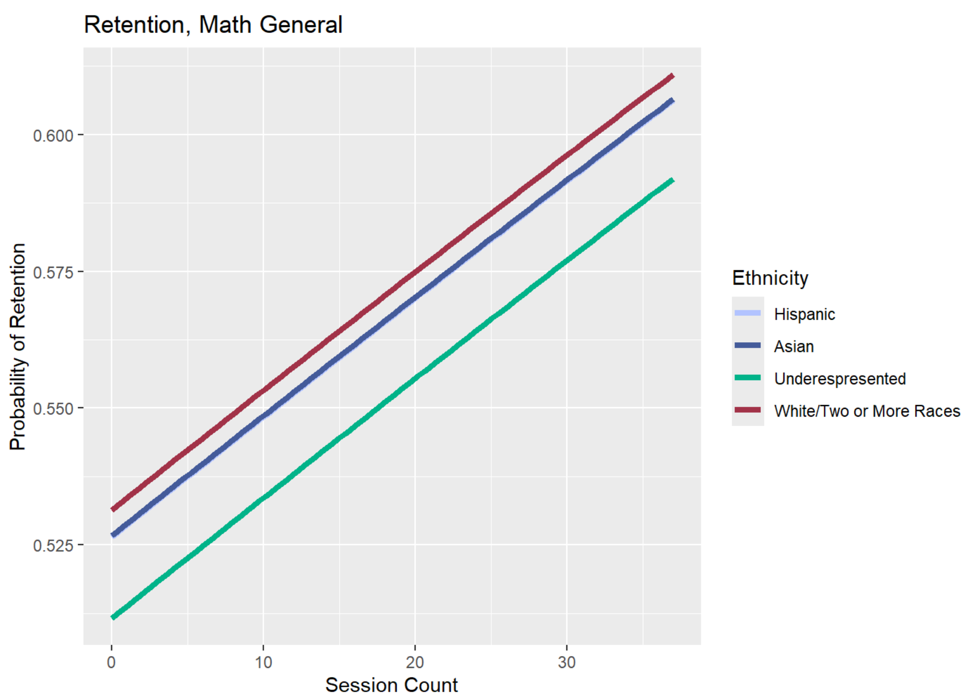

Figure 22: Probability of Fall to Fall Retention among General Math Students, by Ethnicity

The student retention results are present in figures 21 and 22. In table 20, session count is not a significant predictor which is reflected in the plot where student retention probabilities are rising at a constant rate. Asian students have higher predicted probabilities of retention followed by White/Two or more races, Hispanic students and Underrepresented students. Retention results for general math students illustrate an increasing rate, however, this increase in probability is from about 0.52 to 0.60 [14].

8.3.2 Discussion

A trend present in all plots is a positive relationship between tutoring and student outcomes; the more tutoring a student attends, the higher the probability of success, retention, and persistence. Some interesting results, very pronounced in the success rate plot, are significantly higher probabilities among embedded students. In general, students enrolled in math courses that feature an embedded tutor perform better than students enrolled in math courses without an embedded tutor, with respect to all outcomes of interest. These results potentially indicate that simply having an embedded tutor in a math class produces positive results for students, whether students attend additional tutoring sessions or not.

The persistence plots show that students tend to be highly persistent even without tutoring, and the retention plots show that the probability of retention among students enrolled in math courses without embedded tutors hovers around fifty percent, while the probability of retention among students enrolled in math courses with an embedded tutor is quite a bit higher, between about sixty and eighty percent. Asian students tend to perform the best of the ethnic groups, while "Underrepresented" students tend to perform the worst. The plots of success and persistence for embedded students show the performance gap between ethnicities tend to shrink somewhat with additional tutoring, another positive aspect of embedded math tutoring.

[14] Session count occasionally and frequently were significant predictors in the general math model

8.3.3 Chemistry Embedded and General

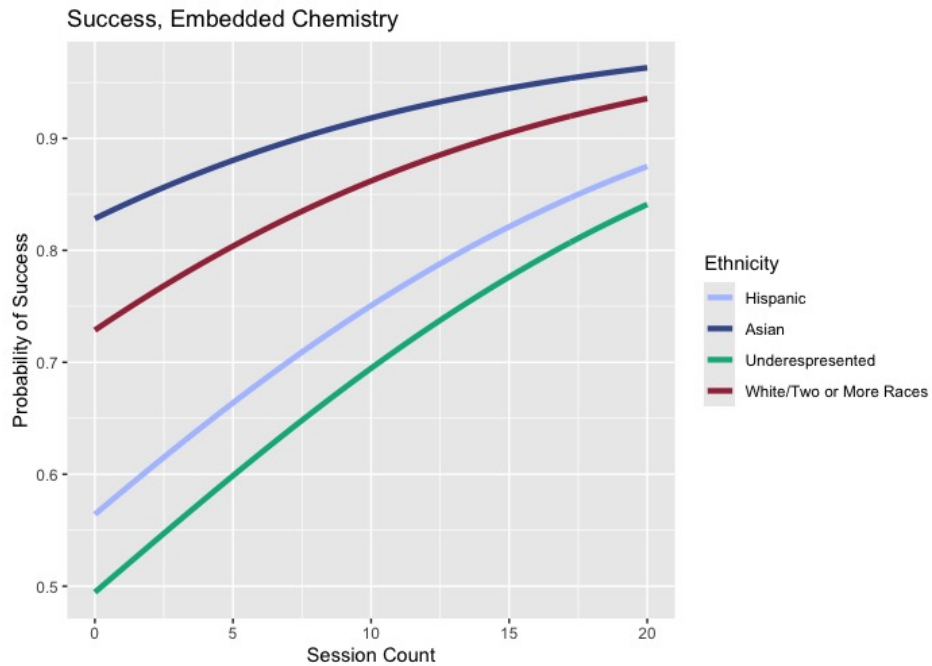

Figure 23: Predicted Probability of Success among Embedded Chemistry Students by Ethnicity

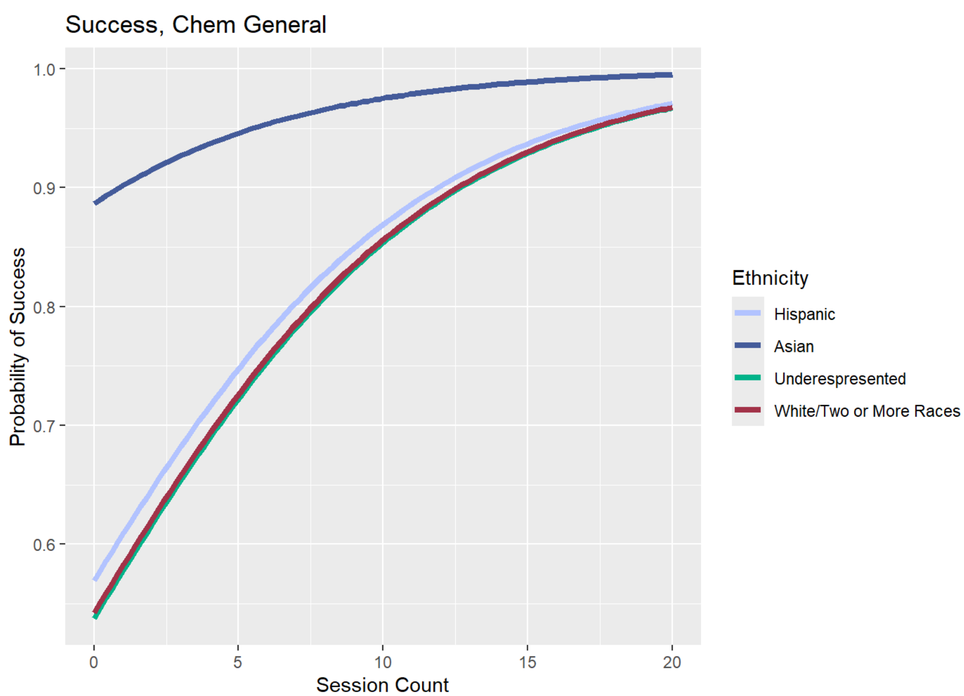

Figure 24: Predicted Probabilities of Success among General Chem Students,by Ethnicity

Figures 23 and 24 present the prediction curves for embedded and general chemistry students respectively. As the number of session counts that a student attends increases the logistic models predict that the probability of success for both students increases[15]. As seen in the math models, students are highly persistent. However, there is a difference in ethnic trends of persistence between the embedded and general students/ For instance, in figure 23 as session count increases the logistic model predicts that Asian and White/two or more races and Hispanic/Latino and Underrepresented students will have similar probabilities of success. On the other hand, in the general logistic model Asian students are outperforming the other ethnic groups which are clustered together. However, students in general chemistry courses that went to tutoring are achieving higher probability of success when compared to the embedded students. The difference in probability of success can be seen in the appendix table 23.

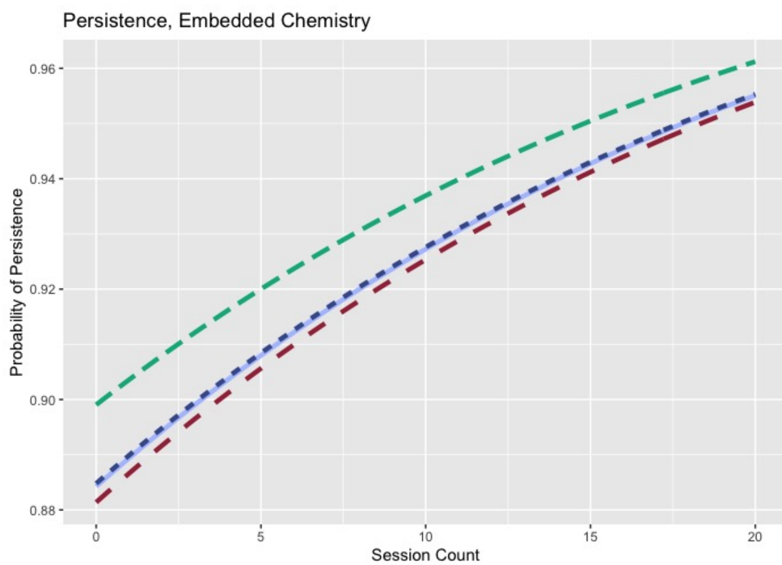

Figure 25: Predicted Probability of Fall to Spring Persistence among Embedded Chemistry Students by Ethnicity

Figures 25 and 26 present the persistence prediction for our students[16]. Like in the math models, we can observe high probabilities of persistence. Among embedded and general chemistry, the Underrepresented group is more persistent [17] A larger gap between the ethnic groups can be observed in the general chemistry results where followed by the Underrepresented group White/two or more races are more persistent followed by Asian students and Hispanic/Latino students. Unlike in the embedded students, Asian, Hispanic and White/two or more race students have very similar predicted probabilities of persistence as session count increases.

[15]Occasionally and frequently were significant predictors in the embedded and general chemistry models.

[16]Frequently was a significant predictor in the embedded model where persistence was the response. In the general model, none of the session count categories were significant

[17]In the chemistry group category there were very few students in the Underrepresented category and all these students were persistent.

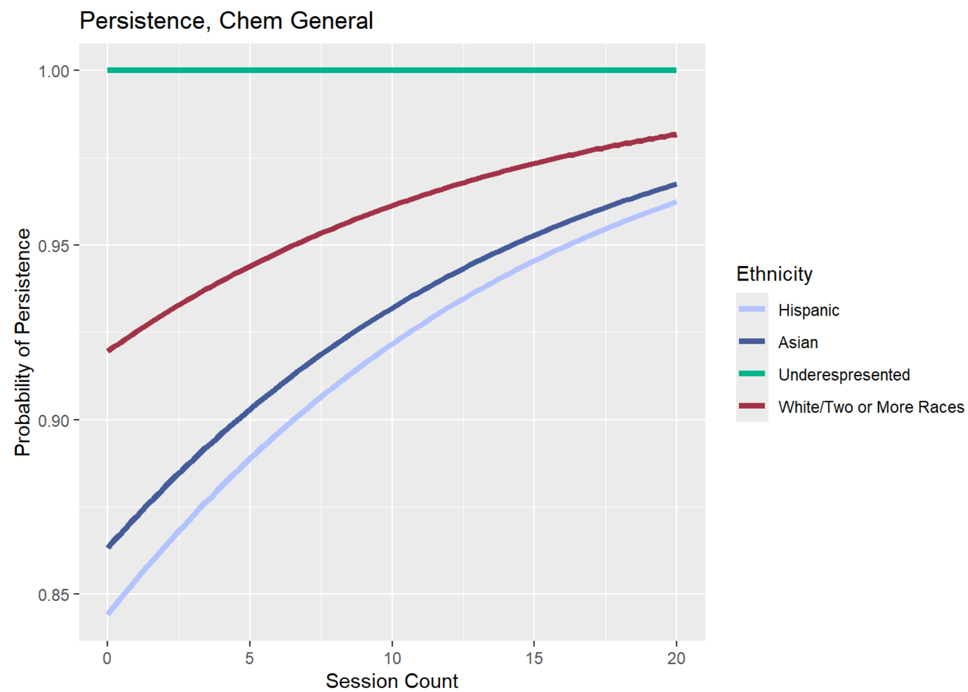

Figure 26: Predicted Probability of Fall to Spring Persistence among General Chem Students, by Ethnicity

8.3.4 Discussion

Similar to the math data, we generally see a positive relationship between tutoring and all student outcomes, though the effect is not so pronounced in the chemistry data. What is not present in the chemistry data is a significant positive effect of embedded tutoring. The success rate plots show that "white/two or more races" students may benefit from embedded chem tutoring, but this effect is not seen for the other ethnic categories. "Asian" students, in fact, seem to perform better in chem courses without embedded tutors, and the gap in success between Asian students and students of other ethnicities is significant in the general chem group. The persistence plots shows that "underrepresented" students are the most persistent, though the probabilities of persistence by ethnic category tend to start around ninety percent without tutoring, and approach one hundred percent with tutoring. The one hundred percent persistence rate for "underrepresented" students enrolled in chem courses without embedded tutors demonstrates an issue with our chem data that was not present in our math data: a lack of students. There are only seven "underrepresented" students enrolled in chem courses without embedded tutors from Fall 2019 to Fall 2023. The retention plots[18] demonstrate that tutoring has a very slight effect, positive in the embedded chem group and negative in the general chem group. Probabilities of retention tend to be between forty and fifty percent in both plots.

[18]Present in the appendix: Figures 41 and 42 present the retention results. None of the session count categories were significant for retention which explain the constant slope in both plots.

9 Appendix

9.1 Aggregated Model XGBoost

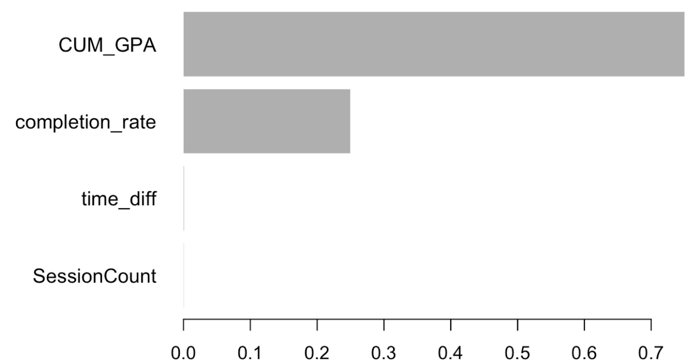

Figure 27: XGBoost Importance Plot of All Variables in the Aggregated Data Set to Predict Success Rate

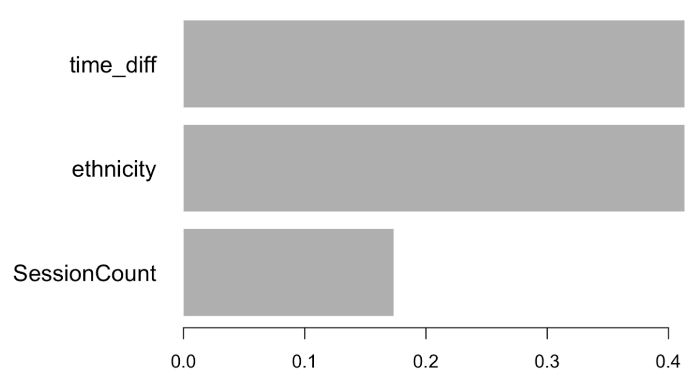

Figure 28: XGBoost Importance Plot of All Variables in the Aggregated Data Set to Predict Success Rate without cummulative GPA and completion rate

9.2 Fall 2019 Math Embedded Plots Continued

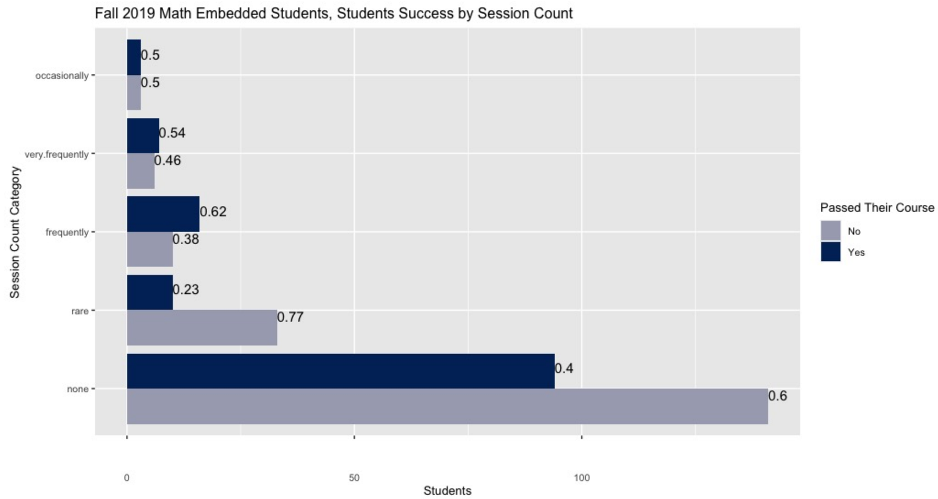

Figure 29: Success by session count among Embedded Math Fall 2019 students

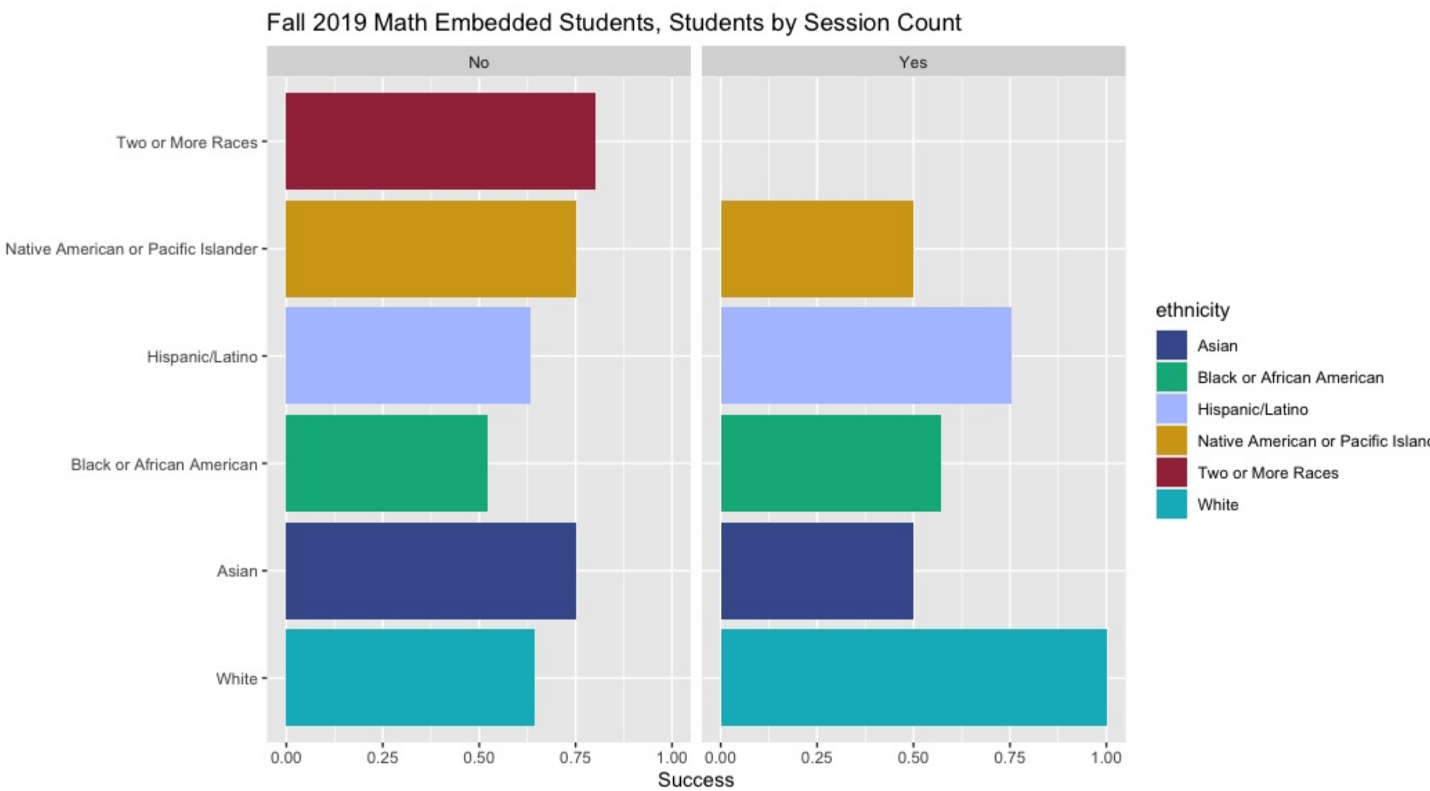

Figure 30: Session Count by Success

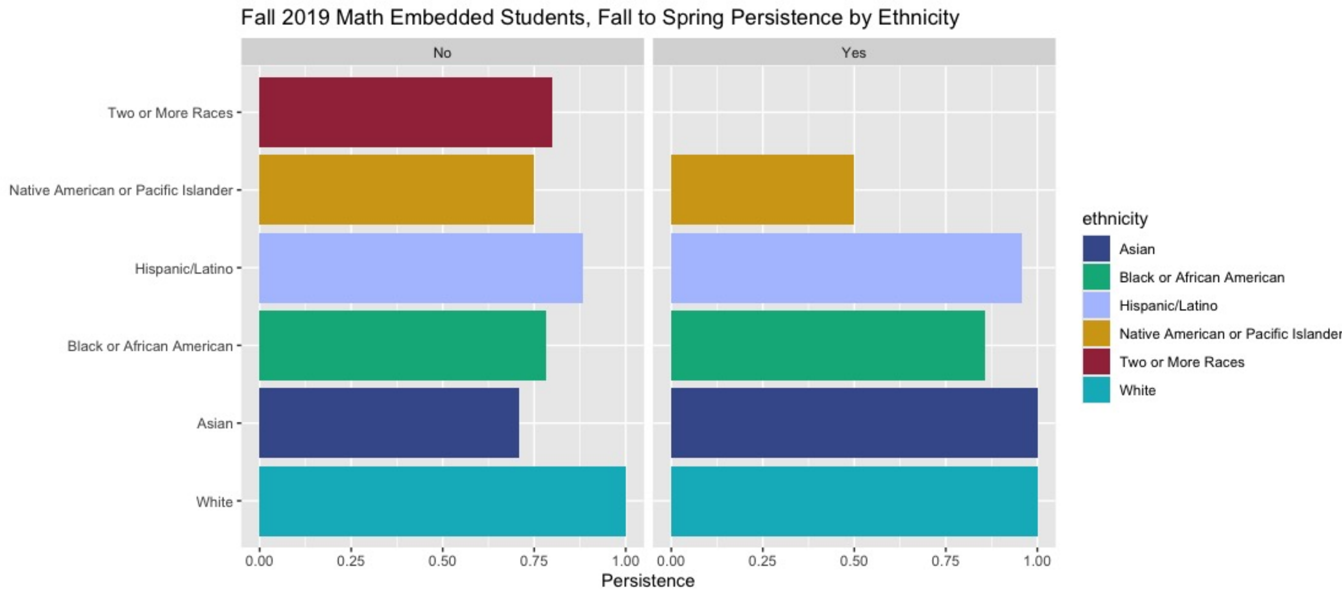

Figure 31: Persistence Rate by Ethnicity

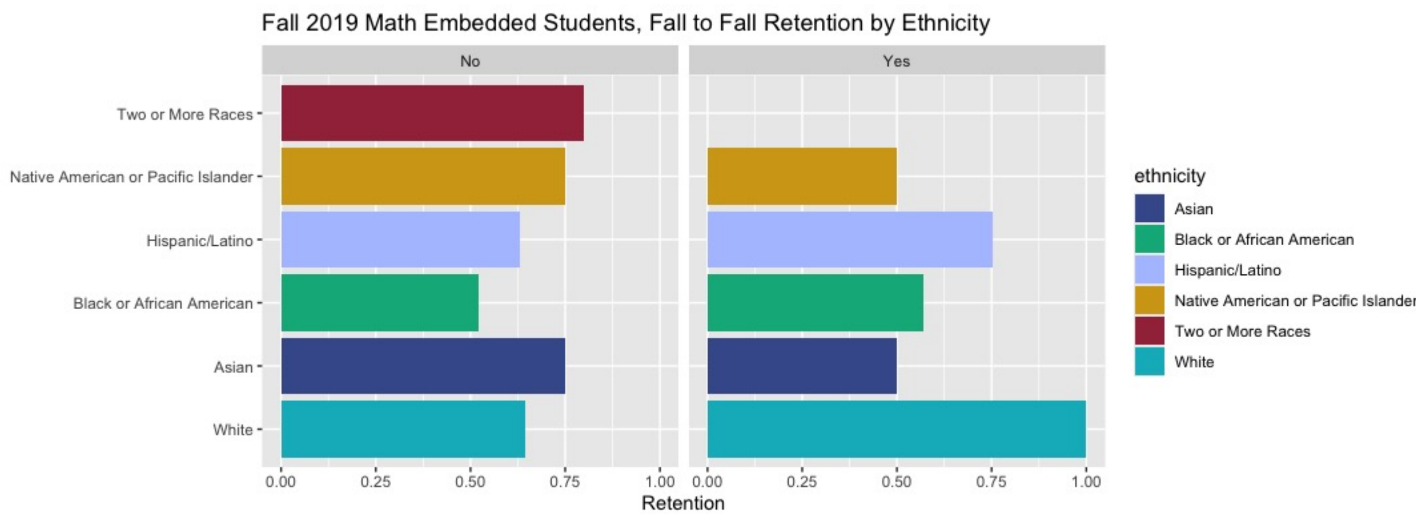

Figure 32: Retention Rate by Ethnicity

9.3 Fall 2019 Chemistry Plots

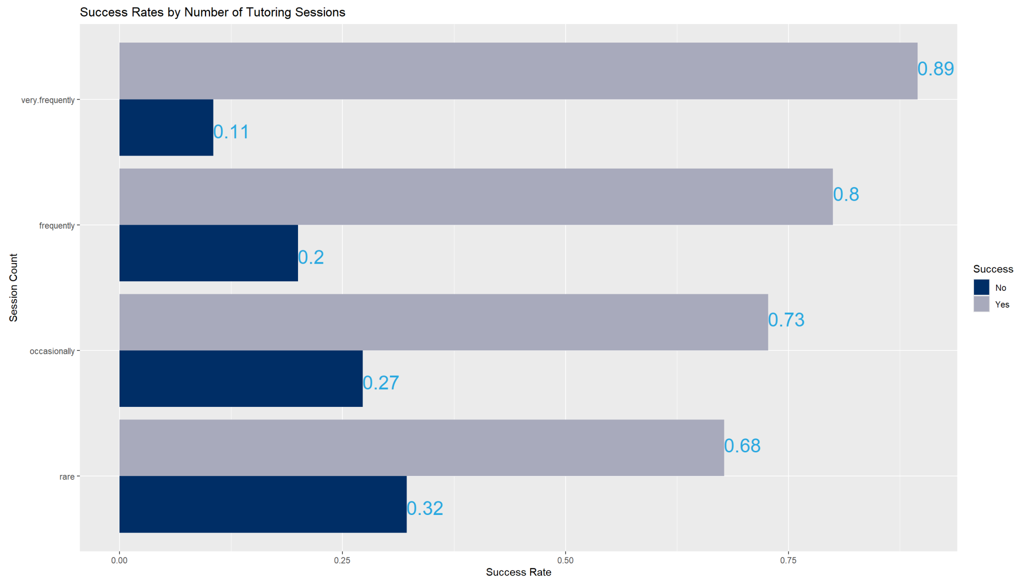

Figure 33: Success by session count among general chemistry students

Figure 34: Success by ethnicity among general chemistry students

9.4 Importance plots

9.4.1 Embedded Math Persistence and Retention

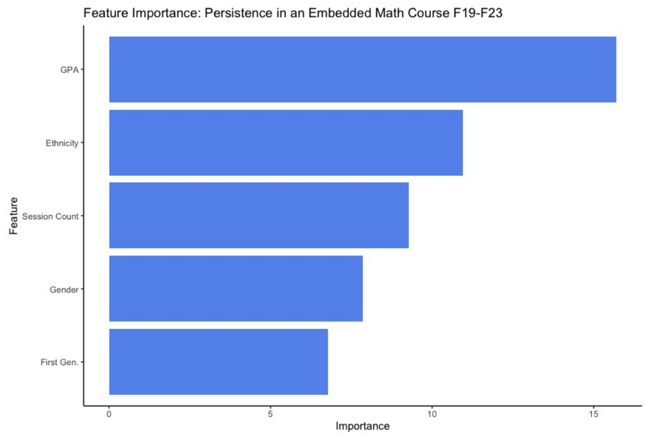

Figure 35: Importance of Persistence predictors among Embedded Students

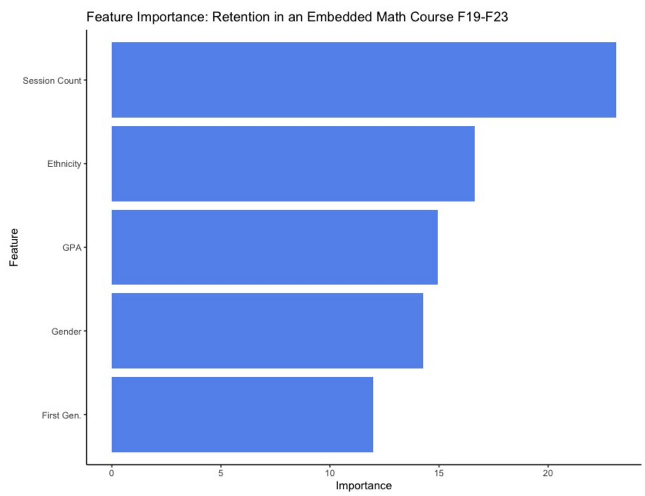

Figure 36: Importance of Retention predictors among Embedded Students

9.4.2 General Math Persistence and Retention

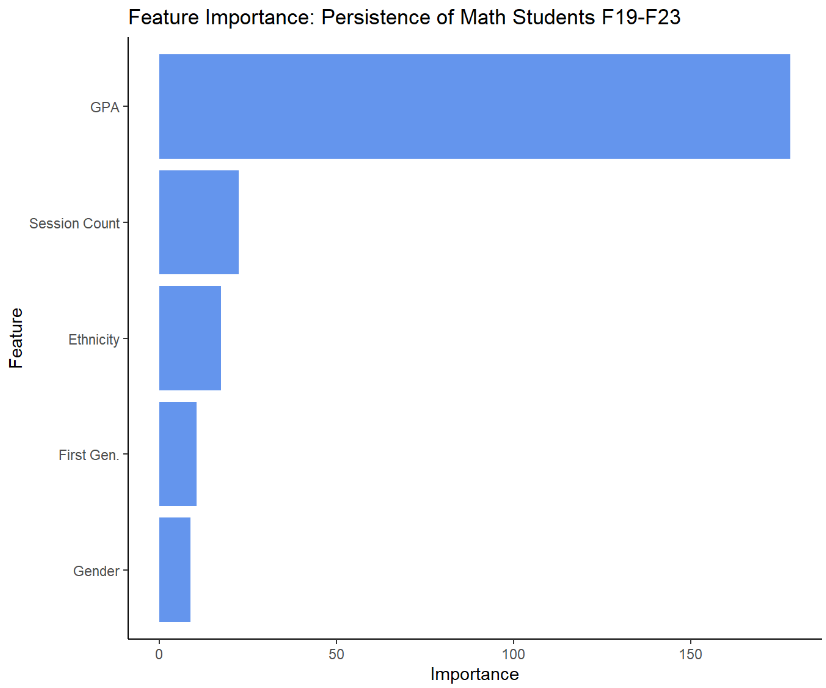

Figure 37: Importance of Persistence Predictors Among General Math Students

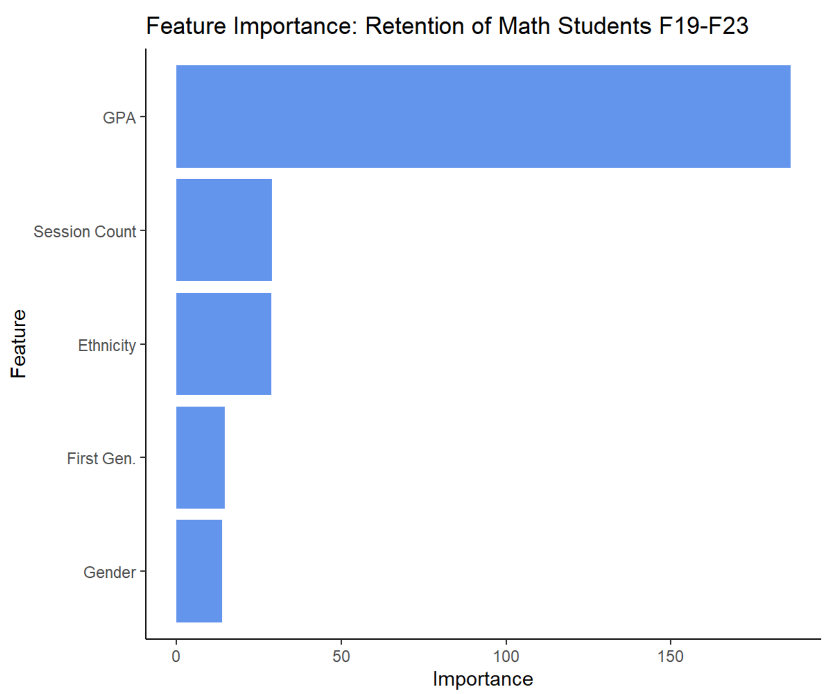

Figure 38: Importance of Retention Predictors Among General Math Students

9.5 General Math Cross Validation

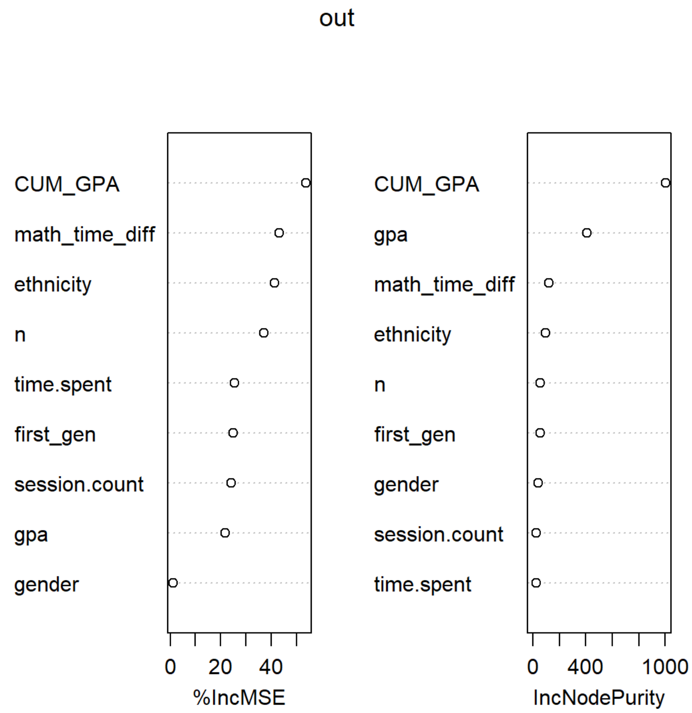

Figure 39: The variable importance plot from a saturated Random Forest Model. Many of these features are highly correlated; we can reasonably reduce the feature set without the aid of technology.

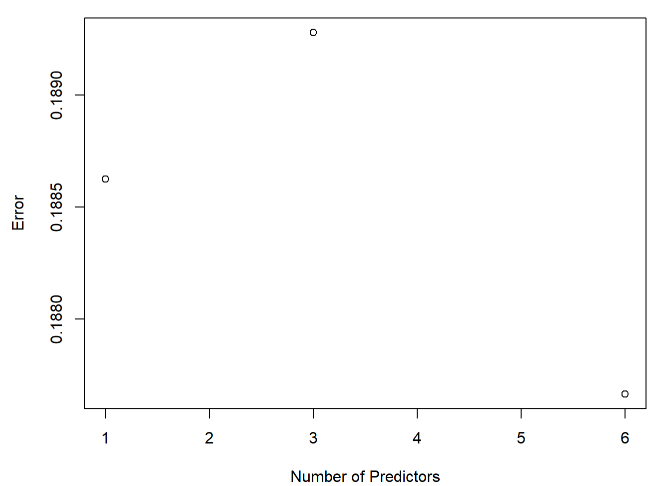

Figure 40: Cross-validation of saturated Random Forest model demonstrates similar accuracy regardless of the number of features.

9.6 Preliminary Models: Embedded Math Probability Tables

	IV: Session Count (Fall 2019 - Fall 2023)		
	1.Success	2.Persistence	3.Retention
Black/AA	15.61%***	46.18%	42.59%
Hispanic/ Latino	33.05%**	57.60%	48.97%
Native American or Pacific Islander	1.01e-07%	64.70%	44.49%
Two or More Races	34.37%	43.49%	49.69%
White	37.37%	72.35%*	46.91%
First Gen.	39.21%**	48.16%	46.77%
First Gen: Unknown	37.89%*	51.03%	43.16%
Male	49.85%	54.07%	51.46%
Gender: Unknown	54.00%	58.41%	63.63%
Intercept:			

Table 15: Probabilities of Session Count Categories: Coefficients of the predictors in table 9 were converted into probabilities using $\frac{e^{x_i}}{1+e^{x_i}}$. Values with an asterisk indicate significant predictors in the logistic model.

9.7 Final Modeling: Semester Data

9.7.1 Chemistry Prediction Curves: Retention

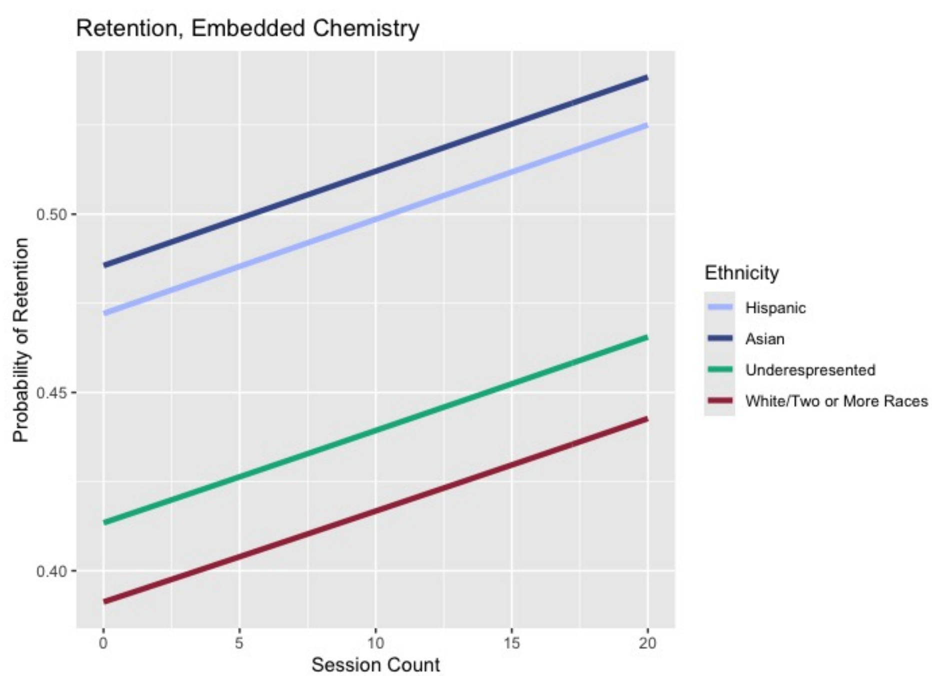

Figure 41: Predicted Probability of Fall to Fall Retention among Embedded Chemistry Students by Ethnicity

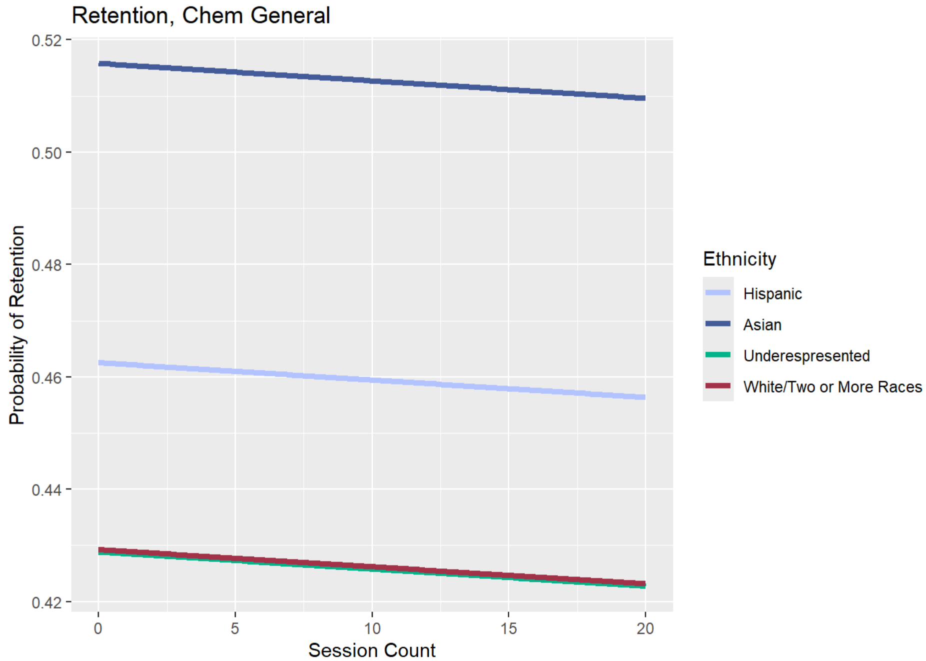

Figure 42: Predicted Probabilities of Fall to Fall Retention among General Chem Students, by Ethnicity

9.7.2 Logistic Model Tables: Mathematics

The significance of the predictors are denoted as follows:
(***) for p-value approximately zero
(**) for p-value < 0.001
(*) for p-value < 0.01
(.) for p-value < 0.05

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally	Frequently**
Underrepresented.	27.31%	30.18%	44.19%
Hispanic/ Latino	51.34%	54.84%	68.98%
White/Two or More Races	55.49%	58.92%	72.43%
Asian*	75.12%	77.62%	86.64%

Table 16: Probabilities of Success for Embedded Math Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally*	Frequently***
Underrepresented*	31.04%	35.18%	49.56%
Hispanic/ Latino	38.27%	42.78%	57.52%
White/Two or More Races**	47.27%	51.95%	66.19%
Asian***	55.34%	59.91%*	73.14%

Table 17: Probabilities of Success for General Math Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally	Frequently
Underrepresented$^{\cdot}$	77.15%	76.57%	87.26%
Hispanic/ Latino	89.74%	89.43%	94.67%
White/Two or More Races	82.87%	82.24%	90.77%
Asian	85.07%	84.65%	92.05%

Table 18: Probabilities of Persistence for Embedded Math Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally**	Frequently***
Underrepresented	73.45%	82.71%	84.32%
Hispanic/ Latino	77.79%	85.83%	87.2%
White/Two or More Races	77.35%	85.52%	86.91%
Asian	79.88%	87.29%	88.53%

Table 19: Probabilities of Persistence for General Math Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally	Frequently
Underrepresented	53.49%	60.43%	56.35%
Hispanic/ Latino	62.62%	68.98%	65.28%
White/Two or More Races	68.21%	74.01%	70.65%
Asian	70.12%	75.70%	72.48%

Table 20: Probabilities of Retention for Embedded Math Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally***	Frequently***
Underrepresented	47.73%	54.43%	59.17%
Hispanic/ Latino	49.16%	55.86%	60.55%
White/Two or More Races	49.52%	56.2%	60.89%
Asian	49.2%	55.89%	60.58%

Table 21: Probabilities of Retention for General Math Students by Ethnicity

9.7.3 Logistic Model Tables: Chemistry

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally**	Frequently***
Underrepresented	46.05%	59.22%	65.36%
Hispanic/Latino	53.30%	66.01%	71.61%
White/Two or More Races**	70.39%	80.18%	84.02%
Asian***	81.08%	87.93%	90.45%

Table 22: Probabilities of Success for Embedded Chem Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally*	Frequently**
Underrepresented	48.35%	63.74%	81.05%
Hispanic/Latino	53.44%	68.3%	83.98%
White/Two or More Races	51.41%	66.51%	82.86%
Asian**	87.44%	92.89%*	96.95%

Table 23: Probabilities of Success for General Chem Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally	Frequently**
Underrepresented	88.57%	91.15%	96.46%
Hispanic/Latino	87.03%	89.92%	95.94%
White/Two or More Races	86.78%	89.72%	95.85%
Asian	87.06%	89.94%	95.95%

Table 24: Probabilities of Persistence for Embedded Chem Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally	Frequently
Underrepresented	100%	100%	100%
Hispanic/Latino	88.8%	82.66%	92.25%
White/Two or More Races	93.44%	91.18%	96.27%
Asian	88.84%	85.24%	93.51%

Table 25: Probabilities of Persistence for General Chem Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally	Frequently
Underrepresented	40.57%	40.79%	48.02%
Hispanic/Latino	46.57%	46.80%	54.11%
White/Two or More Races	38.61%	38.83%	45.98%
Asian	47.93%	48.16%	55.46%

Table 26: Probabilities of Retention for Embedded Chem Students by Ethnicity

	Session Count (Fall 2019 - Fall 2023)		
	None	Occasionally	Frequently
Underrepresented	42.11%	43.42%	27.24%
Hispanic/Latino	47.49%	48.82%	31.77%
White/Two or More Races	43.97%	45.28%	28.77%
Asian	52.93%	54.25%	36.66%

Table 27: Probabilities of Retention for General Chem Students by Ethnicity

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