

# Using Multiple Measures to Predict Success in Students' First College Math Course

An examination of multiple measures  
under Executive Order 1110 in the  
California State University system

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# Table of Contents

<b>Using Multiple Measures to Predict Success in Students' First College Math Course</b>	<b>2</b>
Multiple Measures for Placement	3
Research Questions	5
Study Sample	5
Methodology	7
How Multiple Measures Are Used for QR Placement Under EO 1110	8
Findings	11
Discussion	16
Additional Considerations	17
<b>References</b>	<b>19</b>
<b>Appendix A</b>	<b>21</b>
Model Specification	21
<b>Appendix B</b>	<b>22</b>

# Using Multiple Measures to Predict Success in Students' First College Math Course

WestEd has undertaken a multiyear series of implementation studies intended to inform the California State University (CSU) system about the implementation of Executive Order 1110 (EO 1110). A major policy adopted by the CSU Chancellor's Office in 2017, EO 1110 requires CSU campuses to eliminate noncredit developmental courses (often known as "remedial" courses) in Written Communication (WC) and Mathematics/Quantitative Reasoning (QR), change the process for how students are placed into WC and QR courses, and improve how students are supported to succeed. Earlier reports in the series have described the variation in course models and instructional approaches adopted by campuses, examined student progress during the first year of implementation, compared progress of students both before and after implementation of the new policy, and examined short-term outcomes for students who participated in revamped summer Early Start programs. This fifth and final report of the series focuses on how students are placed into entry-level math courses. Specifically, it focuses on the use of multiple measures for placing students and examines the predictive power of the measures for anticipating students' success in their first college math course.

A significant aspect of EO 1110 is that it brought about a major change in how students entering the CSU system are placed into entry-level math and writing courses. Specifically, it required that CSU campuses discontinue using the English Placement Test (EPT) and Entry-Level Mathematics (ELM) placement exams and instead consider a series of “multiple measures” for placing students into entry-level QR and WC courses. In this report, WestEd analysts consider the extent to which the most commonly used measures are able to predict student success in entry-level math courses.

## Multiple Measures for Placement

Previous researchers have found that factors such as high school grades tend to be much better predictors of student success in college-level math than a single placement test (Scott-Clayton, 2012; Belfield & Crosta, 2012; Bostian, 2012; Burdman, 2012) and that multiple indicators used together tend to provide even greater predictive power. Aligned with that research, CSU’s new policy called for a move away from the use of placement exams and toward a new system that takes into account additional measures of college readiness. Rather than relying on a single high-stakes exam to determine whether a student entering the system was required to take noncredit developmental coursework, EO 1110 called for consideration of a collection of measures, including high school grades and test scores, to determine which type of baccalaureate-level courses the students should enroll in upon entry to the university. The move to multiple measures was particularly significant for QR placement, as campuses had relied heavily on the ELM exam to place students in math courses. In contrast, many campuses had already eliminated the use of the EPT and instead relied on a Directed Self Placement<sup>1</sup> process to place students in entry-level writing courses. Because the move to multiple measures had less impact in WC than in QR placement, this examination focuses on multiple measures identified for placement in QR courses.

EO 1110 calls for the use of multiple measures to place students into one of four categories for QR (Box 1). Placement designations determine whether a student is considered to have already met their General Education requirement in QR and, if not, to determine whether they are ready to enroll directly in a traditional General Education math course or whether they would be better served by a course that provides additional supports in either a one- or two-semester format (Bracco et al., 2019).

Most research on the efficacy of multiple measures for placement suggests that although high school grade point average (GPA) is the strongest predictor of success in entry-level coursework, combining that measure with other factors such as test scores, grades in specific courses, and potentially some noncognitive indicators can provide even greater predictive

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<sup>1</sup> Directed Self Placement (DSP) is a process used on many campuses to allow students to determine, through self-reflection, the entry-level writing course that best fits their needs. Campuses design their own DSP tools, which typically include questions about educational goals, overall workload, and perceived skill level.

power (Ganga & Mazzariello, 2019). Researchers have identified different approaches to using multiple measures, some of which use the measures in combination and others that use a more hierarchical approach, relying on additional measures only if a student does not meet the threshold in one primary indicator, such as a test score (Bracco et al., 2014).

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## Box 1 – California State University placement categories, based on multiple measures

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**Category I:** Has fulfilled the requirement for General Education (GE) Subarea A2 (for Written Communication, or WC) or B4 (for Mathematics/Quantitative Reasoning, or QR)

- Student has met the CSU GE Breadth Subarea A2 and/or B4 requirement via Advanced Placement examination, International Baccalaureate examination, or transferable course

**Category II:** Place in a GE Subarea A2 or B4 course

- Student has met examination standards and/or multiple measures–informed standards

**Category III:** Recommend placement in a supported GE Subarea A2 or B4 course

- Based on new multiple measures, student needs additional academic support
- Participation in the Early Start program is recommended and may be highly advisable for some students, particularly STEM majors

**Category IV:** Require placement in a supported GE Subarea A2 or B4 course or the first term of an applicable stretch course

- Based on new multiple measures, student needs additional academic support
- Participation in the Early Start program is required

**Note:** Placement categories for WC and QR courses are determined by a combination of student grades and test scores. For a detailed description of the various ways in which a student can be placed into the different categories, see <https://calstate.policystat.com/policy/6656541/latest/>.

## Research Questions

In this study, WestEd analysts sought to address several related research questions:

- What is the relationship between the measures used to determine placement and students' success in their first college math course?
- How does such a relationship differ by placement category and by student major (non-STEM versus STEM) within each category?
- Is any measure more effective than other measures in predicting success in the first college math course? If so, how sensitive is that measure in predicting success?

## Study Sample

Data from two student cohorts from all 23 CSU campuses were used in the study: students who entered the CSU system in fall 2018 as first-time, first-year students and those who entered in fall 2019 as first-time, first-year students. The sample was further refined to include students who had data on each of the four measures available for the largest percentage of students: the scale score on the SAT's math section (SAT-math), the scale score on the Early Assessment Program/Smarter Balanced Assessment (EAP-math), weighted high school math GPA, and weighted high school overall GPA.<sup>2</sup> For the 2018 cohort, the first math course attempted was taken in fall 2018 or spring 2019. For the 2019 cohort, due to the uncertainties brought on by COVID-19 and the switch to remote learning in the middle of the spring 2020 term, only students who attempted a first math course in fall 2019 were included in the analyses. Tables 1 and 2 list the study sample by placement category (at the beginning of fall semester) and by major within a category for each of the cohorts. The same analyses were done for both cohorts, and the outcomes were similar. Because the outcomes were so similar and because the 2019 entering cohort included only one semester of data, this report focuses on the findings for the 2018 entering cohort, for which two semesters of data were available. This focus allowed researchers to test the placement model for predictive fit whether the student opted for math in fall 2018 or deferred taking a math course until spring 2019.

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<sup>2</sup> The analytical sample includes only records with complete data on the predictors and outcomes used in the study. There does not appear to be any bias associated with the missing data patterns. The distribution of students by placement category and by major (STEM/non-STEM) is the same for both the analytic sample and excluded sample. Although the sample population includes a larger percentage of Hispanic students and a smaller percentage of White students than does the population of the excluded sample, analytical tests conducted on the excluded sample show a similar pattern of relationship between available predictors and outcomes.

**Table 1. Study sample for 2018 entering student cohort**

QR Placement Category	Non-STEM Major	STEM Major	Total
I	753	3,171	3,924
II	15,452	9,549	25,001
III	4,761	638	5,399
IV	3,178	2,175	5,353
<b>Total</b>	<b>24,144</b>	<b>15,533</b>	<b>39,677</b>

Note: Total number of first-year entering students who attempted a math course in the 2018/19 academic year was 57,880. Sample was refined to include only students for whom complete information was available on all four variables of interest in this study (SAT-math score, EAP-math score, weighted high school math GPA, and weighted high school GPA).

**Table 2. Study sample for 2019 entering student cohort**

QR Placement Category	Non-STEM Major	STEM Major	Total
I	742	3,291	4,033
II	11,121	8,210	19,331
III	3,809	631	4,440
IV	1,805	1,909	3,714
<b>Total</b>	<b>17,477</b>	<b>14,041</b>	<b>31,518</b>

Note: Total number of first-year entering students in 2019 who attempted a math course in the fall 2019 term was 44,503. The sample was refined to include only students for whom complete information was available on all four variables of interest in this study (SAT-math score, EAP-math score, weighted high school math GPA, and weighted high school GPA).



## Methodology

WestEd analysts conducted a series of logistic regression analyses to answer the research questions. The outcome of interest of each analysis is a binary variable indicating whether a student passed their first college math course taken, with passing defined as having earned a grade of C minus or higher.<sup>3</sup> For students who took more than one math course in a given semester, the course taken for the most credits was designated as the first math course. If courses had the same number of credits, WestEd analysts selected the course in which the student earned the higher grade. The predictors include SAT-math score, EAP-math score, weighted high school math GPA, and weighted high school GPA. According to the placement criteria, those predictors (along with other measures) are used in placing first-year college students into different categories. Analysts chose to use these four measures in the predictive model because they were the four measures that were available for the largest percentage of students. Additional information on the model is in Appendix A.

To determine which model fits the data best, analysts looked at various statistics that include the log-likelihood function, Akaike information criterion (AIC), and Bayesian information criterion (BIC). A model with a smaller value of AIC or BIC is considered more accurate. Analysts also examined how well the model predicts and classifies the students by looking at the positive predicted value, classification accuracy, and the area under a Receiver Operating Characteristic (ROC) curve. The *positive predicted value* (in percentage) is the proportion of students who are predicted to pass their first college math course and actually do so, divided by the total number of students who are predicted to pass their first college math course. The *classification accuracy* is the proportion of students who are predicted to pass their first math course and actually do so, plus the number of students who are predicted *not* to pass their first math course but actually do so, divided by the total number of students in the analytic sample. ROC is a probability curve. The area under the curve represents the degree to which, or the measure of how much, the model can distinguish between students who can and cannot pass their first math course with a C minus or higher grade. It ranges between 0 and 1, with 0 being completely indistinguishable (the worst scenario) and 1 being 100 percent distinguishable (the perfect scenario).

Consistent with the placement criteria, the analysis was conducted by category and by major (non-STEM versus STEM) for a given category. Students placed into Category I were not included in the study as they were deemed to have already met the General Education requirement in QR and therefore not required to take a math or quantitative reasoning course.

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<sup>3</sup> In a small number of cases, students earned credit for the first college math course with a "P" grade, and those instances are counted as successful completion.

## How Multiple Measures Are Used for QR Placement Under EO 1110

Although many different possible measures can be used to determine student placement in QR courses under EO 1110, the placement process uses a somewhat hierarchical approach.<sup>4</sup> Test scores are considered first, then a combination of test scores and high school senior year experience, and then high school grades. As a result, there are several ways in which a student can meet the criteria for being placed into Category I or II, and although many students may meet several of these thresholds, the measures are considered in order. Therefore, placement into a category is made based on the first designated threshold that a student meets.

### Placing Students in Category II

Box 2 provides an example to illustrate the decision tree that is used to determine how students who do not meet the criteria for Category I might be placed into Category II.

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## Box 2: Determining Placement in QR Category II

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Students who do not meet the criteria for being placed in QR Category I can be designated as Category II (eligible for General Education QR without additional supports) if they meet at least one of the following measures, which are considered in order:

- Math test score (on the SAT, ACT, or EAP) is at or above a designated threshold.
- Math test score (on the SAT, ACT, or EAP) is below the designated Category II cutoff but above a slightly lower threshold *and* the student has completed a senior year math experience beyond algebra.
- Overall high school GPA is 3.7 or greater.
- For non-STEM majors, student has a combination of an overall GPA of at least 3.5 *and* completion of four years of math/quantitative reasoning *or* a math GPA of 3.0 or higher *and* completion of a senior year math experience<sup>5</sup> or fifth year of high school math.
- For STEM majors, student has a combination of a math GPA of at least 3.5 *and* completion of a senior year math experience or fifth year of high school math.

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<sup>4</sup> For a full list of options for placement in Categories I through IV for both QR and WC, see “CSU Placement of First Year Students Based on Academic Preparation,” <https://calstate.policystat.com/policy/6656541/latest/>.

<sup>5</sup> A senior year math experience is defined as a course taken during the senior year of high school that has either Algebra II or Integrated Math III as a prerequisite.

Because of the way the placement algorithm works, the highest percentage of students in the sample for this study were placed into Category II based on either their SAT-math scores, EAP-math scores, or performance on these tests in combination with having completed a senior year math experience (Table 3):

- Almost 83 percent of students in STEM majors and 64 percent of non-STEM majors who were placed in Category II met that threshold based on measures that included either test scores alone or test scores in combination with math course taking in high school.
- A much smaller percentage of students who were placed in Category II were so placed based solely on having a high school GPA of 3.7 or higher (7.2 percent of STEM majors and 11.3 percent of non-STEM majors), but many of the students who were placed into the category based on a test score measure would also likely have met this GPA threshold.

There are several measures that were used to place less than 3 percent of students into Category II, potentially raising the question of the value of including those measures in the placement algorithm. Notably, a very small percentage (just over 1 percent) of STEM students in the sample who were placed into Category II were placed based solely on their math GPA.

**Table 3. Percentage of Category II students in cohort by placement measure**

Placement Measure Description	Percentage of non-STEM students placed in Category II by meeting this measure	Percentage of STEM students placed in Category II by meeting this measure
Placement based on SAT-math score; student has scored 570 or higher on the math section of the new SAT (effective fall 2016) or scored 550 or higher on SAT subject test in math (Level I or II)	22.9%	30.74%
Placement based on initial EAP-math score	10.18%	21.22%
Placement based on SAT-math result and successful completion of an approved senior experience; student was formerly conditionally placed based on SAT-math test result	11.99%	11.82%
Placement based on EAP-math; student was formerly conditionally placed based on EAP-math score and successfully completed an approved senior experience	19.44%	19.08%
Placement based on high school GPA $\geq 3.7$	11.33%	7.23%
Placement based on high school GPA $\geq 3.5$ and 4 years of math (Area C and Area G) — non-STEM	7.42%	.89%*
Placement based on math GPA $\geq 3.0$ and senior year math — non-STEM	6.65%	.75%
EAP-math “Standard Met: Conditionally Ready for CSU” and 4 years of math (Area C and Area G) — non-STEM	2.39%	.22%
Placement based on math GPA $\geq 3.5$ and senior year math — STEM	.14%*	1.25%

Note: Sample includes 25,002 first-year students in QR Category II for whom information was available on each of four placement variables: SAT-math, EAP-math, overall GPA, and math GPA. Totals do not add to 100 percent.

\*In a small number of cases, placement codes intended only for non-STEM majors were given to STEM majors and vice versa.

### Placing Students in Category III or IV

Although there are many different ways that a student may meet criteria for placement in Category II, the determination of whether a student will be designated as Category III or IV is based solely on high school grades. Students who do not meet any of the criteria for placement in Category II but have a math GPA of 3.3 or better are placed into Category III regardless of

major; non-STEM majors can also be designated as Category III if their overall GPA is 3.0 or better. Those who do not meet any of these cutoffs are placed into Category IV. The analysis shows that approximately 98 percent of non-STEM students who were placed into Category III had an overall GPA of 3.0 or better. Even though STEM students are supposed to have a math GPA of 3.3 or higher in order to be placed into Category III, only about 48 percent of the Category III STEM students in the study's sample were placed according to their math GPA. Others were placed based on their overall GPA, suggesting that not all campuses differentiated between STEM and non-STEM students for placement into Category III.

## Findings

### Model Fit (SAT-Math/EAP-Math/Math GPA/High School GPA)

In most of the comparisons, a model that includes all four predictors fits the data better than models with fewer predictors. The high school GPA is the strongest predictor (with the most significant and higher odds ratio), followed by either the SAT-math score or the EAP-math score (both are the significant predictors). However, based on the model-fit statistics used in the study, a model without the high school math GPA (but one that does include the other three predictors) could perform equally well, compared with the model with all four predictors. Appendix B provides additional details on the correlations, sensitivity and predictive values for the models.

### Using High School GPA Alone to Predict Students' Success in Their First College Math Course

As indicated earlier, the high school GPA, out of any of the predictors used in the analyses, tended to be the strongest predictor of students' success in their first college math course. In most cases, a model that includes high school GPA alone could predict the outcomes similarly to the model with all four predictors included (see Appendix B). To further explore how sensitive the model with high school GPA alone is in predicting students' success in their first college math course, analysts ran additional regression analyses by category and by major within a given category. Because the placement criteria for Category III are similar to those for Category IV, the research team compared the findings between those two groups to understand how the students may perform similarly or differently.

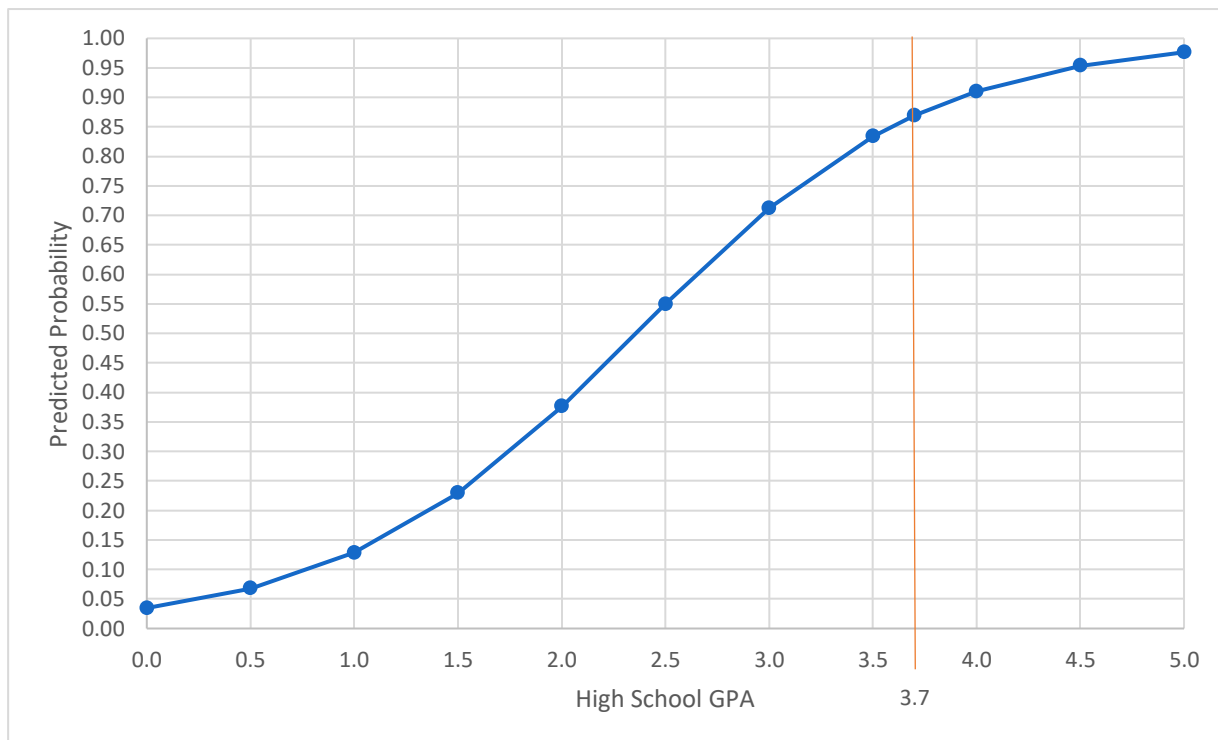
#### Category II Findings: High School GPA

##### *Non-STEM Students*

Based on the analysis of regressing the passing of the first college math course on high school GPA, a graph was plotted to demonstrate the relationship between the high school GPA and the predicted probability of passing the first college math course. Figure 1 indicates a positive

correlation: the higher the high school GPA, the higher the predicted probability that a first-year student would succeed in their first math course. For example, with a high school GPA equal to 3.0, the predicted probability to pass is about 70 percent; when GPA increases to 3.5 or 3.7, the likelihood rises to about 83 percent or 87 percent, respectively. Based on the multiple measures placement criteria, non-STEM students who had a high school GPA of 3.7 or higher can be placed into Category II, regardless of their performance on other measures. The vertical red line on Figure 1 shows that cutoff mark.

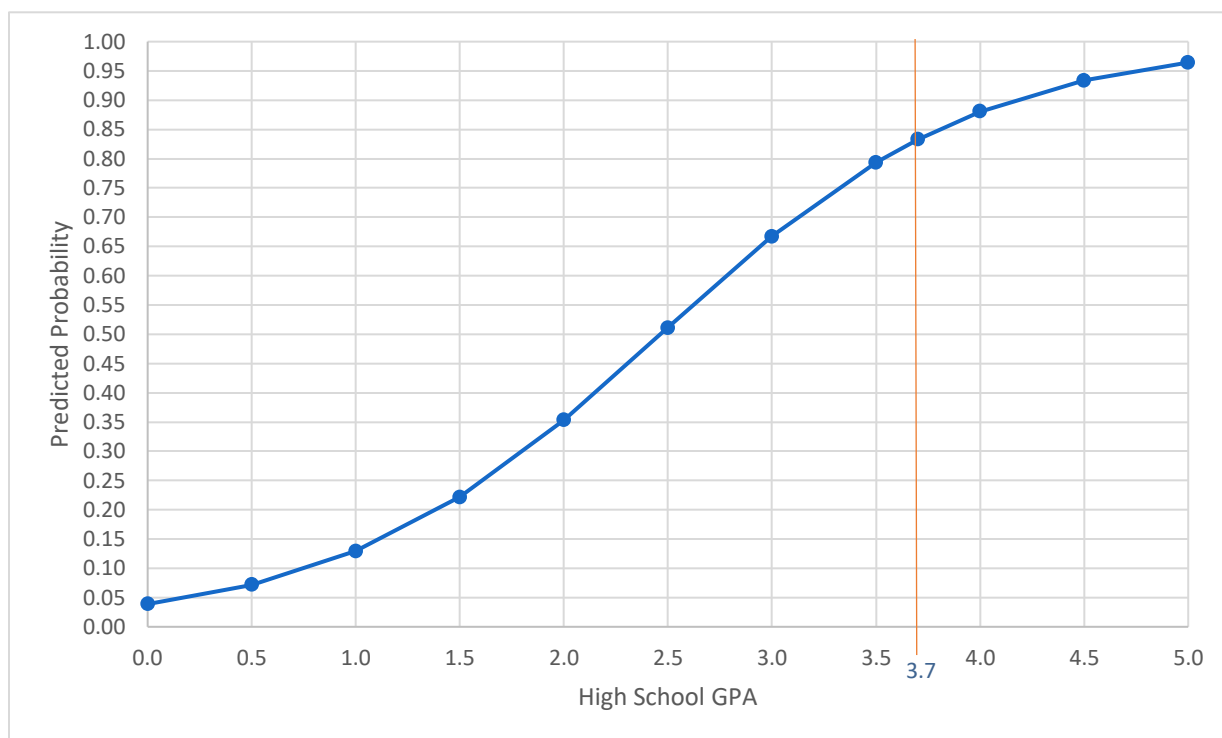
**Figure 1. Predicted probability of passing the first college math course based on only high school GPA for non-STEM students placed in Category II**



### STEM Students

The pattern for STEM students in Category II is quite similar to the one for the non-STEM students, though the corresponding predicted probability for a given high school GPA appears lower (Figure 2). For example, for STEM students with a high school GPA of 3.0, their predicted probability of passing their first math course is 67 percent; that probability increases to 79 percent for those with a high school GPA of 3.5 and to 83 percent for those with a GPA of 3.7. The slightly lower predicted probability for passing the first math course for STEM versus non-STEM students may be due to the fact that STEM students are more likely enrolling in more intensive algebra-based courses, including calculus.

**Figure 2. Predicted probability of passing the first college math course based on high school GPA for STEM students placed in Category II**



### Category III and Category IV Findings: High School GPA

The main difference between placement in Category III and Category IV is that students in Category IV are technically *required* to attend an Early Start program (though many choose not to do so),<sup>6</sup> whereas Early Start is *recommended* for students in Category III. Students in both categories are placed in entry-level math courses that provide some kind of additional support. Because students in both categories are often placed in the same supported courses on a given

<sup>6</sup>See Bracco et al. (2021b) for more information on Early Start under EO 1110.

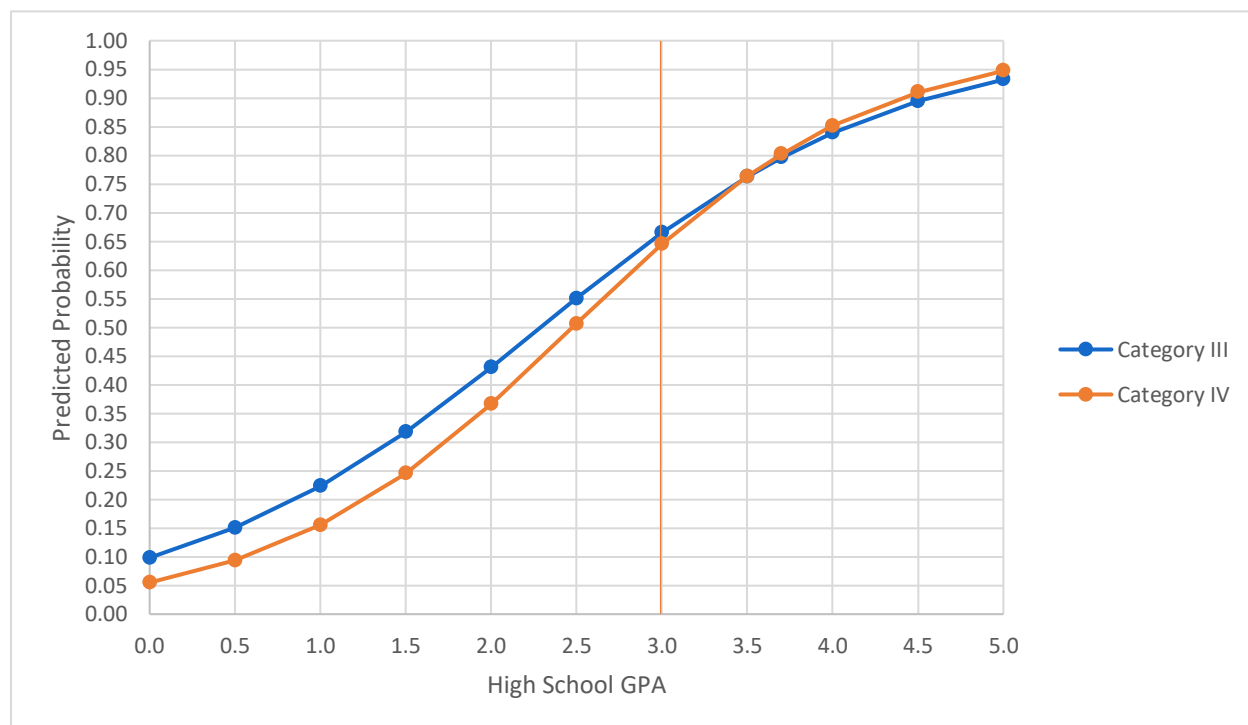
campus, the outcomes for Categories III and IV are compared together in the following analyses.

### Non-STEM Students

There was a similar pattern of predictive probability for non-STEM students placed in Categories III and IV (Figure 3). Although Category III students with high school GPAs below 3.0 had a slightly higher chance of succeeding in their first college math course than their counterparts in Category IV, there is little difference in predictive probability for students with a GPA of 3.0 or higher.

According to the placement criteria, those non-STEM students in Category III with a high school GPA below 3.0 would have been placed in Category IV unless their high school math GPA was 3.3 or above. If students were placed into Category III based on their higher math GPA, it might not be surprising to see a slightly higher likelihood of passing that first college math course than their counterparts who did not do quite as well in their high school math courses. However, the overall curve for both categories is remarkably similar, raising the question of the value of distinguishing between these two placement categories.

**Figure 3. Predicted probability of passing the first college math course based on high school GPA for non-STEM students placed in Category III and Category IV**

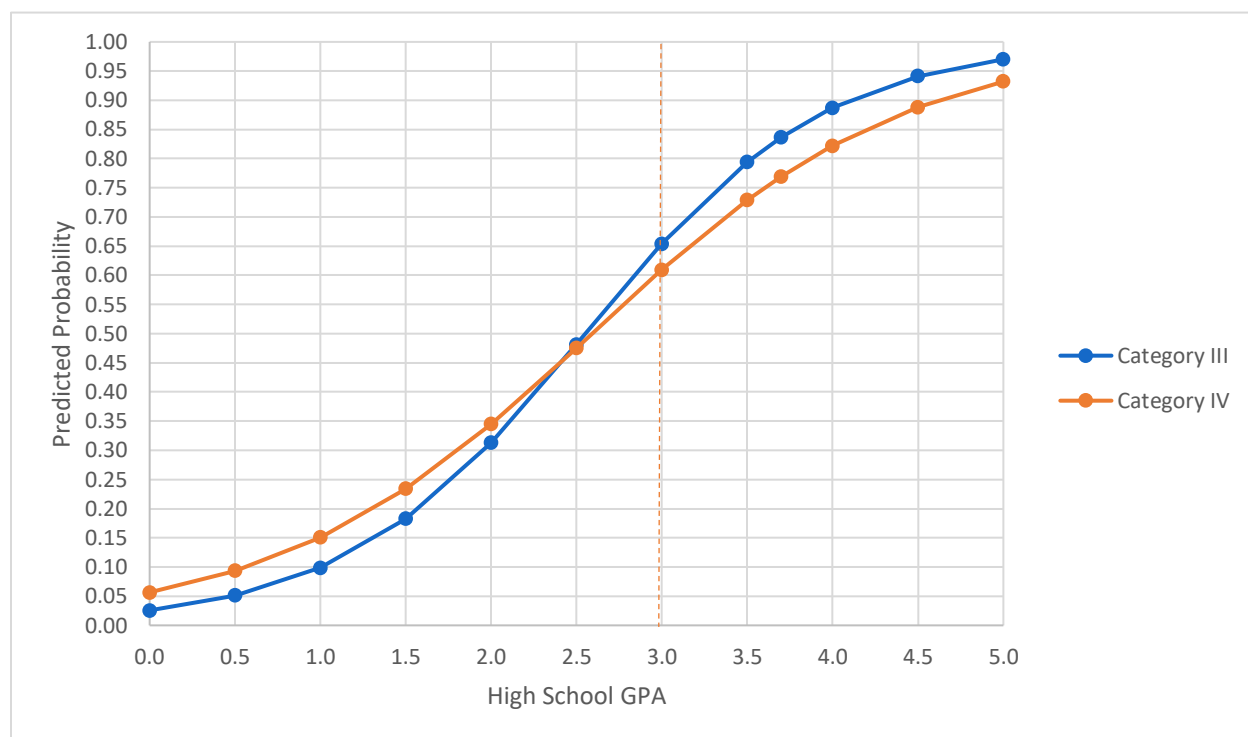




### STEM Students

Based on the placement criteria, the math GPA is the only criterion used to distinguish between placement in Category III versus Category IV for STEM students, regardless of overall high school GPA. However, this study's analysis showed that a high percentage of STEM students who were placed into Category III actually had math GPAs below the 3.3 cutoff, suggesting that there was either a problem with the math GPA variable or, more likely, that some campuses did not differentiate between STEM and non-STEM majors when placing students in Category III. Those Category III students with a high school GPA equal to or less than 2.5 had a lower chance than their counterparts in Category IV of passing their first college math course (Figure 4), which implies that those students should have been placed in Category IV or that the current criterion to place STEM students in Category III may not work as expected. In other words, the use of high school math GPA alone to place STEM students in Category III may not be sufficient to predict future success in their first college math course. Adding another factor such as high school GPA, a strong predictor as indicated by this study's analyses, may improve the classification accuracy and effectiveness in the placement decision.

**Figure 4. Predicted probability of passing the first college math course based on high school GPA for STEM students placed in Category III and Category IV**



## Discussion

This study's analyses illustrate that a student's overall high school GPA is the best predictor of success in a first college math course for students in all placement categories in the CSU system. Because of the way the system's placement algorithm works, a high percentage of students were actually placed into Category II based on their test scores, but the analyses suggest that the GPA is a better predictor of whether a student will be successful in that first course. The findings raise several questions for consideration with regard to the use of multiple measures for QR placement.

### What Are the Appropriate GPA Cutoffs for Placement into Category II?

Currently, if a student does not meet one of the test score thresholds, the GPA cutoff is 3.7 for placement into Category II. Based on the study's analysis, students with that GPA who are non-STEM majors have an 87 percent probability of passing their first college math course with a grade of C minus or better; for STEM majors the probability is 83 percent. A slightly lower GPA of 3.5 still yields a relatively high probability of passing their first college math course: 83 percent for non-STEM majors and 79 percent for STEM majors. Interpreting the appropriateness of these likelihood estimates is a matter of making a policy choice regarding the question: What should the targeted predictive passing rate be to determine whether the GPA cutoff for Category II placement is appropriate or whether it should be lowered?

### What Is the Role of Standardized Testing, Now and in the Future?

In general, the EO 1110 multiple measures policy is based on a hierarchical decision tree — students can be placed into Category II by meeting one of a number of different thresholds, whether through high school overall GPA, high school math GPA, standardized test scores, or a combination of these measures with completion of a senior year math experience. Based on the study's analysis, adding the SAT and EAP scores to the model does very little to increase the predictive strength of the measures. For the next two years at least, because of COVID-19 testing policies, these scores will not likely be available as students will not have had the opportunity to take these exams. Many institutions across the country are moving away from requiring standardized tests such as the ACT and SAT, and the CSU system could move in that direction as well. Given the uncertainty of whether such standardized tests will continue to be required for admission, the CSU system may wish to consider how or whether other measures might be added to the decision architecture.

### What Additional Measures Should Be Considered for Placement?

Although a student's math GPA might be expected to be a significant predictor of success in their first college math course, the analysis shows that this measure really does not add to the predictive strength of the model. The math GPA is so highly correlated with the overall GPA

that its effect is mostly washed out. In addition, very few students were placed using this measure, suggesting that it did not have a significant impact on placement for Category II.

One factor that this study cannot fully address is the impact of a student's high school senior year math experience in predicting success in their first college math course. Analyzing differences in senior year experiences and the extent to which those courses help predict success in first college math courses is beyond the scope of this report but may be an important measure for future consideration, particularly as it is the one measure that is used in combination with other measures (whether test scores or grades).

### Should There Be a Distinction Between Category III and Category IV?

The multiple measures policy uses only grades to differentiate between Category III and Category IV placement for students. For those who are in non-STEM fields, either the overall high school GPA or high school math GPA can result in placement in Category III; for STEM majors, only the math GPA is used to differentiate between Categories III and IV. However, the study's analyses show very similar outcomes for students in their first college math course based on their high school GPA, raising questions about whether there are significant enough differences in the support needs of the two categories to warrant the separation. Currently, the difference between placement in Category III versus Category IV is that students in Category IV are *required* to attend a summer Early Start program, whereas students in Category III are *recommended* to do so. However, the study team's most recent report in this series on EO 1110 illustrates that despite the requirement, not all students who are placed in Category IV enroll in Early Start (Bracco et al., 2021b),<sup>7</sup> which further calls into question the value of distinguishing between these two placement categories.

### Additional Considerations

Consideration of the above policy questions will be an important next step as the CSU system tries to determine how best to set up students for success in entry-level math courses. Additional analyses may be necessary to understand both the longer term implications of the placement policy for STEM students as well as the extent to which results of the analyses might look different on different campuses. Although understanding the extent to which these measures are good predictors of students' success in their first college math course is important, that is only an initial step, particularly for students in STEM fields. For STEM students, understanding how successful they are as they progress through a STEM math sequence will be critical.

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<sup>7</sup> In WestEd's analysis of Early Start outcomes on seven CSU campuses, only about 57 percent of students placed in QR Category IV enrolled in Early Start, despite being technically required to do so.

Finally, while this study's analyses can illustrate systemwide patterns, they do not take into account the nuances of the different courses and different supports provided on individual campuses. Understanding analytically the extent to which differences in high school GPA lead to different first-course outcomes on an individual campus, and whether those differences are greater for STEM versus non-STEM students, might be useful. In addition, understanding the relative success in first courses of students who have been placed in Categories III and IV on an individual campus will be important to understanding whether the types of support models currently provided need to be reexamined.

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# Appendix A

## Model Specification

The study used a logistic regression to estimate the relationship between the following four predictors and a binary outcome of students' passing their first college math course during their first year in college: the student's scale score on the SAT's math section (SAT-math), their scale score on the Early Assessment Program/Smarter Balanced Assessment (EAP-math), their weighted high school math grade point average (GPA), and their weighted high school overall GPA.

The model takes the following form:

$$\Pr(\text{pass} = 1) = \text{logit}^{-1}(\beta_0 + \beta_1\text{SAT}_i + \beta_2\text{EAP}_i + \beta_3\text{Math}_i + \beta_4\text{HS}_i + \varepsilon_i)$$

in which the subscript refers to student  $i$ , and in which  $\text{SAT}_i$ ,  $\text{EAP}_i$ ,  $\text{Math}_i$ , and  $\text{HS}_i$  represent the score or GPA of the corresponding predictor for student  $i$ .  $\beta_0$  and  $\beta_1$ - $\beta_4$  are parameters (coefficients) to be estimated from the data that are presented as odds ratios; each coefficient tells the reader how the odds of students' passing their first college math course change for a one-unit change in the predictor. For example,  $\beta_1$  indicates how the odds of passing the first college math course vary with a one-unit change in the SAT-math scale score.  $\varepsilon_i$  represents the residual error term where  $\varepsilon_i \sim N(0, \theta)$ . The logit function was used because the outcome variable is binary. This model is described more fully by Tabachnick and Fidell (2018).

## Appendix B

Tables B.1 through B.6 provide the summary of model-fit statistics for students by category and STEM/non-STEM for the 2018 and 2019 cohorts. As noted in the body of the report, analysts looked at various statistics, including the log-likelihood function, Akaike information criterion (AIC), and Bayesian information criterion (BIC). A model with a smaller value of AIC or BIC is considered more accurate. The analysis also looked at how well the model predicts and classifies the students by looking at the positive predicted value, the classification accuracy, and the area under a Receiver Operating Characteristic (ROC) curve. The *positive predicted value* (in percentage) is the number of students who are predicted to pass their first college math course and actually do so, divided by the total number of students who are predicted to pass their first college math course. The *classification accuracy* is the number of students who are predicted to pass their first college math course and actually do so, plus the number of students who are predicted *not* to pass their first college math course but actually do so, divided by the total number of students in the analytic sample. ROC is a probability curve. The area under the curve represents the degree to which, or the measure of how much, the model can distinguish between students who can and cannot pass their first college math course with a C minus or higher grade. It ranges between 0 and 1, with 0 being completely indistinguishable (the worst scenario) and 1 being 100 percent distinguishable (the perfect scenario).



**Table B.1. Category II, 2018 cohort: Summary of model-fit statistics along with classification information**

Model	Predictor	Odds ratio	p-value	Log likelihood	DF	AIC	BIC	Positive predictive value (%)	Classification accuracy (%)	AUROC	N
<b>Category II: Non-STEM</b>											
<b>1</b>				-6689.990	5	13389.98	13428.21	82.57	82.16	0.6982	15,452
	SAT-math	1.002764	<.001								
	EAP-math (SS)	1.004344	<.001								
	Math GPA	0.923426	0.097								
<b>2</b>	High school GPA	4.348932	<.001								
				-6691.372	4	13390.74	13421.33	82.55	82.18	0.6977	15,452
	SAT-math	1.002789	<.001								
	EAP-math (SS)	1.004274	<.001								
<b>3</b>	High school GPA	4.063464	<.001								
	High school GPA	4.099403	<.001	-6917.99	2	13839.98	13855.27	82.21	82.17	0.6493	15,452
<b>Category II: STEM</b>											
<b>1</b>				-4508.719	5	9027.438	9063.259	80.01	79.64	0.6826	9,549
	SAT-math	1.002031	<.001								
	EAP-math (SS)	1.004494	<.001								
	Math GPA	1.040388	0.475								
<b>2</b>	High school GPA	3.243993	<.001								
				-4508.974	4	9025.947	9054.604	80.01	79.62	0.6825	9,549
	SAT-math	1.002032	<.001								
	EAP-math (SS)	1.004539	<.001								
<b>3</b>	High school GPA	3.363619	<.001								
	High school GPA	3.672828	<.001	-4634.834	2	9273.668	9287.997	79.72	79.67	0.6400	9,549

**Table B.2. Category III, 2018 cohort: Summary of model-fit statistics along with classification information**

Model	Predictor	Odds ratio	p-Value	Log likelihood	DF	AIC	BIC	Positive predictive value (%)	Classification accuracy (%)	AUROC	N
<b>Category III: Non-STEM</b>											
<b>1</b>				-2740.277	5	5490.554	5522.896	72.23	71.81	0.6270	4,761
	SAT-math	1.003382	<.001								
	EAP-math (SS)	1.004359	<.001								
	Math GPA	0.986119	0.852								
	High school GPA	2.162869	<.001								
<b>2</b>				-2740.295	4	5488.589	5514.462	72.23	71.81	0.6270	4,761
	SAT-math	1.003381	<.001								
	EAP-math (SS)	1.004351	<.001								
	High school GPA	2.145840	<.001								
<b>3</b>	High school GPA	2.629556	<.001	-2822.918	2	5649.835	5662.772	71.59	71.56	0.5564	4,761
<b>Category III: STEM</b>											
<b>1</b>				-352.939	5	715.8783	738.17	74.20	73.67	0.6291	638
	SAT-math	1.002932	0.173								
	EAP-math (SS)	1.001912	0.264								
	Math GPA	0.618700	0.012								
	High school GPA	4.812405	<.001								
<b>2</b>				-356.1263	3	718.2527	731.6277	74.13	73.67	0.6170	638
	Math GPA	0.676112	0.034								
	High school GPA	5.244016	<.001								
<b>3</b>	High school GPA	4.154648	<.001	-358.4219	2	720.8439	729.7606	74.17	74.14	0.6008	638

**Table B.3. Category IV, 2018 cohort: Summary of model-fit statistics along with classification information**

Model	Predictor	Odds ratio	p-value	Log likelihood	DF	AIC	BIC	Positive predictive value (%)	Classification accuracy (%)	AUROC	N
<b>Category IV: Non-STEM</b>											
<b>1</b>				-2062.796	5	4135.592	4165.912	63.22	62.02	0.6236	3,178
	SAT-math	1.004173	<.001								
	EAP-math (SS)	1.002585	<.001								
	Math GPA	1.156338	0.133								
	High school GPA	2.934581	<.001								
<b>2</b>				-2063.923	4	4135.845	4160.101	63.14	61.93	0.6233	3,178
	SAT-math	1.004166	<.001								
	EAP-math (SS)	1.002661	<.001								
	High school GPA	3.160068	<.001								
<b>3</b>	High school GPA	3.149128	<.001	-2108.183	2	4220.365	4232.493	61.16	61.11	0.5711	3,178
<b>Category IV: STEM</b>											
<b>1</b>				-1353.713	5	2717.426	2745.850	67.25	65.61	0.6524	2,175
	SAT-math	1.004106	<.001								
	EAP-math (SS)	1.004168	<.001								
	Math GPA	0.840039	0.160								
	High school GPA	1.004106	<.001								
<b>2</b>				-1354.703	4	2717.407	2740.146	66.83	65.06	0.6515	2,175
	SAT-math	1.004084	<.001								
	EAP-math (SS)	1.004028	<.001								
	High school GPA	2.808969	<.001								
<b>3</b>	High school GPA	2.963908	<.001	-1397.976	2	2799.952	2811.322	64.35	63.45	0.6004	2,175

Model	Predictor	Odds ratio	p-value	Log likelihood	DF	AIC	BIC	Positive predictive value (%)	Classification accuracy (%)	AUROC	N
<b>Category IV: All Majors</b>											
<b>1</b>				-3429.262	5	6868.523	6901.45	64.75	63.40	0.6301	5,353
	SAT-math	1.004005	<.001								
	EAP-math (SS)	1.002965	<.001								
	Math GPA	0.996882	0.967								
	High school GPA	2.475579	<.001								
<b>2</b>				-3429.262	4	6866.525	6892.867	64.76	63.42	0.6301	5,353
	SAT-math	1.004005	<.001								
	EAP-math (SS)	1.002963	<.001								
	High school GPA	2.471153	<.001								
<b>3</b>	High school GPA	2.752239	<.001	-3508.964	2	7021.928	7035.099	62.33	62.08	0.5835	5,353

**Table B.4. Category II, 2019 cohort: Summary of model-fit statistics along with classification information**

Model	Predictor	Odds ratio	p-value	Log likelihood	DF	AIC	BIC	Positive predictive value (%)	Classification accuracy (%)	AUROC	N
<b>Category II: Non-STEM</b>											
<b>1</b>				-4827.501	5	9665.001	9701.584	82.36	81.86	0.7074	11,121
	SAT-math	1.003380	<.001								
	EAP-math (SS)	1.004280	<.001								
	Math GPA	0.959387	0.500								
<b>2</b>	High school GPA	4.634492	<.001								
				-4827.729	4	9663.458	9692.724	82.34	81.86	0.7073	11,121
	SAT-math	1.003401	<.001								
	EAP-math (SS)	1.004241	<.001								
<b>3</b>	High school GPA	4.482988	<.001								
	High school GPA	4.460478	<.001	-5021.364	2	10046.73	10061.36	81.86	81.72	0.6631	11,121
<b>Category II: STEM</b>											
<b>1</b>				-3963.043	5	7936.087	7971.152	79.15	78.77	0.6794	8,210
	SAT-math	1.003966	<.001								
	EAP-math (SS)	1.003768	<.001								
	Math GPA	0.968526	0.608								
<b>2</b>	High school GPA	2.914891	<.001								
				-3963.175	4	7934.350	7962.402	79.15	78.81	0.6793	8,210
	SAT-math	1.003962	<.001								
	EAP-math (SS)	1.003732	<.001								
<b>3</b>	High school GPA	2.830442	<.001								
	High school GPA	2.995640	<.001	-4114.949	2	8233.899	8247.925	78.82	78.76	0.6208	8,210

**Table B.5. Category III, 2019 cohort: Summary of model-fit statistics along with classification information**

Model	Predictor	Odds ratio	p-value	Log likelihood	DF	AIC	BIC	Positive predictive value (%)	Classification accuracy (%)	AUROC	N
<b>Category III: Non-STEM</b>											
<b>1</b>				-2184.580	5	4379.161	4410.386	72.24	71.83	0.6346	3,809
	SAT-math	1.004104	<.001								
	EAP-math (SS)	1.003540	<.001								
	Math GPA	0.939989	0.511								
	High school GPA	2.990771	<.001								
<b>2</b>				-2184.796	4	4377.593	4402.573	72.28	71.88	0.6342	3,809
	SAT-math	1.004099	<.001								
	EAP-math (SS)	1.003492	<.001								
	High school GPA	2.883322	<.001								
<b>3</b>	High school GPA	3.694222	<.001	-2244.02	2	4492.040	4504.530	71.66	71.59	0.5771	3,809
<b>Category III: STEM<sup>8</sup></b>											
<b>1</b>				-351.407	5	712.813	735.0495	74.36	72.90	0.7001	631
	SAT-math	1.006057	0.004								
	EAP-math (SS)	1.007135	<.001								
	Math GPA	0.618559	0.010								
	High school GPA	7.548898	<.001								
<b>3</b>	High school GPA	5.684423	<.001	-376.4501	2	756.900	765.795	70.70	70.52	0.6064	631

<sup>8</sup> All four predictors were significant in Model 1 for Cat III STEM students; with no non-significant predictors to eliminate from the model, Model 2 was not run for this subgroup.

**Table B.6. Category IV, 2019 cohort: Summary of model-fit statistics along with classification information**

Model	Predictor	Odds ratio	p-value	Log likelihood	DF	AIC	BIC	Positive predictive value (%)	Classification accuracy (%)	AUROC	N
<b>Category IV: Non-STEM</b>											
<b>1</b>				-1166.349	5	2342.697	2370.189	63.65	62.83	0.6111	1,805
	SAT-math	1.002812	0.011								
	EAP-math (SS)	1.003062	<.001								
	Math GPA	1.056999	0.676								
<b>2</b>	High school GPA	3.086860	<.001								
				-1166.436	4	2340.872	2362.865	63.67	62.88	0.6108	1,805
	SAT-math	1.002825	0.011								
	EAP-math (SS)	1.003097	<.001								
<b>3</b>	High school GPA	3.171694	<.001								
	High school GPA	3.174266	<.001	-1188.058	2	2380.116	2391.113	62.62	62.77	0.5640	1,805
<b>Category IV: STEM</b>											
<b>1</b>				-1150.988	5	2311.977	2339.749	69.55	67.57	0.6863	1,909
	SAT-math	1.006538	<.001								
	EAP-math (SS)	1.004799	<.001								
	Math GPA	1.087091	0.541								
<b>2</b>	High school GPA	3.159485	<.001								
				-1151.175	4	2310.35	2332.567	69.59	67.68	0.6862	1,909
	SAT-math	1.006548	<.001								
	EAP-math (SS)	1.004847	<.001								
<b>3</b>	High school GPA	3.307686	<.001								
	High school GPA	3.661321	<.001	-1215.662	2	2435.325	2446.433	64.85	63.96	0.6199	1,909

Model	Predictor	Odds ratio	p-value	Log likelihood	DF	AIC	BIC	Positive predictive value (%)	Classification accuracy (%)	AUROC	N
<b>Category IV: All Majors</b>											
<b>1</b>				-2340.203	5	4690.407	4721.506	66.02	64.54	0.6419	3,714
	SAT-math	1.004281	<.001								
	EAP-math (SS)	1.003595	<.001								
	Math GPA	1.026627	0.780								
	High school GPA	2.304588	<.001								
<b>2</b>				-2340.242	4	4688.485	4713.364	66.00	64.51	0.6420	3,714
	SAT-math	1.004287	<.001								
	EAP-math (SS)	1.003611	<.001								
	High school GPA	2.339051	<.001								
<b>3</b>	High school GPA	2.758112	<.001	-2410.944	2	4825.888	4838.328	63.27	63.09	0.5879	3,714