# An Analysis of Performance, Standard Mastery, and (Re)assessment Behaviors in a Coordinated College Algebra Course


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*The purpose of this report is to identify specific content topics and assessment or reassessment behaviors to classify students' performance in a College Algebra course using alternative grading. Our data consist of students' individual standard mastery marks, reassessment frequency, standards reassessed, and final letter grades (which were primarily based on the number of standards mastered in the course). Our analysis involved constructing logistic models and a random forest to identify predictor variables that reduced the Akaike Information Criterion (AIC) and the mean Gini Index. Our results describe two content standards and reassessment behaviors whose attributes were central to our classification models, which can inform the instruction or revision of traditional- and alternative grading-based College Algebra courses.*



*Keywords:* Alternative grading, College Algebra, reassessment, function composition, exponential and logarithmic functions


Alternative grading (AG) practices (e.g., standards-based grading, mastery-based grading, specifications grading, ungrading) are common in secondary (Guskey, 2008) and gaining momentum in undergraduate mathematics education courses (Lewis, 2022). More than 65 years after Bloom's (1968) introduction of learning for mastery, researchers have demonstrated this system's ability to improve both student and teacher perceptions of mathematical learning and coursework. For example, students in AG courses tend to exhibit lower test anxiety (e.g., Harsy et al., 2021; Henriksen et al., 2020; Lewis, 2022), consider assessments to be learning opportunities (Harsy & Hoofnagle, 2020), focus office hours conversations on constructing meaning for math topics instead of answer-getting (Zimmerman, 2020), and provide positive reflections on their experiences in their courses (Collins et al., 2019; Harsy et al., 2021; Henriksen et al., 2020). Instructors of AG courses often report increased feelings of responsibility, coupled with higher expectations for students, which lead to an overall improvement in their attitudes toward teaching their courses (Guskey & Gates, 1986).

Many of the reports cited in the previous paragraph describe (a) implementations of alternative grading, (b) affective advantages to students in courses using alternative grading, or (c) comparisons of students' experiences and perceptions of assessment in traditional and alternative grading courses (Swanson et al., 2025). In contrast, there has been minimal research on the use of student data to identify central topics in AG courses or behaviors that correlate with students' overall mastery of course content. The purpose of this report is to provide insights into such topics and behaviors in the context of a coordinated AG College Algebra course. To this end, we provide the following research questions (RQ) to guide our discussion:

1. Which mathematical topics are most correlated with student's mastery of course content in a College Algebra course utilizing alternative grading?
2. Which student study practices are most correlated with student mastery in such a course?

## Theoretical Background and Course Structure

The AG College Algebra course instructors created the course in accordance with the Four Pillars of Alternative Grading (Clark & Talbert, 2023) and Collins et al.'s (2019) characteristics of Mastery-based Testing (MBT). We describe the course composition using the Four Pillars.

### Pillar 1: Clearly Defined Standards

Clark and Talbert (2023) do not provide a rigorous definition of the term *"standard,"* leaving the decision on what constitutes acceptable student work open to the instructor's discretion. Still, Collins et al. (2019) state that whatever standards are determined, these standards must be clearly worded and communicated to students on study guides and assessments.

To determine the *standards* for the College Algebra course, instructors implemented a three-step procedure reminiscent of grounded theory (Strauss & Corbin, 1998). First, they analyzed the common final exam and compiled a list of skills they believed students would need to complete the questions (i.e., open coding). Second, they organized the skills into overarching topics that appeared (to them) suitable to serve as units within the course (i.e., axial coding). The instructors utilized the term *standard* to refer to each of the content topics that emerged from the organization process. The final, recurring, stage is to refine the list of standards through implementation iterations until it appears that the standards list encompasses the material conventionally covered in a traditional College Algebra course (i.e., theoretical saturation). The current iteration of the AG College Algebra course includes a list of 18 content standards, some of which are shown in Table 1 below. Students must show proficiency twice on a standard to achieve mastery of that standard. To facilitate this process, the course also includes feedback systems (Pillar 2), marks systems (Pillar 3), and a three-part assessment structure (Pillar 4).

*Table 1. A sample of three standards from our AG College Algebra Course*

| | |
|---|---|
| Standard F8 | Add, subtract, multiply, divide, compose, and decompose functions given in any of the four representations, and simplify when necessary/possible. Find the domain and range of the combined functions. |
| Standard EL4 | Solve logarithmic and exponential equations. Solutions are either approximate or exact. |
| Standard EL5 | Model and solve applications with exponential functions (compound interest, exponential decay and growth). |

### Pillar 2: Helpful Feedback

Instructors in the College Algebra course provide targeted, specific feedback on students' assessment and reassessment attempts in the course. The purpose of such feedback is to create a loop through which students know which ideas to revisit before reassessing. Collins et al. (2019) also recommend providing feedback to help students progress toward mastery of course topics, rather than as a penalty, which might disincentivize future attempts at mastery.

### Pillar 3: Marks Indicate Progress

Instructors use a binary system to provide marks on students' assessments and reassessments: *pass* and *not pass yet* (Clark & Talbert, 2023). They also condition *passes* on conceptual mastery of a topic and use *not pass yet* marks to facilitate future student learning opportunities of course material, rather than penalizing (often computational) mistakes (Collins et al., 2019).

Instructors use a standardized system, based on the number of standards students master throughout the semester, to assign final letter grades. We show the number of standards corresponding to each letter grade in Table 2 below. The possible addition of a + or – modifier to a student's letter grade is contingent upon engagement activities, such as homework completion and course attendance. Consequently, students' final letter grade in the course is an indication of the amount of AG College Algebra content for which they have exhibited proficiency. When we describe productive predictors for classifying students by letter grade in the results section, we consider our claims to be synonymous with describing specific content or behaviors whose acquisition is associated with students' mastery of AG College Algebra material.

*Table 2. The mastery-based grading scheme to determine final letter grades in AG College Algebra*

| Standards Mastered | 0-8 | 9-11 | 12-14 | 14-16 | 17-18 |
|---|---|---|---|---|---|
| Final Letter Grade | F | D | C | B | A |

**Pillar 4: Reattempts Without Penalty**

A central component of all alternative grading strategies is allowing students to perform reassessments to demonstrate growth and mastery of course content (Clark & Talbert, 2023). College Algebra instructors provide three opportunity types for students to reassess course standards: (a) required weekly in-class assessments (which contain some instructor-chosen previously assessed standards), (b) optional weekly reassessments of student-chosen standards, and (c) optional reassessment opportunities on the final exam. In this report, we focus a portion of our analysis on reassessment opportunity (b), the optional weekly reassessments.

## Methodology

In this section, we describe our data collection and analysis methods. We will use three statistical terms to organize our descriptions. First, we use the term *predictor variable* to refer to student behaviors or standard mastery for which we collected data. We have included a list of some predictor variables in Table 3 below. Second, we use the term *observation* to refer to the unit of analysis in our study, i.e., individual AG College Algebra students. Finally, we use the term *category* to refer to the response variables whose relationship with the predictor variables we attempted to determine (e.g., the final grade in the course).

**Data Collection Methods**

**Population and data sources.** The population we chose to study for this report consisted of all students enrolled in an Alternative Grading (AG) College Algebra or College Algebra Corequisite course at a mid-sized regional university in the Pacific Northwest. To construct a sample of students from this population, we collected internal and institutional data for the 134 students enrolled in one of the six Spring 2025 sections of traditional or corequisite AG College Algebra offered at the institution. The first author of this report was an instructor for one of the corequisite courses. We collected data from three sources. First, we imported data from a Qualtrics form used throughout the semester for students to schedule weekly reassessments in the proctor room. The information we imported from this form included students' names, the dates and times of reassessments, and the standards they intended to reassess at each appointment (a maximum of two standards weekly). Second, we collected students' individual standard mastery data from all but one instructor after the semester. Finally, we collected students' final letter grades and demographic data from the institutional research staff.

**Predictor variables and sample refinement.** In preparation for data analysis, we determined two classes of predictor variables to investigate in relation to students' final letter grade. First, we created three predictors for each standard according to possible mastery level (0 passes-not met; 1 pass-partially met; 2+ passes-fully met). This class of predictors aligned with the intent of RQ1, i.e., determining content concepts with explanatory potential for students' performance (e.g., final grade outcome). Second, we created predictors for behaviors related to the reassessment room, including (a) the total number of reassessment appointments made and (b) the number of standards reassessed throughout the semester. This class of predictors aligned with the intent of RQ2, i.e., determining behaviors that may help explain students' performance.

We used our focal predictors to restrict our initial sample to the set of observations (i.e., students) exhibiting both predictor classes. To this end, we removed 28 students from our initial sample. Of these students, 12 did not have assessment, reassessment, or standard performance data (typically students with early withdrawals), and 16 students were removed due to an instructor not providing standards mastery data. Our final sample consisted of 106 students.

*Table 3. A selection of predictor variables guiding our data collection and analysis*

| | |
|---|---|
| F8 | Categorical (binary) variable indicating whether the student mastered Standard F8 or not, i.e., achieved two or more passes. |
| Total.standards.scheduled | Discrete variable describing the number of standards students scheduled for reassessment throughout the semester. |

**Data Analysis**

The second and third authors prepared the data for formal analysis and importation into the R studio platform. This process included (a) assigning identifiers across the disjoint data sources and (b) compiling three distinct spreadsheets into a centralized document containing the 106 observations to import into R studio.

**Statistical Techniques.** The second author of this paper led the data analysis for this project, which included techniques related to (a) stepwise selection on logistic models using the Akaike Information Criterion (AIC) and (b) creating and measuring the decision trees in a random forest by Gini Index to construct a variable importance plot. We explain these components of our analysis in the paragraphs below.

Statisticians use logistics models to predict the category (e.g., final letter grade) associated with a specific observation (e.g., student with a particular set of standard and reassessment properties). When building a logistic model, a common approach is to use forward or backward step-wise selection. This process involves starting with either no predictor variables in the model (forward selection) or all predictors in the model (backward selection) and then adding (i.e., forward) or removing (i.e., backward) predictor variables to determine how the change improves the explanatory power of the model to classify the observations correctly. A central component of determining a final logistic model is minimizing the AIC value, which reduces the predictors in the model while maintaining explanatory power. Although the forward and backward selection processes can identify different variables as important, any variables that appear in both models provide a strong argument for predictors of high-performing students. Our analysis involved creating both forward and backward selection logistic models to determine important standard mastery (i.e., RQ1) and reassessment behavior (i.e., RQ2) predictors that we could use to categorize our students' final grade performance (i.e., content mastery).

Statisticians use random forest (i.e., a collection of decision trees) as an alternative method to predict the category (i.e., final letter grade) associated with a particular observation (i.e., student performance and behavior). In our instance, we measured the Gini Index to determine the distribution of the predictor variables across the decision trees in the random forest. A low Gini Index (i.e., close to 0) indicates that a particular predictor variable (e.g., mastering Standard F8) produces the cleanest separation of observations into those that correspond or do not correspond with the category (e.g., students who master Standard F8 generally get A grades and those who do not master F8 generally receive lower grades). We used the data from the Gini Index measurements across the random forest to construct a variable importance plot, which shows the predictor variables that contributed the most to improving the tree's predictions throughout the forest. In this plot, the higher the importance score, the more the Gini Index is reduced (i.e., decreased) across all splits in a given decision tree. In other words, a high importance score (e.g., greater than 3) indicates an essential predictor variable for categorizing students' final grades in the College Algebra course. Through our analysis, we identified the two content standards (RQ1) and student behaviors (RQ2) that provided the most explanatory power for the students' final letter grades in the course. We describe these results in the following section.

## Results

### RQ1: Content Standards Corresponding with Overall Standard Mastery

Our initial logistic models indicated several important predictor variables, both from the forward and backward selections. Among these variables, we found two standards, F8 and EL4, with associated predictors that indicated high explanatory power for students' final letter grades in the course (i.e., mastery of course content; see Table 1 for the text of these standards). For instance, we determined that students' eventual mastery of these standards substantially lowered the AIC across our logistic models. Although only students' reassessment of Standard EL4 was a statistically significant predictor for students' final course performance ($p = 0.004$), we found that manually removing students' mastery of F8 and EL4 from our models led to a drastic increase in the AIC value (e.g., by a factor of 2 to 3 depending on the model). These results indicate that students' mastery of function composition topics (i.e., Standard F8) and ability to solve logarithmic or exponential equations (i.e., Standard EL4) are crucial predictors for students' final letter grades (and subsequent success) in AG College Algebra.

To further investigate the potential importance of standards F8 and EL4 in relation to student success in College Algebra, we created a random forest, measured the corresponding Gini Index, and constructed a variable importance plot. We share a sample decision tree from the random forest and our variable importance plot in Figures 1a and 1b below. We note that the first two branches in the sample decision tree (Figure 1b) are F8 and EL4, and each predictor has a mean decrease in the Gini Index above 5 (Figure 1a), indicating their importance in classification across the decision trees in the random forest. Taken together, the reduction in AIC and the strong decrease in the Gini Index confirm the central nature of standards F8 and EL4 as classification tools for students' letter grades in our course.

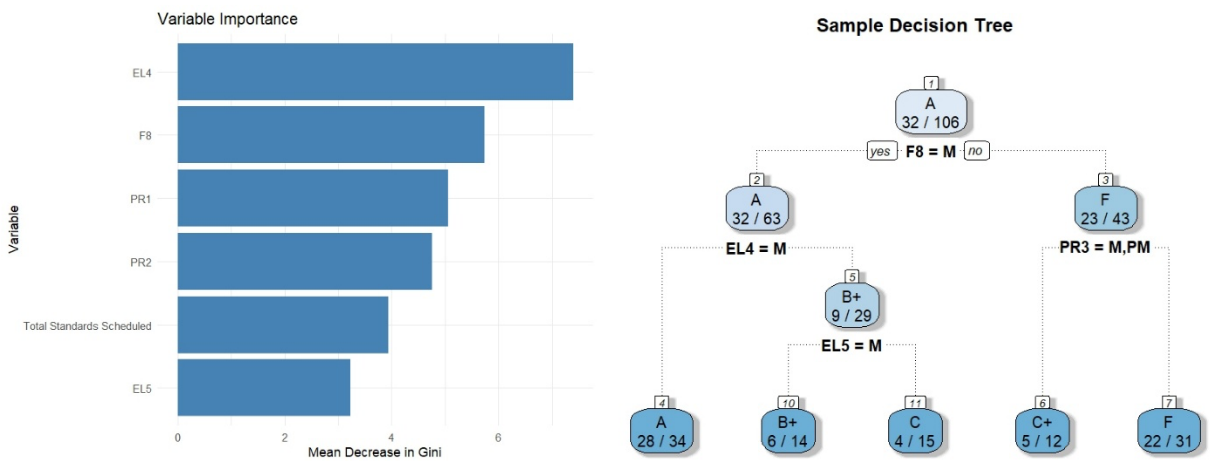


*Figure 1. (a-left) A variable importance plot of the largest mean decrease in Gini Index. (b-right) A sample decision tree from the Random Forest method.*

**RQ2: Students' Assessment Behaviors Corresponding with Overall Standard Mastery**

Our results related to RQ1 indicate that the predictors with the most explanatory power related to students' letter grade performance in the AG College Algebra course were content (i.e., standard) related. We anticipated that some students' (re)assessment behaviors might also function as crucial classification tools of students' final letter grades, due to the central nature of reassessment in the AG course. Through our analysis, we identified two predictors that served as useful classification tools. First, we found that the total number of standards that students reassessed over the course of the semester (a) reduced the AIC in both the forward and backward directions of the logistic models and (b) produced a reduction in the Gini Index above 3. Second, we found that the total number of reassessment appointments that students scheduled and subsequently completed also consistently reduced the AIC in logistic models and produced a Gini Index reduction above 3. We note that among our list of predictors, which included students' performance on all 18 standards and various (re)assessment behaviors, students' total number of standards reassessed produced the fifth most significant decrease in the Gini Index, and the number of completed reassessment appointments contributed the twelfth largest decrease. Taken together, these data indicate that the most important student (re)assessment behaviors for classifying students' final letter grades in AG College Algebra involve their reassessment actions. Specifically, students who complete scheduled reassessment appointments and reassess larger numbers of standards tend to achieve higher grades in the course.

## Discussion

This report highlights our use of reassessment and student performance data in a coordinated AG College Algebra course to increase our understanding of students' achievement of particular letter grades (i.e., standard mastery) in the course. To this end, we proposed two research questions related to (a) the central course standards and (b) (re)assessment behaviors that could provide explanatory power for students' mastery of the content in the course.

Our data analysis related to RQ1 revealed that students' mastery of function arithmetic and composition (Standard F8), and algebraic fluency with solving exponential and logarithmic equations (Standard EL4) provided a framework for effectively classifying the letter grades of a large number of our students. Our findings reinforce those of prior researchers who claimed that building conceptual meanings for function concepts is not easy for students (Breidenbach et al., 1992; Thompson & Carlson, 2017), whether (a) learning function composition in preparation for the chain rule in calculus (Clark et al., 1997), (b) building meaning for exponential functions (Ellis et al., 2016), or (c) reasoning about logarithmic functions (Kuper & Carlson, 2020). Additionally, our results extend these findings by showing evidence of the importance of composition, exponential, and logarithmic topics in students' success in a mastery-oriented College Algebra course.

From an instructional perspective, our results related to RQ1 imply that an increased focus, or at least increased attention to these topics, may lead to improved student success in College Algebra courses using alternative grading. Although our study does not include a comparison with students in traditionally-graded (i.e., weighted average) College Algebra or calculus courses, our results suggest that (a) traditional College Algebra course instructors might similarly profit from increased focus on composition, exponentials, and logarithms, and (b) addressing students' notions of function composition, exponential functions, and logarithmic functions may be a productive focus for diagnostic or remedial tools in higher mathematics coursework (e.g., calculus).

Our data analysis related to RQ2 question revealed that students' willingness to schedule and perform reassessments across various standards correlated with higher performance (i.e., increased mastery of content) in the course. Our findings provide empirical evidence that reassessments can be employed as learning opportunities (Collins et al., 2019) and that students who avail themselves of these opportunities often progress toward mastery. While we recognize that our results regarding reassessments may not be fully transferable to College Algebra or other courses using traditional grading systems, we use our results to highlight the possibility that all instructors can modify some (or all) of their assessments to create student learning opportunities (rather than penalizations or unchangeable marks of failure).

We are continuing to collect data on students' standards mastery and (re)assessment practices during the Fall 2025 semester. We anticipate that the analysis of this additional data in the coming months will provide further refinement of the results we presented in this report. Specifically, we plan to test whether our logistic models, in general (and Standards F8 and EL4, and students' reassessment practices in particular), continue to serve as effective classification tools for students' final letter grades. Our eventual results will serve to further the discussion of centrally important topics in College Algebra and the refinement of AG College Algebra courses.

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