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Student Ability Best Predicts Final Grade in a College Algebra Course

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ABSTRACT

Historical student data can help elucidate the factors that promote student success in mathematics courses. Herein we use both multiple regression and principal component analyses to explore ten years of historical data from over 20,000 students in an introductory college-level Algebra course in an urban American research university with a diverse student population in order to understand the relationship between course success and student performance in previous courses, student demographic background, and time spent on coursework. We find that indicators of students' past performance and experience, including grade-point-average and the number of accumulated credit hours, best predict student success in this course. We also find that overall final grades are representative of the entire course and are not unduly weighted by any one topic. Furthermore, the amount of time spent working on assignments led to improved grade outcomes. With these baseline data, our team plans to design targeted interventions that can increase rates of student success in future courses.

Notes for Practice

- Past studies have found that student grades are influenced by several factors, including student ability, student demographic background, and course specific factors.
- This study finds that student prior performance in past courses is the best predictor of final grade outcome in an introductory mathematics course.
- We recommend early interventions to target at-risk students, particularly students with low grade-point averages, students who are part time, and first semester students.
- We found that time spent on assignments is associated with higher grades. Therefore, to the extent possible, assignments should be given in an online format that incorporates a timestamp, thereby allowing instructors to identify in real-time students who may need intervention.

Keywords

Data mining, mathematics, learning analytics, Algebra, student ability.

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1 INTRODUCTION

Mathematics courses demonstrate high rates of failure at a global scale (Faridhan, Loch, & Walker, 2013). This is especially problematic in early mathematics courses, where a failing grade may significantly influence the probability of student retention and continuance (Arnold & Pistilli, 2012). Thus, understanding the factors that promote success in early mathematics courses may assist higher education institutions with boosting retention and graduation rates. This is especially important for online or mixed-methods sections, which face much higher drop rates than traditional face-to-face (F2F) courses (Morris, Wu, & Finnegan, 2005).

Additionally, United States retention rates at four-year degree-granting institutions is as low as 64.2% for students progressing from first to second year, while persistence to degree rates are as low as 36.4% (American College Testing, 2012).

One of the strongest predictors of student retention and graduation is first-year course success (Arnold & Pistilli, 2012). This knowledge creates incentives for early interventions with students identified as high-risk, which should in turn increase rates of completion. The field of learning analytics provides opportunities for educators to uncover variables among students that help to predict success in courses (Siemens, 2012; Bakharia et al., 2016; Kovanović et al., 2017). Analyses of long-term course data (educational datamining), paired with learning analytics, may uncover patterns of learning among students that can be useful in designing targeted interventions (Baker & Inventado, 2014; Berland, Baker, & Blikstein, 2014). This study investigates the influence of various student and course specific factors on predicting student grades in mathematics courses by utilizing analytics and datamining.

Current research highlights several factors that may contribute to student success in a course, including student ability (measured as grade-point average [GPA] and test scores), student background (race, income, transfer credits), and course specific variables (instructor, semester; Snyder, Hackett, Stewart, & Smith, 2003; Haynes, Mullins, & Stein, 2005). Several of these variables have been explored in previous studies. Davidson (2015) found that the number of credit hours completed in a student's first year at a community college had a large positive impact on degree completion. In a similar light, Tempelaar, Rienties, and Giesbers (2015) found that prior mathematics experience was the best predictor of success in a college-level mathematics course. On the other hand, Diaz (2002) found that a student's prior GPA strongly influenced their persistence in an online mathematics course. Thus, we see that past studies have consistently identified prior course experience and prior GPA as strong predictors of a student's final course grade (Kuh, Kinzie, Buckley, Bridges, & Hayek, 2006; Cavanaugh & Jacquemin, 2015). Differences between student demographics have also been well studied. For example, Richardson (2008, 2012a, 2012b) found that minority students consistently performed worse than white students in the United Kingdom university system across fields in both F2F and online sections. This trend has also been well documented in Science, Technology, Engineering, and Mathematics (STEM) fields (Bahr, 2010; Kuh et al. 2006 and references therein; Ro & Loya, 2015).

When courses are delivered online, several additional considerations arise. These are important to consider because online learning is rapidly growing at Universities around the world (Berk, 2013; Ali & Smith, 2014; Mann & Hennebbery, 2014). For example, online students are less likely than students enrolled in F2F courses to have satisfactory course outcomes; they have higher rates of withdrawal and reduced course satisfaction (Hauck, 2006; Smith et al., 2011; Ali & Smith, 2015; Nfor, 2015; Callister & Love, 2016). However, some studies have shown that online students may perform better than, or equal to F2F sections (Lattimore, 2012; Ali & Smith, 2014; Cavanaugh & Jacquemin, 2015; Biel & Brame, 2016). Several studies suggest that this discrepancy in outcomes is explained by an interaction between instructional modality and a student's prior performance, producing different outcomes for online students of different skill levels (Bigelow, 2009; Lu & Lemonde, 2013; Driscoll, Jicha, Hunt, Tichavsky, & Thompson, 2017). Understanding what leads to student success in F2F and online sections is especially important in mathematics courses, where students have been shown to perform even more poorly than other subjects in online sections (Oliver, Kellogg, & Patel, 2010).

Many recent research studies have examined related topics in massive open online courses (MOOCs), such as grade prediction (Gadhavi & Patel, 2017; Meier, Xu, Atan, & Van Der Schaar, 2015) and the use of intelligent tutoring systems to assist students (Crow, Luxton-Reilly, & Wuensche, 2018; Kulik & Fletcher, 2016). However, the educational context of these studies is not always transferrable to traditional university classroom scenarios. For example, the open nature of MOOCs makes data collection in those courses contextually different than data collected in smaller, private, selective enrollment courses. Additionally, the goal of this study was to look at student success through whatever lens the data presented, without limiting the lens to grades or specific intervention methods such as intelligent tutoring. Therefore, the analysis of predictive factors in historical data collected in traditional face-to-face and online mathematics courses at an urban American university was identified as lacking in the current literature.

Building on our literature analysis, this study investigates the influence of various student and course specific factors on predicting student final grades in an introductory mathematics course. This study investigates the following questions:

RQ1: What demographic variables best predict student success?

RQ2: Are the most predictive variables related to student performance, student background, or course specific factors?

RQ3: What is the effect of time spent on assignments and the final grade of students in online sections?

2 METHODS

2.1 Dataset Generation and Preparation

The authors and a team of graduate student assistants compiled two datasets. The first included anonymous student data spanning the academic terms of Fall 2009 to Spring 2017 from mathematics 1302, a College Algebra course at the University of Texas at Arlington. This is a large, public research university in an urban environment, with a diverse student population including a large proportion of first-generation students. Our data included students from traditional in-person lecture sections, entirely online sections, and mixed-methods sections. This dataset included 20,776 student entries across all semesters. Due to some students enrolling in the course multiple times, there were 3201 students repeated at least twice in the dataset (up to six entries). Our dataset included 20 predictor variables that we used to predict final grade (A–F,W; Table 1). We classified variables into three categories: course specific variables (instructor, term year, instruction mode), student performance (test scores, GPA), and student demographic background (Pell eligible, race, completed hours). We chose our variables to capture the effects of student background, prior knowledge, and any effects driven by the course or instructor outside of the student's control. Our decision on which variables to include in the analyses was based upon their availability. Therefore, we do not consider other variables that may also influence course outcome such as high school performance metrics.

Table 1. The 20 Predictor Variables Included in our Model

Variable	Details
Academic term during enrollment	–
Instructional Mode	F2F, Online, Mixed
Semester during enrollment	Fall, Spring, Summer
Course Section	–
Instructor ID	–
Major college	College of Business etc.
Gender	Male, Female, Not specified
Academic load	Full, Part time
Race	African American, Hispanic/Latino, White, Asian-American, Multiple ethnicity, International student, Native American, Pacific Island, None
Academic Standing	Good, Probationary
Total transfer credit	# credit hours
Transfer type	Some or none
Total completed credit hours	At course enrollment
Completed credit hours bin	0–14 or 15–29
Pell status	Eligible, Not eligible, Did not apply for FAFSA
Cumulative GPA	At course enrollment
Prior college mathematics	Yes or no
SAT mathematics score	–
SAT cumulative score	–
ACT mathematics score	–

The second dataset encompassed online sections of the same course from the Fall 2013 semester to the Summer 2017 semester. These data included assignment, quiz, and exam grades, as well as the amount of time spent on each task. This course covered five chapters. Homework assignments ranged from 1–5 per chapter, with two quizzes for each chapter and three exams throughout the semester. One final exam was also included in the dataset, as well as the final grade for the course. There were 285 students included in this dataset. Demographic information was not included with these data, as we were only interested in the effects on the final grade of particular assignments and the amount of time spent.

2.2 Data Exploration

We began by exploring the demographic constitution of the students in our dataset. We primarily used Tableau Desktop V10.2.2 (Tableau Software, Seattle, WA) for data exploration. This dataset included 34 academic semesters (Fall, Spring, Summer), and 64 course sections taught by 59 instructors. Our dataset included 51.1% of students participating in face-to-face (F2F) sections, 33.8% of students online, and 15.1% of students in a mixed-mode section. The drop, fail, or withdraw rate (DFW) was 39.3%. Additional summary statistics of interest are shown in Tables 2 and 3 (see Appendix). As an initial exploratory step, we assessed the data for significant differences between the course outcomes of each categorical grouping. Significant differences between predictor variables were quantified in SPSS using either a two-tailed t-test (for comparisons of two groups), or an ANOVA (for three or more groups). We conducted one-way ANOVAS, as well as multi-way ANOVAS for identified significant variables to investigate interactions between variables.

2.3 Regression Analysis of Demographic Variables

Multiple regression analyses were conducted using SPSS v.24.0.0.1 (IBM Corp., Armonk, NY). The automatic linear modelling tool was utilized to identify which features of student performance and background best predicted performance in the course. We first checked that our data did not violate any assumptions of multiple regression analysis. Model selection was then conducted using a forward stepwise approach based on the corrected Akaike information criterion (AICC). We cross-validated the previous approach using the best-subsets model selection, as well as including all variables in our analysis without model selection. No significant differences were found between analyses. All other model parameters were left as default, including the automatic data preparation feature. This feature removes outlier values that are greater than three standard deviations away from the mean for any variable, replaces all missing values, and merges categories across individuals (binning) to maximize model fit based on AICC. All 20 predictor variables were included in our exploratory analysis. Each variable was coded numerically, and variables were classified accordingly as nominal or scalar. Each analysis attempted to predict the average grade, which included only F–A scores scaled as 0–4, or the final grade, which included students who had withdrawn (W–A, coded as 1–6). The program predicted the fit of the best model as a percentage based on the AICC score of that model. We also conducted a binary logistic regression of all variables to predict students who would pass or fail by coding DFW grades as 0 and all other grades as 1.

2.4 Principal Component Analysis and Regression of Assignment Scores

We investigated the dataset to see if any subsets of assignments and quizzes were more strongly associated with the final grade than would be expected by random chance. To do so, we conducted a series of principal component analyses in SPSS, comparing individual assignment grades for all assignments, and the final grade, as well as individual assignment grades, time spent on the assignment, and the final grade. We also conducted a multiple regression analysis in SPSS to examine the relationship between time spent on an introductory assignment, median time spent per assignment, and the final grade.

3 Results

3.1 Data Exploration

We began our analysis by exploring the distribution and mean grades of several predictor variables identified as significant in past studies, with an emphasis on race and instruction mode (Tables 1 and 3). We first investigated the four largest racial categories for all instruction modes: Black/African American, White, Hispanic/Latino, and Asian-American (Tables 2 and 3). We excluded other racial categories because sample sizes were less than 1000 students. The category of "not-specified" was also excluded for this analysis. Initially, we found differences in the mean grades and average GPA of each race (Table 3). Mean grades (1 = D, 2 = C, 3 = B, 4 = A) were 1.6 (standard deviation [stdev] = 1.4, n = 2382) for Black/African American students, 2.2 (stdev = 1.4, n = 5779) for White students, 1.9 (stdev = 1.4, n = 3298) for Hispanic/Latino students, and 2.6 (stdev = 1.3, n = 1373) for Asian-American students (Figure 1A–B). We used a one-way ANOVA to confirm that these mean grades were significantly different ($p < 0.001$). The ANOVA testing for differences in GPA among racial groups was also significant ($p < 0.001$).

Interestingly, we were able to identify patterns suggesting an interaction between race and instruction mode (Figure 1B–C). By plotting the proportion of each grade received by students in a certain racial category, and separating these by instruction mode, we found that racial groups had different propensities (in terms of proportion of students) for dropping the course, and that this propensity differs between online and F2F sections (Figure 1C). Among F2F Black/African American students, the distribution of grades, including W's, evenly distributed across grade categories, although fewer students received A's (Figure 1C). Yet among online students we observed large number of W's and F's, while other grades appeared unimodal (Figure 1C). This indicates that Black/African American students are more likely to drop or fail the course when taking an online section (Figure 1C). Among White students, the trend is similar. Grades among F2F students show no clear pattern, although the most common grade was a B. In online sections, more students withdrew than received any other grade (Figure 1C). However, students who did not withdraw were more likely (as a proportion of total students) to receive a C–A grades than an F or D grades (Figure 1C). Among Hispanic/Latino and Asian-American students, a larger proportion of students dropped the course in online sections than in the F2F sections (Figure 1C). Interestingly, 73% of Asian-American students in the F2F course received a grade higher than a D, compared with an average of 54% in the other racial groups (Figure 1C). Thus, we see that racial groups responded with different distributions of grades in F2F and online sections, and that the propensity to drop or fail the course was much higher in online sections, when measured as a proportion of total students.

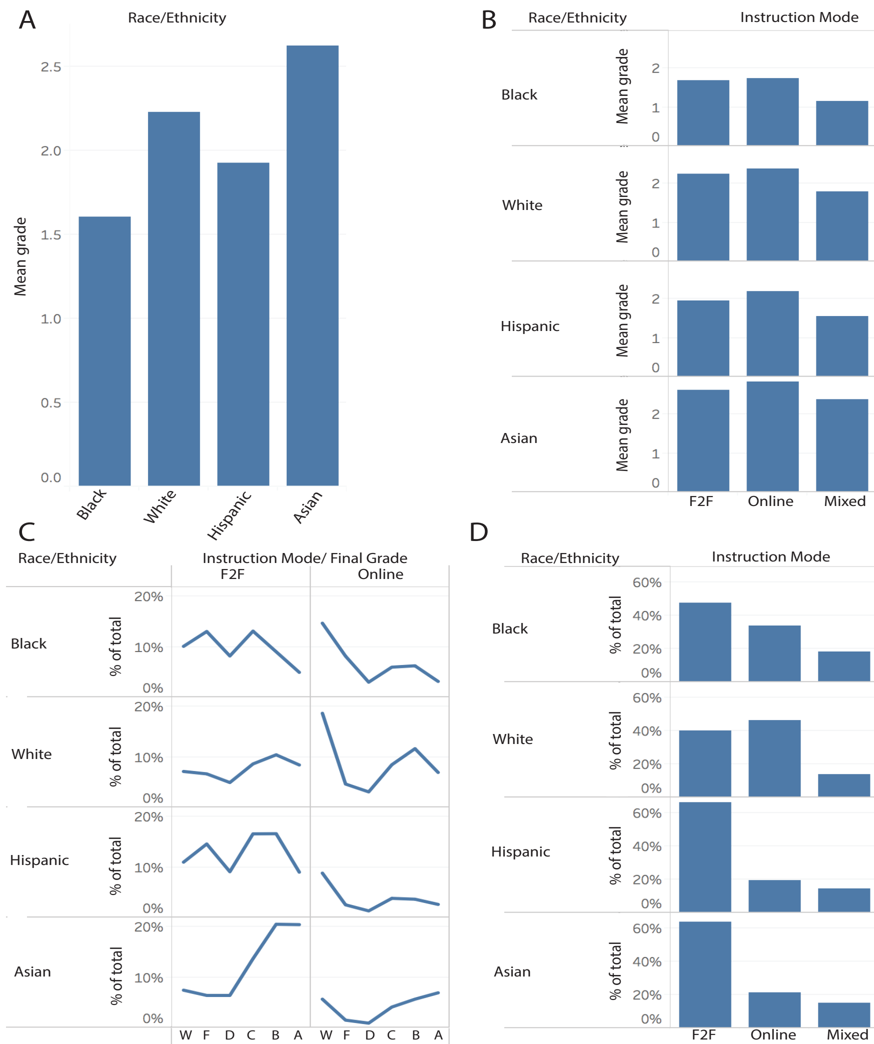

Figure 1. Associations of race and instruction mode. A) Mean grade for each of the four largest racial groups in this study. B) Mean grade for each racial group divided by instruction mode. C) Distributions of grades for each racial group split into Face to Face (F2F) and online sections. Mixed methods had low enrolment and were thus excluded from figures showing percent of total enrollment. D) Enrollment differences between racial groups in F2F, online, and mixed methods sections.

We also observed large differences in the propensity of racial groups to enroll in different instruction modes (Figure 1D). For example, Hispanic/Latino, and Asian-American students enrolled in higher numbers in F2F sections than in online sections (Figure 1D). Black/African American students were almost equally likely to enroll in online verses F2F sections, while White students were more likely to enroll in online sections (Figure 1D). When we sorted this data by gender we observed that among Black/African American students, females were equally likely to take the course F2F vs. online, but males were more likely to take the course F2F (Figure 2). Among White students, males were more likely to participate in F2F sections, while females were much more likely to take the course online (Figure 2). In both Hispanic/Latino and Asian-American students, both genders were more likely to take the course F2F (Figure 2).

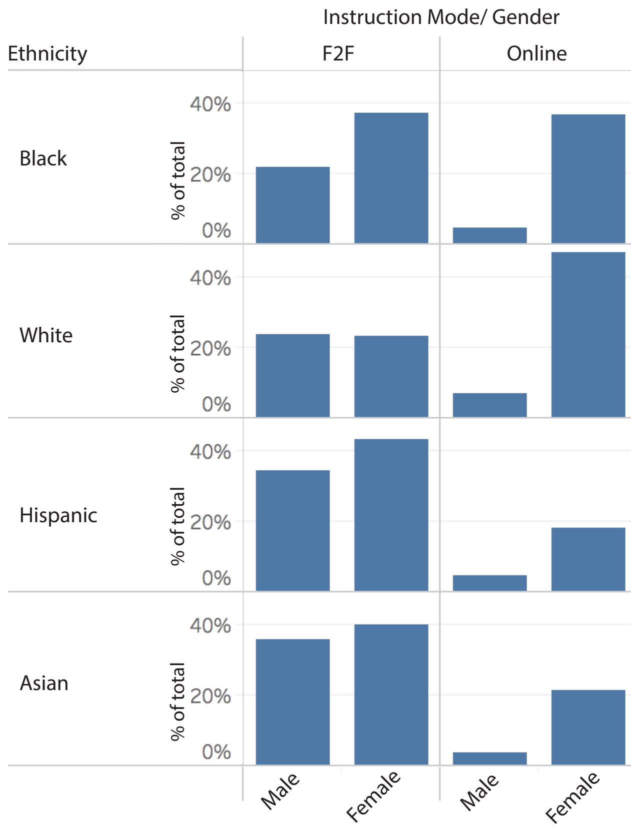

Figure 2. The interaction of instruction mode, race, and gender. This figure shows the propensity of each gender within each racial group to enroll in each instruction mode.

We also explored differences in grade distributions and means between different instruction modes. We plotted the distribution of scores for each instruction mode, and found that a higher proportion of students dropped the course in the online (35%) or mixed mode (23.4%) sections than in the F2F section (14.7%; Figure 3). We calculated the mean grade excluding withdrawals and found a similar mean grade in F2F (mean = 2.1, stdev = 1.4, n = 8876) and online (mean = 2.2, stdev = 1.4, n = 4555) or mixed mode (mean = 1.64, stdev = 1.4, n = 2358).

We explored other student variables such as academic load, and found that full-time students had a mean grade of 2.1 (stdev = 1.4, n = 10,832) compared with a mean grade of 2.0 (stdev = 1.4, n = 4957) for part-time students (t-test non-significant). We did observe a significant difference in mean grade based on student academic standing. Students in good standing received a mean grade of 2.4 (stdev = 1.2, n = 12,385) compared with those with a probationary record scoring 0.7 (stdev = 1.04, n = 3401) on average ($p < 0.001$). The distribution of grades for students of good and poor standing is also quite different, with students in good standing more likely to drop the course, but students with probationary records more likely to fail than to receive any other score (Figure 4A). Students who had not previously enrolled in a college-level mathematics course scored better than those who had previous college mathematics credits (mean = 2.2, stdev = 1.4, n = 10,201 vs. mean = 1.8, stdev =1.4, n = 5588, $p < 0.001$). Yet, transfer credit was not a significant predictor of final grade, with an average grade of 2.1 (stdev = 1.4, n = 5993) for students without transfer credit, and 2.0 (stdev = 1.4, n = 9793) for students with transfer credit (t-test non-significant). However, we did find that the distributions of grades were quite different for these two groups, with transfer students much more likely to withdraw or fail when measured as a proportion of the total (Figure 4B). We also explored the role of income on grades and found a large difference between income groups. Pell-eligible students (those receiving need-based Federal aid) received a mean grade of 1.8 (stdev = 1.4, n = 6768), compared with 2.1 (stdev = 1.4, n = 4200) in non-eligible students, and 2.4 (stdev = 1.3, n = 4815) in students who did not complete a Free Application for Federal Student Aid (FAFSA; $p < 0.001$). Yet, the distributions of grades for these three groups were similar (Figure 4C).

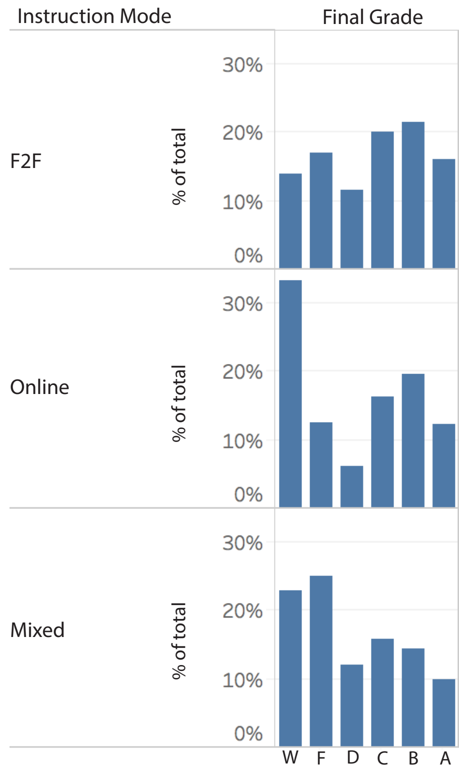

Figure 3: Grade distributions for each instruction mode.

We further tested these patterns using a multi-way ANOVA that investigated interactions between race, gender, and instruction mode. When predicting the mean grade, we recovered no significant interactions, but when predicting final grades (grade "W" included), we recovered a significant interaction between gender and instruction mode ($p = 0.003$). Thus, although different racial groups, and the two gender groups, behave differently in terms of dropping or failing the course, the only differences that predict the final grade are those associated with the interaction of gender and instruction mode.

Nonetheless, there were several factors that did not associate with final grade across all analyses. One of these factors was gender. Not only did gender never contribute to any of the multiple regression models presented in the next section, but we also observed no relationship between gender and instruction mode (Figure 4D). There was no significant different in mean grades between genders as tested using a t-test, but we did observe much higher enrollment in the course by females (n = 10,137) than by males (n = 5649). This imbalance is likely explained by the disproportionate number of nursing students enrolled in this course (38.6%; Figure 5), who were more likely to be female.

3.2 Multiple Regression

After exploring the distribution patterns and testing the difference in means of different variables, we used multiple regression analyses to determine the contribution of each variable to the prediction of final grade (Table 4). The first analysis used all predictor variables to predict the average score (A–F). Grades were treated as a discrete quantitative variable by coding numerically from 1–5. Our final model had a 57.7% accuracy fit to the data based on the AICc value. The program weighed the contribution of each predictor variable to the total model fit. Cumulative GPA had the greatest contribution to the model, explaining 54% of the variance. Cumulative credit hours explained 16% of the variance. These were followed by course section (8%), major college (4%), ethnicity (2%), academic standing (2%), ACT mathematics score (1%), and instruction mode (1%). Thus, GPA and cumulative credit hours explained most of the variance, but several other variables contributed to the model. The analysis was repeated to predict the final grade, which included students who had dropped the course before the end of the semester (grade W). This model fit the data with an accuracy score of 46.8%. Cumulative credit hours explained 50% of the variance, while the course section explained 13%, academic load 12%, GPA 8%, SAT mathematics 5%, College 4%, ACT mathematics 2%, Ethnicity 2%, academic standing 1%, and academic semester 1%.

Finally, we wanted to understand what factors in the data best predicted a student passing or failing the course. Using a logistic regression, we found that the academic load of the student best predicted their passing of the course (Exp(B)= 15.5), followed by completed course hours (Exp(B) = 1.6) and SAT mathematics test score (Exp(B) = 1.0).

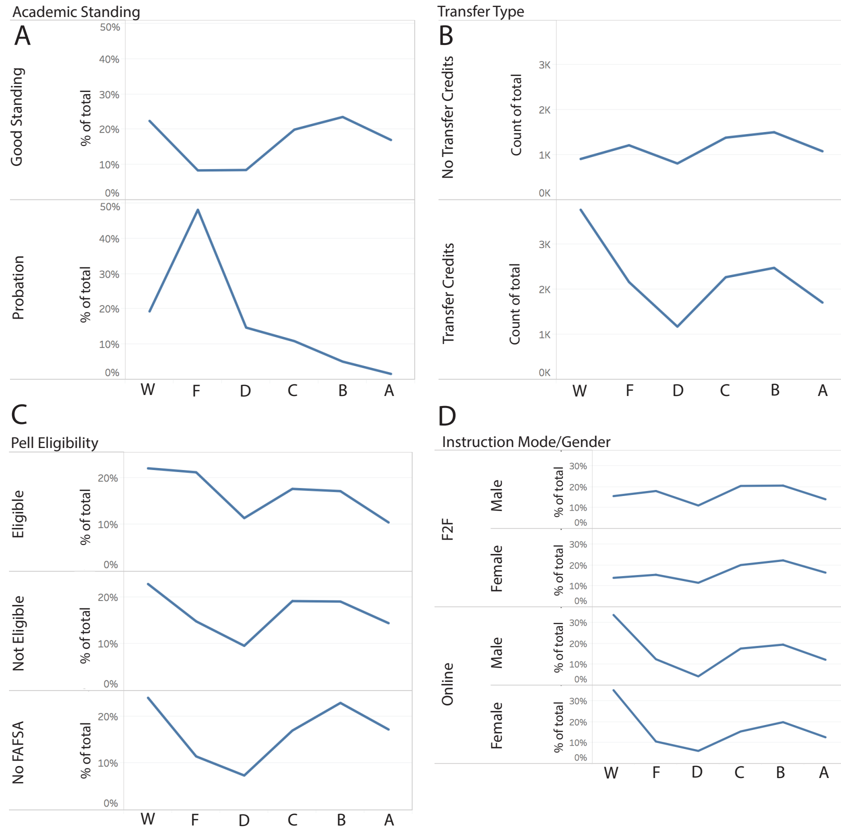

Figure 4. Grade distributions for miscellaneous predictor variables. A) Grade distributions for students in good and poor academic standing. B) Grade distributions for transfer and traditional students. C) Grade distributions for students based on Pell eligibility status, hereserving as a proxy for income. D) Grade distributions for male and female students divided by instruction mode.

Based on these findings, we used simple linear regressions to better understand the influence of GPA and cumulative hours on student course success. We found that for a student to pass the course with at least a D grade, they would need a 2.19 GPA. However, when we removed students who had withdrawn from the course, the GPA needed dropped to 1.55. As for cumulative hours, regardless of the instruction mode, far more students took the course in their first semester than in their second semester (18,504 verses 2,264). This discrepancy suggests that our results should be interpreted with some caution. However, second semester students performed better in the course, regardless of instruction mode, race, or gender (mean = 1.9, stdev = 1.4, n = 13,637 vs. mean = 2.8, stdev = 1.0, n = 2149, t-test $p < 0.001$).

3.3 Principal Component Analysis and Regression of Assignment Scores

Almost all the variation in grades was attributable to a single principal component (eigenvalue = 25.25, 26 variables). The loading scores of each assignment onto this first component roughly increased as the number of assignments increased. Overall the indication was that the final grade was not overly influenced by any one assignment or quiz, and, unsurprisingly, that students who performed well in the latter part of the semester did better in the class overall. The multiple-regression analysis found a significant relationship ($p < 0.001$) between the median time spent on each assignment and the final grade. Thus, students who spent more time working on assignments received a better final grade than those who spent less time.

4 Discussion

Exploration of the data identified several predictor variables associated with large differences in final grade. We found substantial differences between grades based on instruction mode, racial category, academic standing, and previous mathematics experience. Most interesting perhaps is the difference in the distribution of these grades based on certain factors such as race and instruction mode. We found that students from different racial groups, as well as students enrolled in different instruction modes, had different propensities to drop rather than fail the course. Also, we found that different racial groups were more likely to enroll in the online sections, and that this differed by gender within racial groups. Yet, we found no significant differences in grades based on gender. We were surprised in particular to find that students with no prior college mathematics experience scored better on average than those with previous mathematics enrollment. This finding conflicted with that of Tempelaar et al. (2015), who found that prior mathematics experience was a strong positive predictor of performance in college mathematics courses. We hypothesize that this finding is indicative of the students who enroll in introductory mathematics at the University of Texas at Arlington, where no prerequisite mathematics courses are required. Because the course under consideration is introductory, those with prior college mathematics experience likely took a remedial course before entering this course and thus these may be students already at a disadvantage for college-level mathematics courses.

Table 4. Grade Distribution for Selected Predictive Factors*

Section	W	F	D	C	B	A	N	Mean grade	DFW	GPA
All	22.8	16.5	9.7	17.9	19.5	13.6	20460	3.4	39.3	2.7
F2F	4	9.3	9.5	21.9	29	26.0	10403	3.6	13.3	2.5
Online	11.3	8	5.9	20.5	31	23.4	6983	3.1	19.3	2.9
Mixed	7.7	16.4	11.8	20.6	23.7	19.7	30773	3	24.1	2.4
Black	25	23.2	11.9	18.63	13.9	7.3	3188	1.6	48.2	2.4
White	25.5	12.8	8.5	17	21.5	14.8	7761	2.2	38.3	2.9
Hispanic	20.6	18.2	10.7	20	19.7	10.9	4151	1.9	38.8	2.5
Asian-American	13.1	8.9	7.9	17.2	25.9	27	1580	2.6	22	2.8

* All values represent percentages except for the mean grade (0–4 = F–A), and GPA (0–4.0). W = Withdrawal.

Linear modelling with 20 predictor variables revealed that many of the factors we had previously explored had small effects on the students' final grades. The two factors consistently recovered as significant predictors of final grade were the student's GPA, the number of cumulative credit hours a student had, academic load, and course section. The first two variables are positively correlated, as students with more course hours have had more time to accumulate GPA points. These findings support two ideas. The first is that the students' past performance is predictive of future success. Next, second semester students perform better because they have had additional time to develop the study and self-regulation skills that they need to perform well in this course. This emphasizes the need to identify students who have developed skills necessary for success, and to find ways to encourage those who do not yet have these skills to develop them. Due to our finding of only a minor difference in scores between students with or without transfer credits (2.04, 2.07), we do not expect that transfer credits are driving this trend. Multiple regression analyses also support the finding that full-time students perform better than part-time students. These findings may also correspond to our finding that increased time spent on course tasks in the online section (Section 3.3) led to higher mean grades. Finally, our study found that the course section contributed significantly to the linear regression model predicting final grade (grade "W" included). Although many instructors taught several sections in our dataset, no instructor effect was recovered. This suggests that the cohort of students enrolled in a specific course may make a large difference in student grades and may provide a fruitful avenue for future research.

Universities are often interested in creating interventions to prevent students from dropping or failing, as these grades may have detrimental effects on a student's future success. However, the mean grade across a demographic group may not capture a signal of the difference in the propensity of dropping, or staying in the course. For example, this study did not recover a statistical difference in the mean grade for transfer students (2.04) compared to traditional students (2.07). Thus, we could expect that these two populations would exhibit similar grade distributions. However, Figure 4D suggests that transfer students are much more likely to drop than to fail, while traditional students are more likely to fail than to drop. Thus, interventions can be designed differently for transfer and traditional students to target these behaviour patterns (Berger & Malaney, 2003). We observed similar trends in different racial groups, especially when broken down by instruction mode (Figure 3). This sort of information could be used by educators to design interventions that offer certain students additional help to reduce DFW rates (Tinto, 1975; Onah, Sinclair, & Boyatt, 2014). On the other hand, we found that income categories (Pell eligibility) had different mean grades, but the distribution of these grades was similar, indicating that lower- and upper-income students do not behave differently (in terms of their propensity to drop or "stick it out"), but that higher-income students do perform better on average (Figure 4C). This may have more to do with prior experience during high school. Future studies may be able to conduct similar analysis with the inclusion of high school information to test this hypothesis.

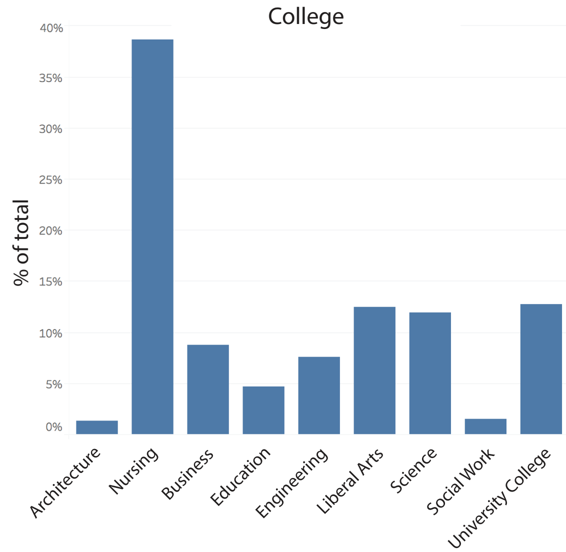

Figure 5. Proportion of students belonging to each academic college. Nursing students contributed the largest proportion of enrolled students in this study.

Our study corroborated the findings of many past studies, especially in showing that online and minority students performed more poorly than F2F and White or Asian-American students. However, we also found that when analyzed together, race and instruction mode contributed little to the likelihood of a student succeeding in the course. Rather, the student's GPA, prior course credits, and academic load best predicted a high final grade. This suggests that new and low-performing students should be targeted for intervention rather than certain racial, gender, or instruction mode categories (Heublein, 2014; Stinebrickner & Stinebrickner, 2014). Perhaps the driver of lower online scores has more to do with the types of students participating in these courses, rather than the format of the course. Yet we found that students in online courses had lower average cumulative hours (F2F = 9.6, stdev = 4.7, n = 10,613; Online = 6.8, stdev = 5.3, n = 7017; Mixed = 8.6, stdev = 5.0, n = 3138; $p < 0.001$), but higher average GPAs (F2F = 2.5, stdev = 1.0, n = 10,613; Online 2.9, stdev = 1.0, n = 7017; Mixed = 2.4, stdev = 0.9, n = 3138; $p < 0.001$).

Our analysis of online students found that no individual assignment or quiz significantly influenced the final grade. Rather, the amount of time students spent working on assignments was the best predictor of final grade. This suggests that students who put more effort into the course performed better. Nonetheless, it can be misleading to correlate time spent with effort. For this reason, students who spend more time could be those who are working harder to understand the material, or those most engaged with the course (Zacharis, 2015). In either case, we would expect a positive relationship between effort (time spent) and grade. Alternatively, this could represent the demographic who are struggling the most with the material, though if this were true, we would expect an inverse relationship between time spent and overall grade. Past research primarily supports the first hypothesis, that students who work harder in the course (more time spent) perform better (Cheema & Sheridan, 2015; Farkas, Mazurek, & Marone, 2015).Overall, this relationship suggests that any effort on the part of the instructor that encourages students to spend more time with the material may prove beneficial. It also suggests a way for instructors to take immediate action and points to a region of pedagogical methodology that needs further investigation and development. Regression analysis suggested that full-time students were more likely to pass the course than part-time students, presumably because they are working less at an external job.

5. Conclusions and Implications for Practitioners

Practitioners and researchers need to be careful in trying to apply a "one size fits all" approach, as this study found that course section also had a notable effect on student performance. This suggests that some level of performance is section/course specific rather than student specific (Gašević, Dawson, Rogers, & Gasevic, 2016). Additionally, it should be noted that these results are from a study at one university with a higher diversity in student population than many other universities, so results may not transfer to other institutions. However, practitioners wishing to act upon these results should primarily focus on a student's GPA, number of incoming credit hours, and academic load to predict student success and develop early interventions. We suggest that academic advisors could be equipped with this knowledge to encourage at-risk students (part-time, new, and low GPA) to seek tutoring or other help. In addition, at-risk students could be identified and targeted by instructors using new online tools (Pardo et al., 2017). Future research projects could identify students who have taken a prior mathematics courses and investigate the specific factors or skills that contribute to current success. Finally, investigators may be able to target students based on the amount of time they are spending on assignments to better understand what time spent means for student course performance.

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Appendix A.

Table 2. Summary of Statistical Analyses used in this Study

Modelling Method	Prediction/Test
T-test	Compare means between demographic groups
ANOVA	Compare means between demographic groups
Multiple Regression	Discrete Grades A–F
Binary logistic Regression	Pass Fail
Principal component analysis	Association between assignments/quizzes and final grade
Multiple Regression	Time spent and Final Grade

* All values represent percentages except for the mean grade (0–4 = F–A), and GPA (0–4.0). W = Withdrawal.

Table 3. Additional Summary Statistics

Subcategory	Category	Percent of course demographic
	Instructional Mode	
F2F		50.8
Online		34.1
Mixed		15.0
	Major College	
College of Nursing and Health Innovation		38.7
University College		12.8
	Gender	
Male		34.2
Female		65.8
	Academic load	
Full time		65.1
Part time		34.9
	Race/Ethnicity	
White (Total)		37.9
Hispanic (Total)		20.3
Black/African American (Total)		15.6
Asian-American (Total)		7.7
	Academic Standing	
Good standing		77.7
Probationary status		20.7
	Transfer Type	
Some transfer credits		79.5
No transfer credits		20.4
Some transfer credits (F2F)		91.1
Some transfer credits (online or mixed methods)		64.7

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Total course credit hours	
Average credit hours (all sections)	8.5
Pell Status	
Eligible	42.6
Not eligible	26.6
Did not apply for FAFSA	30.9
GPA	
Mean all sections	2.64
Mean F2F	2.64
Mean online	2.59
Mean mixed mode	2.54
Prior College Mathematics	
Yes	36
No	64

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