Predictors of First-Year Retention among Undergraduate Engineering Students Who Earn a C in their First-Semester Math Course

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Abstract

This Complete Research Paper examines non-cognitive predictors of first-year engineering retention for students who received a C in their first semester mathematics course at the University of Louisville. Scores across eight non-cognitive measures served as model predictors, obtained at the beginning of the first year, including: value interest in engineering, perceived effort, opportunity, and psychological costs, perceived belonging uncertainty, contingencies of self-worth: academic competence, test anxiety, and self-efficacy. Using least absolute shrinkage and selection operator regression, we found that value interest and test anxiety were the strongest predictors of C-student retention. The results from this study inform research on the decision-making of students that have potential for graduation but are at risk of leaving engineering. Our results indicate that a strategic intervention in increasing interest in engineering may lead to strong gains in engineering retention at this university, and potentially others as well.

Introduction

Increasing the number of engineers in the US is a national priority [1], [2]. In addition to attracting more K-12 students into engineering undergraduate programs, improving the retention of these programs is also critical to produce more graduates. Keeping students in engineering has proven to be a difficult task due to many deterring factors such as challenging curricula, competitive classroom environments, and feelings of isolation and imposter syndrome (e.g., [3]). Over 40% of a typical engineering student cohort leaves engineering before completing a degree [4].

One major predictor of engineering student retention is their performance in first-year mathematics courses [5]–[7]. Many students who do not perform well in their first semester of mathematics do not stay in an engineering major, and vice versa, students who perform well tend to complete their degree. Because of this filtering effect, calculus is widely acknowledged as a barrier course for undergraduate engineers [8]–[11]. Performance in STEM barrier courses is a strong predictor of engineering student retention.

Performance in calculus is often linked to high school mathematics preparation [12]–[15]. Generally, engineering students have performed well in their high school mathematics courses, however the content and quality of the courses vary. Some students enter college having taken a precalculus course, while others have taken AP calculus or even advanced college calculus courses. Level of mathematics course alone has been found to predict performance in first-year engineering mathematics courses. High school mathematics preparation has also been to predict engineering retention directly.

In addition to mathematics preparedness, many non-cognitive and demographic factors have been found to be significant predictors of engineering retention. Motivational factors such as self-efficacy [3], [16], [17], sense of belonging [18], [19], interest in engineering [3], [20], and expectancy-value beliefs [21], as well as test-anxiety [14], [22], [23], all have been found to affect persistence in engineering. Engineering education researchers have suggested that engineering students be considered holistically to understand the many reasons for attrition and to improve retention rates [24].

Several theoretical models have combined non-cognitive and performance elements to better predict engineering student retention. Veenstra, Dey, and Herrin [25] proposed a progressive model of pre-college characteristics, first year experiences, and first year performance. Bean and Eaton [26] proposed a more cyclical psychological progression, with initial psychological factors developing during students' first year experiences, and mid-point psychological variables leading to better or worse integration and performance. Hargrove and Burge [27] proposed a six-sigma model for improving retention. In these models, performance, psychological parameters, and the institutional environment are all utilized.

Because we know that many factors are important for student retention, and that performance is specifically predictive, in this paper we analyzed the students that were "at-risk" yet still capable of graduating: the students who received a C in engineering mathematics in their first semester. By narrowing the sample to C-students, we eliminated performance as a variable and were able to investigate other non-cognitive factors more directly. At the J. B. Speed School of Engineering at the University of Louisville, 34% of the engineering students get a C in their first semester math course. Prior research at this University indicated that students who earned an A or B in their first semester math course were very likely to be retained, and that students who earned a D or F were very likely to leave engineering. After two complete years in the engineering school, the students who earned C in their first math course had either completed the four-semester math sequence (a strong predictor of graduation), were still enrolled in the math sequence, or were not retained in the engineering school. These prior results are represented in Figure 1 from [28].

At J. B. Speed School of Engineering, a survey is administered online at the beginning of the fall semester to all first-year engineering students. The survey is the result of the collaboration of an interdisciplinary research group (GEARS – the Guild for engineering Education, Achievement, Retention, and Success) over the last 10 years [29]. This group includes members from departments of Engineering Fundamentals, Psychological and Brain Sciences, Education, and Educational Psychology, as well as members of student and faculty success programs at the university. Students are given time in their introductory engineering methods course to complete the survey, and as a result, response rates are typically over 90%.

This paper presents the analysis of the non-cognitive factors from the first-year survey to determine which factors best predict first year retention for students who received a C in their first math course.

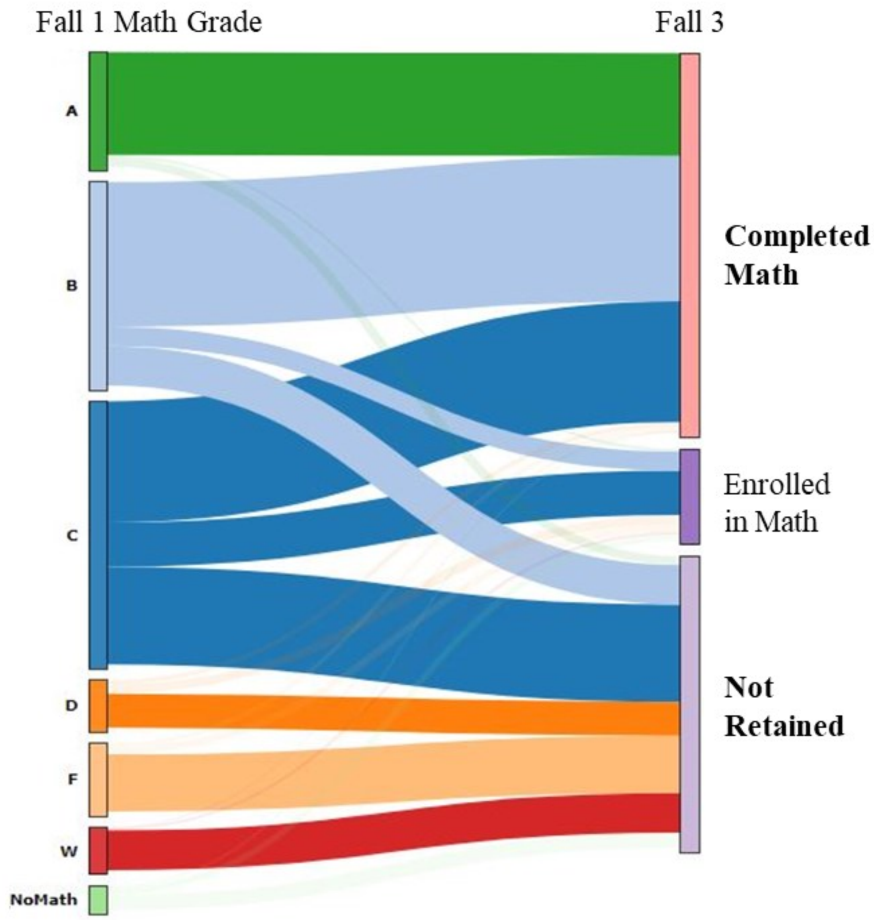

Figure 1: Initial math performance and corresponding math completion rates (a proxy for graduation rates) at the J. B. Speed School of Engineering at the University of Louisville, as reported in [28].

Methods

This study was approved by the Institutional Review Board.

Data

Demographic, performance, and survey data was gathered for all students within the first-time full-time 2018 cohort who earned C grade in their first undergraduate mathematics course ($N = 163$). This represented 32.79% of the first-year students (total cohort $N = 497$). Among the sample, 77.91% ($n = 127$) were retained after the first year, whereas 22.09% ($n = 36$) did not re-enroll. The sample was 20.9% Female, and 82.8% White, 4.9% African American, 3.7 % Latino, 3.7% Asian, and 4.3% Two or more races.

Instrumentation

A total of eight indicators were included in the model to predict persistence (defined as summer enrollment) after the first year. Students' average scores were calculated for each scale.

Value Interest. Five-item survey designed to measure students' beliefs towards their value interest in engineering (5-point Likert scale: 1 = *Not at All* to 5 = *Very True*; [30]). Example items include: "Engineering is practical for me to know," and "Engineering is exciting for me." The Cronbach's coefficient alpha was .89.

Cost Effort. Four-item survey designed to measure students' beliefs towards the cost associated with their effort in engineering (6-point Likert scale: 1 = *Strongly Disagree* to 6 = *Strongly Agree*; [31]). Example items include: "I am anxious about whether I fit in at college," and "When I face difficulties in college, I wonder if I really fit in." The Cronbach's coefficient alpha was .81.

Cost Opportunity. Four-item survey designed to measure students' beliefs towards the cost associated with the opportunity to pursue engineering (6-point Likert scale: 1 = *Strongly Disagree* to 6 = *Strongly Agree*; [31]). Example items include: "I'm concerned that I have to give up a lot to do well in engineering school," and "Studying for engineering school takes a lot of time away from other activities that I want to pursue." The Cronbach's coefficient alpha was .81.

Cost Psychological. Three-item survey designed to measure students' perceived psychological costs associated with engineering (6-point scale: 1 = *Strongly Disagree* to 6 = *Strongly Agree*; [31]). Example items include: "I'm concerned about being embarrassed if my work in engineering school is inferior to that of my peers," and "I worry that others will think I am a failure if I do not do well in engineering school." The Cronbach's coefficient alpha was: .86.

Belonging Uncertainty. Three-item survey designed to measure students' personal sense of uncertainty with being in engineering (5-point Likert scale: 1 = *Strongly Disagree* to 5 = *Strongly Agree*, [32]). Example items include: "I'm concerned about being embarrassed if my work in engineering school is inferior to that of my peers," and "I worry that others will think I am a failure if I do not do well in engineering school." The Cronbach's coefficient alpha was .81.

Contingencies of Self Worth: Academic Competence. Four-item survey designed to measure students' personal sense of worth associated with their academic achievement (7-point scale: 1 = *Strongly Disagree* to 7 = *Strongly Agree*, [33]). Example items include: "My opinion about myself isn't tied to how well I do academically," and "My self-esteem is influenced by my academic performance." The Cronbach's coefficient alpha was .78.

Motivated Strategies for Learning Questionnaire (MSLQ): Test Anxiety. Five-item survey designed to measure students' personal sense of worth associated with their academic achievement (7-point scale: 1 = *Strongly Disagree* to 7 = *Strongly Agree*; [34]). Example items include: "When I take a test, I think of the consequences of failing," and "I feel my heart beating fast when I take an exam." The Cronbach's coefficient alpha was .85.

MSLQ: Self-Efficacy. Seven-item survey designed to measure students' personal sense of self-efficacy associated with their academic achievement (7-point scale: 1 = *Strongly Disagree* to 5 = *Strongly Agree*; [34]). Example items include: "I'm confident I can understand the most complex material presented by the instructor in this course," and "I'm certain I can master the skills being taught in this class." The Cronbach's coefficient alpha was .92.

Data Analysis

We first looked carefully at descriptive and inferential statistics to examine the predictive utility of non-cognitive self-beliefs to predict persistence after the first year among students with an earned C grade in their first mathematics course. Descriptive statistics were used to understand students' standing across the non-cognitive measures, whereas Pearson Product moment correlation was used to examine the strength and association of the relationship among the study variables.

The least absolute shrinkage and selection operator (lasso, [35]) was used for parameter estimation and to identify significant predictors of engineering persistence after the first year, based on a logistic regression model. Lasso represents a regularization approach to prediction that addresses concerns associated with model overfitting with traditional regression approaches (e.g., ordinary least squares, [36]). Specifically, regularization methods (e.g., ridge [37], elastic net [38]) overcome model overfitting concerns through the use of a penalty parameter that constrains the regression coefficients. Instead of each predictor having a nonzero regression coefficient, the penalty parameter, or tuning parameter (λ), suppresses the regression coefficients such that some are equal to zero. Thus, those with little relationship to the outcome are suppressed, and only the strongest predictors are retained in the final model with nonzero coefficients. The tuning parameter restricts the magnitude of the regression coefficients, which can range from 0 to ∞. As λ approaches zero, the lasso regression coefficients approach those obtained in a traditional regression model. Higher λ values place a greater restriction on estimated regression coefficients resulting in their values being approximately, or equal to, zero. Predictor variable selection occurs with the sequential addition and removal of variables until a desired criterion is reached (i.e., low prediction error). Those predictor indicators with nonzero regression coefficients are kept in the model and those with values of zero are dropped from the model. The downward bias of regression coefficients reduces the variance of the coefficients and results in more stable parameter estimates to generalize the estimates beyond the study sample [39].

In this study, cross-validation was used to identify an appropriate tuning parameter for the lasso model to apply logistic regression. First, the data was randomly divided into training (80%) and test (20%) samples. Cross-validation included randomly partitioning the training data into 10 folds. The model was sequentially applied to each of 9 folds; one-fold served as the training data and the 9 folds were the test data. The tuning parameter is that which has the lowest error associated with the estimated model coefficients. Subsequently, the full lasso model is conducted using the selected tuning parameter to estimate the final model parameters (e.g., regression coefficients). Subsequently, the test data was used to determine the model's accuracy to correctly predict students' retention after the first year (0 = *was not retained*, 1 = *retained*).

Results

Table 1 reports the descriptive statistics of the study variables, including the minimum and maximum scores. Higher scores are indicative of increased standing on the measured trait. For example, on average, students' Value Interest ratings fell between true and very true, with scores falling between 2.50 and 5. In terms of cost effort, students generally disagreed that there were high costs associated with engineering (e.g., "For me, engineering school just might not be worth the effort"). Except for Value Interest and Academic Competence, students' scores spanned the entire score continuum.

Table 1: Descriptive Statistics of Study Variables (N = 163)

Scale	Likert Max.	No. Items	Mean	SD	Minimum	Maximum
Value Interest	5	8	4.23	0.60	2.50	5.00
Cost Effort	6	4	2.32	1.00	1.00	6.00
Cost Opportunity	6	4	3.58	1.30	1.00	6.00
Cost Psychological	6	3	3.74	1.46	1.00	6.00
Belonging Uncertainty	5	3	2.04	0.94	1.00	5.00
Academic Competence	7	4	5.66	0.94	3.00	7.00
Test Anxiety	7	5	4.30	1.44	1.00	7.00
Self-Efficacy	7	7	5.22	0.98	1.57	7.00

Table 2, below, reports the correlations among the study's predictor variables. As reported, the correlation among scores ranged from negligible to moderate. The strongest relationships were between Value Interest and Cost Opportunity (r = 0.58), followed by Test Anxiety and Cost Psychological (r = 0.47) and Belonging Uncertainty (r = 0.44), indicating students' general sense of uncertainty of belonging and psychological cost were moderately related to their corresponding test anxiety. Overall, correlations were in the expected direction and suggest that the predictors are not overly redundant for consideration in the subsequent regression analysis.

Table 2: Correlation among Study Variables

Scale	1	2	3	4	5	6	7	8
1. Value Interest	1.00							
2. Cost Effort	-.30	1.00						
3. Cost Opportunity	-.18	.58	1.00					
4. Cost Psychological	-.11	.42	.47	1.00				
5. Belonging Uncertainty	-.25	.36	.37	.45	1.00			
6. Academic Competence	.17	-.08	.06	.39	.19	1.00		
7. Test Anxiety	-.04	.31	.37	.47	.44	.26	1.00	
8. Self-Efficacy	.31	-.34	-.31	-.35	-.36	-.07	-.35	1.00

Cross-validation resulted in the tuning parameter (minimum lambda) of 0.036 for use in the full lasso model. The subsequent lasso model resulted in two statistically significant ($p < 0.05$) predictors of persistence after the first year, among students with an earned C in their first mathematics course. Specifically, Value Interest had a reported regression coefficient of 0.36, and Test Anxiety had a reported regression coefficient of 0.09. Model accuracy, based on the test sample data, indicated a classification accuracy of 0.7812, or 78.12%.

Discussion

This analysis examined non-cognitive factors associated with engineering persistence among students earning a C in their first semester mathematics course. Students with a C in engineering mathematics have performed well enough to be able to succeed in engineering school but may not persist for other reasons. Of the variables included in the analysis, the best model consisted of two factors: value interest and test anxiety.

Table 3: Lasso Coefficients (*ns* = Non-significant)

Predictor	**Coefficient**
Intercept	-.64
Value Interest	.36
Cost Effort	*ns*
Cost Opportunity	*ns*
Cost Psychological	*ns*
Belonging	*ns*
Academic Competence	*ns*
Test Anxiety	.09
Self-Efficacy	*ns*

Interest in engineering is commonly reported to be a significant factor for retention (e.g., [31], [40]). It is not surprising that a students' incoming interest in the field would cause them to persist through the new experiences in engineering school such as high workloads, competitive grading, and increased time management expectations. The interesting finding is that value interest predicts retention better than factors of cost-value, belonging, academic competence, and self-efficacy that are also commonly cited in the literature. Our elastic-net regression analysis allowed us to vary the weights of each of these factors in a regression to determine the model with the best fit. Traditional logistic regression could have resulted in several significant factors without generating a predictive model.

The other significant factor in our model was test anxiety. The regression coefficient was positive, indicating that students with higher test anxiety were more likely to be retained in engineering after the first year. Although test anxiety can have a negative effect on achievement (e.g., [41], [42]), it has been described as following a Yerkes-Dodson inverted U-shaped curve [43]. This curve describes an increase in performance with respect to text anxiety up to some quantity, after which performance decreases. Very low and very high test anxiety result in the worst performance. It is therefore possible that a mean increase in test anxiety could increase performance if it started on the lower half of the curve. Alternatively, it is also possible that students received lower grades due to test anxiety. A student with more knowledge but higher test anxiety may get a C grade due to test anxiety but might be more successful later on. Lastly, it should be noted that the regression coefficient value was small (.09). Because we do not know the exact reason for this positive coefficient, more detailed investigations are needed before such an intervention is recommended.

The current analysis is limited to a single cohort at a single university. We plan to replicate this study using additional cohorts as part of our future work.

Conclusions and Future Work

This paper presented an elastic-net regression analysis of non-cognitive factors to predict engineering retention for students who received a C in mathematics. We found that of the eight factors measured in an annual survey, value interest and text anxiety were significant predictors of first-year retention. Results indicate that a value interest intervention may increase retention for students who receive a C in mathematics in their first semester at the J. B. Speed School of Engineering. Curricular ways to improve interest in engineering include design-based learning experiences, introducing current real-world engineering challenges, and connecting students to potential employers. Future work will include identifying or designing an interest intervention and measuring its impact with a controlled research design.

In addition to designing an interest intervention for C-students, we plan to do several more analyses to get a better understanding of factors that influence retention at our engineering school. We will look in more detail at the relationship between test anxiety and retention, run analyses for different cohorts to see if similar factors are significant, and look at responses to surveys taken at the end of the first semester. We will also run similar analyses on different breakdowns of the data such as gender, race, and SES. Identifying interventions that improve retention of underrepresented minorities and at-risk students are incredibly valuable.

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