Modeling Engineering Persistence through Expectancy Value Theory and Machine Learning Techniques

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***Abstract*—This Research to Practice Full Paper presents an investigation of engineering retention using machine learning models. We use random forests and artificial neural networks in the form of multilayer perceptrons to analyze the interaction between different factors, such as demographic information, standardized test scores, first semester grades, and surveys to predict student retention in engineering. We find that obtained models can predict with good accuracy if students will remain in engineering, with F1 scores of at least 75 percent. We find that each model places different levels of importance on distinct factors.**

***Index Terms*—STEM education, retention, expectancy value theory, machine learning**

I. Introduction

The science, technology, engineering, and mathematics (STEM) workforce is critical to US national innovation and competitiveness [1]. Despite the critical importance of these skills, the growing demand, and the high-paying careers that follow from a successful STEM education, low retention rates of undergraduate students in STEM fields have been a persistent problem [2]. High dropout rates in engineering programs are common across many universities.

Persistence in engineering depends upon a wide variety of interrelated factors (e.g., pre-college preparation, first-semester grades, scholarship requirements, minority status, and noncognitive attributes) [3], [4]. A relevant framework that describes students' academic decision-making holistically is the Situated Expectancy Value Theory (SEVT [5]–[7]). SEVT suggests that students persist in engineering based upon their (a) expectations of success, and (b) the perceived value and costs of an engineering degree. As evidenced in Eccles (2020) [6], the breadth and depth of variables of the full SEVT framework is quite extensive. The number of variables and interactions is too large for typical quantitative analyses like binary logistic regression, and research is often reduced to one or a limited number of important factors [8]. But considering all the factors simultaneously may be necessary to understand the whole picture of why a student chooses to remain in, or drop out, of engineering school. For example, numerous papers have researched the interplay of sex, race, and expectancy value theory [9]–[14]. A potential interaction would be if members of minority racial or gender group had lower views of their academic competence due to imposter syndrome.

Machine learning tools can consider these complex systems. Neural networks, for example, have been called "universal approximators" for their ability to handle a multi-dimensional space with a high degree of accuracy [15]. Multilayer Perceptron (MLP) is a class of feedforward artificial neural networks. An MLP consists of systems of interconnected perceptrons, the basic unit in artificial neural networks emulating a neuron cell, that applies nonlinear activation functions over the linear combination of its inputs. Such modeling approach aims at a nonlinear mapping between input and output vectors. It is the superposition of many simple nonlinear transfer functions that enables MLPs to approximate extremely complex behaviors [16]. Random forest models, alternatively, are a combination of decision tree predictors (i.e., an ensemble learning method), where the predictions are derived from in individual trees. This method was derived to mitigate the underlying "overfitting" issue that occurs with individual predictors.

Various machine learning tools therefore provide opportunities for researchers to understand student persistence in engineering. However, to make improvements in engineering persistence, more work is needed beyond understanding important factors at play. One potential action is to intervene on the most important factor for a whole cohort of students. For example, Walton and Cohen aimed to improve undergraduate students' "sense of belonging" and found a significant improvement in persistence [17]. However, other researchers did not find the same improvement with the same intervention [18]. Although there are many potential reasons that this work may not have replicated, one is the difference between institutions - different factors may be important in different contexts. Similarly, different factors may be important for different students.

Another tactic would be to first identify students that are likely to leave engineering and identify the important factors for each student at risk, and intervene with targeted interventions. Having an accurate predictive model would allow researchers to meet the needs of specific students. For example, we found in previous work that approximately half of the students who received C's in their first math course stayed in engineering [19], making them a unique sample for targeted interventions, as shown in Figure 1. If we could identify which of these students would leave based on other factors, we could intervene for those individuals alone. To the best of the authors' knowledge, no research to date has followed this strategy.

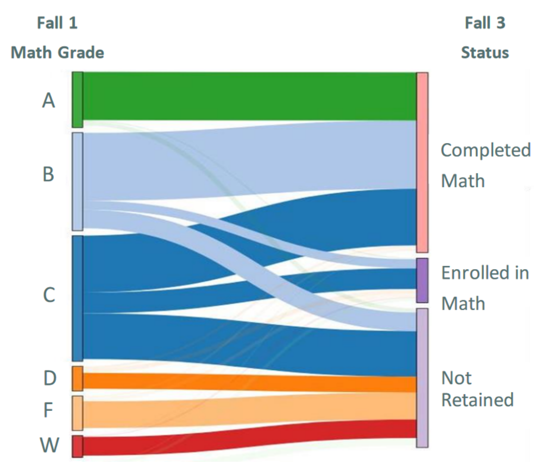

Fig. 1. Engineering persistence based on first-semester math grade as reported in [19]. C students are equally likely to leave or stay, revealing that math performance is not the only important variable in engineering persistence.

Therefore, in this full-length research paper, we investigate undergraduate engineering retention at the University of Louisville by using machine learning techniques to complete two goals: (1) develop a predictive model using demographic and noncognitive factors alongside first semester grades simultaneously, and (2) use the predictive model to identify student groups that are similarly at risk for attrition that may respond to targeted interventions. As mentioned earlier, we found that students who received a C in their first mathematics course were good candidates for interventions. In previous work [20], we conducted preliminary analyses with academic performance and SEVT survey data. In the current work, we expanded the analyses by adding demographic and financial aid data. This new analysis looks to examine the importance of all these factors in the engineering persistence predictive models.

Our research questions are as follows:

- RQ1: What is the accuracy of various machine learning models in "flagging" students at risk of dropping out of engineering at our university?
- RQ2: Are SEVT scores and demographics enough to accurately predict student retention?
- RQ3: Which tool has better performance: a random forest or multilayer perceptron model?
- RQ4: What are the biggest factors in predicting student retention at our university?

II. Methods

A. Data

We retrieved de-identified student data gathered from our engineering students over the 2018-2019 school years, with restricted inclusion of first-time full-time students in fall of 2018 or 2019 (N = 995). The study was approved by the university's institutional review board.

The SEVT survey was administered at the beginning of the first semester. Survey items included measurements for (1) self-efficacy [21] and (2) contingencies of academic competence (academic competence subscale [22]), (3) interest in engineering [23], and (4) perceived costs of engineering school [24]. Scales 1 and 2 are expectancies, whereas scales 3 and 4 are subjective task values with respect to pursuing a degree in engineering.

Table I specifies all features (input variables) included in the analyses to predict retention result (whether student stayed in the engineering school in the fall of the second year). Of the 995 students, 291 (29.5%) left engineering school before the fall of second year. It is important to highlight that some of the input features included in the early stages of this study are related to our attempt to answer RQ4. Meaning that one of our research interests is to explore and identify which factors play a significant impact in our models prediction capabilities. Hence, some features presented in Table I will not be included in our final predictors, based on the importance of these factors in the models performance.

B. Analysis

1) Data Pre-processing: Categorical variables were dummy coded. First-term letter grades were standardized to the 4.0 scale, with students who failed or withdrew coded as 0. Continuous variables (ACT score and survey rating score) were standardized from 0 to 1.

2) Predictive Modeling: Predictive modeling was conducted with the Random Forest (RF) [25] and the Multilayer Perceptron (MLP) [26] algorithms. RF and MLP are two well-known traditional nonlinear machine learning models we chose to begin with. In future work, we hope to expand to other machine learning models. Records with missing data

TABLE I
INPUT VARIABLES

Demographics	
Sex	Male, Female
Race	Including four categories: White, Asian, Black/African American, Hispanic/Latino
Grades	
ACT Score	English, Math, Science, and Composite
First-term Grades	Math, Chemistry, Physics and Engineering Fundamentals
SEVT Survey	
Self-efficacy	8 items, from [21]
Academic Competence	5 items, from [22]
Interest in Engineering	8 items, from [23]
Effort Cost	4 items, from [24]
Opportunity Cost	4 items, from [24]
Psychological Cost	3 items, from [24]
Financial Aid (FA)	
Eligibility category	Whether the student was eligible for financial aid based on merit or need
Sources of awarded FA	Private (third party), institutional, federal, state, other
Type of awarded FA	Scholarship, grant, loan, work-study

were excluded. Python packages from the scikit-learn library were used for programming.

To estimate the predictive performance, we performed 10-fold cross-validation for all modeling: the whole data sample was shuffled and randomly divided into 10 portions, and each portion take turns to be the test set. We assessed predictive capacity with metrics of accuracy, precision, recall, and F1 score as the means of the 10-folds.

"Accuracy" is the percentage of correct predictions. *"Precision"* is a metric accounting for the ratio between the number of student's retained and correctly predicted so, divided by the total number of students predicted to be retained. The *"Recall"* metric is a similar ratio, but here the models predicted number of retained students are divided by the total true number of retained students. *"F1 Score"* is the harmonic mean between the precision and recall metrics. For binary classification, 50% accuracy means the model has no predictive power (i.e., it is by chance), whereas greater than 90% accuracy potentially indicates an overfit model. A satisfactory performance is highly dependent on the specific domain/problem. However, since this is an exploratory analysis, we do not have expectations of predictability for these variables and this outcome. We therefore look for higher (but not greater than 90%) F1 values to determine the relative success of the models.

We were interested in testing the predictive power for different conditions: 1) predicting the retention results of all students; and 2) focusing on the students who got a C grade in their first-term math course, since their retention decisions seemed to be the most diverse from our previous analysis. In addition, we were also interested in 1) modeling with all features available; 2) testing the predictive power of SEVT, demographics and financial aid data with grades excluded, since from previous study we have already known that grades had biggest predictive power. Therefore, there were four modeling scenarios: *i* - prediction with all students and all features, *ii* - with all students but excluding grades from the analysis, *iii* - only students with C in math and all features, and *iv* - only on students with C in math but excluding the remaining grades from the analysis. For each scenario we tested both RF and MLP, giving a total of 8 scenarios to be tested.

3) Inspection on Permutation Feature Importance: There has been recent interest on inspecting the biases of machine learning models, as well as trying to explain black box models [27]. One method that emerged was the permutation feature importance [25]. For a trained model, it estimates the importance of a feature by calculating the change in the model's prediction performance after permuting the feature. This method does not require retraining the model, and because it is model-agnostic, it is comparable across different models. It is noticeable that importance is given to the feature in the particular model, which is not necessarily reflective for the whole dataset - it may underestimate the importance of variables if their impact was mediated by other variables (i.e. if the input variables were highly-correlated) [28]. In the current study, we calculated the permutation feature importance for all models (importance score again calculated as the mean of 10-folds), and show the results below.

III. RESULTS

A. Demographics and Descriptive Statistics

The demographic information of the students is shown in Table II. This table shows that females at our university are more likely to be retained than male students, and Asian students are more likely to be retained than other races. Financial aid data is given in Table III. Our university automatically grants scholarships based upon high school GPA and standardized test scores. As many students who are enrolled in our engineering program have high GPAs and test scores to be admitted, we see that most of our students have merit scholarships.

Figure 2 shows the comparison between students who were retained and not retained in the average of SEVT values. The differences in average were not huge, but students not retained generally showed lower self-efficacy, interest in engineering, and academic competence. Figure 3 shows the comparison between students who were retained and not retained in the median of first-term grades and ACT scores. Here we see an apparent difference in the math and chemistry grades.

B. Prediction Performance

Table IV shows the prediction performance of models with all features used. The highest score we achieved was over 97 percent recall for predicting if students were retained in engineering if they received a C in math. Generally, our models were better at recall than precision.

Table V shows the prediction performance of models with ACT and first-term grades excluded. When we compare Table V with Table IV, we see a modest drop in F1 scores when we predict retention among all students. Interestingly, we see that the models perform similarly for students who receive

TABLE II
DEMOGRAPHICS

Category	n	% of Data	% Retained
Sex			
Male	778	78.19%	68.12%
Female	217	21.81%	80.18%
Race			
White	797	80.10%	70.01%
Asian	60	6.03%	78.33%
Black/African American	46	4.62%	69.56%
Hispanic/Latino	44	4.42%	68.18%
Economic			
Pell-Eligible	253	34.09%	66.40%

TABLE III
FINANCIAL AID DATA

Category	n	% of Data	% Retained
Category			
Merit	981	98.59%	70.94%
Need	400	40.20%	66.75%
Type			
Grant	283	28.44%	67.84%
Scholarship	965	96.98%	71.08%
Loan	433	43.51%	65.12%
Work-study	29	2.914%	72.41%
Source			
Federal	525	52.76%	66.85%
Institutional	861	86.53%	72.24%
Private	317	31.85%	75.07%
State	810	81.40%	71.08%

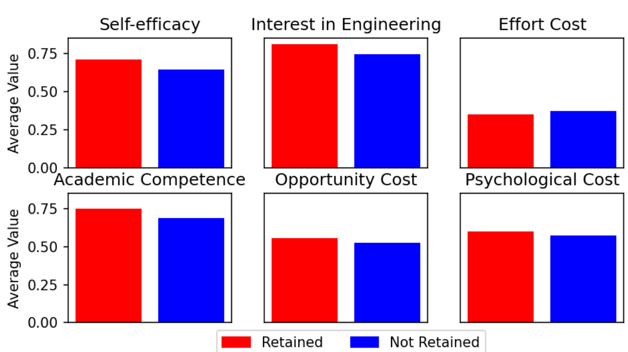

Fig. 2. Average Values for SEVT framework

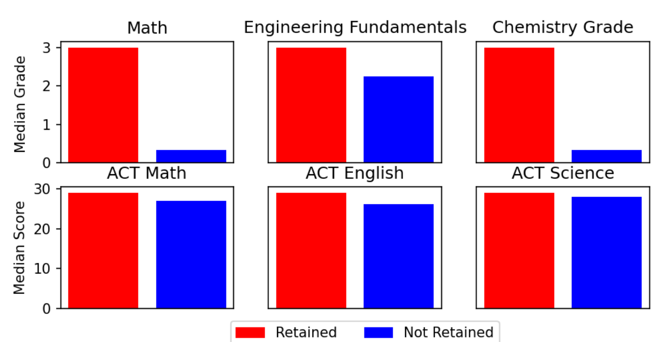

Fig. 3. Median first-term grades and ACT scores.

TABLE IV
PREDICTION PERFORMANCE OF MODELS WITH ALL FEATURES

	Accuracy	Precision	Recall	F1 Score
All students				
RF	80.69%	82.80%	91.99%	87.00%
MLP	80.50%	84.13%	89.61%	86.67%
C math students				
RF	76.93%	78.70%	96.56%	86.47%
MLP	74.19%	77.72%	94.27%	84.80%

C's in math with or without grades included. This suggests that for students who receive C's in math, non-grade factors are important at retention prediction. In both Table IV and V, we see that the RF predictors performed slightly better than the MLPs, which suggests, as shown in the next section, that SEVT can be a good way to determine if students are retained.

TABLE V
PREDICTION PERFORMANCE OF MODELS WITH GRADES EXCLUDED

	Accuracy	Precision	Recall	F1 Score
All students				
RF	69.75%	72.14%	93.18%	81.29%
MLP	66.64%	72.98%	83.89%	77.98%
C math students				
RF	74.61%	76.99%	95.90%	85.08%
MLP	71.45%	78.40%	88.01%	82.22%

C. *Inspection on Feature Importance*

While we see in Table IV and Table V that our models are quite accurate, it is also important to understand what variables are most relevant in the model's decision in predicting student persistence. Figures 4 to 7 presents the main results of the permutation feature importance analysis for both predictive models (RF and MLP). In Fig. 4 results for the scenario where all student data and all available features considered is presented, while Fig. 5 relates to the scenario also considering all features but focusing on the students with C in first-term math course. Similarly, Fig. 6 addresses the scenario where all student data is considered, but ACT and first-term grades excluded, whereas, Fig. 7 presents the scenario also excluding ACT and first-term grades excluded, but targeting C students. More in depth discussions of these findings will be presented in the next section.

IV. DISCUSSION

We see that across our various predictive models when we include all available factors, the demographics of our students consistently ranked relatively low in importance in comparison to grades and ACT scores. Gender ("Sex") ranked 8^{th} in importance for predicting retention for C math students in the MLP model with all factors (see Fig. 4), which is the highest ranking achieved by a demographic indicator. When we take out grades and ACT scores (Figs. 6 and 7), we begin to see an increased relevance of financial aid information in the MLP predictor and SEVT metrics in the RF model. Additionally, as both models still perform quite well when excluding this data, as shown in Table V, this suggests that we can still create

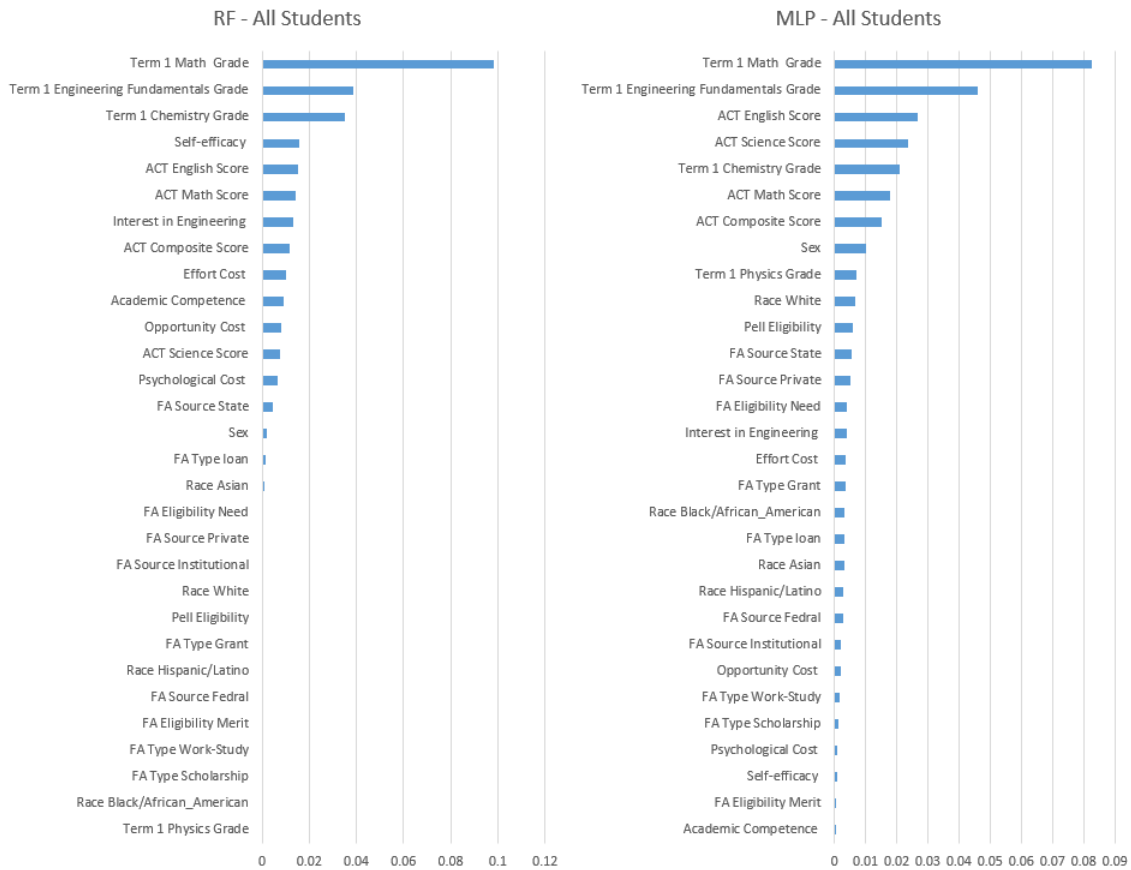

Fig. 4. Feature Importance for Models with All Students, All Features.

accurate predictors even without knowing students first-term grades. For the scenarios in which we focused on C students (Figs. 5 and 7) it is noticeable the increased relevance of the financial aid factors across both models, even raising as the most relevant factor for the MLP predictor when first-term grades and ACT scores are removed (Fig. 7). This interesting finding supports other parallel research being performed at this university [20]. Financial aid status could have a large impact on C students, as maintaining a certain grade point average could be essential to a students' financial aid package. Receiving poor grades could cause students who are dependent on financial aid to drop out of school because they can no longer afford to be there.

When we exclude ACT scores and first-term grade factors, as shown in Figs. 6 and 7, we consistently see that the SEVT variables presents a higher relevance in the RF predictor than in the MLP. This suggests that the SEVT data can be a good linear divider (for instance, students who lose interest in engineering are more likely to drop out), while demographic information such as financial aid, has a higher relevance when considering nonlinear effects, and potential interplay between the factors, explaining its higher impacts on the MLP predictor. More research is needed to determine why we observe such behaviors. Moreover, it is also possible that the datatype of these factors is significantly influencing the analysis, given that in our evaluations, financial aid data were modeled as binary variables, whereas SEVT variables are scalar values.

Lastly, we consistently see that grades and ACT scores rank highly in importance across the analyses. This is an expected trend - after all, students who are not well prepared for engineering and do not perform well in the first semester are more likely to drop out. However, we will not know students' grades until after the first semester, and sometimes that is too late to retain the students. Next, we will present a more detailed assessment of each of the 8 considered scenarios.

A. RF - All Factors, All Students

Results from running the RF predictor on all students are shown in Figure 4. As seen in previous work, we notice that grades are overwhelmingly the most important factor for the predicting engineering retention. We note that as confirmed in our previous study [20], the term 1 math grade was the most significant factor. After grades, we can see that the SEVT values has the next highest impact on retention. Self-efficacy was the most important SEVT factor (only below first-term grades), followed by interest in engineering (ranked 7^{th}), effort cost (ranked 9^{th}), academic competence (ranked 10^{th}), opportunity cost (ranked 11^{th}), and psychological cost (ranked 13^{th}).

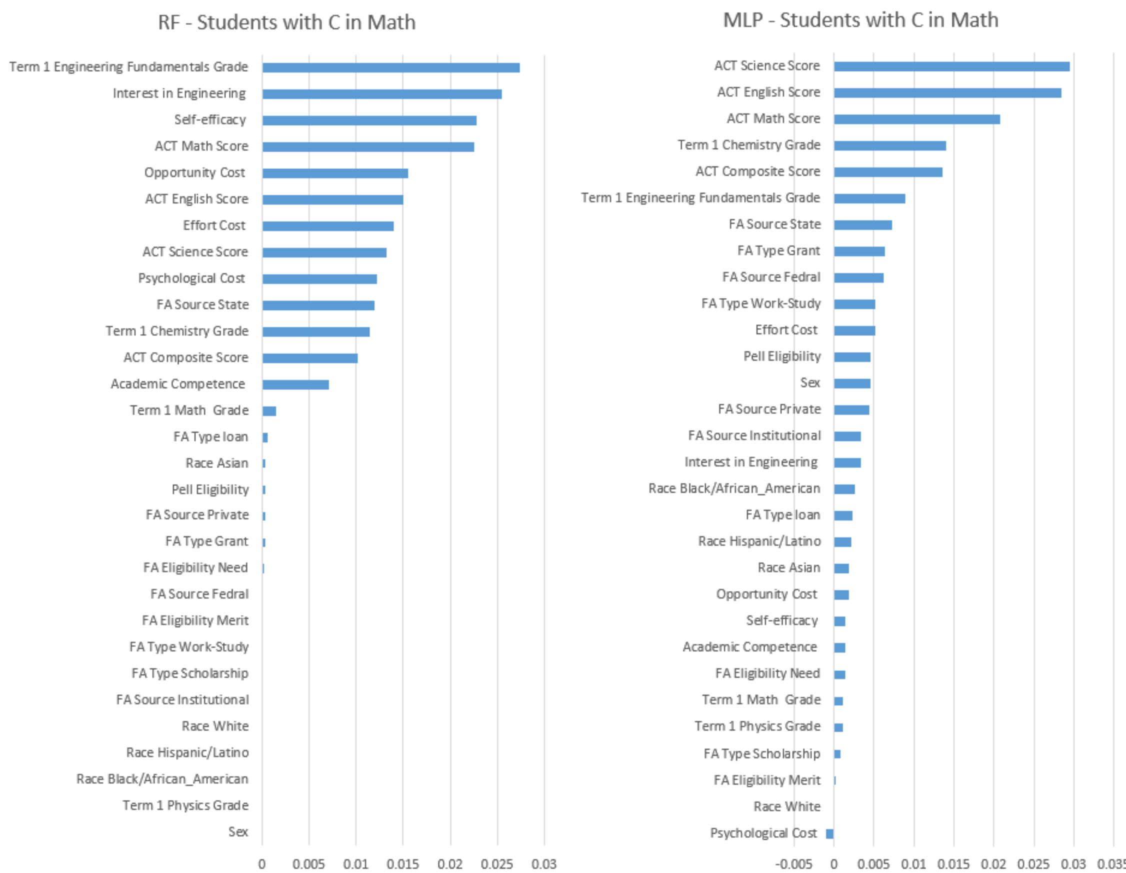

Fig. 5. Feature Importance for Models with Students with C in math, All Features.

B. MLP - All Factors, All Students

Results from the MLP predictors on this scenario are also shown in Figure 4. While this neural network model also confirms the importance of grades on student retention, this predictor also gives a high relevance to ACT scores in student retention prediction. As the MLP is more likely to pick up on non-linear relationships as compared to the random forest, we infer that ACT scores might have an impact on other student factors, making ACT scores not as important by themselves, but highly relevant due to its interplay with other variables.

C. RF - All Factors, C Math Students

The main results of this analysis is presented by Fig. 5, where we can see that for the students who received a C in math, their term 1 engineering fundamentals grade becomes the most significant factor, closely followed by SEVT values related to interest in engineering and self-efficacy. At our university, the engineering fundamentals class is designed to be a relatively easy course to help students adjust to college and engineering. Therefore, we can conclude that if students get a C in math and do poorly in engineering fundamentals, they are probably not putting forth effort in school due to the easiness of the class. Here, the math grade might be directly impacting the students' interest in engineering and their expectancies, which could help explain the high significance of these factors in predicting retention.

D. MLP - All Factors, Students with C in Math

These results are illustrated by Fig. 5. Like the analysis considering all students, ACT scores remain an important for predicting retention in the MLPs. Interestingly, English and science scores rank more highly than math at predicting retention, which shows that comprehensive abilities are also important for engineering students. For the MLPs in this analysis SEVT values ranked significantly low, with the highest ranked associated with effort cost (11^{th}). It worth mentioning again that these results might be related to the datatype structure, where the MLPs would be more impacted by binary variables, such as the financial aid data.

E. RF - No Grades, All Students

This analysis is illustrated by Fig. 6. Here, in the absence of grade information, the RF predictor was significantly impacted by the SEVT values, where the six SEVT variables were the main factors in the analysis, with self-efficacy and interest in engineering ranked at the top. This suggests that for many of our students who leave engineering, the combined effects of their self-belief (self-efficacy), their perception about

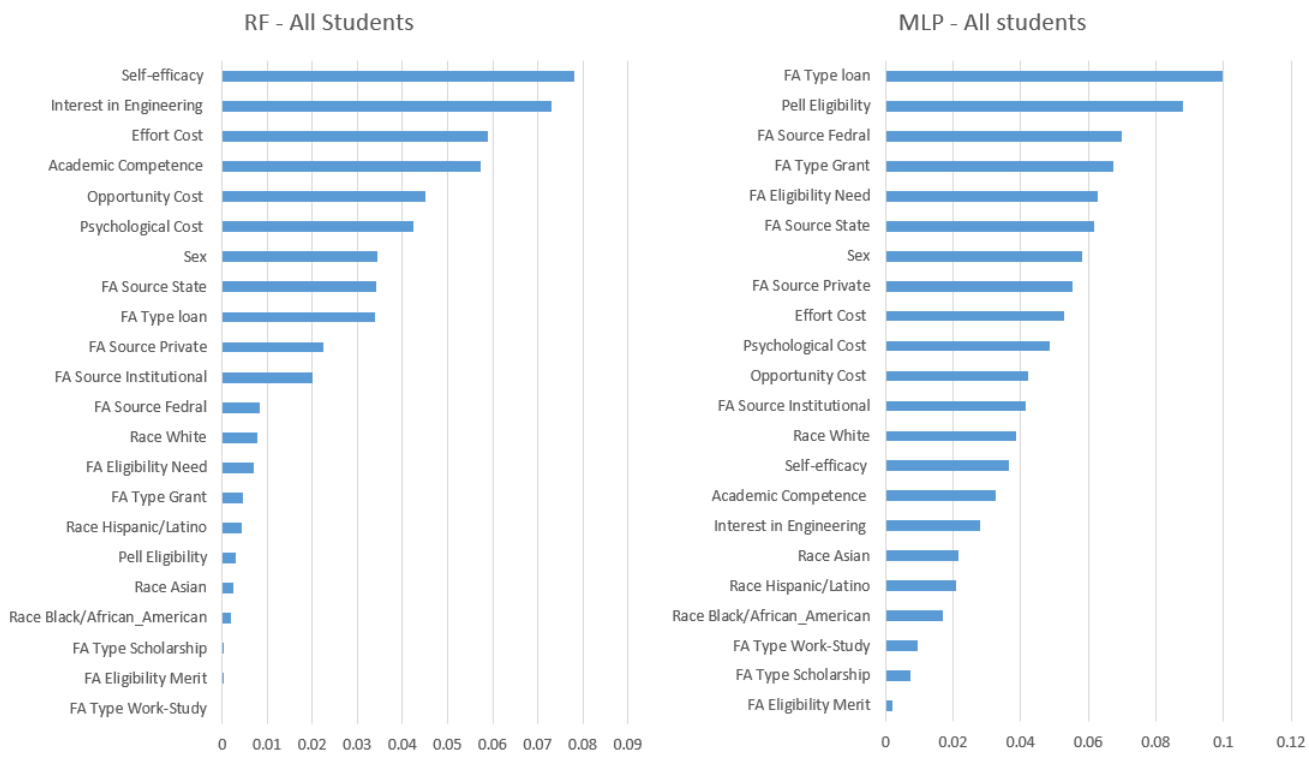

Fig. 6. Feature Importance for Models with All Students, Grades Excluded

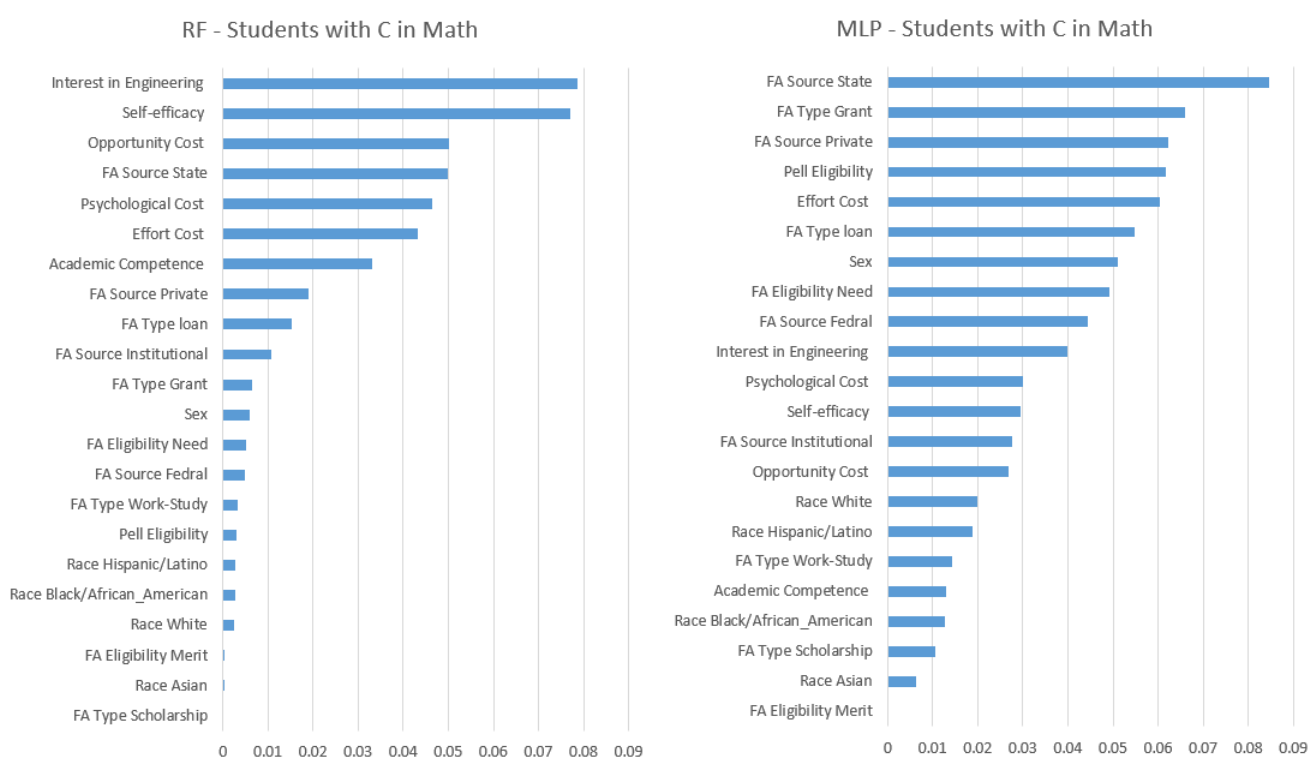

Fig. 7. Feature Importance for Models with Students with C in math, Grades Excluded

engineering, along with the effort costs to stay in the program, plays a very significant role in their decision.

F. MLP - No Grades, All Students

Results are shown in Fig. 6. Here, once first-term grades and ACT scores are removed from the analysis, financial aid data rises as the most impactful factors in the MLP predictions. Once more, for the MLPs, SEVT values ranked lower, with the highest ranked associated with effort cost (9^{th}). Again, these results might be related to the datatype structure, due to the binary nature of the financial aid data. However, due to the non-linear nature of the MLPs, these results suggests that the interplay between first-term grades and eligibility to maintain financial aid are key contributors in our students' decisions to remain in the program.

G. RF - No Grades, Students with C in Math

This scenario is presented by Fig. 7. As in the previous analyses, we see that the RF predictor consistently prioritizes SEVT variables. Interest in engineering and self-efficacy are the main factors for predicting student attrition. In this analysis, financial aid in the form of state support was raised as a significant factor, in agreement with the MLP results.

H. MLP - Students with C in Math

These results are also illustrated by Fig. 7. As in the previous MLP analyses, financial aid data were identified as the main contributors for retention in the students who received C's in math. Once more, these results, in addition to the previous analyses, strongly suggests that combined effects of first-term grades and eligibility to maintain financial support are a crucial in our students' decisions to leave engineering.

I. Limitation and Future Work

One limitation of this work is that some of these factors, mainly first semester grades, are not known until the end of the semester. In future work, we hope to limit the predictors to those that are present at the beginning of a student's academic career: ACT values, SEVT values, financial aid data, and demographic information. In this way, we can work to identify students who are at risk before they even begin college, and design appropriate interventions to help them succeed.

Additionally, a main goal of the SEVT framework is to identify relevant interventions for specific students. Different interventions are available to help students who have low interest in engineering, or low self-efficacy, for instance. Future work will also be to predict which values of the SEVT framework individual students are most likely to identify with, so that we as educators can help to improve student success.

The current work tested RF and MLP as two widely-used models. Future work will explore the predictive performance of other models. We will be especially interested in expanding our model to predict student retention without information gathered after the end of the first semester, such as first term grades.

V. Conclusions

Through this analysis, we have found the answers to our preliminary research questions below:

A. RQ1: What is the accuracy of various machine learning models in "flagging" students at risk of dropping out of engineering at our university?

As reported in Table IV, our models showed some predictive power, with F1 scores of at least 75 percent for all models. Additionally, accuracy for the model that included all data was at least 74 percent for our C students, and at least 80 percent for all students. As grades remain important for predicting student retention, we still recommend that professors follow up with students who are doing poorly in the class. However, Table V and Figures 6 and Figures 7 show that even without grades, we can still build machine learning models by leveraging survey and financial aid data.

B. RQ2: Are SEVT scores and demographics enough to accurately predict student retention?

Yes. Table V shows us that this is possible. This suggests that there is more to student retention than just grades, and that it is important to understand how students feel about engineering and themselves as they enter the program. As they progress, we need to be mindful about good interventions to help improve student retention.

C. RQ3: Which tool has better performance: a random forest or multilayer perceptron model?

We see that across the various experiments in Table IV and Table V, the random forest model consistently performed better than the MLP model. However, the MLP models were better able to pick up on non-linear relationships between our data variables.

D. RQ4: What are the most important factors in predicting student retention at our university?

Results vary across the models. The random forest models identify grades and SEVT values as the most important. The MLP model find ACT scores and financial aid data important as well. It is worth mentioning that the demographic factors of gender and race were of low importance in all models. This indicates that gender and race are less important for retention than the other SEVT factors.

E. Summary

In conclusion, we see that when considering all factors, grades and ACT scores consistently remain important for predicting whether a student will stay in engineering. However, more importantly, we see that it is also possible to create a predictive algorithm using other, non-grade factors, such as SEVT values. By measuring factors such as students' interest in engineering, their self-efficacy, and other factors, we can work to create a model which will design interventions for students to help them stay in engineering school, which will help attrition and lead to a more educated workforce which can solve the technological challenges of the future.

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