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Predicting Success in Pre-Calculus and Engineering Problem Solving

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Predicting Success in Pre-Calculus and Engineering Problem-Solving

Abstract

The purpose of this research paper is to determine if a student's ACT math score is a significant variable in predicting grades in first year mathematics and engineering courses as well as determine if it is the only variable that plays a significant role in an engineering student's grades. Other variables were selected for consideration based on extant literature, with emphasis on prior knowledge, including high school rank, GPA, and ACT component scores as well as demographic variables. Using linear regression with forward selection, this work found that at Louisiana Tech University, a student's ACT math score is significant in terms of grade in both Pre-Calculus (the first math class an "on track" engineering student will take) and Engineering Problem Solving I (the first engineering class a freshmen student will take). However, high school GPA was a better predictor in both cases. Of the variables commonly available in student records systems, we conclude that both ACT math score and high school GPA should be considered when predicting performance in Pre-Calculus and Engineering Problem Solving, as each adds considerable explanation of variance.

Introduction

Multiple criteria are used to decide which math class an engineering student needs to take at the beginning of their college career. Some universities use a placement exam or a combination of a placement exam and student data (for example, high school GPA or number of high school math classes taken) to determine the class a student will enter. At the University of Arizona, students take either a placement test that covers intermediate algebra skills or one that covers college algebra and trigonometry [1]. At St. Olaf College in Minnesota, a combination of student data, including high school rank and GPA, as well as a placement test coupled indicates where a student is placed [2]. A self-assessment test is given to all incoming students at the University of Sydney to assist them in deciding whether or not to enroll in the highest level math class available to freshmen [3]. Other institutions use certain pieces of high school information, such as GPA and/or standardized test scores [2, 4, 5]. At the study institution, a southern public university, a student's ACT math score is used to place students. This placement criteria was instituted in 2006. The goal of the placement requirement is to set a foundation on which students can succeed as they continue their college career. This is particularly important for engineering students as they continue to take classes which involved a large amount of higher level mathematics. However, is the criteria used to place students one that is actually predictive of freshmen math grades?

Literature Review

Although Louisiana Tech University uses ACT math score, variables besides standardized test scores have been shown to also be predictive of freshmen grades. Many researchers have stated that standardized test scores, including that SAT or ACT score, are positive indicators of success for college students [6, 7, 8, 9, 10]. Patterson and Mattern stated that the correlation between first year GPA and SAT score as well as high school GPA is strong [11]. Camara and Echternacht even indicate that high school grades are marginally better predictors of freshman grades over SAT scores while both are significant [12]. Multiple other studies have identified high school grades, or GPA, as a predictor of success for students [13, 14, 15]. At an Australian university, “previous high academic performance” was one of the indicators of success for a freshmen student in terms of first semester grades [16]. A study concerning health science majors proved that a non-Indigenous status and the sex of a student (specifically, being female) are factors that are associated with a positive academic performance for first year students [17]. Race, along with SES, was indicated as a factor that has significant effect on freshmen student retention from a study at a university in the New York City area [18].

According to the literature, it is possible that other variables besides ACT math score could be predictive of a freshmen engineering student’s grade in a freshmen mathematics class. Therefore, this study will specifically analyze ACT math score along with other variables as they relate to grades in freshmen math and engineering classes in order to gain an idea about what variables are significant in predicting these grades. Determining this information could also assist future research concerning the placement policies at Louisiana Tech University. If variables besides ACT math score are predictive of freshmen math and engineering grades, then potentially the placement process at the university should be reviewed and changed.

Research Questions

More specifically, this research will attempt to answer the following questions:

- Is ACT math score a significant influence on the final grades of Pre-Calculus for engineering students?
- Do other variables have a significant relationship with the same outcome?
- Do the same variables have a significant relationship with Engineering Problem Solving I?

It is expected that the results will indicate that ACT math score may not be the best predictor of success, at least not singularly. Other studies have found that standardized test scores were not the best indicators of success in math classes. For example, Foley-Peres and Poirier conducted a study involving SAT scores versus college math placement scores and found that SAT scores were less predictive than placement scores [19]. Another study focused on a placement test versus student’s high school information and concluded that testing at the university in the first year is more useful [3]. A third study using data from the Los Angeles Community College district indicated that multiple variables are useful when conducting the placement process, such as high school GPA combined with prior math background [20].

Theoretical Framework

This study is guided by a constructivist framework, whereby background (or prior) knowledge influences accumulating knowledge in the future. A basic definition of background knowledge is “the raw material that conditions learning” [21]. Others define it as what a person already knows about a certain concept or “all knowledge learners have when entering a learning environment that is potentially relevant for acquiring new knowledge" [22, 23]. When a student begins attending classes at a university, particularly a first time freshmen, the prior knowledge a student has obtained is the basis upon which all other knowledge will be built. In other words, background knowledge "acts as mental hooks for the lodging of new information and is the basic building block of content and skill knowledge" [21]. As many studies have determined, prior knowledge (denoted by mathematical preparedness in most studies) has a significant effect on a student's academic success – the more knowledge a student has about a topic, the better prepared they are to build upon the topic and the less knowledge a student has about the topic, the less likely he or she is to easily acquire new knowledge [24, 25, 26, 27, 28]. ACT math score is a measure of prior knowledge, as is (to a lesser extent) high school GPA and rank, and therefore these types of variables will be included in the model that tests how prior knowledge influences grades in freshmen mathematic and engineering classes. As mentioned in the literature review, the variables used in this study have also been shown to be predictive of freshmen achievement at a variety of other institutions.

Methodology

Institution Specifics

At Louisiana Tech University, freshmen students may choose one of eight engineering disciplines: basic, biomedical, chemical, civil, electrical, industrial, mechanical, or nanosystems. Basic engineering acts as a placeholder major for students who are undecided; students may choose this major initially, but must change their major to a specific engineering discipline by the beginning of their second year. Regardless of engineering major, all "on track" freshmen take three specific math classes and three specific engineering classes during their first year through the university's quarter system. "On track" in this case means that the student's ACT math score of 26 or above placed them in Pre-Calculus. Students with an ACT score less than a 26 are placed in either Trigonometry, College Algebra, or Developmental Math depending on specific ACT score and are unable to enroll in the first engineering course (Engineering Problem Solving I) until they are also enrolled in Pre-Calculus.

Variables

The specific variables included in the study are: high school GPA, high school rank, sex, race, ACT math score, ACT English score, ACT reading score, ACT science score, and in-state/out-of-state. To analyze the data, all variables were assigned numeric values. The values and ranges of the variables are given below (Table 1). Most variables are self-explanatory with a few exceptions. High school rank was transformed into a percentage by dividing the rank of the student by the number of students in that student's high school class and then multiplying by one hundred. Low numbers indicate higher high school rank. In other words,

$$\text{High School Rank} = \frac{\text{Rank in the Class}}{\text{Number of Students in the Class}} \times 100$$

As for race, only two options are listed in the table – White and Black. This is because the sample size for each of the other possible race/ethnicity categories were not large enough to include in the analysis. Of the original 3529 students, only 57 self-identified as Hispanic. Other categories of race (Asian or Pacific Islander, American Indian/Alaskan Native) each had less than fifty students. Two hundred and twenty five students declined to choose a race, and 106 students indicated that they were international students and therefore no race was recorded. These students were also excluded from the study because they are not meaningful groupings.

The outcome variable for the model is grade in Pre-Calculus for the first model and grade in the first freshmen engineering class (Engineering Problems Solving I) for the second model. The study only included students who completed the class or withdrew from it; therefore, if the grade was recorded as an audited class or incomplete, then those observations were excluded. Dropping the class, or withdrawing, was counted as an "F" in the class. In most cases, students drop classes when they are in danger of failing the courses, and if dropped then the student will have to take the course again before moving on to the next class. Additionally, other studies have grouped these cases similarly [29, 30]. As a result, the Pre-Calculus model included 3,280 participants and the engineering class model included 2,735 participants. Grades were changed to a 4.0 scale (4 replaced "A", a 3 replaced "B", and so on).

Table 1. Study Variables

Variable (Abbreviation)	**Range/Values**	
Sex (Sex)	0 = Male	1 = Female
Race (Race)	0 = White	1 = Black/African American
Louisiana Residency (State)	0 = Non-Resident	1 = Resident
High School Rank (HSRank)	0.2 – 100	
High School GPA (HSGPA)	1.59 – 4.0	
ACT component scores		
Science Score (ACT S)	7 – 36	
Mathematics Score (ACT M)	14 – 36	
English Score (ACT E)	11 – 36	
Reading Score (ACT R)	12 – 36	

Participants

The participants involved in this study include first-time-in-college (FTIC) freshmen who entered the university in any school year between 2006 and 2015 and declared an engineering discipline as their major. Enrollment in a university seminar class that all FTIC freshmen are required to take was used to ensure that only FTIC students were included in the study. Therefore, it should be noted that no transfer students are in the pool of participants.

In the following tables, descriptive statistics of the participants are given. As mentioned earlier, only two options for race are included in the models due to small sample sizes. In Table 2, the percentage given for state indicates the percentage of students who are residents of Louisiana. In the Table 3, averages for high school GPA, rank, and ACT component scores are given.

Table 2. Demographic Descriptive Statistics

White	**Black**	**Female**	**Male**	**State**
87.7%	12.3%	14.9%	85.1%	86.7%

Table 3. Academic Descriptive Statistics

		ACT			
GPA	**Rank**	**S**	**M**	**E**	**R**
3.5	26.11	25.2	25.4	25.0	25.2

Additionally, the correlation between ACT math score and each of the other variables has been calculated (Table 4). ACT Math has a moderate correlation with other ACT component scores and a weak correlation with HSGPA.

Table 4. Correlation Between ACT Math Score and Other Variables

					ACT		
HSGPA	**Rank**	**Sex**	**Race**	**State**	**S**	**E**	**R**
0.34	-0.23	-0.23	-0.29	-0.07	0.59	0.56	0.46

Linear Regression

To analyze the data, a multiple linear regression model with forward selection was implemented. Linear regression, in a very general sense, is finding the line of best fit from a set of data with a dependent variable (y) and one or more independent variables (x). Mathematically, the model is represented by an equation of the form

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon$$

where each x represents a different input variable, each β represents an unknown coefficient, and ε is a random error component. The multiple linear regression model used for this study can also be called an empirical model as the relationship between the dependent and independent variables is unknown and the model will attempt to discover a reasonable approximation to the unknown function. It is also possible to add interaction effects to a model, which changes the equation slightly. The equation for a model with two independent variables and the interaction between the two variables would be as follows:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{12} x_1 x_2 + \varepsilon$$

The independent, or input, variables for the model in this study are demographic and background variables available from the university. The dependent variable will be grade in Pre-Calculus in the first model, and in the second model it will be grade in the first freshmen engineering course.

To determine which variables to add to the model, forward selection was used. In this case, each individual variable is regressed against the outcome variable, and the variable which explains the most variance (largest R^2 value) in the model is added. The second step is to fit a linear regression model with two regressors: the variable added from step one and each of the other variables available in the model. Again, whichever pair of variables explain the most variance in the model are kept for step three. This process continues until none of the remaining variables add any substantial explanation of variance.

Expected Outcomes

It is expected that ACT Math will be predictive of final grades and that other variables may also be significant predictors. Reisel says “the use of math ACT scores as a predictor of success in the program is reasonable, but should be used with caution” while studies by Hoffman and Lowitzki, Munro, and Zheng et al. argue that high school GPA is more predictive than standardized test scores [14, 31, 32]. Foley-Peres and Poirier found that SAT scores were less important than placement test scores, and Ngo and Kwan indicated that multiple variables should be included when placing students in the initial math class [19, 20]. Given this literature, it is reasonable to expect that ACT Math score will be a significant variable in the model as well as other variables such as high school GPA.

Limitations

As with any study, there are limitations to this research. First, the data analyzed for the study came from a single university instead of multiple institutions. Including more data from different universities would give more validity to the results and increase the generalizability of the study. A second shortcoming was that due to small sample sizes, only two races were included in the study – White and Black. Other races/ethnicities, such as Hispanic, Asian or Pacific Islander, and American Indian/Alaskan Native, were not included as they collectively represented less than five percent of the total population of participants. Furthermore, the data used did not contain variables such as marital status, SES, self-efficacy, and transfer credit/dual enrollment. Other studies have indicated that these variables may have an effect on first year grades of freshmen students and even graduating with an engineering degree, and inclusion of said variables could have changed the outcomes of the analysis [33, 24, 34, 35]. A fourth disadvantage of the study is the use of ACT scores as variables in the model. In relation to college readiness standards, the ACT scores of Caucasian and Asian students typically meet at least three of the four subject standards about fifty percent of the time. Unfortunately, African American student generally struggle to meet any of the standards [36]. On a positive note, the difference between genders is less noticeable in regards to ACT scores as the average difference between the two is less than three-tenths of a point [37]. Finally, we do not study math placement itself, rather, the metric used for math placement is evaluated in its relationship with the grades students earn when they reach pre-calculus, regardless of where they were placed by ACT score or what class they actually took.

Results and Discussion

The first research question asked, “Is ACT math score a significant influence on the final grades of Pre-Calculus for engineering students?” In order to answer this, a linear regression model testing the significance of ACT math score against Pre-Calculus grades and then Engineering grades.

Table 5. ACT Math as a Predictor of Pre-Calculus and Engineering Grades

Model	Coefficient	Std. Error	Conf. Interval 2.5%	Conf. Interval 97.5%	Adjusted R^2	p-value
Pre-Calculus						
ACT M	.145	.007	.132	.159	13.5%	< 2e-16 ***
Engineering						
ACT M	.128	.007	.114	.142	10.5%	< 2e-16 ***

· p<0.1, *p<0.05, ** p<0.01, *** p<0.001

As seen in Table 5 above, ACT math score is significant for both models. Therefore, we see that ACT math is a significant influence on grade in Pre-Calculus and Engineering Problem Solving for engineering students.

The second research questions asked if other variables also had a significant influence on grades for engineering students in addition to ACT math score. In order to test this, a linear regression model with forward selection was employed for two models; one with an outcome of grade in Pre-Calculus and one for the grade in the engineering class. The regressors for the models included: high school GPA, high school rank, state residency, sex, race, ACT English score, ACT reading score, and ACT science score. A variable related to ACT math score also needed to be included, but there were two options for this variable. The first was to simply use a student's ACT math score, and the second was to split the scores into two sets – those above the cutoff to enroll in Pre-Calculus and those below. To decide which variable was a better predictor and should be included in the model, another linear regression was performed testing the cutoff variable. The variable was named "Cutoff" and transformed ACT math scores 26 and above to 1 and scores 25 and below to 0.

Table 6. Cutoff as a Predictor of Pre-Calculus and Engineering Grades

Model	Coefficient	Std. Error	Conf. Interval 2.5%	Conf. Interval 97.5%	Adjusted R^2	p-value
Pre-Calculus						
Cutoff	.832	.052	.730	.934	8.3%	< 2e-16 ***
Engineering						
Cutoff	.740	.053	.636	.845	6.6%	< 2e-16 ***

· p<0.1, *p<0.05, ** p<0.01, *** p<0.001

Although both variables were significant, the first variable (ACT math) explains more variance in the model over the second variable (Cutoff). Therefore, ACT math scores and not Cutoff was added to the model. A second decision also had to be made concerning including interaction terms in the model. Therefore, the study used the hierarchical principle – an interaction term can only be added if both of the variables that make up the interaction are included in the model.

For the first linear regression model, the outcome variable was grade in Pre-Calculus. Using forward selection to add the variable that explains the most variance in the model (using adjusted R^2), the first variable included was high school GPA. It accounted for 22.8% of the variance in the model and was significant. The second variable added to the model was ACT math score.

Adding this term increased the adjusted R^2 to 27.5% and both variables in the model were highly significant. The third variable that was suggested to add to the model was sex. However, when adding this term the adjusted R^2 increased less than one percent. The results of each of these model are detailed in Table 7.

Table 7. Pre-Calculus Models

Model	Coefficient	Std. Error	Conf. Interval 2.5%	Conf. Interval 97.5%	Adjusted R^2	p-value
Pre-Calculus Model 1					***22.8%***	
HSGPA	1.76	0.061	1.64	1.88		< 2e-16 ***
Pre-Calculus Model 2					***27.5%***	
HSGPA	1.47	0.063	1.35	1.59		< 2e-16 ***
ACT M	0.092	0.007	0.079	0.105		< 2e-16 ***
Pre-Calculus Model 3					***28.2%***	
HSGPA	1.41	0.064	1.28	1.53		< 2e-16 ***
ACT M	0.095	0.007	0.082	0.109		< 2e-16 ***
SEX	0.342	0.064	0.216	0.468		1.04e-07 ***

· p<0.1, *p<0.05, ** p<0.01, *** p<0.001

Since the adjusted R^2 did not increase significantly by adding the term sex, Model 2 was chosen as the final model before considering interaction terms. With only two variables in the model, the only interaction term that could be added was high school GPA with ACT math score (Table 8).

Table 8. Pre-Calculus Model with Interaction Term

Model	Coefficient	Std. Error	Conf. Interval 2.5%	Conf. Interval 97.5%	Adjusted R^2	p-value
Pre-Calculus Model 4					***28.8%***	
HSGPA	-1.40	0.404	-2.20	-0.610		0.00053 ***
ACT M	-0.310	0.056	-0.421	-0.200		4.11e-08 ***
HSGPA*ACT M	0.114	0.016	0.083	0.145		8.58e-13 ***

· p<0.1, *p<0.05, ** p<0.01, *** p<0.001

When the interaction term is added to the model, the explanation of variance increased by seven-tenths of a percentage. It should also be noted that the interaction affected the signs of the coefficients for the other two variables. It was decided that this small increase in explanation of variance was not worth the added complexity and therefore the chosen model for predicting calculus grade is Model 2. Model 2 included high school GPA and ACT math score as shown:

$$Grade\ in\ Pre-Calculus = -5.71 + 1.47(HSGPA) + .092(ACT\ M)$$

According to the model, high school GPA plays a larger role in determining the final grade of a student (HSGPA alone explained 22.8% of the variance, while ACT math alone explained only 13.5%). In light of this information, the replacement requirement could be changed so that it also takes into account GPA and not only ACT math score.

For example, new requirements for placing into Pre-Calculus could be more restrictive. Using the equation generated by the linear regression model and the original placement requirement of needing a 26 or above ACT math score, the new model suggests that the student with an ACT math score of 26 should also have a high GPA of at least 3.62 in order to make at least a C in the class.

$$Grade\ of\ \text{"C" in}\ Pre - Calculus = -5.71 + 1.47(HSGPA) + .092(26)$$

$$2 = -5.71 + 1.47(HSGPA) + .092(26)$$

$$3.62 = HSGPA$$

Another option would be to move the ACT cutoff score to a different number and then take into account GPA. The national average for ACT math score in 2015 was 20.8 [38]. Rounding up the average, if a student has a score of 21 then it must be accompanied by a GPA of at least 3.93 in order to be eligible to enroll in Pre-Calculus.

$$Grade\ of\ \text{"C" in}\ Pre - Calculus = -5.71 + 1.47(HSGPA) + .092(21)$$

$$2 = -5.71 + 1.47(HSGPA) + .092(21)$$

$$3.93 = HSGPA$$

A third option is simply using the equation generated by the model. In this case, a student would insert their GPA and ACT math score into the equation, and if the outcome was greater than 2 (indicating that it is likely the student will pass Pre-Calculus with a C or higher) then the student could take the on track class. For instance, a student A with a GPA of 3.8 and ACT math score of 24 would generate a score of 2.08 and therefore be eligible to take the class. However, student B with a 3.8 GPA and only a 20 on the ACT math would not be able to enroll in Pre-Calculus. In this case, the student scored a 1.72.

Student A

$$Predicted\ Grade\ in\ Pre - Calculus = -5.71 + 1.47(3.8) + .092(24)$$

$$Predicted\ Grade\ in\ Pre - Calculus = 2.08$$

Student B

$$Predicted\ Grade\ in\ Pre - Calculus = -5.71 + 1.47(3.8) + .092(20)$$

$$Predicted\ Grade\ in\ Pre - Calculus = 1.72$$

The third research question asked if Pre-Calculus and the engineering class grades were influenced by the same factors. Are the requirements to enroll in Pre-Calculus the same ones that should be used to enroll in the engineering class? For this analysis, linear regression with forward selection was again implemented with the outcome variable being grade in Engineering Problem Solving I and the regressors being the same as the Pre-Calculus model's variables.

The first variable added to the model was high school GPA. It explained around 14.1% of the variance and was extremely significant. Generating the same results as Pre-Calculus, the second variable added was ACT math score. The adjusted R^2 increased to 18.5% when adding this term. ACT science score was selected as the third variable to include in the model.

Table 9. Engineering Models

Model	Coefficient	Std. Error	Conf. Interval 2.5%	Conf. Interval 97.5%	Adjusted R^2	p-value
Engineering Model 1					***14.1%***	
HSGPA	1.39	0.066	1.26	1.52		< 2e-16 ***
Engineering Model 2					***18.5%***	
HSGPA	1.11	0.068	0.978	1.25		< 2e-16 ***
ACT M	0.074	0.007	0.074	0.103		< 2e-16 ***
Engineering Model 3					***19.0%***	
HSGPA	1.08	0.068	0.949	1.22		< 2e-16 ***
ACT M	0.069	0.009	0.052	0.086		2.24e-15 ***
ACT S	0.033	0.008	0.017	0.049		6.24e-05 **

· p<0.1, *p<0.05, ** p<0.01, *** p<0.001

The adjusted R^2 increased only slightly when adding ACT science score to the model, from 18.5% to 19.0%. Therefore, the model using variables without interaction is Model 2. The next step dictated that the interaction between high school GPA and ACT math score be added.

Table 10. Engineering Model with Interaction Term

Model	Coefficient	Std. Error	Conf. Interval 2.5%	Conf. Interval 97.5%	Adjusted R^2	p-value
Engineering Model 4					***19.0%***	
HSGPA	-0.693	0.446	-1.57	0.182		0.12044
ACT M	-0.165	0.062	-0.287	-0.043		0.00817 **
HSGPA*ACT M	0.071	0.017	0.037	0.106		4.34e-05 ***

· p<0.1, *p<0.05, ** p<0.01, *** p<0.001

Adding the interaction term to the model increased the amount of variance explained, but not by a significant amount. So, the final results are similar to the Pre-Calculus model, high school GPA and ACT math score are the most significant variables that explain the most of variance in predicting grade in the first freshmen engineering class. This model is shown below and predicted grades in engineering are calculated for Student A and Student B mentioned above. Similar to the Pre-Calculus results, Student A is expected to earn a higher grade in Engineering than Student B.

$$Predicted\ Grade\ in\ Engineering = -4.03 + 1.11(HSGPA) + .088(ACT\ M)$$

Student A

$$Predicted\ Grade\ in\ Engineering = -4.03 + 1.11(3.8) + .088(24)$$

$$Predicted\ Grade\ in\ Engineering = 2.30$$

Student B

$$Predicted\ Grade\ in\ Engineerings = -4.03 + 1.11(3.8) + .088(20)$$

$$Predicted\ Grade\ in\ Engineering = 1.95$$

Overall, the results from the model indicate that ACT math is not the only variable that influences freshmen math and engineering grades, and therefore the current placement process should be reviewed. Specifically, the linear regression suggests that high GPA should be taken into account in addition to ACT math score when placing freshmen engineering majors into the initial math class.

Conclusion and future work

Using linear regression with forward selection, different models indicated three specific outcomes. First, ACT math score is influential towards freshmen math and science grades. Secondly, the best model to predict grade in Pre-Calculus, given the input variables, had two regressors: high school GPA and ACT math score. Third, the model for predicting grade in the engineering class was the same form as for Pre-Calculus – the two variables in the model were high school GPA and ACT math score.

Two conclusions were made from this results. One, it appears likely that the placement requirements for engineering students at Louisiana Tech University should be reviewed as ACT math score was not the only significant variable in the two models. Two, the linear regression model suggests that high school GPA should be accounted for when placing freshmen students into an initial math class.

Continued analysis of this work should be undertaken to determine how accurate the equation generated by the linear regression model is at predicting grade in Pre-Calculus. The final product of the research will be deciding what changes, if any, should be made to the placement process at Louisiana Tech University.

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