The Mechanics of SUCCESS: How Non-Cognitive and Affective Factors Relate to Academic Performance in Engineering Mechanics

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Abstract

One particular academic area of engineering student difficulty is in the field of mechanics. Mechanics, including introductory physics, statics, and dynamics, forms the basis of many upper division engineering courses and often causes students considerable conceptual and problem-solving difficulty. These courses sometimes have the highest failure rate for engineers and can be an engineering student's first experience with academic difficulty. Although grades might be predicted by factors such as high school GPA or standardized test results (e.g., ACT/SAT), we postulate that non-cognitive factors such as grit and motivation might play a larger role in student performance in mechanics. The Studying Underlying Characteristics of Computing and Engineering Student Success (SUCCESS) survey was designed to investigate how these types of non-cognitive and affective (NCA) competencies can better predict academic success. Using results of the SUCCESS survey given to hundreds of students at a large western public engineering school, this work investigates the correlation between the 14 constructs measured by the survey (including such factors as Self Control, Motivation, Grit, Identity and Belongingness) to performance in introductory engineering physics courses, engineering statics, and engineering dynamics. Adding NCA factors to traditional predictors of Math SAT score and high school GPA increased the R^2 values by up to 0.1. Test anxiety was a strong negative predictor for all mechanics course grades, and Time and Study environment was positively correlated to grades in statics and dynamics.

Introduction

Engineering coursework is known for being extremely rigorous, and for many students the most challenging classes can be the series of required mechanics courses. These courses include physics, statics, and dynamics. Additionally, they are the foundation for many upper division courses. So not only are they very difficult courses, often having the highest failure rates, but they are also some of the most important since this information will be built on in future coursework. So it is crucial that students not only pass these classes but retain the valuable skills and concepts learned in order to succeed as they progress. Students surveyed attend a public state university that greatly emphasizes a student's ability to apply concepts learned in class to industry and laboratory assignments. This stresses the need for students to develop a concrete understanding of the core classes when first beginning university.

Background

Context

Although most students at this comprehensive polytechnic state university come in with strong high school GPAs and high SAT/ACT scores, many of them still struggle to do well in their classes. This initial struggle can be very intimidating for students since it may be the first time they have been challenged academically. College is structured differently than high school and some students are not prepared for the adjustment. Many students will perform poorly in their courses, and some will switch out of their major or out of engineering entirely. The heavy course load that is thrust upon them in college can greatly throw students out of their comfort zones, despite being the top of their high school class. Since the university wants their students to do well, it is of interest to know if there is a reliable method for predicting students' success, and what types of interventions might prove most effective. Thus, we will be studying the relation between the non-cognitive and affective factors of students and their grades in the mechanics courses. The survey will allow us to look at 14 constructs with a total of 28 dimensions to determine if there is a positive or negative correlation between those scores and grades in mechanics courses.

Mechanics Courses

In order to study the varying constructs that compose an overall depiction of a student, a survey has been designed to target 14 different constructs composed of 28 dimensions that measure the non-cognitive and affective (NCA) factors of students. The Studying Underlying Characteristics of Computing and Engineering Student Success (SUCCESS) survey allows us to gather data on the student populations at a large western public university and has been used to track students' development as they progress through their academic careers. The 14 different constructs that are explored are big-five personality [1, 2], grit [3], identity [4-6], mindset [7], motivation [8,9], gratitude [10], mindfulness [11], belongingness [12], test anxiety [13], time and study environment [13], perceptions of faculty caring [12], self-control [14], student life stress [15], and meaning and purpose [16]. A short description of each of these, as well as how we chose and validated these constructs, can be found in our earlier work [17,18].

Methods

Data Collection

The study was approved by our institutional review board and informed consent was obtained from each student. For the current study, the SUCCESS survey was distributed to students in first-year engineering classes during Winter of 2018. Students were allotted 30-40 minutes to complete the survey during their class. The survey collected self-reported factors such as GPA and test scores like ACT and SAT, along with information regarding demographics and background. With a total of 41 questions, most with multiple parts, we used an anchored 7-point scale to examine the factors. The survey included attention checks such as "If you are reading this, fill in option two". Demographic information for the sample is provided in Table 1.

Statistical Analysis

First, we computed the 28 NCA factors from the survey results and reduced the dataset to only include students who continued as a major in the college of engineering (e.g., if a student subsequently switched majors to physics or business, they were excluded from the study). We dropped twelve students from analysis due to empty survey fields that lead to missing values of calculated NCA factors. For the remaining students, we obtained their grades from three mechanics courses required for most engineering majors: General Physics 1, Engineering Statics, and Engineering Dynamics; they had to have completed all three courses to be included in the study. In the case that a student took a class multiple times, we look at the grade of their first attempt.

Table 1: Demographic profile of participants at Cal Poly

Race/ethnicity	**Number of participants**	**Percentage**
White	229	57.5%
Asian	67	16.8%
Hispanic or Latinx	42	10.6%
Black or African-American	3	0.754%
Native American	2	0.503%
Multi-racial	37	9.30%
Declined to answer	18	4.52%
Gender Identity		
Female	133	33.4%
Male	265	66.6%
Non-binary	0	0%
Determining First-generation status		
Neither parent attended college	32	8.04%
One or more parent had some college or 2-year graduate	29	7.29%
One or more parent had 4-year graduate or post-graduate education	327	82.2%

Further, we got traditional predictors of academic success from the Office of the Registrar—specifically math standardized test scores (SAT and/or ACT) and high school GPA. For students who only took the ACT, we converted the ACT math score to the SAT point scale using the 2018 ACT SAT concordance table provided by the College Board [19]. After this transformation, all students who were surveyed had an actual or computed math SAT score. All predictor variables were standardized before models were created.

The goal of this analysis was to predict these course grades using the noncognitive factors determined during their first year in school. We then compare the accuracy of these models to those using traditional predictors (math SAT and high school GPA). Finally, we analyze the improvement upon the traditional models when NCA factors are added. Each model is built using linear regression, selecting the best model with backwards stepwise selection optimizing for Akaike information criterion (AIC) [20]. Backwards stepwise selection is a variable selection method which iteratively removes the least important predictors to select the best subset of variables. Optimizing for AIC aims to obtain the best fitting model while keeping it as simple and explainable as possible, penalizing for models with more predictors. Regression assumptions and multicollinearity were checked [20].

Adjusted R^2 values are used to directly compare model fits when predicting the grade of a course. A partial F-test is used to inspect the improvement upon the traditional models when NCA factors are added. This tests whether there is a statistically significant improvement to the model when the selected NCA factors are added to the baseline model using only traditional predictors. Finally, because variables were standardized before models were created, we can compare the relative importance of predictors in each model by looking at their coefficients.

Results

The adjusted R^2 values of the best model for each course and set of predictors are shown in Table 2. Here, we compare models using only the NCA Factors to those using traditional predictors of college academic success (Math SAT score and High School GPA) as well as models using both.

Table 2: Adjusted R^2 values from linear regression modeling grades with NCA factors

Course	**NCA Factors**	**Traditional Predictors: Math SAT score and High School GPA**	**Traditional Predictors + NCA Factors**
General Physics 1	0.238	0.292	0.392
Engineering Statics	0.155	0.170	0.238
Engineering Dynamics	0.205	0.200	0.301

For all class grades, the best model uses both traditional predictors and NCA factors. For General Physics 1 and Engineering Statics, the model using only traditional measures outperformed the one using only NCA factors. For Engineering Dynamics, the NCA factors are slightly better. For all classes, adding the NCA factors to the traditional model resulted in a statistically significant improvement in the model (all partial F-test p-values < 0.001).

We can inspect the best linear models using NCA factors and traditional measures as predictors to look more in-depth at the relative importance of these factors on academic success. Table 3 summarizes these associations for the three models of grades versus NCA factors. Each of these coefficients can be interpreted as the estimated change in the course grade (4.0 scale) in response to a one standard deviation increase in the predictor. For example, after adjusting for the other predictors, a one-standard deviation increase in empathetic faculty understanding is associated with a 0.125 higher grade in General Physics 1, while a one-standard deviation increase in text anxiety results in a 0.148 lower grade in General Physics 1.

Table 3: Significant coefficients and p-values of predictors in best linear regression models for grades. Factors that are significant predictors for multiple courses are shaded in gray. The coefficient represents the response in grade to a 1.0 standard deviation increase in the construct score.

Construct	**Dimension**	**Association with Physics Grade** coeff. (p-value)	**Association with Statics Grade** coeff. (p-value)	**Association with Dynamics Grade** coeff. (p-value)
Big Five Personality	Extraversion			
	Conscientiousness			
	Openness			
	Agreeableness			
	Neuroticism			
Grit	Consistency of interest	-0.119 (0.023)		
Identity				
	Interest			
	Recognition			
Mindset				
	Mindset			
Motivation	Expectancy			
	Connectedness			
	Instrumentality			
	Value			
	Future Perception		-0.157 (0.035)	
Gratitude	Gratitude			0.176 (0.006)
Mindfulness	Mindfulness			
Belongingness	Belongingness			
Test Anxiety	Test Anxiety	-0.148 (0.013)	-0.118 (0.037)	-0.143 (0.048)
Time and Study Environment	Time and Study Environment		0.126 (0.023)	0.213 (0.002)
Perception of Faculty Caring	Empathetic understanding	0.125 (0.013)		
	Social support			
Self-Control	Impulse control			
Student Life Stress	Changes			-0.190 (0.0096)
	Frustration	-0.151 (0.009)		
	Conflicts			
	Reactions			
	Support			
Meaning and Purpose	Meaning and Purpose			
Traditional Measures	High School GPA	0.191 (<0.001)	0.187 (0.001)	0.258 (<0.001)
	Math SAT Score	0.332 (<0.001)	0.171 (<0.001)	0.241 (<0.001)

Four NCA factors as well as both traditional measures of success are significant (p-value < 0.05) predictors of an engineering student's grade in General Physics 1: empathetic faculty understanding (coefficient = 0.125), high school GPA (0.191) and SAT Math score (0.332) were positively associated while consistency of interest grit (-0.119), test anxiety (-0.148), and stress – frustrations (-0.151) are negatively associated. Three NCA factors as well as both traditional measures are significant predictors of grade in Engineering Statics: time and study environment (0.126), high school GPA (0.187), and math SAT score (0.171) are positively associated while perceptions of future motivation (-0.157) and test anxiety (-0.118) are negatively associated. Four NCA factors as well as both traditional measures are significant predictors of grades in Engineering Dynamics: gratitude (0.176), time and study environment (0.213), high school GPA (0.258), and math SAT score (0.241) are positively associated while test anxiety (-0.143) and stress – changes (-0.190) are negatively associated.

Figures 1-3 below summarize these associations for the three models of grades versus NCA factors. As stated before, the coefficient of the scaled predictor represents how a 1.0 standard deviation increase in the construct affects the grade (based on a 4.0 scale) in the respective classes.

Figure 1: Relative importance of predictors for general physics grade

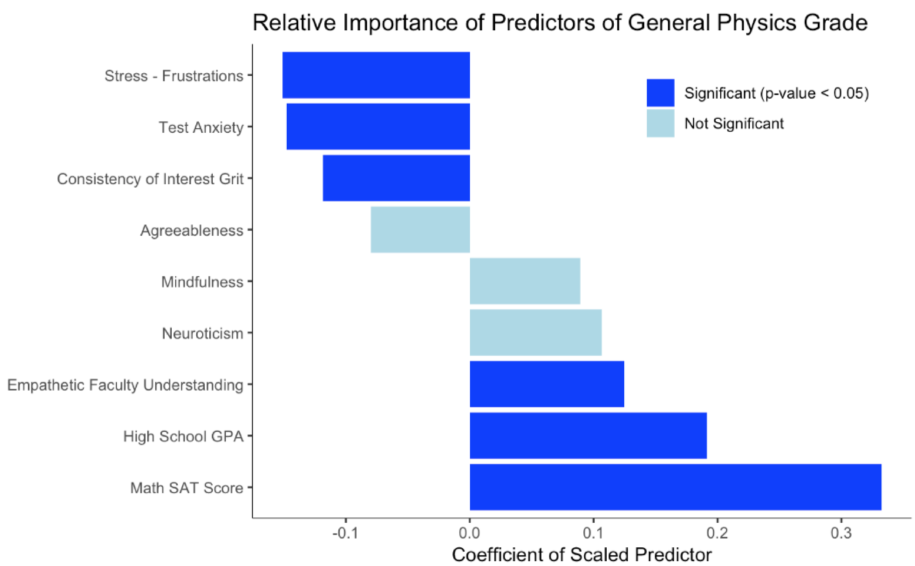


Figure 2: Relative importance of predictors for engineering statics grade

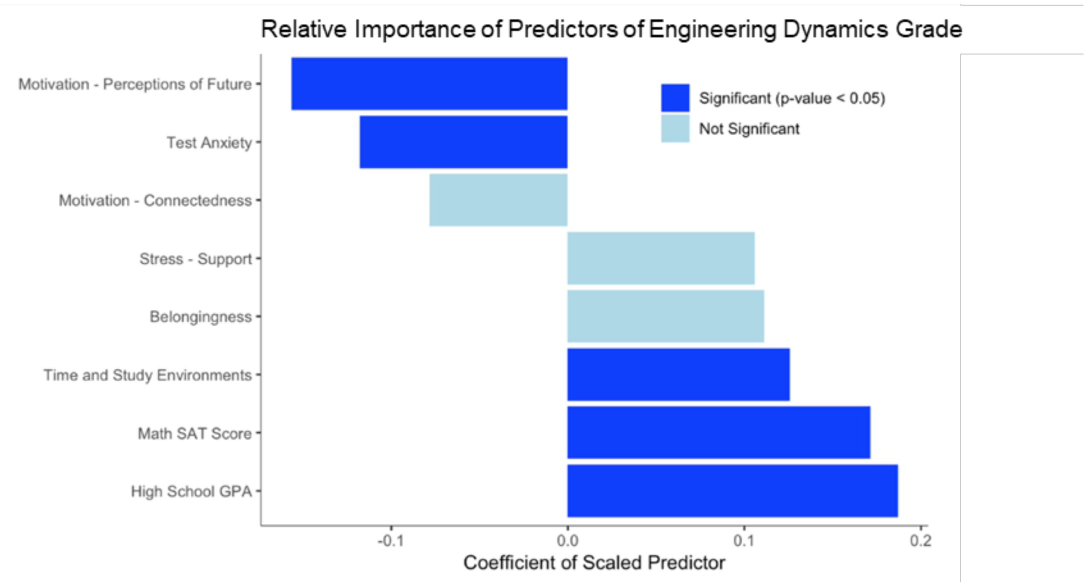
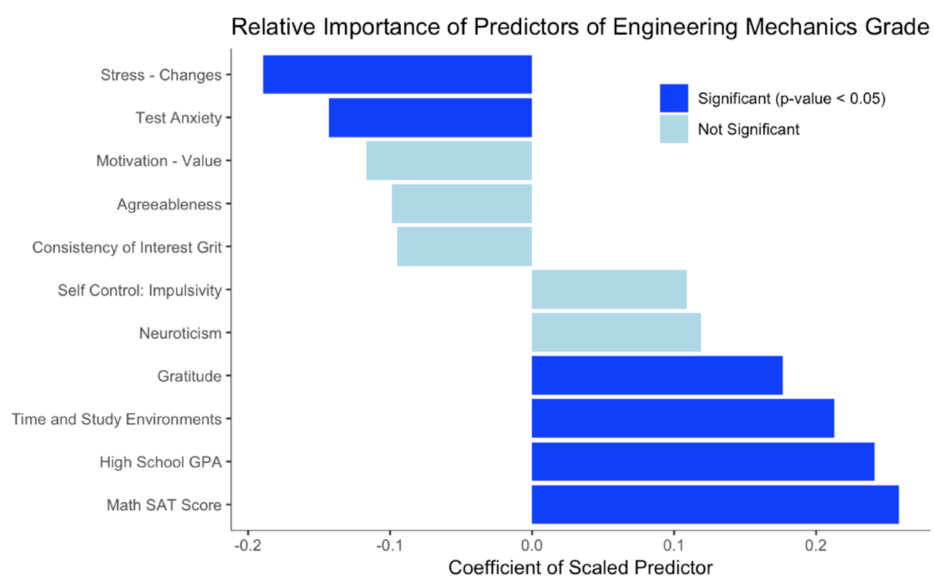


Figure 3: Relative importance of predictors for engineering dynamics grade



These models using NCA factors and traditional measures as predictors can be further improved by incorporating the grades of prerequisite classes in each model. General Physics 1 is an introductory class, but it is a prerequisite for Engineering Statics, and both are prerequisites for Engineering Dynamics. Table 4 shows the adjusted R^2 values of the best model for each course and predictors.

Table 4: Adjusted R^2 Values, Linear Regression for Course Grades, Factors + Traditional vs. Factors + Traditional + Prerequisites

	NCA Factors + Traditional	**NCA Factors + Traditional + Prerequisites**
General Physics 1	0.392	-
Engineering Statics	0.238	0.303
Engineering Dynamics	0.301	0.437

For both classes that have prerequisites, the addition of prerequisite grade(s) to the model with NCA factors and traditional measures as predictors is a statistically significant improvement (partial F-test p-value < 0.001).

Discussion and Conclusion

Looking at the models using NCA factors as predictors of engineering grades, we can see that there are clear patterns in how the factors influence success. Many of the NCA factors are malleable, so understanding these patterns is a crucial step towards introducing initiatives in the classroom to help students reach their full potential. The strongest pattern is that test anxiety is consistently a significant predictor and is negatively associated with grades. The takeaway here is that interventions focused on reducing test anxiety could be beneficial towards student success. Note that we can only confirm association, not causation.

In the other direction, the NCA factor time and study environment is shown to be a positive influence on grades in Statics and Dynamics. Certainly, providing better study environments or adopting good study habits, both on campus and at home, can help improve student success. Our future work will examine how different initiatives affect student grades in these foundational mechanics courses, as well as how the NCA factors evolve over time.

Some of the predictors are a bit puzzling. For instance, grit (consistency of effort) showed a negative correlation with the Physics grade and motivation (future perception subscale) showed a negative correlation with the Statics grade. The other positive predictors (gratitude, perception of faculty caring, time and study environment), and negative predictors (test anxiety, student life stress: changes and frustration) are more along the lines of what we would expect.

Future studies

For this study, we only examined the student's first grade when taking the course, and acknowledge that some students may have repeated one or more of the classes. Future work could consider how retaking different courses affects student performance. We did not look at how course instructor or ways the individual instructors may have attempted to alter things such as test anxiety or perception of faculty caring. Additionally, in this study we have not examined demographic differences, or differences in first-generation college student status. In future work, we plan to examine these factors and to see how initiatives to improve different NCA factors such as belongingness and grit affect student success. Finally, we also acknowledge that student grades are only one aspect of student success, and are interested in finding different ways to measure and define this metric.

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