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Impact of Non-Cognitive Factors on First-Year Performance

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Impact of Non-Cognitive Factors on First Year Performance

Abstract

This research paper describes the study of non-cognitive factors and their impact on student academic outcomes, above and beyond the impact from previous academic performance. The connection between prior academic performance factors, such as high school GPA and standardized test scores, and the performance of first year students (as measured by GPA) has been well established. While it has been shown that typically 20%-25% of the variation in first year student performance can be explained by a combination of high school GPA and standardized test scores, this still leaves over half of the variation unaccounted for. Some of this variation may be accounted for by a collection of non-cognitive factors.

A non-cognitive inventory was created using the 10-Item Big Five Survey, the Short Grit Survey, and two subscales from the Motivated Strategies for Learning Questionnaire (Test Anxiety and Time and Study Environment). Data was collected using this survey from freshman through senior engineering students at a large, public research-intensive university in the Midwest. Using a hierarchical multiple regression, students' first year grades were regressed onto their previous academic performance as well as their scores in the non-cognitive inventory. Initial results indicate that the inclusion of non-cognitive factors alongside previous academic performance improved the predictability of students' first year GPA by an additional 7 percentage points compared to a model that only included previous performance.

This paper also explores the variations in impact of non-cognitive factors on performance for different classroom settings. A series of multiple regressions illuminates distinct differences in the non-cognitive factors that most strongly affect academic performance in technical lecture, technical team, and liberal arts courses. Implications for student support in those different classroom contexts are described.

1. Introduction

Many engineering programs recruit from the upper echelon of high school students, meaning that most incoming engineering students begin their college careers with strong academic credentials. Given the high GPAs and standardized test scores (cognitive factors) of the majority of incoming students, it seems clear that these students have the cognitive capacity to succeed at the university. However, what we see instead is a large number of students not performing to their potential, or worse yet failing courses and being forced to drop out or change majors. This observation suggests a number of unmeasured non-cognitive factors that play an important role in determining the success or failure of engineering students in their first year at university.

Students are most likely to leave STEM programs in their first year[1], [2], meaning that improving the prediction of and support for first year student performance can maximally improve student retention and success, leading to benefits for the university, the student population, and engineering industry. According to DeWinter and Dodou[3], being able to predict student performance allows for universities to more efficiently use recruitment resources and enroll high performing students that may not have initially been admitted. It also guides universities in provisioning appropriate academic and personal support services for its students.

Knowing which students could perform poorly would not necessarily lead to them being rejected from enrollment in the university. Instead, accurately predicting performance would allow for students likely to struggle to be offered appropriate interventions early in their collegiate career. These students could be supported with the academic and personal tools to enhance their performance and sense of fulfillment, allowing them to succeed in engineering.

1.1 Related Work

The purpose of this study is first to show that non-cognitive factors add predictive value to student performance models based upon prior academic achievement, and second to show that predictors of performance vary by classroom setting. While studies aimed at predicting or explaining variations in college student GPA are fairly common, the majority of such studies use some combination of high school GPA and standardized test scores (ACT and/or SAT) as the only independent variables[4], [5]. These independent variables are usually shown to predict between 20% and 25% of the variation in college student GPA, meaning that by most estimates over three quarters of the variation in student performance is still unexplained.

Similarly, studies have correlated non-cognitive factors such as personality type[6] and study skills[7] to college GPA. These non-cognitive factors have been shown to correlate to college GPA at levels as high as $r = 0.50$. However, as was the case with the previous performance only studies, no independent variables outside of a specific non-cognitive factor are included.

In the few studies that attempt to combine non-cognitive factors alongside cognitive ability in an effort to explain college GPA, it has been shown that non-cognitive factors such as study skills and effort explain significant variance in college GPA beyond cognitive ability[8], [9]. One study has shown that learning skills and study strategies alone can provide a 10% increase in predictive validity when added to cognitive-only models of academic performance[9]. Similarly, a recent meta-analysis showed that non-cognitive factors such as conscientiousness, test anxiety, and academic self-efficacy can explain as much variance in college GPA as high school GPA and SAT scores [10]. While these studies provide intriguing results, the volume of literature in this area is limited. Of particular interest is the lack of research in this area that focuses on specific populations such as engineers or specific classroom settings; the literature that exists at this point considers the entire population of university students, missing out on the difference that exist between academic programs, classes, or student sub-populations.

Essentially all prior studies connecting non-cognitive factors to academic performance use traditional academic metrics: first-year GPA, cumulative GPA, retention, or graduation rate. However, we know that classroom setting can have a profound effect on academic performance; for instance, we know that STEM students in particular benefit when classrooms shift from lecture-based pedagogies to active and collaborative learning [11], [12]. The literature currently has very little to say about the role of non-cognitive factors in student academic performance across different classroom settings. This work begins to address that gap in the literature.

Our goal is to answer the following research questions:

1. To what extent do non-cognitive factors predict first year academic performance for engineering students above and beyond prior academic performance?

   Hypothesis: Given the clustering of incoming engineering students at the upper ends of high school GPA and standardized test scores, we believe that cognitive factors alone will prove to be a poor predictor of first year engineering performance, and that non-cognitive factors will provide a significant increase in predictive power.

2. How do predictive models of first year engineering performance vary based on classrooms setting?

   Hypothesis: We believe that academic context affects student performance, and as such we expect to see different non-cognitive factors as significant predictors of success in different classroom settings.

Our study differs from much of the previous work in three major facets:

1. The sample is restricted to engineering students at a large, Midwestern research-intensive university. This specific sample will change how our study matches other, similar studies of a more holistic university population. These differences will be discussed in more detail in the following sections.
2. Non-cognitive factors are included alongside prior performance to create a predictive model of first year student GPA. As previously stated, many other studies tend to focus either on previous performance or on a specific non-cognitive factor alone. Combining non-cognitive factors with previous performance should lead to an overall improvement in the predictive power of the model.
3. First year GPA is analyzed holistically, as well as broken down by class setting. The GPAs for first year technical lecture courses, first year team-based courses, and first year liberal arts courses are taken individually as dependent variables in order to discover how the independent variables differ in terms of predictability for various classroom settings.

The following sections discuss the methods and results of this study, with an emphasis on the areas of continued research and potential impacts.

2. Methods

The non-cognitive factors in this study consist of the Big Five Personality Traits (extraversion, openness, agreeableness, conscientiousness, and neuroticism), grit, test anxiety, and time and study environment. A 45-item survey was created combining the Ten-Item Big Five Inventory (10 items, 5 point Likert scale)[13], the Short Grit Survey (8 items, 5 point Likert scale)[14], two subscales of the Motivated Strategies for Learning Questionnaire[15] (test anxiety and time and study environment; 5 and 8 items respectively, 7 point Likert scale), and a number of demographic questions. The survey was delivered electronically to upwards of 3000 students, with consent and complete responses from exactly 500. Of these 500 students, 71 were first year students enrolled in the first year engineering program and 429 were sophomore through senior students in mechanical engineering. This research is part of a broader study focused specifically on the mechanical engineering population at our institution, and this is why our participants were predominantly from mechanical engineering. Several students in our sample did not have GPA data, standardized test scores, or high school GPAs on file. Therefore, from the 500 total responses only 418 were kept and used in the analysis.

It is important to note that a majority of the students in this sample have already began study in mechanical engineering, meaning they have successfully completed their first year curriculum and earned a high enough GPA to gain admittance to the mechanical engineering program. Therefore, it was expected that the mean GPAs for each course, as well as overall, for our student sample were higher than the general population of first year engineering students. Also, among all metrics for academic success we could have chosen for this study, given the population and the lack of longitudinal data we decided that GPA was the best metric for our sample as opposed to retention or other possibilities. We also see very strong similarities between GPA by class standing for our sample of students and the population of mechanical engineers as a whole.

Regardless of year, all students in our sample were required to take the same 8 courses (Calculus 1, Calculus 2, Physics 1, Intro Engineering 1, Intro Engineering 2, Chemistry 1, Basic Composition, Public Speaking) and one of two technical electives (Intro Computer Programming or Chemistry 2) in their first year in engineering. Grades in these nine courses make up the first year GPA for the students in our sample. The students' first year courses were also categorized by classroom setting into three mutually exclusive groups: technical lecture, technical team-based, and liberal arts. The two courses provided by the school of liberal arts were placed in the liberal arts category. Of the remaining courses, those in which at least 25% of the course grade was determined by team-based activities (i.e. team-based labs, projects, etc.) as defined on the course syllabi were placed in the technical team-based group. Finally, the remaining courses were placed in the technical lecture group. The course breakdown for each group can be seen in Table 1. Courses in the technical-team group met the criteria in different manners. Intro Engineering 1 and 2 have a heavy emphasis on team-based projects, Chemistry 1 and 2 have a large in-lab component, while Intro Computer Science has an emphasis on in-lab, paired programming work.

Table 1. First Year Engineering Courses and their Assigned Group

Technical Lecture Group	Technical Team Group	Liberal Arts Group
Calculus 1	Intro Engineering 1	Basic Composition
Calculus 2	Intro Engineering 2	Public Speaking
Physics 1	Chemistry 1	
	Chemistry 2	
	Intro Computer Science	

Since not all incoming students were required to take either the SAT or ACT, the standardized test scores variable was calculated using the ACT-provided SAT to ACT conversion tables[16]. Where a composite ACT score was available, that value was used as the student's standardized test score. If a student had an SAT score but no ACT score, the conversion was used to find their estimated ACT score, which was then used as their standardized test score. If no standardized test score was provided, that student was not considered in this study.

A second important note is that while the focus of this study was on first year engineering GPA, a large portion of our student population already completed their first year of study. We therefore needed to establish the stability of non-cognitive factors over time allow us to use the older populations of students in this study. It has been shown that during the collegiate years the only personality trait likely to change is openness[17], [18]. Since openness did not prove to be a significant predictor in any of our models (as shown later), this potential change did not impact our study. However, in order to confidently use all of the data from upperclassmen in our sample without skewing results, we proved using several ANOVAs that within our sample there was no significant difference between any two years for any of the non-cognitive factors. Table 2 shows the means and standard deviations for each non-cognitive factor by year.

Table 2
Means and Standard Deviations of the Eight Non-Cognitive Factors Used (N = 418)

Variables	*M(SD) – Freshmen*	*M(SD) – Sophomore*	*M(SD) – Junior*	*M(SD) – Senior*
Extraversion	4.03(1.43)	4.01(1.66)	4.46(1.52)	4.41(1.54)
Agreeableness	4.76(1.11)	4.64(1.19)	4.65(1.02)	4.36(1.18)
Openness	5.38(1.05)	5.23(1.04)	5.46(0.89)	5.27(1.18)
Conscientiousness	5.56(1.11)	5.46(1.16)	5.64(1.07)	5.60(1.07)
Neuroticism	4.97(1.31)	4.88(1.28)	4.80(1.21)	4.93(1.45)
Test Anxiety	4.28(1.39)	4.39(1.28)	4.64(1.41)	4.65(1.28)
Time and Study Environment	4.90(0.95)	4.82(0.91)	4.83(0.94)	4.64(0.95)
Grit	3.50(0.54)	3.43(0.49)	3.31(0.62)	3.43(0.61)

From this information we concluded that the non-cognitive factors of upperclassmen did not differ from the underclassmen, and therefore their data will not skew results.

3. Results and Discussion

3.1 Study one—non-cognitive factors and overall first year GPA

In order to determine the efficacy of including non-cognitive variables in a model predicting undergraduate engineer's first year performance, a hierarchical multiple regression was run regressing first year GPA onto previous performance followed by non-cognitive factors (Table 3). These two models accounted for 6.1% and 13.1% of the variance in first year engineers' GPA respectively.

In this portion of the study, two models were created:

- Cognitive-Only Model: This model contained only prior performance, as measured by high school GPA and standardized test score. These two variables were regressed onto students' composite first year GPA to ascertain the predictive power of cognitive factors alone.
- Non-Cognitive Model: This model added seven non-cognitive factors on top of the two cognitive factors. These additional variables were regressed onto students' composite first year GPA to discover if non-cognitive factors predict first year GPA better than the model with cognitive factors alone.

In the Cognitive-Only Model high school GPA and standardized test score predicted a significant amount of variance in first year GPA ($F(2,327) = 10.60$, $p < .001$). Also, high school GPA ($b = .40$, $SE = .11$, $p < .001$; $\beta = .19$) and standardized test score ($b = .02$, $SE = .007$, $p < .05$; $\beta = .11$) were both significant individual predictors in the model.

The non-cognitive factors added in the Non-Cognitive Model consisted of the Big Five traits of extraversion, agreeableness, openness, conscientiousness, and neuroticism, as well as two MSLQ subscales: test anxiety, and time and study environment. Due to the significant correlation between grit and conscientiousness[19], grit was left out of the group of non-cognitive variables. These seven remaining non-cognitive factors, alongside the two cognitive factors described above, predicted a significant amount of variance in first year GPA ($F(9,320) = 5.34$, $p < .001$). The model containing non-cognitive factors also accounted for significantly more variance than the cognitive-factor-only model ($F\Delta(7,320) = 3.67$, $p < .001$). Significant individual predictors in the non-cognitive model included high school GPA ($b = .36$, $SE = .11$, $p < .01$; $\beta = .18$), extraversion ($b = -.03$, $SE = .01$, $p < .05$; $\beta = -.13$), conscientiousness ($b = .05$, $SE = .02$, $p < .05$; $\beta = .14$), and test anxiety ($b = -.05$, $SE = .02$, $p < .001$; $\beta = -.19$).

This initial regression analysis yielded two particularly interesting results. First, the R^2 for our Cognitive-Only Model was lower than most other published models that have been used to predict college GPA. Given that our sample included only engineering students, this provides evidence supporting the idea that since engineering students generally matriculate with very similar and strong high-school credentials, their cognitive ability alone is not sufficient to create a strong predictive model. Second, the single most significant individual predictor in the non-cognitive model was test anxiety, a factor that is known to be malleable[20]. This shows that first year engineering GPA is not necessarily capped by cognitive ability, and that by improving certain non-cognitive attributes students may be able to improve their first year academic performance.

3.2 Study two—non-cognitive factors and academic performance in specific contexts

The second part of this study was designed to examine the differences in models predicting first year GPA for technical lecture courses, technical team-based courses, and liberal arts courses, while using the same independent variables. The independent variables in each model were the same nine used for the Cognitive-Only and Non-Cognitive Models in Table 3. These models predicted 12% of the variance in technical lecture course GPA, 10% of the variance in team based course GPA, and 7% of the variance in liberal arts course GPA. The independent variables in each of these three models were centered at their means.

Table 3
*Summary of Hierarchical Regression Analysis for Variables Predicting First Year Engineers' GPA (*N *= 330)*

	Cognitive-Only Model			Non-Cognitive Model		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Intercept	3.44	.02	0	3.44	.02	0
Standardized Test Score	.02	.007	.11*	.01	.007	.08
High School GPA	.40	.11	.19**	.36	.11	.18**
Extraversion				-.03	.01	-.13*
Agreeableness				-.002	.02	-.006
Openness				-.02	.02	-.06
Conscientiousness				.05	.02	.14*
Neuroticism				-.007	.02	-.02
Test Anxiety				-.05	.02	-.19**
Time and Study Environment				.01	.02	.03
R^2			.06			.13
F for change in R^2			10.60**			3.67**

Note: All variables were centered at their means.
*p < .05. **p < .01.

The Technical Lecture section in Table 4 shows the model regressing first year engineering students' GPA in technical lecture courses onto their cognitive and non-cognitive factors. These nine factors were able to predict a significant amount of the variance in lecture course GPA ($F(9,314)$ = 4.60, p < .001). Standardized test score (b = .05, *SE* = .01, p < .01; β = .19), and test anxiety (b = -.10, *SE* = .03, p < .01; β = -.20) were both significant individual predictors. High school GPA (b = .40, *SE* = .21, non-significant [ns]; β = .11) was a trend-level individual predictor (p-value between .05 and .10), and would likely be significant with a larger sample size.

The Technical Team-Based section of Table 4 shows a summary of a regression model taking first year engineering students' team-based course GPA as the independent variable. The mix of nine cognitive and non-cognitive factors created a significantly predictive model ($F(9,243)$ = 3.83, p < .01). Two independent variables – extraversion (b = -.06, *SE* = .02, p < .01; β = -.19) and high school GPA (b = .41, *SE* = .15, p < .01; β = .16) – were significant individual predictors in this model. Time and study environment (b = .07, *SE* = .03, ns; β = .12) was a trend-level predictor and would likely be significant with a larger sample size.

The regression model predicting the final dependent variable, liberal arts course GPA, can be seen in the corresponding section of Table 4. Again, the series of cognitive and non-cognitive factors predicted a significant amount of variance in liberal arts course GPA ($F(9,307) = 2.36$, $p < .05$). In this model, two of the independent variables turned out to be individual significant predictors: high school GPA ($b = .48$, $SE = .20$, $p < .05$; $\beta = .14$) and conscientiousness ($b = .10$, $SE = .04$, $p < .01$; $\beta = .17$).

Across these three models no single variable was a significant individual predictor in each, although high school GPA may have been with a larger sample. Only high school GPA was a significant predictor for two models: technical team-based and liberal arts course GPA. Three independent variables were significant individual predictors in only one model: test anxiety for lecture course GPA, extraversion for team-based course GPA, and conscientiousness for liberal arts course GPA. While there were few similarities between the models, all three were determined to predict a significant amount of variance in their dependent variable.

One particularly interesting result is that extraversion is a significant predictor of both cumulative first year GPA as well as team-based course GPA. Intuitively, many assume that extraverts would perform better than introverts in team-based courses. The focus of team-based courses on effective communication and interpersonal interactions on the surface seems to benefit extraverted students. However, it has been shown on many occasions that extraverted students had a more difficult time ignoring distractions and maintaining good study habits than introverts, and consequently tended to perform worse academically[21]–[23]. The structured, forced interactions in team-based courses may come with inherent distractions that make these courses more difficult for extraverts than introverts.

It is also worth noting again that our sample pulled in large part from mechanical engineering students who had already completed their first year course requirements at the time the survey was administered. Therefore, the subset of students that performed poorly, changed majors, or dropped out during or after their first year in engineering was not captured. We hypothesized that by surveying that subset of students we will see a larger variation in course performance in our sample, and the inclusion of more varied data would lead to our models becoming more significant.

In an effort to examine the effect of our Technical Team course cutoff of 25%, we reran the regressions including only courses in which at least 50% of the course grade was determined by team based activities in the Technical Team group. This adjusted cutoff moved Chemistry 1, Chemistry 2, and Intro Computer Science from the Technical Team group into the Technical Lecture group. The resulting Technical Lecture regression model was slightly more predictive than the original model ($F(9,321) = 5.48$, $p < .001$), while the resulting Technical Team regression model was less predictive ($F(9,250) = 1.92$, $p < .05$). Standardized test score ($b = .04$, $SE = .01$, $p < .01$; $\beta = .19$), test anxiety ($b = -.10$, $SE = .02$, $p < .01$; $\beta = -.23$), and high school GPA ($b = .44$, $SE = .18$, $p < .05$; $\beta = .14$) were all significant individual predictors in the adjusted Technical Lecture model. However, in the adjusted Technical Team model there were no significant individual predictors.

Table 4

Regression Analysis for Variables Predicting First Year Engineers' GPA in Each Course Group

	Technical Lecture *(N = 309)*			Technical Team *(N = 305)*			Liberal Arts *(N = 314)*		
Variable	*B*	*SE B*	*β*	*B*	*SE B*	*β*	*B*	*SE B*	*β*
Intercept	3.02	.03	0	3.50	.03	0	3.62	.04	0
Standardized Test Score	.05	.01	.19**	-.008	.01	.04	-.009	.01	-.04
High School GPA	.40	.21	.11	.41	.15	.16**	.48	.20	.14*
Extraversion	-.03	.03	-.06	-.06	.02	-.19**	-.02	.02	-.04
Agreeableness	-.03	.03	-.05	-.01	.02	.02	-.004	.03	-.006
Openness	-.0005	.04	-.0008	-.01	.03	-.03	.02	.04	.03
Conscientiousness	.05	.04	.08	.03	.03	.07	.10	.04	.17**
Neuroticism	-.001	.03	-.002	.0004	.02	.001	-.01	.03	-.03
Test Anxiety	-.10	.03	-.20**	.03	.02	-.09	-.01	.03	-.03
Time and Study Environment	.01	.05	.02	.07	.03	.12	.04	.04	.06
R^2			.12			.10			.07
F-Statistic			4.60**			3.83**			2.36*

Note: All variables were centered at their means.

*p < .05. **p < .01.

4. Conclusion

The takeaways of this work are two-fold. First, we showed that a combination of cognitive and non-cognitive factors lead to a significantly more predictive model of first year engineering GPA than cognitive factors alone. In addition, we showed that for a sample of academically high performing applicants, cognitive factors alone do a poor job of predicting first year engineering performance. A potential implication of this result is that students' first year performance is not only a function of their past performance. Instead, non-cognitive factors such as test anxiety and conscientiousness provide very important information as to how well students are likely to perform. Potentially more important than the improved predictability, however, is the fact that many non-cognitive factors are malleable. For example, in our sample reducing a student's test anxiety (measured on a scale from 1-7) from 6 to 4 would result in an expected GPA increase of 0.1 points. Changes in non-cognitive factors can lead to a non-trivial increase in student GPA.

Second, we have shown that performance in different classroom settings is related to different sets of cognitive and non-cognitive factors. An obvious implication of this result is that certain students perform better in specific classroom settings. For example, a student that experiences large amounts of test anxiety will likely perform better in a team-based course than in a technical lecture course, while a highly extraverted student is likely to perform worse in a team-based course than a technical lecture course. Similarly, where these results may enlighten us as to which students will perform better in specific classes, we can also use the results to attempt to mitigate the downside of a specific classroom setting. Technical lecture classes may make use of group, open-note, or take-home exams to mitigate the negative impacts of test anxiety in those classrooms, while team-based classrooms may take efforts to ensure their highly extraverted students have the proper support to perform well. The point is not only that non-cognitive factors add additional predictive power in models of first year engineering GPA, but also that where these non-cognitive factors have impacts, we can make changes that benefit our students.

These results also lead into an interesting discussion about interventions. As stated above, changing students' non-cognitive profiles can lead to noticeable changes in their academic performance. However, we have also shown that students' non-cognitive factors impact their academic performance in different ways depending on the context. Therefore, we would not expect large scale, highly structured interventions to have a distinct impact. For example, while a text anxiety intervention aimed at engineering students en masse may seem like an effective way to improve first year engineering student GPA overall, it will do little to benefit students struggling in their liberal arts courses. From these results it seems that non-cognitive interventions are a viable way to improve student academic performance, but they need to be tailored to individual classes, or better yet individual students, to account for differences in both non-cognitive attributes and academic context.

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