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Predicting Academic Behaviors of First-Year Engineering Students by Modeling Non-cognitive Factors and their Interactions

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Introduction

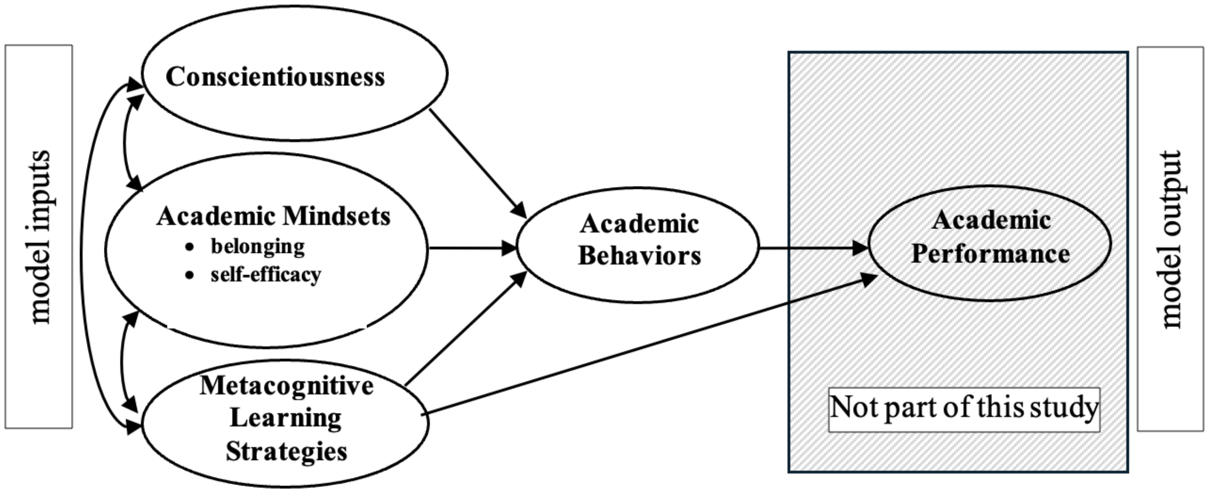
A common reason for many first-year engineering students to leave their degree program are their first mathematics courses [1], upon which all subsequent engineering concepts rely. Beyond mastering foundational calculus concepts and their practical applications, engineering students are honing their skills in mathematically framing, executing, and articulating solutions within diverse problem-solving contexts [2]. While success in these endeavors is often connected to cognitive predictors such as the student's GPA and past academic success, test scores, and intelligence [3], they only account for about 15% of the variance in academic success [4]. In contrast, non-cognitive predictors, generally defined as those skills, attitudes, beliefs and strategies that affect academic performance but are not measured by cognitive tests [5] account for around 25% of variance in academic success [4]. Identifying and improving the non-cognitive skills of undergraduate engineering students can support improvement in both performance and retention.

Building on that literature we hypothesize that these non-cognitive factors may be malleable through a well-structured problem-solving communication rubric that can serve as an effective feedback tool for students. Our ultimate goal is to explore whether such rubric can positively impact these non-cognitive factors. This study is the first step toward that goal and consists of the development of a model that accurately measures selected non-cognitive factors and predicts academic behaviors.

Literature Review

A meta-analysis by Richardson et al. [6] identified 42 non-cognitive constructs in 241 data sets and highlighted interrelationships between an array of non-cognitive factors, articulating the challenge for drawing conclusions and designing interventions based on studies which examined only one or two constructs at a time. They recommended researchers distill available constructs and measures into a parsimonious, mechanistic model that simultaneously incorporates multiple factors to predict performance. Our hypothesized model (Figure 1) draws on this work and heeds the recommendation that more empirical studies are needed that bring the factors together in a coherent manner [7]. We explored the role of conscientiousness, academic mindsets, and metacognitive learning strategies, because these constructs have been shown to directly impact the things students do – their academic behaviors – which ultimately lead to academic performance [5], [7], [8]. With academic performance measures still pending, we restrict this study to explore how the non-cognitive factors can usefully predict academic behaviors as the first stage of the larger project to be completed later. In the coming stages, we will analyze the impact of the rubric use on the non-cognitive factors and academic performance in calculus classes.

Figure 1. *Hypothesized Model Predicting Academic Performance*



Conscientiousness

Conscientiousness is defined as the extent to which a student is achievement and goal oriented, hardworking, organized, persistent, responsible, rule-following, and self-disciplined [9], [10], [11], [12]. These qualities have a reciprocal connection with academic mindsets as they can be reinforced by a positive mindset but can also nurture and strengthen the growth orientation and the sense of self-efficacy embedded within academic mindsets [5], [13]. Likewise, the qualities of conscientiousness align well with predictions of leading to positive academic behaviors. Conscientiousness may also inform a student's choice of learning strategies, aiding in setting of proper goals, self-regulation, and metacognitive processes [5]. Conscientiousness has been repeatedly, strongly, and positively linked with academic outcomes, predicting, for example, GPA and retention [13], [14], [15], [16]. In this study, conscientiousness was measured by modifying a conscientiousness subscale from a widely used personality assessment [17], [18] to align the items for an academic context. The original subscale demonstrated good internal consistency, with a Cronbach alpha of $\alpha = .83$ for adolescents aged 14-20, and $\alpha = .82$ for adults aged 21-91 [17]. Cronbach's alpha is a measure of how consistently the items within a scale assess the same construct. It is commonly accepted that items above 0.70 suggest usefulness for educational context.

Academic Mindsets

Research synthesized by the National Research Council [19], the University of Chicago Consortium on School Research [5] and the Gardner Center at Stanford University [20] all concluded that students' psycho-social beliefs and attitudes – collectively labeled as 'academic mindsets' – strongly affect their school engagement and learning [21]. Two of the key academic mindsets were described by Farrington et al. [5], each of which has been independently associated with increased perseverance, better academic behaviors, and higher grades. These two were students': 1) sense of belonging in the academic community; and 2) self-efficacy or belief that they can succeed academically. In our study, the academic mindsets construct was measured through surveys of sense of belonging [22] and self-efficacy adapted from Pintrich et al. [23].

Metacognitive Learning Strategies

Metacognition, often used interchangeably with self-regulated learning in the literature [24], refers to students' abilities to track and control their own learning. Metacognition is a key aspect for successful learning, problem-solving, and reasoning. Metacognitive learning strategies can be taught [25], [26], [27] and have been shown to be an advantageous skill that is a strong predictor of academic achievement in mathematics and other areas [28], [29], [30], [31], [32]. Our study created a scale grounded in the literature to capture this construct.

Academic Behaviors

Academic behaviors include the observable actions to execute a learning strategy or to express enactment of academic mindsets or conscientiousness and serve as the medium through which all other non-cognitive and cognitive factors are expressed. In his study of college and career readiness, Conley [33] argued that a student's lack of attention to positive academic behaviors is one of the greatest challenges for first-year college students. He found this to be the case even if those students possessed adequate content knowledge and appropriate cognitive strategies. It is ultimately what students do that leads to success or failure in academic courses. Based on a survey of literature related to how researchers operationalize academic behaviors, we synthesized a measure around four primary categories: study habits, how students use homework, the nature of mental engagement (in-class and out-of-class study), and how students leverage outside resources such as online tutorials, explanations, or symbolic calculus calculators.

Methods

Study Participants

Data for this study were collected from first-year calculus and pre-calculus engineering students enrolled at the University of Louisville. All students were asked to complete the online study survey in the first two weeks of their class in exchange for homework points. Student were advised that their consent to allow their responses to be used in the current study is voluntary and will not impact their homework grade, as well as that their course instructors will remain blind to their responses until the final grades are assigned. A total of 321 students completed the survey and provided consent to participate in the study. Participants' demographic information is summarized in Table 1. Note that percentages for race add up to over 100% because some participants could choose multiple categories. Twelve survey responses were eliminated due to missing data, leaving a total of 309 surveys for the analyses.

Table 1
Demographic Information (not all students chose to give responses)

Demographic	% of students
Gender	
Female	18.7
Male	66.0
Transgender female	.6
Gender nonconforming	.3
Prefer not to answer	1.6
Different identity	.6
Race	
Asian first	10.0
Asian American	4.7
Hispanic first	5.3
Latino/Latina first	5.0
White European/White American	71.0
Middle Eastern/North African	1.9
Black/African American	4.0
Native Hawaiian/Other Pacific Islander	.3
Native American/Alaska Native	.9

Analyses

Structural equation modeling (SEM) was chosen over other analytic approaches because it offers a comprehensive way of understanding the complex interplay of factors influencing academic outcomes. Moreover, by incorporating latent constructs such as conscientiousness and academic mindsets, SEM enables the exploration of underlying factors that may not be directly observable but play a crucial role in shaping student outcomes. This holistic approach accommodates the interconnectedness of various factors contributing to student success, moving beyond simple linear relationships to capture the complexity of the academic experience. For an introduction to the basic ideas of SEM, see Maruyama [34] for a clear articulation of the underlying logic, strengths, and limitations.

SEM fit indices are various measures that quantify how well the model fits the observed data from the sample. To evaluate the fit of a particular SEM model to observed data, it is generally considered best practice to report a suite of fit indices that represent multiple perspectives on determining model fit [35], [36]. For our study, in alignment with the recommendation by Kline [37], we report a set of three fit indices for each iteration of the model: (a) the goodness of fit index (GFI) which represents an absolute fit index that indicates information analogous to the proportion of explained variance of the data; (b) the comparative fit index (CFI) which captures the model fit comparative to the fit of an independent, or null (no causal relationships between any variables), model; and (c) the root mean square error of approximation (RMSEA) which is a parsimony-adjusted index capturing model misfit (‘errors’) per model degree freedom. Although there are several different interpretation guidelines for what value is considered a good fit for each fit index, a common set of interpretation guidelines for good fit is: GFI $\geq$0.90; CFI $\geq$0.90; RMSEA $\leq$0.08.

Analyses include two sequential aspects: first establishing the measurement model (the three left-side ovals in Figure 1 that are intercorrelated) and then establishing the structural model whereby these 3 are modeled as predictors of academic behaviors. Note that the academic performance ultimate outcome is not a part of this study (see Figure 1) because those data are not yet available at the time of crafting these preliminary results. Each aspect of the model (measurement first, then structural) will be crafted in stages, using the suite of fit indices, potential modification indices returned by the SEM software, and the chi-square 'badness-of-fit' metric to inform subsequent stages until the model modification reaches an adequate fit.

Results

Development of Measurement Model Iterations

Stage 1 Results (Model 1)

The baseline measurement model, from which subsequent iterations will build, contained the interrelationships of the four latent variables: conscientiousness (measured by 12 items C1-C12), two academic mindsets measures (belonging measured with items B1-B4; and self-efficacy measured with items SE1-SE8), and metacognitive learning strategies (measured by items LS1-LS12). After removing items LS1 and LS2 which were causing model non-convergence due to multicollinearity, we found a model fit that indicated potential for additional modifications to strengthen the measurement model (see fit indices for Model 1 in Table 2).

Stage 2 Results (Model 2)

For the next iteration, Model 2, learning strategy survey items LS6 and LS9 were removed since the baseline model output indicated they contributed non-significant loadings onto their latent variable. The model demonstrated improvement in chi-square, GFI, and CFI, while RMSEA remained consistent (see Table 2, Model 2). Modification indices suggested additional model modification may be warranted.

Stage 3 Results (Model 3)

Modification indices from Model 2 output suggested covarying survey self-efficacy items SE2 and SE4, which is logical, given that both items assess comprehension of complex material and are likely to share residual correlations. Iteration 3, Model 3 covaried items SE2 and SE4, which resulted in a significantly enhanced model fit (see Table 2, Model 3). However, sense of belonging item B3, a reverse-worded survey item, showed moderate cross-loadings with most "self-efficacy" items, suggesting that the reverse-wording may have been confusing or that this item does not exclusively measure the "belonging" construct but may overlap conceptually with aspects of "self-efficacy". As such, we determined that removing this problematic item would likely improve the model's fit.

Stage 4 Results (Model 4)

Excluding B3 resolved its cross-loading issues, yielding the best-fitting model (see Table 2, Model 4, which is the final iteration of the measurement model). No additional large modification indices emerged, suggesting no further modifications were warranted. This model served as our final measurement model for subsequent analyses. A summary of fit indices for all iterations are in Table 2. Note that the GFI and CFI fit indices are slightly lower than what is considered a good fit, but are considered reasonable given that our measures are new and untested, plus these surveys were completed by students in the first weeks before having experienced much of the engineering program. For our exploratory phase of this work, we will continue to build on this measurement model with the intent to explore potential future revisions to items or the model itself as additional data become available.

Table 2
Sequence of Measurement Model Iterations

Model Iterations	Chi-square (df)	GFI	CFI	RMSEA [90% CI]
Model 1 (baseline)	1042 (489)	.833	.850	.061 [.056-.066]
Model 2 (remove LS6, LS9)	943 (428) [a]	.838	.859	.062 [.057-.068]
Model 3 (covary SE2-SE4)	878 (427)	.848	.876	.059 [.053-.064]
Model 4 (remove B3) Final model	780 (398) [b]	.856	.890	.056 [.050-.062]

[a] $\Delta \chi^2 = 99$ for Δ df = 61, $p < .05$, indicating a significantly better fit, as the critical value for $\Delta \chi^2$ with 60 degrees of freedom is 79.
[b] $\Delta \chi^2 = 98$ for Δ df = 29, $p < .05$, indicating a significantly better fit, as the critical value for $\Delta \chi^2$ with 29 degrees of freedom is 43.
Note. $\boldsymbol{X^2}$ = model 'badness of fit' chi-square; ***df*** = model degrees freedom; **GFI** = Goodness of Fit Index, **CFI** = Comparative Fit Index, **RMSEA [90% CI]** = Root Mean Square Error of Approximation [90% Confidence Interval]

Development of Structural Model Iterations

The structural model builds upon our finalized measurement model by introducing academic behaviors as a new latent variable predicted by conscientiousness, belonging, self-efficacy, and metacognitive learning strategies. We aimed to examine whether the theoretical relationships hypothesized in the study align with the observed data and test how well these non-cognitive constructs predict students' academic behaviors, measured with 10 survey items AB1-AB10.

Stage 1 Results (Model 1)

Our baseline structural model (Model 4 in Table 2) combined all predictors and academic behaviors, with the initial fit indices suggesting a reasonable starting point but identifying room for improvement. Regression weights indicated that conscientiousness and metacognitive learning strategies significantly predicted academic behaviors, but self-efficacy and belonging did not. See Table 3, Model 1 for fit indices and for standardized regression weights for these 4 latent predictors.

Stage 2 Results (Model 2)

Although self-efficacy and belonging were not significant predictors of academic behaviors, they were not removed at this stage to preserve the theoretical framework and to allow for the possibility that their influence might emerge in later refinements or through indirect effects within the structural model. In addition, we aimed to make incremental changes to the model and avoid conflating the outcomes of multiple simultaneous changes. Modification indices from stage 1 suggested adding covariances between errors terms of academic behaviors items AB9 and AB10, AB8 and AB10, AB3 and AB8, and conscientiousness items C2 and C6 to improve model fit, which was labeled as the next iteration, Model 2, in Table 3. All fit indices showed substantial improvement with these modifications.

Stage 3 Results (Model 3)

In the next iteration, Model 3, we removed the three survey items (AB3, AB9, AB10) with low or non-significant contributions to the academic behaviors construct. In addition, we set the regression weights of self-efficacy and belonging to zero. This allowed us to keep these paths to academic behaviors for conceptual purposes but test the impact of removing them as predictors. Model 3 showed meaningful improvements in chi-square, GFI, and CFI (see Table 3, Model 3). The output for this model did not suggest any further modifications that could improve the fit, and thus Model 3 is the final iteration of the structural model. A summary of fit indices for all structural model iterations are in Table 3.

Table 3
Sequence of Structural Model Iterations

	Chi-Square (df)	**GFI**	**CFI**	**RMSEA [90%CI]**	**Standardized Regression Weights**
Model 1	1529 (729)	.796	.807	.060 [.055-.060]	Belong= .085 SE=-.050 Consc= .546*** Meta=.501***
Model 2 (added covariances)	1374 (725)	.814	.843	.054 [.050-.058]	Belong= .067 SE=-.067 Consc= .552*** Meta=.504***
Model 3 (self-efficacy & belonging set to zero weight)	1195 (619)	.823	.854	.055 [.050-.060]	Belong= 0 SE=0 Consc= .543*** Meta=.450***

Note. ***Chi-Square*** = model 'badness of fit' chi-square; ***df*** = model degrees freedom; **GFI** = Goodness of Fit Index, **CFI** = Comparative Fit Index, **RMSEA [90% CI]** = Root Mean Square Error of Approximation [90% Confidence Interval]; **Belong** = Sense of Belonging in College; **SE** = Self Efficacy; **Consc** = Conscientiousness; **Meta** = Metacognitive Learning Strategies
*** $p < .001$.

Discussion

The findings of this study highlight both the strengths and limitations of our structural model in predicting academic behaviors among first-year engineering students. The adapted measure for conscientiousness and the developed measures for learning strategies and academic behaviors had not been tested prior to this study for this population. It is possible that some of the items may be overlapping or ambiguous and need to be refined to more accurately capture the constructs they aim to represent. This likely contributed to the measurement model GFI and CFI indices being slightly weaker than desired.

Incremental adjustments yielded substantial improvements in the final structural model, showing it to be potentially useful yet also indicating room for refinement to account for the complexities of predicting academic behaviors in this population. Future research might also explore incorporating additional non-cognitive factors, such as motivation, which is a significant predictor of academic performance, even after accounting for prior achievement [38], time management, which is also associated with academic success [39], or positive affect and optimism, which are linked to stress mastery and overcoming setbacks [40] which might contribute meaningfully to academic behaviors.

Interestingly, the results show that sense of belonging and self-efficacy do not directly predict academic behaviors at students' first week of their college calculus or precalculus class. Given that prior research robustly indicates that these constructs have predictive power [21], [39], [40], the likely explanation for our results is that the participants, having just transitioned from high school, may not yet have developed a sense of belonging at college and have not had the opportunity to test or inform their ability to feel self-efficacious. We anticipate the data collected at the end of the first semester will present a different picture, with belonging and self-efficacy playing a greater role in academic behaviors as the participants will have had a full term to transition from high school to college and therefore evolve their academic mindsets to influence their behaviors in meaningful ways.

In contrast, the model shows conscientiousness and metacognitive learning strategies are strongly predictive of academic behaviors, with each unit of their increase resulting in .45 unit increase in academic behaviors as evidenced by standardized regression weights exceeding .45. Conscientiousness encompasses qualities such as persistence, organization, and goal orientation [9], [11], [12], [41], which translate into effective academic habits. These traits develop before students enter college and provide a critical foundation for managing the rigorous demands of engineering coursework. Likewise, students likely began developing their metacognitive learning strategies prior to their first semester of college, enabling them to actively monitor and adjust their learning approaches, as well as tackle complex material more efficiently. The strength of these predictors highlights their role as essential components of academic success, especially in the initial stages of college when students are establishing foundational behaviors.

This study underscores the dynamic nature of the factors influencing academic success and the importance of timing in understanding their interplay. The early effects of conscientiousness and metacognitive learning strategies during the transitional phase of students' academic journey presents them as valuable assets in nurturing helpful academic behaviors. Future analysis of end-of-semester data may shed some light on how belonging and self-efficacy change through time, and whether they may begin to fulfill their potential in also influencing academic behaviors. The end-of-semester 2024 surveys, soon to be analyzed, will allow us to evaluate student changes in these non-cognitive factors and their relationship to academic performance operationalized by their final exam calculus and pre-calculus scores. The final step will be to analyze particularly how the use of the rubric may influence these variables.

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