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Understanding and Improving the Non-Cognitive Factors that Affect First-Year Engineering Performance

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UNDERSTANDING AND IMPROVING THE NON-COGNITIVE FACTORS THAT AFFECT FIRST-YEAR ENGINEERING PERFORMANCE

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To my love. Your love and support have meant everything to me throughout this process. Without you none of this would have been possible.

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ABSTRACT

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To maintain America's status as a global technological leader, there has been a longstanding effort to increase the quality and quantity of engineers in the workforce. Previous research and government reports have called on the education system at all levels to increase enrollment and persistence in college engineering programs. Additionally, engineering employers continue to be dissatisfied with the skills obtained by those students who do persist to graduation, in part because those students that may become the best engineers are leaving engineering. In order to effectively recruit and retain the best engineering students, the factors that affect engineering student success need to be better understood. In addition, we need to understand how to improve these factors in students to guide them to becoming successful in engineering However, in engineering undergraduate programs, where many students are matriculating with exceptional academic credentials, "cognitive" factors such as high school GPA and standardized test scores are poor predictors of student success. Therefore, in order to gain a better understanding of the drivers of academic success for first-year engineering students, additional non-cognitive and demographic factors must be considered.

The initial goal of this research was to determine the cognitive, non-cognitive, and demographic factors that affect the academic performance of first-year engineering undergraduates. To accomplish this, a 41-item non-cognitive and demographic survey was administered to 375 first-year engineering students to measure a collection of non-cognitive, and demographic factors. An exploratory factor analysis was performed on the non-cognitive survey items to determine the underlying factors present in the data, and these factors were included alongside traditional cognitive and demographic factors in a step-wise linear regression model. Finally, a structural equation model was created to better understand the direct and indirect effects of the cognitive, non-cognitive, and demographic variables on first year engineers' academic performance.

The subsequent goal was to recruit students for an intervention intended to improve a subset of those non-cognitive factors. Initially, students were recruited for an academic coaching intervention with the intention of improving their study habits, time management, and test anxiety. An additional set of students was then recruited for a second round of interventions, where academic coaches were given the quantitative results so they could better prepare for and target their sessions to individual students.

The results of this research show that the inclusion of non-cognitive and demographic factors creates a much better model for predicting engineering students' first year performance. For instance, with this sample of students, test anxiety had a significant negative relationship with cumulative first year GPA, while high school GPA was a non-significant predictor. In addition, academic coaching interventions were found, both quantitatively and qualitative, to improve students' study skills, time management, and test anxiety. All students mentioned that they thought academic coaching would improve their academic performance, and on average students' test anxiety and study skill survey results improved.

This research shows how engineering students' academic success can be better modeled with a more holistic collection of factors, and that a subset of these factors can be improved with the goal of improving academic performance. These results can be used by faculty and academic

advisors to better understand why students may be struggling and can be used to more effectively recruit students for interventions. The academic coaching system can also use these results to create more effective and personalized interventions. Ultimately, this research can be used in numerous ways to better understand students and guide them towards academic success.

INTRODUCTION

The Need for More Engineers

For more than a decade there has been a consistent push for an increase in the quantity and quality of engineers entering the workforce. Numerous reports have called out the education systems at all levels to improve the rate at which engineers graduate, as well as their preparedness for college and eventually the engineering workforce [Committee on Science, Engineering, and Public Policy (COSEPUP) and Policy and Global Affairs (PGA), 2006; National Academy of Engineering (NAE), 2004, 2005]. To this day, the need for engineers continues to be on the rise. The Bureau of Labor Statistics shows that the number of college educated engineers needed in the workforce is expected to grow faster than the overall average workforce growth between now and 2024, with estimated increases for certain disciplines as high as 20% (Bureau of Labor Statistics, 2015). Additionally, according to the National Science Board (2015) the number of non-engineering jobs that still require college-level engineering expertise is similarly on the rise. Yet, even with the need for more engineering graduates, there is a problem getting students interested in engineering from an early age, which in turn impedes the requisite flow of students into engineering programs (Maltese & Tai, 2011).

Lowell, Salzman, Bernstein, and Henderson (2009), however, disagree with the idea that too few students are deciding to enter engineering programs. They argue that the total number of incoming engineering students is adequate; the lack of graduating engineers prepared to contribute in the engineering workforce is instead bred from engineering programs' inability to admit and retain the highest achieving engineering students. If that is indeed the case then the issue is not how to broaden the interest in engineering in an effort to recruit more students, but instead it is how to ensure the highest quality engineers are entering engineering programs. Specifically, graduating engineers need to be able to effectively solve the problems that they will face in their career. The Accreditation Board for Engineering and Technology (ABET), an organization that accredits university engineering programs, has created a list of student outcomes. ABET requires that universities provide evidence that their students attain these outcomes, or other outcomes of interest defined by the university, before graduation in an attempt to ensure engineering students have all skills necessary to be successful engineers (ABET Engineering Accreditation Commission, 2017). Since ABET has created these outcomes there has been an improvement in some–namely mathematical skill and the ability to use modern tools and technology–however, engineering employers remain dissatisfied with incoming engineers' communication skills, teamwork, and ability to self-regulate (Lattuca, Terenzini, & Volkwein, 2006; Nair, Patil, & Mertova, 2009; Ramadi, Ramadi, & Nasr, 2016). In order to make sure that engineers graduate with these relevant skills and are able to meet workforce expectations, there is a need to ensure the students accepted into engineering programs are of the highest quality. One method by which this can be accomplished is through the traditional engineering admissions system. While many of the engineering admissions processes are considered holistic (Holloway & Reed-Rhoads, 2008) two variables are particularly prevalent in determining students' academic ability–high school GPA and standardized test scores.

Determining the Best Students

According to the Educational Testing Service (ETS), the purpose of standardized tests is to provide a fair and balanced measure by which students' ability can be judged. Yet it has been shown that female students perform worse on the SAT math portion than male students with similar grades (Holloway, Reed, Imbrie, & Reid, 2014). This gender bias has been well documented and ultimately results in an under-prediction of female students' college GPA (Young & Kobrin, 2001). Additionally, College Board, the institution that administers the SAT, has shown that standardized tests are less predictive of first year GPA than high school GPA, while ACT Inc. admits that standardized tests should carry less weight than high school GPA when trying to predict final college GPA (ACT Research, 2008; Kolbrin, Patterson, Shaw, Mattern, & Barbuti, 2008). As such some institutions are slowly moving towards a "test optional" or "test flexible" admissions system (Beth Ann Myers, 2016). However, a majority of engineering institutions continue to use standardized tests as a major factor in their admissions decisions (Myers & Sullivan, 2014).

High school GPA, on the other hand, is one of the strongest predictors of academic success in college (Komarraju, Ramsey, & Rinella, 2013; Veenstra, Dey, & Herrin, 2008). However, GPA as a predictive measure loses statistical power for high achieving students (Sawyer, 2013), and engineering students are among the most high achieving. One engineering institution showed that over the span of 2006-2010, median high school GPA of its admitted students was nearly 4.0 and the median class rank was in the top 10%. Beyond simply being high-achieving as a whole, incoming engineering students show very little variation in their high school achievement levels (Holloway et al., 2014). While high school GPA is a powerful predictor of college performance in most circumstances, in a high performing population with little variability (such as many engineering student populations), it becomes much less predictive.

With the usual factors of standardized test score and high school GPA ineffective in predicting the success of engineering students, the question becomes: how can the highest quality engineers be found? One attempt was made by Bourne, Klingbeil, and Ciarallo (2014) to measure non-cognitive factors of students by determining the student's level of academic commitment, defined by their determination to complete their college degree. Commitment was classified into one of four quadrants, which were described as having a combination of a high or low high school GPA with a high or low ACT score. However, this strategy suffers a problem similar to using GPA as a predictor alone: there is not enough variation in engineering admits' high school achievement to find meaningful results. Therefore, a more direct use of non-cognitive factors and demographics is necessary to elicit and understand the differences between students that affect their academic performance.

Beyond Admissions

The purpose of finding such differences, however, should not purely be to improve upon the engineering admissions process. Alternatively, finding such difference should be used to inform first year faculty and staff about the composition of their incoming class and prepare them to best assist their students to succeed. Understanding the non-cognitive factors of students would allow for staff to effectively recommend individualized academic strategies, and could provide faculty with the knowledge necessary to make curricular changes that better align their practice to incoming students. Additionally, this information could be used to advise the creation of large-scale interventions for first year students. Students during their first year may substantially benefit from interventions targeting non-cognitive factors. The transition from high school to college is a large stressor for students during their first year of study, and during that time students are more likely to face academic difficulties and leave engineering when compared to other years (Lu, 1994; Seymour & Hewitt, 1997; Watkins & Mazur, 2013). Furthermore, the students who do end up leaving engineering are not significantly different than those who stay in terms of high school grades or standardized test scores (Lent, Brown, & Larkin, 1986). This lack of variation points to the possibility that non-cognitive factors are important factors in their decision to leave.

Beyond improving persistence, interventions targeted at students' non-cognitive factors are also be expected to improve their academic performance in college. Numerous studies have shown that a variety of factors–both attitudinal and behavioral–are predictive of college students' academic performance. For example, study skills, self-efficacy, and several personality traits have regularly been shown to correlate highly with college GPA. In addition, several of these factors correlate more strongly with college GPA than high school GPA and standardized test scores do (Abraham, Richardson, & Bond, 2012; Komarraju et al., 2013).

The reason that many talented engineering students are not achieving or persisting in engineering programs seems to be only weakly related to their high school performance, because incoming engineering students tend to be similar in terms of high school GPA and standardized test scores. This result suggests that non-cognitive factors could play a prominent role in student achievement. Consequently, there is a need for comprehensive models of academic performance, including non-cognitive factors, that specifically target high performing populations.

Research Overview

This research was guided by two overarching goals. The first was to create a comprehensive model targeting an academically high-performing population. More specifically, the model is comprehensive in the sense that it will examine students' cognitive, non-cognitive, and demographic factors, and will be used to predict the academic performance of first-year engineering students. Other measures of student success, such as life satisfaction (Rode et al., 2005; Xiao, Tang, & Shim, 2009), do exist, but the scope of this research is focused solely on academic performance. The second goal of this research was to determine if a subset of the non-cognitive variables in the model can be improved via intervention and examine how students experience such interventions. To accomplish these goals, this research was divided into several research questions:

RQ1: To what extent do the items probing non-cognitive factors load onto their expected non-cognitive factors, or onto higher-order latent factor?

Hypothesis 1: According to DeYoung (2006) and Digman (1997), higher order factors exist within the Big Five personality traits. Using a factor analysis, I expect that similar higher order factors exist within this grouping of non-cognitive variables.

RQ2: To what extent do the resulting non-cognitive factors account for variance in the academic performance of first year engineers beyond the variance predicted by cognitive factors alone?

Hypothesis 2: Given the clustering of incoming engineering students at the upper ends of high school GPA and standardized test scores, I expect 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. Therefore, I expect that non-cognitive factors will provide a significant increase in predictive power over cognitive variables alone.

RQ3: To what extent do demographic factors–such as time spent caring for family members–account for additional variance in the academic performance predictions of first-year engineers beyond the variance predicted by the combination of cognitive and non-cognitive factors?

Hypothesis 3: While it is hypothesized that including both cognitive and non-cognitive factors will significantly improve the ability to predict the first-year performance of *engineering students, I expect that significant unexplained variance will still remain. Therefore, I hypothesize that demographic factors will be able to explain a significant amount of this remaining variance.*

RQ4: How can structural equation modeling be used to create a more sophisticated model of first year engineers' academic performance that includes cognitive, non-cognitive, and demographic factors?

Hypothesis 4: Structural equation modeling allows for the explicit inclusion of discovered meta-factors as latent constructs in the model, and allows for a more complex representation of the interconnection between variables. Therefore, the expectation is that SEM will provide a more comprehensive and accurate prediction of academic performance.

RQ5: How do these predictive models of first year engineers' academic performance differ by classroom setting?

Hypothesis 5: Evidence shows that learning varies between different classroom settings (Freeman et al., 2014; McKenzie et al., 2013). *Therefore, I expect that the significant predictors in the predictive models will change depending on classroom context.*

RQ6: What are the experiences of those undergoing and delivering an intervention targeting students' non-cognitive factors, and how do those experiences align with each other?

RQ7: How can these interventions be improved with knowledge of a student's non-cognitive factors and the impact of those factors on student success?

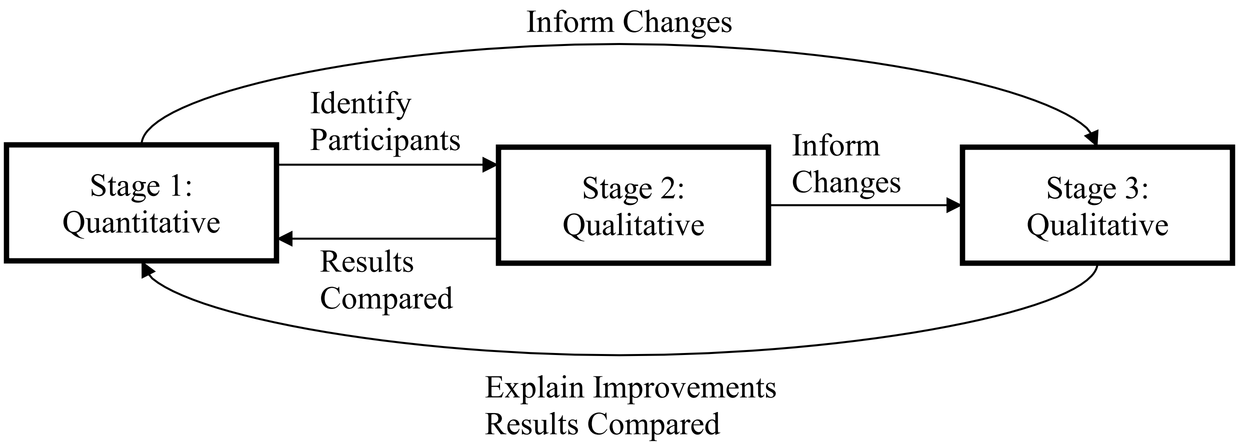
A grounded theory approach was used to answer RQ6 and RQ7, so no hypotheses were made for those research questions.

Preliminary results to research questions 1, 2, and 3 were presented at ASEE 2016 (Senkpeil & Berger, 2016). Additional results for research questions 1, 2, 3, and 5 were published in Senkpeil and Berger (2018).

To answer these questions in full, this research uses a multistage, sequential mixed methods research design. According to Creswell and Plano Clark (2007), mixed methods research focuses on collecting, analyzing, and mixing data from qualitative and quantitative sources. The use of both qualitative and quantitative data allows for a better understanding of the research problems than one source alone. Based on this terminology created by Creswell (2003), this research follows a sequential explanatory mixed methods design. Data are mixed in two aspects: connecting and embedding. Quantitative data is used to identify participants for qualitative data collection, thereby connecting the two data sources. Qualitative data also provides information as to how the quantitative findings can be changed or improved, thereby embedding the qualitative data within the quantitative.

This mixed methods research is undertaken in three stages. Stage one answers RQ1, RQ2, RQ3, RQ4, and RQ5. It is purely quantitative and makes use of a cross-sectional survey administered to first-year engineering students. Stage two answers RQ 6 and is a qualitative analysis of student experiences in an intervention aimed at improving their non-cognitive factors and academic performance. Stage three answers RQ7. It uses the results of Stage one and Stage two to inform an improved intervention by including participating students' non-cognitive factors and their impact on student success. These stages are grouped into the overarching quantitative and qualitative portions of this research. Stage one is in the quantitative portion and attempts to address the first goal of the research, while Stages two and three are in the qualitative portion and address the second goal. A visual representation of the mixed methods design is shown in Figure 1 below.

Figure 1: Visual representation of mixed methods design

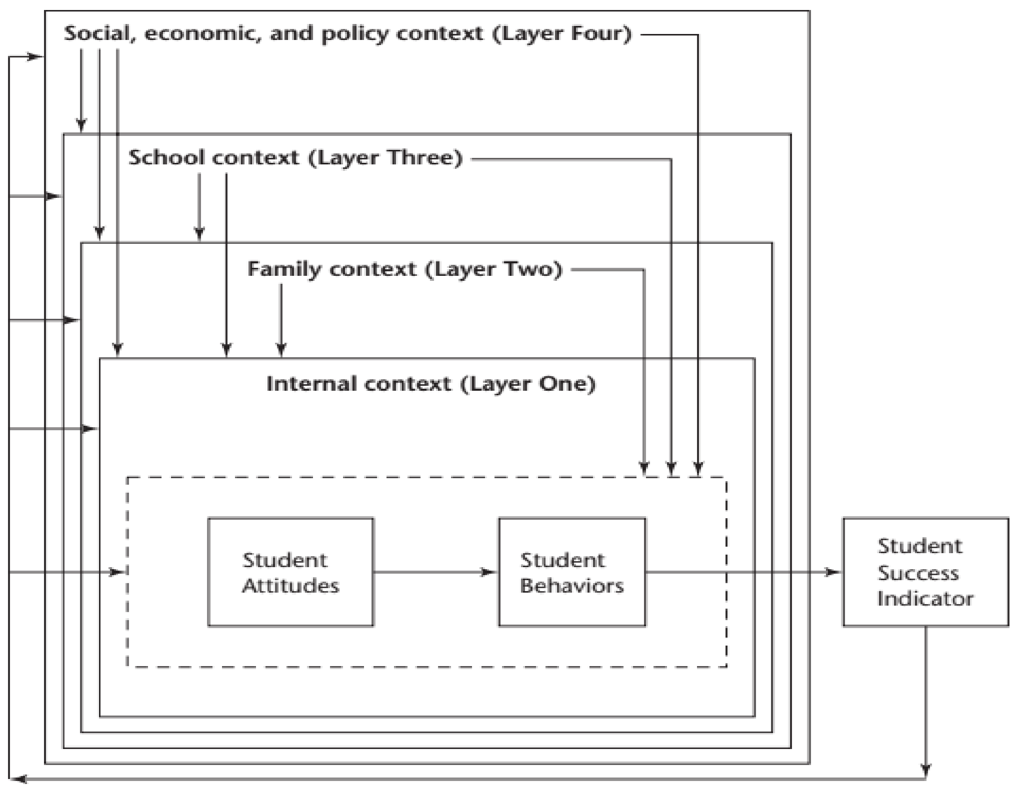


Conceptual Framework

This research was guided by Perna & Thomas' (2008) conceptual model of student success. Decisions made in the research process, such as which variables to collect and how to define student success, were made in concordance with this frame work. A graphical depiction of Perna and Thomas' (2008) conceptual model of student success can be seen in Figure 2 below. As Perna and Thomas describe, what makes this framework unique is that it combines the perspectives that multiple disciplines have on student success. Different disciplines focus on different indicators of student success, so by including multiple perspectives student success can be more comprehensively understood. For example, Perna and Thomas found that student success studies from Psychology most often use academic performance as a success indicator, while Economics and Education studies more frequently use persistence to graduation. Additionally, only Economics and Education studies on student success examine the phenomenon from the state or institutional level. Without each of these perspectives, important details as to what factors shape student success could be lost.

Perna and Thomas also mentioned two key traits of their framework that make it particularly applicable to this line of research. First, in this framework student success is shaped by multiple levels of context. This research examines how student success is not accurately captured by factors with a narrow focus. To completely understand student success, a broad and inclusive collection of factors that represent all aspects of a student must be considered, and this framework facilitates that endeavor. Second, this framework also recognized that student success is not only driven by multiple contexts, but also by individual students' "situated contexts." A students' situated context refers to how social, cultural, or other differences can cause students to take varying routes to achieve success. This is captured in part though this research by examining how the factors affecting success differ across classroom settings.

Figure 2: Perna and Thomas' (2008) conceptual model of student success



LITERATURE REVIEW

Holistic modeling of student academic performance–using a mix of cognitive, non-cognitive, and demographic variables–is still in its infancy. Until very recently, the focus of most research was on investigating the impact of individual variables or small groups of variables on academic performance. Therefore, the initial focus of this literature review will be to study previously created models of college student performance, with an emphasis on understanding the significance of individual variables. In addition, the variables that will be included in this study will be discussed in detail and the reasons for excluding other variables will be stated. Finally, this review will conclude with an explanation for the creation of non-cognitive meta-factors and how they can be improved using interventions.

Cognitive Models of Student Success

For several decades, the concept of predicting college student GPA has been consistently of interest to educators and education researchers. Many educational researchers consider GPA as a proxy for academic success, and therefore an important variable to understand (York, Gibson, & Rankin, 2015). Many of these models focused on using cognitive predictors, such as high school GPA and standardized test scores, to predict college performance. Goldman and Slaughter (1976) laid some of the earliest groundwork for predicting college GPA by analyzing the relatively low validity of predictions of student's average grades in all courses, defined as composite GPA. However, they found that the validity of predictions of single course grades were quite high. This results means that the independent variables–specifically high school GPA and SAT scores–are not to blame for poor predictions. Instead, the issue lies in the fact that when creating a composite GPA, all courses are considered equivalent. In reality, the impact of the independent variables may vary significantly between courses. For example, Goldman and Slaughter found that high school GPA is a very strong predictor of performance in introductory psychology and sociology courses, but non-significant in general chemistry and biology courses. They also found that among common predictors of college performance, high school GPA, is a better predictor overall than SAT score.

Ramist, Lewis, and McCamley-Jenkins (1993) altered the landscape of college performance prediction by determining the predictive validity of SAT scores. Their study included 38 colleges of varying size and selectivity, and heeded the warnings of Goldman and Slaughter by stratifying performance into groups based on subject matter. They found that highest correlation between SAT and performance was $r = 0.61$ in biological sciences courses, and the lowest was $r = 0.21$ in physical education courses. However, correlations in all courses were significant, indicating that SAT scores were a valid predictor of college performance.

Research on the predictive validity of standardized test scores continued, ultimately showing that not all standardized tests provided information that is equally useful for predicting academic achievement (Geiser & Studley, 2002). Specifically, it was shown that achievement-oriented standardized tests are significantly better at predicting college GPA than aptitude-oriented measures. Geiser and Studley (2002) compared the predictive validity of the SAT I (aptitude oriented) and the SAT II (achievement oriented) tests, colloquially known as simply the SAT and the SAT subject tests, when predicting college GPA. They found that the SAT II is consistently a better predictor of college GPA than the SAT I, and that incremental gains in explained variance are marginal when the two tests are used together. Also, the authors showed that the SAT II is less affected by student demographics than SAT I. Finally, the most recent theoretical discussions on predicting college performance have shifted focus back to using high school GPA as the primary predictor. According to Geiser and Santelices (2007) high school GPA is the single strongest predictor of college performance, and has consistently been more robust to the effect of student demographics when compare to standardized tests.

Numerous specific models of college GPA that use these cognitive predictors have been created and presented in the literature. Many such articles come from the organizations that create standardized tests. For example, College Board conducted a large scale study that included nearly 200,000 students at 110 universities across the United States in an effort to prove that SAT scores predict additional variance in first year college GPA compared to high school GPA alone (Kolbrin et al., 2008). The authors found that a combination of all sections of the SAT correlates with first year GPA slightly less than high school GPA ($r = 0.35$ and $r = 0.36$, respectively). Together, those cognitive factors correlated with performance at a rate higher than either one individually ($r = 0.46$). Additionally, the authors showed that SAT is a better predictor of first year performance at more selective universities, while high school GPA is more predictive at their less selective counterparts. However, as the authors stated, the results are limited by the fact that their sample of universities was not representative of the population of all institutions. Also, the first year GPAs collected by the authors ranged from 0 to 4.27, and no mention was made of how traditional 4.0 GPA scale universities were scaled to fit this range, which could further add to the skewing of data between universities.

Noble and Sawyer (2002) performed a similar large scale study with over 200 universities and more than 500,000 students. Their goal was to predict the likelihood that students achieve any GPA between 2.00 and 3.75 at increments of 0.25. To this end they created several logistic regression models using high school GPA and composite ACT score as their independent variables. They found that such models are highly accurate at predicting students’ first year GPAs when it was between 2.0 and 3.25. However, high school GPA became a weaker predictor and composite ACT a stronger predictor when attempting to predict higher first year GPAs. In addition, the authors showed that high school GPAs below 3.0 provide little ability to discriminate first year performance. Sawyer's later work expanded upon his initial research by studying the ability of high school GPA and ACT scores to predict success at the institution level as opposed to the student level. He defined success in four ways: the ability to achieve a 2.0, 3.0, 3.5, and 3.7 first year GPA. He found that both more selective universities and a higher definition of success led to ACT scores being a better predictor, while for less selective universities and lower definitions of success high school GPA was the better predictor (Sawyer, 2013).

Other regression models, aimed at predicting a student's specific GPA or likelihood to graduate in engineering, have been created using GPA and standardized test score as the main independent variables. The most accurate of such models were able to explain up to approximately 25% of the variance in their selected dependent variable (De Winter & Dodou, 2011; Zhang, Anderson, Ohland, & Thorndyke, 2004; Zwick & Sklar, 2005). Despite still being effective, predictive models of performance, some researchers have pointed to the three-quarters of unexplained variance as a reason to explore other potential independent variables and their potential influence on student performance.

Demographic-Included Models of Student Success

Of these other independent variables used to explain student success, demographics are common. Maruyama (2012) argued that demographic group differences–such as in gender, socioeconomic status, or ethnicity–can be exaggerated when only considering performance assessment, or cognitive, variables. For example, both Young (1991) as well as Young and

Kobrin (2001) have shown that models of college GPA slightly, but consistently, underpredict female students' academic performance. In the same vein, Astin (1993) concluded that high school GPA is the single best predictor of college performance, and he also indicated that gender was a useful variable in predicting first year college GPA. Similarly, Zhang et al. (2004) found that while gender was only a significant predictor of graduation in about half of the universities surveyed, when it was predictive it showed more often than not that female students were less likely to graduate in engineering than their male counterparts. Specifically, they determined that at one institution women were 1.5 times more likely to graduate, but at three others they were between 0.87 and 0.55 times as likely to graduate as male students.

Race/ethnicity is also a common demographic variable seen in college performance predictions, but its impact is more difficult to quantify than gender because of the sheer number of groups that need to be included (Young & Kobrin, 2001). However, reports have shown that models using a combination of high school GPA and SAT score overpredict college GPA for African American and Hispanic populations when compared to Asian American and White populations (Bridgeman, McCamley-Jenkins, & Ervin, 2000; Cowen & Fiori, 1991). In addition, Zwick and Sklar (2005) argued that first language is important to consider alongside ethnicity by showing that Spanish-speaking Hispanic students had lower four and five year graduation rates than English-speaking Hispanic students (4-year: 34% versus 31%, 5-year: 66% versus 50%).

A third demographic variable, socioeconomic status (SES), has frequently been found to be a strong predictor of student success in college (Robbins et al., 2004). Traditional cognitive predictors of student success in college lose statistical power when other variables such as social support or academic goals are included. However, the strength of SES as a predictor seems to be more independent of outside influences. In fact, studies have shown that SES is not only a predictor of academic performance, but also influences SAT scores, meaning that some traditional predictors of academic performance are dependent on a student's socioeconomic status (Sackett, Kuncel, Arneson, Cooper, & Waters, 2009). Specifically, the authors found that SES correlates at $r = 0.41$ with SAT scores.

It should be noted that while each of the cited studies has found significant differences in performance across demographic groups, none of these results imply that the demographic variables themselves are the cause of these differences. Instead, demographics serve as a proxy for larger equity issues, biases present in measurement and modeling of student success, and the social situations faced by students that may all impact students' academic performance. Therefore, while it is important to understand how academic performance varies across demographic groups, it is equally important to ensure that differences in performance across demographic groups are not conflated with inherent differences between those groups.

Non-Cognitive Models of Student Success

Beyond demographics, another set of variables used to explain student success is known as "non-cognitive." Studies frequently call for non-cognitive factors–such as personality, study skills, self-control, and several others–to be used to improve upon the existing predictions of student success (Kuncel, Hezlett, & Ones, 2001, 2004). However, measuring and understanding these factors has been a topic of much debate and comes with a specific set of challenges. Chief among those is the ambiguity of the "non-cognitive" moniker (Duckworth & Yeager, 2015). The origin of the term is from Messick (1979), where he stated: "Once the term cognitive is appropriated to refer to intellective abilities and subject-matter achievement in conventional school areas…the term non-cognitive comes to the fore by default to describe everything else" (p. 282). It is within that "everything else" categorization that the ambiguity of the non-cognitive label is born. Yet, as Easton (2013) stated, even though the term is debated, it is still used because "…everyone knows roughly what you mean when you use it and no one has a much better alternative" (p. 8). To mitigate the ambiguity, however, the specific non-cognitive factors researchers refer to or measure ought to be made explicit. A number of these specific non-cognitive factors and their impact on student success will be discussed in the following section.

One such non-cognitive factor is study skills, which is defined by the abilities to acquire, record, organize, synthesize, remember, and use information (Hoover & Patton, 1995). The impact of study skills on student success has been of interest of researchers for decades, with one of the earliest attempts to quantify the relationship coming from Brown and Holtzman (1955). In their study, the authors developed study-attitudes survey, and were able to show that positive attitudes towards studying were significantly correlated with higher performance (r = 0.50). A more recent meta-analysis of the ability for study skills to predict student success showed that it strongly correlated to retention (ρ = 0.366), but more weakly correlated to student GPA (ρ = 0.161; Robbins et al., 2004). A final examination of the impact of study skills on academic performance included both how and where students studied (Lynch, 2006). The author found that this conceptualization of study skills was significantly correlated with both first year (r = 0.19) and upper level GPAs (r = 0.27). All of these studies indicated a significant positive influence that study skills had on student performance.

There are also non-cognitive factors that can have negative influences. One such non-cognitive factor is test anxiety. The earliest studies looking at performance differences in students with test anxiety came out of Yale University in the 1950s. In these studies, students were grouped by high or low test anxiety and then given a series of aptitude tests. Researchers found that the low anxiety students completed the tests in less time and received higher scores than the high anxiety students (Mandler & Sarason, 1952). The authors also showed that low anxiety students have higher SAT scores on average than higher anxiety students (Sarason & Mandler, 1952). Additional studies have verified the significant difference in test scores between high and low test anxiety students, but have gone further and showed that test anxiety can predict up to 8% of the variance in a student's score on an exam (Cassady & Johnson, 2002). Where past exam performance can only predict up to 25% of the variance, the impact of test anxiety provides significant increase in predictive validity.

A third group of non-cognitive variables are self-efficacy and self-regulation. Self-efficacy, originally conceptualized by Albert Bandura (1977), is the belief in one's ability to succeed in a specific situation. When applied to academic situations, self-efficacy has been closely linked to self-motivated behavior and academic goal-setting in students (Zimmerman, Bandura, & Martinez-Pons, 1992). Academic self-efficacy has also been shown to be significantly correlated with student GPA ($r = 0.29$) and has strong indirect impacts on academic performance through variables such as academic performance expectations (Chemers, Hu, & Garcia, 2001). The second variable in this category, self-regulation or self-regulated learning, was originally conceptualized by Zimmerman (1994). Self-regulated learning consists of a cycle of planned, practiced, and evaluated actions by students, punctuated in each phase by metacognitive reflection. As a measured construct, self-regulation is a significant predictor of both student grades and standardized test scores (Zimmerman & Kitsantas, 2014).

While both self-regulation and self-efficacy are strong predictors of academic performance, there is considerable overlap between these and other variables. However, a more recently created non-cognitive trait contains aspects of both self-efficacy and self-regulation: grit. Grit was originally conceptualized by Duckworth, Peterson, Matthews, & Kelly (2007), and is defined as perseverance and passion for long-term goals. As a measured construct, grit is comprised of two parts: perseverance of effort and consistency of interest. Grit can predict a significant amount of variance in students' levels of academic self-efficacy, self-regulated learning, and success measured both by retention and performance (Eskreis-Winkler, Shulman, Beal, & Duckworth, 2014; Muenks, Wigfield, Yang, & O'Neal, 2016; Wolters & Hussain, 2015). While grit is a newly created construct and not without its issues–such as the link between grit and risky behavior or costly perseverance (Lucas, Gratch, Cheng, & Marsella, 2015)–it provides a unique look at common non-cognitive factors.

The final non-cognitive trait considered here, personality, is not so much a single trait as an attempt to understand an individual's innate characteristics. In one of the earliest explorations of personality, Henry Murray (1938) defined it as "…the sum total of the habitual responses [of an individual]" (p. 7). However, attempts to create more narrow representations of this all-encompassing definition quickly followed. One of the earliest of such representations is known as the five-factor model of personality. The five-factor model was born from the work of Raymond Cattell. Cattell (1943) studied a list of 4500 personality related terms and used this list to develop 171 bipolar scales. Cattell (1945) then used these scales to develop 35 clusters of related terms, analyzed these clusters, and determined five distinct factors or traits: extroversion, agreeableness, neuroticism, conscientiousness, and openness. These factors have also been called the "Big Five" model of personality.

An alternate attempt to represent personality is known as the Myers Briggs Type Indicator (MBTI). The MBTI was originally developed by Myers (1962) in an attempt to capture the psychological theories of Jung (1971). The MBTI scores personalities across four dichotomous categories: Extrovert-Introvert (E-I), Sensing-Intuitive (S-N), Thinking-Feeling (T-

F), and Judging-Perceiving (J-P). However, even though these two representations of personality were created entirely independently, evidence shows that every MBTI category significantly correlates with at least one of the Big Five traits (Furnham, Moutafi, & Crump, 2003; MacDonald, Anderson, Tsagarakis, & Holland, 1994). Therefore, regardless of the theoretical grounding of personality, the resulting representations indicate similar latent components.

As for the impact of personality on student success, Felder, Forrest, Baker-Ward, Dietz, and Mohr (1993) showed that students who identified as Intuitive were significantly more likely to get a “C” or better in an introductory engineering course than students who identified as Sensing. Looking at students’ complete Myers Briggs types, as opposed to scores on single scales, Borg and Shapiro (1996) showed that three of the sixteen possible MBTI types were significantly negative predictors of grades in an economics course. Similarly, the Big Five personality traits have been shown to predict up to 15% of the variance in students’ college GPA (Komarraju, Karau, & Schmeck, 2009). An earlier meta-analysis also showed that the Big Five trait conscientiousness is a significant predictor of college student grades (Trapmann, Hell, Hirn, & Schuler, 2007). Overall, even though multiple conceptions of personality exist, the underlying constructs and impacts of each are similar.

In conclusion, numerous cognitive, non-cognitive, and demographic variables significantly affect student success. From the students’ perspective, not considering multiple components of success–cognitive, non-cognitive, and demographic for example–ignores much of what composes the student. As for modeling academic performance, examining the impact of variables independently overlooks the inherently interacting nature of a student’s cognitive, non-cognitive, and demographic factors. The following section will look at the variables that will be included in an inclusive, holistic model of student success.

Independent Variables

In the previous section categories of cognitive, demographic, and non-cognitive variables were discussed with a focus on their potential impact on student success. In this section, the specific variables that will be collected to represent each of these categories will be discussed, as well as how these variables can best be measured.

As stated previously, the common variables that are used to represent students' cognitive factors in college are their high school GPA and standardized test scores. Even though it has been argued that both GPA and standardized tests scores may be poor predictors of academic performance in certain populations, they remain an important indicator of a student's cognitive ability, which is necessary to create a holistic model of student success. According to Frey and Detterman (2004), SAT scores correlate highly with two separate measures of general intelligence (r = 0.86 and r = 0.72). This indicates that the SAT, traditionally a test of college readiness, is also an effective measure of intelligence. Additionally, a significant, albeit smaller, correlation has been found between student GPA and g (Ridgell & Lounsbury, 2004). However, even given these significant correlations, standardized tests scores and g had an almost identical, unique impact on college GPA when modeled together while continuing to strongly correlate with each other (Coyle & Pillow, 2008). Therefore, high school GPA and standardized test scores can serve a dual purpose. Given the strong correlations with general intelligence, they can effectively represent a student's cognitive ability in terms of general intelligence. In addition, since they also predict a unique portion of the variance in college GPA compared to general intelligence, high school GPA and standardized test scores can also be considered a simple representation of college readiness. In collecting GPA and standardized test score data, it has been shown that students tend to incorrectly estimate their own scores (Cassady, 2001). To mitigate this collection error, all high school GPA and standardized test scores will be collected from the university registrar.

Similarly, the demographic data given in the admissions application–specifically, gender, ethnicity, and country of origin–will be collected and used as a subset of the variables representing a student's demographic traits. The remaining demographic trait, socioeconomic status (SES), will be represented using two variables: a percent free and reduced price lunch (PFRL) and expected family contribution (EFC). PFRL is determined by collecting students' high school code, and cross-referencing that with the National Center for Education Statistics data. PFRL provides a measure of the average wealth of a student's high school, and thus is used as a proxy for SES. Such school-level SES information has been proven to be a significant predictor of individual performance (Caldas & Bankston III, 1997). However, there is some concern about the ability for area measures of SES, such as percent free and reduced price lunch, to accurately represent an individual's SES (Geronimus, Bound, & Neidert, 1996; Soobader, LeClere, Hadden, & Maury, 2001). To mitigate this lack of individual accuracy, but also keep some of the area-related effects captured by PFRL, EFC will be used to gain a better understanding of a student's SES. EFC is a value calculated by the U.S. Department of Education that estimates the amount of money a student's parents or guardians can contribute to their tuition. EFC includes several variables depending on the student's financial and family situation, including parent's incomes, number of siblings also in college, a student's own income, and several others (Federal Student Aid, 2017). EFC, however, is only available for students who completed the Free Application for Federal Student Aid (FAFSA), so using it in conjunction with a more accessible SES proxy like zip code will allow for an accurate estimate of SES for a majority of students.

A final set of demographic variables are considered to represent students' family support. The first variable denotes family support of the student and will be captured through whether or not the students are financially supported by their parents. According to Bodvarsson and Walker (2004), self-funded students are less likely to fail classes in college than students who are funded in any part by their parents. The second variable denotes student support of their family and will be captured through the amount of time per week spent caring for a family member, which has been shown to significantly impact student engagement, particularly for older populations such as transfer students (Kuh, 2003). Items measuring both of these variables will be taken from a subset of items found in the National Survey of Student Engagement (NSSE; Kuh, 2003). The NSSE has been shown to have some difficulty predicting student GPA (Campbell & Cabrera, 2011), but given its extensive nationwide use, sound validity and reliability, and use of only a small subset of items, it provides a sensible instrument for collecting the variables of interest (Kuh, 2009; Kuh, Kinzie, Cruce, Shoup, & Gonyea, 2006).

Similar to the family support variables, non-cognitive factors were collected through a variety of self-report survey instruments. The study skills and test anxiety variables were collected using two subscales of the Motivated Strategies for Learning Questionnaire (MSLQ): Time and study environment, and test anxiety (Pintrich, Smith, Garcia, & McKeachie, 1991). Besides containing measurements for two of the desired non-cognitive factors, a major reason for selecting the MSLQ as the measurement tool for the study skills and test anxiety variables is its widespread use in the educational literature. Dozens of studies have used the MSLQ and have shown support for the theoretical structure of the instrument as well as its ability to predict academic performance (Credé & Phillips, 2011). In addition, the creators of the MSLQ have shown that the test anxiety and time and study environment subscales have strong internal reliability (α = .80 and α = .76, respectively) and strong predictive validity of college grades (r = -0.27 and r = 0.28 respectively; Pintrich, Smith, Garcia, & McKeachie, 1999). Despite the low reliability and construct ambiguity of some other MSLQ subscales, the test anxiety and time and study environment subscales remain sound instruments to measure those variables (Artino, 2005).

As alluded to before, the variable used to encompass aspects of both self-efficacy and self-regulation is grit. Since its creation as a measured construct in 2007, grit has seen rapid adoption in a variety of contexts from the military, to marriage, to the national spelling bee (Duckworth, Kirby, Tsukayama, Berstein, & Ericsson, 2011; Eskreis-Winkler et al., 2014). However, being a more recently developed construct has left grit with several potential issues that have yet to be explored (Kohn, 2014). For example, Duckworth (2007) argues that persistence–a core attribute of grit–can be detrimental if it is in a dead-end pursuit. Yet even though that point is valid, the fact remains that grittier students are more likely to engage in costly perseverance (Lucas et al., 2015). A second potential detractor of grit is that relatively few studies look at how grit can affect academic performance as operationalized by GPA (instead of other measures like persistence), and of those that do there seems to be little agreement on the effect size (Duckworth et al., 2007; Strayhorn, 2013; Wolters & Hussain, 2015). However, since grit has gained widespread recognition as a powerful non-cognitive variable, and has shown strong correlations to persistence and other known predictors of GPA, it deserves inclusion in a model of student success. Two instruments exists to measure grit: the 12-item grit-o survey (Duckworth et al., 2007) and the 8-item short grit survey (Duckworth & Quinn, 2009). The short grit survey (grit-s) was a refinement on the grit-o by removing four poorly loading items. The resulting grit-s had four items in the two subscales: perseverance of effort and consistency of interest. In four large scale studies, the grit-s has shown internal consistencies of $\alpha > .70$ in each case, suggesting that the measure is quite reliable (Duckworth & Quinn, 2009). The grit-s instrument also had similar predictive validity compared to the grit-o for variables the grit-o had already been used to study.

The final non-cognitive trait, personality, will be abstracted through the Big Five model of personality. The MBTI was decided against for two main reasons. First, the MBTI is most often used in corporate settings and much less frequently found in educational research. In fact, at one point it was shown that major corporations administered up to 40 percent of all MBTI instruments in a given year (Moore, 1987). Not being designed for educational settings could limit its effectiveness in those contexts. Second, the MBTI uses forced answer, dichotomous preference questions. Boyle (1995) argued that using dichotomous scoring as opposed to continuous scoring limits the level of statistical analysis that can be done, which in turn would significantly limit the complexity of the models of student success that this study is attempting to develop.

All Big Five personality measures, on the other hand, assess all five traits–extraversion, agreeableness, neuroticism, conscientiousness, and openness–using Likert Scale questions. Extraversion refers to sociability and the tendency to experience positive emotion; agreeableness refers to friendly and considerate behavior; neuroticism refers to the tendency to experience negative emotions most notably anxiety and anger; conscientiousness refers to persistence, self-discipline, and need for achievement; openness refers to the tendency to be involved in intellectual activities and new experiences. The most commonly used instrument for measuring these factors is the Revised NEO Personality Inventory (NEO PI-R), developed by Costa and McCrae (1992). This instrument showed exceptional reliability and validity for all five traits, but at 240 questions it has frequently been criticized for its length (Gosling, Rentfrow, & Swann, 2003; McCrae & Costa, 2010).

To mitigate the survey fatigue brought on by the length of the NEO PI-R, several shorter revisions of the survey have been developed, including 44-item, 10-item, and 5-item versions (Gosling et al., 2003; John, Donahue, & Kentle, 1991; Rammstedt & John, 2007). Comparing the five and ten item variations of the NEO PI-R, it has been shown that both take roughly the same amount of time to complete (about one minute), but the ten item is psychometrically superior and has a higher test-retest reliability than the five item (0.72 versus 0.68; Gosling et al., 2003). Compared to the 44-item version's test-retest reliability of 0.83, however, the ten item clearly shows degradation in terms of reliability, although it is still within acceptable levels. Given this, along with self-peer convergent correlations over r = .40 for all traits, the ten item version of the NEO PI-R is the recommended instrument for quickly measuring an individual's personality traits (Gosling et al., 2003; Rammstedt & John, 2007).

To conclude the section on independent variables, a brief explanation on the exclusion of certain variables needs to be made. The main reason that variables were excluded was because they could be represented through a combination of already included variables. For example, the effect of motivation and academic self-efficacy on academic performance is well established in the literature (Busato, Prins, Elshout, & Hamaker, 2000; Chemers et al., 2001), but neither of those variables is present in this model of student success. As stated previously, the perseverance of effort subscale of grit relates strongly to academic self-efficacy. Beyond that, however, academic self-efficacy significantly correlates with big five conscientiousness and openness, study skills, and test anxiety (Busato et al., 2000; Pintrich & De Groot, 1990). Similarly, it has been shown that every big five trait correlates significantly with one of intrinsic motivation, extrinsic motivation, or amotivation, and that the big five traits alone can predict almost half of the variation in academic motivation (De Feyter, Caers, Vigna, & Berings, 2012; Komarraju et al., 2009). In addition, study-skills and test anxiety also have been found to significantly correlate with student motivation (Hancock, 2001; Robbins et al., 2004). Given the strong relationships between academic self-efficacy, motivation, and the independent variables included in this model of student success, those two variables were excluded to reduce redundancy and mitigate the effects of multicollinearity (Licht, 1995). Similarly strong relationships between the included independent variables and numerous other non-cognitive factors, as well as a desire to keep the number of measured variables small to reduce survey fatigue, led to the decision to exclude other non-cognitive variables from this research.

Dependent Variables

Student success as a dependent variable in engineering education studies is usually defined as either student GPA or persistence to graduation in an engineering discipline (Kolbrin et al., 2008; Sawyer, 2013; Zhang et al., 2004). The most common measure for student success, and the one that will be used as the definition for student success herein, is academic performance as measured by student GPA. GPA offers a quantitative glimpse into the academic performance of students; it provides a proxy for a student's learning and is an important predictor of future performance, both academically and professionally (Kuncel, Crede, & Thomas, 2005). The use of GPA to represent student success, however, may present some challenges. GPA is a singular measure of academic performance. As such, it ignores students' professional, extracurricular, and social endeavors that may lead them to consider their college careers successful regardless of their GPA at graduation. From a statistical perspective, the reliability of GPA as a measure has been called into question due to possible variation in grades earned for students in different departments, of different class standings, or taking separate offerings of the same course (Johnson, 1997). However, given GPA's reliability over time and consistency in correlating to external variables such as salary and job performance, it remains an appropriate measure of student success (Poropat, 2009; Roth & Clarke, 1998).

While GPA is a valid representation of student success, the potential classroom-to-classroom variations in GPA discussed by Johnson (1997) still ought to be taken into consideration. To accomplish that, the collection of GPA as the dependent variable should be broken down by classroom setting. Active, cooperative, and problem-based learning classrooms have consistently been shown to increase both students' self-perceived academic achievement, as well as their individual course grades and performance on concept inventories when compared to traditional lecture-based classrooms (Paulson, 1999; Prince, 2004). Freeman et al. (2014) showed that students in STEM courses are up to 1.5 times more likely to fail in a traditional lecture course as opposed to an active learning course. Blended learning classes have also been shown to increase both student performance as well as satisfaction when compared to lecture-based classes (McKenzie et al., 2013). Given the well-established effect of classroom setting on GPA, considering cumulative GPA as the dependent variable alone could call into question its reliability as a representation of student success.

Interventions

The final goal of creating a predictive model of student success is to inform interventions that can be used to improve students' non-cognitive factors and ultimately their success in college.

The literature contains a number of previously constructed interventions for many non-cognitive factors that impact student academic success. For example, test anxiety has been shown to have strong negative impacts on academic performance (Cassady & Johnson, 2002; Chapell et al., 2005), yet effective methods exist that can reduce test anxiety in up to 75% of highly anxious students (Ergene, 2003; Spielberger, Anton, & Bedell, 2015). In addition, study skills interventions can improve both basic study and learning skills (Cottrell, 2013; Hattie, Biggs, & Purdie, 1996) as well as influence test anxiety (Motevalli et al., 2013). Similarly, mental contrasting interventions can improve student self-discipline (Duckworth, Grant, Loew, Oettingen, & Gollwitzer, 2011), and mindset interventions (Dweck, 2006) have been hypothesized to directly influence student grit (Perkins-Gough, 2013).

A final style of intervention–academic coaching–may not be considered a traditional intervention, but has still been shown to strongly influence student success. Academic coaching–an individual support service for students with a focus on reflection, planning, and goal setting–has been shown to improve student success both in terms of retention and student GPA, as well as explicitly targeting time management and study skills (Bettinger & Baker, 2013; Robinson, 2015; Robinson & Gahagan, 2010). In addition, improving time management and study skills can in turn improve test anxiety (Ergene, 2003; Motevalli et al., 2013). With its ability to benefit students in terms of study skills, time management, and test anxiety, academic coaching emerged as the best candidate intervention for this study. However, while the literature suggests academic coaching can be an effective intervention for undergraduates, little is known about the structure of academic coaching or how college students experience it (Robinson, 2015).

METHODS

Survey Development

What is called herein as the Non-Cognitive and Affective Factors (NCAF) survey was created to collect all non-cognitive and family setting variables. As stated previously, each category of independent variable was collected using its own instrument. The necessary parts of each of these instruments were combined to form the NCAF survey. The result was a 45-item survey that combined the Ten-Item Big Five Inventory (10 items, measured on a 5 point Likert scale), the Short Grit Survey (8 items, measured on a 5 point Likert scale), two subscales of the MSLQ (time and study environment, and test anxiety; 8 and 5 items respectively, measured on a 7 point Likert scale), NSSE (2 items, measurement scale dependent on question), and a number of demographic questions. The survey was administered electronically with a response rate of roughly 10%. The complete survey instrument can be seen in Appendix A.

Survey Population

Engineering students at a large Midwestern research university were the target population for this study. Only this university was chosen for this research because it offered access to the student population of interest, and had intervention infrastructure in place. Students were given an in-person recruitment presentation before a mandatory general engineering course for first-year engineering students. During this recruitment presentation the expectations for participating students, as well as the purpose and goals of the research were explained to students. Students subsequently received an email through the Qualtrics survey system prompting them to complete the survey and providing a link. No monetary compensation was offered for completing the survey, nor were students offered class credit or extra credit. Recruitment has occurred periodically since the Fall 2015 semester, and during that span 3306 total students were invited to participate in this study. Of the recruited sample, 320 students responded to the survey. Responses were removed from the dataset if the student attempted none of the questions. The remaining sample size was n = 301 students.

Each student in the final sample consented to the study and allowed access to their admissions data, academic transcript, and financial aid data. The variables collected from these datasets were: current GPA, grades in each course taken at the institution (including retakes), current year in college, high school GPA, scores on all standardized tests taken, gender, ethnicity, country of origin, expected family contribution and eligibility for Pell Grants and federal work study.

To ensure that first year performance was the dependent variable of interest, a "First Year GPA" variable was created based on the student's academic transcript. All engineering students at this institution were required to take the same eight courses (Calculus 1, Calculus 2, Physics 1, Chemistry 1, Intro to Engineering 1, Intro to Engineering 2, Basic Composition, and Public Speaking) and one or both of two technical electives (Intro to Computer Programming or Chemistry 2) in their first year. Grades in all of these courses were averaged to create the First Year GPA. Credit for each of these courses could have been obtained through a combination of Advanced Placement credit, transfer credit, or test-out examinations. If students earned credit for these courses via any method besides taking the course, those courses were ignored in the First Year GPA calculation.

Standardized test scores also required careful handling. The targeted institution allowed applying students to provide ACT scores, SAT scores, or both. To ensure the same data was available for every student, all standardized test scores were converted to the same metric.

Composite ACT score was used as the standardized test score variable, and all collected SAT scores were converted to composite ACT using the SAT-ACT conversion tables (ACT Inc., 2008). If students provided both SAT and ACT scores, only the reported ACT score was used and the converted value was ignored. ACT was chosen as the standardized test score variable because conversions from ACT to SAT score resulted in a range of values as opposed to a single value. For example, an SAT score of 1400 can be converted to an ACT score of 30. On the other hand, an ACT score of 30 would be converted to an SAT range of 1390-1410, and including such a range of potential values would limit the statistical analyses that could be performed.

Finally, of the demographic variables reported through admissions (gender, ethnicity, and country of origin), only gender was used in this research. The way in which ethnicity and country of origin are reported via the registrar, the variable does not accurately capture a student's race/ethnicity. Only domestic students were allowed to report their race/ethnicity, while an international student's race/ethnicity was only indicated as "international." International students could voluntarily provide their country of origin, but that does not necessarily reflect their race/ethnicity. Also, students that identify with more that one race/ethnicity were only marked as "two or more," with no additional detail given as to how they identify. For those reasons, only gender was used out of the demographic variables reported through admissions.

Classroom Setting

The courses included in students' First Year GPA were also grouped into one of three mutually exclusive categories that represents their classroom setting: Lecture-Based, Team-Based, and Liberal Arts. The two courses offered by the College of Liberal Arts, Basic Composition and Public Speaking, were grouped in to the Liberal Arts category. For each of the remaining seven courses, the total portion of the course grade dedicated to teamwork oriented activities–such as in-class group work, pair or group lab activities, and team-based projects–was determined. Each of the remaining courses in which at least 25% of the final course grade was determined by teamwork-oriented activities were grouped into the Team-Based category. Five courses fit this criterion: Intro to Engineering 1, Intro to Engineering 2, Chemistry 1, Chemistry 2, and Intro to Computer Programming. The 25% value was a natural cutoff as small shifts of even 5% in any direction made no impact on the course categorization. Intro to Engineering 1 and Intro to Engineering 2 fit the criterion because of their heavy emphasis on both in and out of class group assignment, Chemistry 1 and 2 because of the importance of group lab work in those courses, and Intro to Computer Programming because of its focus on paired programming techniques. The remaining three courses–Calculus 1, Calculus 2, and Physics 1–were grouped into the Lecture-Based category. The students' GPA for the courses in each category were calculated in addition to their First Year GPA. The distribution of courses in each category can be seen in Table 1.

Table 1: Courses included in each classroom setting

Lecture-Based Courses	Team-Based Courses	Liberal Arts Courses
Calculus 1	Intro to Engineering 1	Basic Composition
Calculus 2	Intro to Engineering 2	Public Speaking
Physics 1	Chemistry 1	
	Chemistry 2	
	Intro to Computer Programming	

Quantitative Data Analysis

Throughout stage 1 of this research, four quantitative statistical techniques were used for data analysis: stepwise multiple regression, exploratory factor analysis, confirmatory factor analysis, and structural equation modeling. All analysis was conducted in R version 3.4.0 (R Core Team, 2014).

Multiple regression is a statistical technique that can be used to determine the significance of the connection between multiple independent variables and a single dependent variable (Licht, 1995). Stepwise multiple regression is a variation on multiple regression where independent variables are entered one at a time or in small clusters. This technique can be used to determine if a single variable or small cluster of variables has a significant effect on the dependent variable beyond the other independent variables already in the model (Stockburger, n.d.; Vogt & Johnson, 2011).

Factor analysis is a method used to explain connections between variables through the existence of underlying factors or latent variables (Cudeck, 2000). These connections are observed through correlations between individual variables. Variables that correlate highly are said to load strongly on the same factor, and are considered influenced by the same latent variable. Exploratory factory analysis (EFA) is a discovery-oriented technique aimed at modeling these correlations between variables. The results of an EFA can indicate the presence of higher-order, latent factors that exist within a data set (Fabrigar & Wegener, 2012). Where EFA is used to discover latent factors, confirmatory factor analysis (CFA) is used to test the hypothesis that such factors exist (Hoyle, 2000). CFA can be used to evaluate the results of an EFA and determine that the discovered factors accurately model the data (Bryant & Yarnold, 1995).

Structural equation modeling (SEM) is a statistical technique that utilizes several methods–including factor analysis, regression, and path analysis–to provide a quantitative prediction of the relationships between observed variables and test a theoretical hypothesized model (Schumacker & Lomax, 2004). Structural equation modeling offers the ability to include latent constructs within the model and test the structure of the constructs using confirmatory factor analysis. The relationship between these latent constructs, and additional observed variables, can be determined using regression and path analysis. SEM performed in four broad steps. The first step is specification, where the measurement and structural models are hypothesized. The measurement model hypothesizes how measured variables load onto latent factors, and the structural model hypothesizes how measure and latent variables relate with one another. Step two is identification. The measurement and structural models are determined to be identified if there are enough indicators and known variables such that exactly one set of model parameters can be accurately estimated. If multiple sets of model parameters can be estimated to produce the same results, the models are under-identified. Third, model parameters are statistically estimated from the data. Fourth and finally, several model fit statistics are considered to determine if the hypothesized models accurately represent the data.

Intervention Recruitment

Students

In the second and third stages of this research, students were recruited for academic coaching interventions. For the stage two intervention, students were recruited during the Fall 2016 semester, and for the stage three intervention students were recruited in Fall 2017. Only students that completed the NCAF survey during the semester recruitment occurred were considered for participation in the intervention. Specifically, participants were recruited based upon their results in the time and study environment subscale of the NCAF survey. Immediately prior to recruitment, students that responded during the active recruitment period were anonymized and subsequently grouped by their time and study environment score. For both stages, 12 students were initially invited to participate: five with low time and study environment scores, four near average, and three with high. During stage two recruitment, only five responded as willing to participate, all of whom identified as Caucasian and male. Of these five students, two entered with low time and study environment scores, two with average, and one with high. Each of these five students formally participated in all phases of the academic coaching intervention. During the stage three recruitment seven students responded as willing to participate. To remain consistent with stage two, only five of the seven were accepted as participants. In an effort to reduce selection bias, the first five students that responded to the recruitment email were selected. Again, all five students were male, three of whom were Caucasian, one African American, and one Asian American. Similar to the students recruited in stage two, of the five students participating in stage three, two entered with low time and study environment scores, two with average, and one with high. Three of the five students in stage three participated in each of the phases of the academic coaching intervention, while two students participated in all but the final follow up interview. Each of the ten total participants received $50 in Amazon gift cards in installments over the course of the study in compensation, while the two students that did not complete the final follow up interview did not receive the final installment.

Coaches

In addition to the students, the academic coaches were also active participants in this study. The university's Academic Success Center was recruited as a partner, and a subset of their existing staff of academic coaches facilitated the academic coaching interventions. Three academic coaches participated in Fall 2016, and four coaches participated in Fall 2017. Each coach was assigned one or two students to coach for the duration of the study.

All participating coaches were graduate assistants for the Academic Success Center, funded by the university for their role as academic coaches. In this role, coaches underwent a two-day training session where they learned coaching theories, were given expectations for their day-to-day work, and were provided with resources they could use during their coaching sessions. In addition to their one or two students assigned as part of this study, all coaches continued their work for the Academic Success Center for the duration of the study. Academic coaches could be students pursing any graduate degree from any department. For this study, coaches were a mixture of Master’s and Ph.D. students in education or engineering.

Qualitative Data Collection

There were three primary data sources for this study:

1. Individual, semi-structured interviews between researcher and student
2. One-on-one intervention sessions between an academic coach and their assigned student
3. Individual, semi-structured interviews between researcher and academic coach

Each of the participating students agreed to take part in three individual interviews with the researcher: pre-intervention, post-intervention, and post-post-intervention. Each of these interviews was loosely structured with a set of guiding questions and lasted for up to 30 minutes. The goals were to engage students on their experiences as an undergraduate engineering student, their experiences in the academic coaching intervention, and their experiences as an undergraduate engineering student considering what they experienced in the intervention, respectively. The pre-intervention interview occurred within a week of students beginning the intervention, the post-interview within a week after the intervention concluded, and the post-post-interview several months after the conclusion of the intervention. The interview protocol can be found in Appendix B.

The intervention undergone by each student took the form of three academic coaching sessions. Each session lasted between 30 and 45 minutes and subsequent sessions occurred one to two weeks after the previous. In their entirety, the coaching sessions ran for roughly the last six weeks of the Fall 2016 and Fall 2017 semesters. However, since these sessions were directed entirely by the academic coach and student, without involvement by the researcher, the content was unregulated and driven by the needs and goals of those involved. The content of these sessions could have contained anything from improving study habits to anxiety mitigation techniques to simple check-ins regarding the student’s academic performance and wellbeing. Ultimately, the academic coaches made decisions about session content based on the needs of the student they were coaching. Coaching sessions were neither video recorded or directly observed at the coaches’ request to keep students as comfortable as possible.

The final primary source of qualitative data was the individual interview between the researcher and the academic coaches. The academic coach interview lasted for about 30 minutes and took place roughly one week after the coaching sessions concluded. The most important use for this data source was to provide an explicit way to compare the experiences of the academic coach and the student they were coaching. To facilitate this comparison, the coaches were prompted regarding their experiences coaching the student or students they were assigned. Beyond that, however, coaches were asked to discuss how the sessions with their assigned student or students compared to a typical coaching session. The purpose for this was to better understand what a “normal” coaching session was and how the sample of students may have differed. At this institution, the majority of current academic coaching attendees are either students referred by advisors, or students on academic probation required to attend coaching by their department. However, the sample of students in this study were all in good academic standing. Therefore, understanding the difference between a typical coaching session and a session with the students in the study may illuminate important qualities of academic coaching.

Quantitative survey data was collected as an additional, secondary data source. All ten participants took the non-cognitive survey used for recruitment an additional time during the post-intervention interview, and eight out of then students took the survey a third time during the post-post-intervention interview. Therefore, most participants' non-cognitive factors were measured at three time points, which allowed for a quantitative glimpse into how these factors were affected by the intervention and whether any potential changes were sustained.

Qualitative Methodology

The qualitative portion of this research took the form of a thematic analysis guided by a Glaserian grounded theory methodology. According to Creswell (2012), in educational research grounded theory is used to generate a "process" theory which is defined as "… an educational process of events, activities, actions, and interactions that occur over time" (p. 426). Specifically, the Glaserian grounded theory approach, as opposed to the Straussian approach, focuses on explaining a social process without coercing data into predefined categories (Creswell, 2012; Heath & Cowley, 2004).

In the qualitative portion of this research, the experiences of students and coaches in an academic coaching intervention were examined. This intervention can be considered both an educational and social process. It is an educational process in the sense that its overall goal is to improve students' academic performance. In addition, any gains to non-cognitive factors–such as time management or test anxiety–are realized in an educational context. On the other hand, academic coaching can also be considered a social process since the interventions are based around one-on-one dialogue between the student and coach. There is also the possibility of coach-to-coach or student-to-student interactions that influence the student’s or coach’s experiences, further adding to the social aspect of academic coaching. Finally, academic coaching remains a largely enigmatic service. Little empirical evidence exists, especially at the college level, that captures the structure of academic coaching services (Robinson, 2015). The combination of these factors led to Glaserian grounded theory being an appropriate methodology to guide the thematic analysis performed in this study.

Qualitative Data Analysis

All interviews and coaching sessions were audio recorded and professionally transcribed. All coding was done using the Nvivo 11 software (QSR International Pty Ltd., 2012). As mentioned previously, a thematic analysis was performed to study the content of these transcripts (Braun & Clarke, 2006), while specifically following the four steps for generating qualitative evidence created by Green et al. (2007). Green et al. describe these steps as: data immersion, coding, creating categories, and identifying themes. Data immersion was completed in this study by conducting the interviews, reading and re-reading the transcripts, and creating multiple candidate coding schemes to represent the qualitative data.

The transcripts were coded inductively and over several phases. In concordance with grounded theory, open coding was performed initially, followed by selective coding (Strauss & Corbin, 1998). Specifically, initial passes through the data used open coding to develop the baseline coding structure. In phase 1, each interview and coaching session transcript was read, and student and coach experiences were coded based upon constantly emerging concepts. The transcripts were re-read several times, allowing the coding structure to be expanded and refined during each pass through the data. This phase concluded once additional passes did not result in a change to the coding structure, indicating that a complete coding structure was created. In phase 2, subsequent passes through the data utilized selective coding to add to the depth of the codes. This was repeated until each transcript was coded according to the complete coding structure.

Following the coding step, the resulting codes were categorized via clustering (Miles, Huberman, & Saldana, 2014). Categories were created by clustering the codes temporally. Those codes that occurred during each individual interview were grouped together, and those that occurred during coaching sessions were grouped together. This allowed for themes to be created that could be tracked throughout a student's academic coaching experience and verified by the coaches' own experiences. Themes were determined based on the common codes in each category. If four students or two coaches from either stages of the intervention referenced a single code, it was considered common. All common codes in each category were themed to create a flow of academic coaching that incorporated student and coach views and actions. The steps of creating categories and identifying themes embody the constant comparative method of grounded theory (Corbin & Strauss, 1990). A list of al common codes can be seen in Table 2 below. If codes appear more than once in the table, they were interpreted in an alternative context depending on the theme the represent and where they were collected.

Table 2: List of all common codes, including their associated theme and where codes where collected

Collected Via	Themes	Codes
Pre-Interview	Student Characteristics	Intrinsic Motivation
		Engage Different Perspective
	Student Perceptions	Stressful
		Challenging Studies
	Student Expectations	Improve Study Habits
		Improve Resource Usage
		Improve Task Performance
Coaching Sessions	Student Concerns	Silly Exam Mistakes
		Lack of Conceptual Understanding
		Underperforming
		Task Performance
	Coach Responses	Reviewing
		Planning
		Resource Usage
		Study Habits
		Test Taking Skills
	Student Responses	Positive Outlook
		Negative Outlook
		Clarifying Coaching
		Contradictory Statements
Post and Post-Post Interviews	Student Gains	Study Habits
		Planning
	Student Outcomes	Positive Outlook
		Negative Outlook
		Task Performance
		Task Efficiency
		Help with Technical Courses
Coach Interviews	Coaching Interactions	Follow Through
		Improving Habits
		More Active
		Motivated
		Planning
		Self-Aware
		Taking Full Advantage

Qualitative Validity and Reliability

Throughout the coding process only a single researcher was responsible for creating the coding structure and identifying themes. Given the need for open coding in a grounded theory design, a single coder is often used since multiple coders would be unlikely to inductively create the same coding structure. In order to ensure the reliability of the single-coder data analysis process, peer debriefing was utilized (Creswell & Miller, 2000). In peer debriefing, someone familiar with the research reviews the data and research process. This reviewer questions assumptions and pushes the researcher to answer difficult methodological questions, thereby honing their research process.

In addition to peer debriefing, two other procedures were used to ensure the validity of the research. The first of which was triangulation, or searching for convergence between multiple sources of data (Creswell & Miller, 2000). On top of the interviews and coaching sessions, this study made use of survey data. Results from the three iterations of the non-cognitive survey taken by the participants provide a quantitative measurement of the factors the academic coaching intervention is attempting to change. These results were therefore used to confirm participants' perceived changes in their study habits and test anxiety.

The final validity procedure used was member checking (Creswell & Miller, 2000). In member checking, the data and conclusions drawn from the data are presented to the study participants, so they have the opportunity to confirm the credibility of the information. To accomplish this in the context of this study, each participant–both student and academic coach–were contacted via email and provided a copy of their coded transcripts and the results of the qualitative analysis so they could review how they were interpreted and the conclusions drawn. The concept of member checking was described to each participant, and they were asked to evaluate if they felt they were accurately interpreted. Six of the seven academic coaches responded, with the one non-response from a coach in the first round of interventions that graduated before the research concluded. Six of the ten students also responded, three from each of the two rounds. All respondents indicated that they agreed with how they were interpreted, and no participants requested that any changes be made to the results.

QUANTITATIVE RESULTS

This chapter summarizes the results of the stage one quantitative analyses. These analyses represent the entire voyage undertaken to better understand the factors that most strongly affect first-year engineering undergraduates' academic success. Throughout that voyage, several analyses were performed, each justifying and informing subsequent steps. The initial quantitative analysis took the form of an exploratory factor analysis, followed by a stepwise multiple regression, and culminated with a confirmatory factor analysis and structural equation model.

Exploratory Factor Analysis

Multiple sources have shown that the non-cognitive factors measured throughout this research occasionally load together on higher-order factors. Specifically, the Grit subscale of Perseverance of Effort and Big Five conscientiousness have been determined to correlate very highly (Duckworth et al., 2007), while the extraversion and openness factors of the Big Five have been found to together compose a higher order factor known as plasticity (DeYoung, 2006; Digman, 1997). With the goal of identifying if these broader categories exist within these data, an exploratory factor analysis was conducted on an initial sample of 269 first-year engineering undergraduate students.

A Promax, oblique rotation was used as some factors correlated at above 0.35. This analysis revealed that seven higher-order factors existed that comprised the original nine non-cognitive factors. These factors were Test Anxiety, Consistency of Interest, Conscientiousness, Study Time, Plasticity, Neuroticism, and Study Environment. Test Anxiety consisted of all five original test anxiety questions from the MSLQ. Consistency of Interest was comprised of the four consistency of interest Grit items, and one of the Grit perseverance of effort items ("I finish whatever I begin"). Conscientiousness was a combination of the two Big Five conscientiousness items and two of the Grit perseverance of effort items. Study Time consisted of five items from the time and study environment subscale of the MSLQ which referred to students' ability to manage their time and keep up with weekly assignments. Plasticity was a combination of the two items measuring Big Five extraversion and one Big Five openness item. Neuroticism was exactly the Big Five neuroticism construct. Finally, Study Environment included the two items of the MSLQ time and study environment subscale that referred to students' tendencies to have a dedicated location set aside for studying. The two factors that were comprised of items from multiple non-cognitive factors–Conscientiousness and Plasticity–were expected given the evidence of their existence in the literature.

Table 3 shows the factor loadings for each of the 31 non-cognitive items. To ensure that all factor loadings were considered statistically meaningful, a cutoff of 0.32 was used (Tabachnick & Fidell, 2007; Yong & Pearce, 2013). No items loaded at higher than 0.32 on more than one factor, therefore it was determined that there was no crossloading (Costello & Osborne, 2005). Of the 31 total non-cognitive items, five of them did not load strongly on any factor and were therefore excluded. Notably, all items from the Big Five agreeableness construct were excluded.

The Test Anxiety ($\alpha = 0.85$), Consistency of Interest ($\alpha = 0.79$), Conscientiousness ($\alpha = 0.75$), Study Time ($\alpha = 0.74$), Plasticity ($\alpha = 0.72$), and Neuroticism ($\alpha = 0.67$) factors had acceptable reliability (Hair, Black, Babin, Anderson, & Tatham, 1998; Loewenthal, 2001). The Study Environment factor, however, had low reliability ($\alpha = 0.58$). Since Study Environment was only a two-item factor, no changes could be made to improve its reliability.

Therefore, Study Environment was excluded from subsequent analysis. All factor reliabilities are in Table 4 below.

Table 3: Factor loadings above 0.35 for each non-cognitive item

Original Construct –Item	Statement	Test Anxiety	Consistency of Interest	Conscientiousness	Study Time	Plasticity	Neuroticism	Study Environment
TA–1	When I take a test I think about how poorly I am doing compared with other students	**0.75**						
TA–2	When I take a test I think about items on other parts of the test I can't answer	**0.75**						
TA–3	When I take tests I think of the consequences of failing	**0.81**						
TA–4	I have an uneasy, upset feeling when I take an exam	**0.76**						
TA–5	I feel my heart beating fast when I take an exam	**0.56**						
CoI–1	New ideas and projects sometimes distract me from previous ones		**0.54**					
CoI–2	I have been obsessed with a certain idea or project for a short time but later lost interest		**0.70**					
CoI–3	I often set a goal but later choose to pursue a different one		**0.69**					
CoI–4	I have difficulty maintaining my focus on projects that take more than a few months to		**0.60**					

	complete							
PoE–3	I finish whatever I begin		**0.59**					
BFC–1	I see myself as dependable, self-disciplined			**0.54**				
BFC–2	I see myself as disorganized, careless			**0.41**				
PoE–2	I am a hard worker			**0.80**				
PoE–4	I am diligent			**0.86**				
TSE–2	I make good use of my study time for my courses				**0.50**			
TSE–3	I find it hard to stick to a study schedule				**0.55**			
TSE–5	I make sure I keep up with the weekly readings and assignments for my courses				**0.43**			
TSE–7	I often find that I don't spend very much time on my courses because of other activities				**0.64**			
TSE–8	I rarely find time to review my notes or readings before exams				**0.52**			
BFE–1	I see myself as extroverted, enthusiastic					**0.91**		
BFO–1	I see myself as open to new experiences, complex					**0.35**		
BFE–2	I see myself as reserved, quiet					**0.75**		
BFN–1	I see myself as anxious, easily upset						**0.69**	

BFN–2	I see myself as calm, emotionally stable						**0.69**	
TSE–1	I usually study in a place where I can concentrate on my course work							**0.88**
TSE–4	I have a regular place set aside for studying							**0.43**
BFA–1	I see myself as critical, quarrelsome **							
BFA–2	I see myself as sympathetic, warm**							
BFO–2	I see myself as conventional, uncreative **							
PoE–1	Setbacks don’t discourage me **							
TSE–6	I attend class regularly **							

****** Items did not load strongly onto any factor

NOTE: The original construct names are abbreviated in the above table: Big Five Extraversion (BFE), Big Five Agreeableness (BFA), Big Five Conscientiousness (BFC), Big Five Neuroticism (BFN), Big Five Openness (BFO), Grit Consistency of Interest (CoI), Grit Perseverance of Effort (PoE), MSLQ Test Anxiety (TA), and MSLQ Time and Study Environment (TSE).

Table 4: Reliability estimates for each non-cognitive factor

Factor	**Chronbach’s Alpha**
Test Anxiety	0.85
Consistency of Interest	0.79
Conscientiousness	0.75
Study Time	0.74
Plasticity	0.72
Neuroticism	0.67
Study Environment**	0.58

** Factor was excluded from subsequent analyses

Each factor, as included in subsequent analyses, were created by taking the mean of all items included in the factors, as detailed in Table 3 above.

Stepwise Multiple Regression

In order to determine the efficacy of including the non-cognitive factors determined by the exploratory factor analysis in a model predicting undergraduate engineers' first year performance, three regression models were created:

1. Cognitive-Only Model: This model contains students' prior performance as measured by high school GPA and standardized test score. ACT scores were used for standardized test scores where possible, and SAT score was converted to ACT score where necessary. These variables were regressed onto students' first year GPA to ascertain the predictive power of cognitive factors alone. Given the established differences in high school performance and standardized test score by gender, it was included in this model as a control (Dornbusch, Ritter, Leiderman, Roberts, & Fraleigh, 1987; Sutton, Langenkamp, Muller, & Schiller, 2018; Wai, Putallaz, & Makel, 2012).
2. Non-Cognitive Model: This model added the six non-cognitive variables found to have acceptable reliability, as described previously, to the two cognitive variables. These additional variables were regressed onto students' first year GPA to discover if the addition of non-cognitive variables significantly improves the ability to predict first year GPA compared to cognitive variables alone.
3. Non-Cognitive Model with Demographic Variables: This model builds upon the non-cognitive model by adding two family-oriented variables–whether students' college tuition was at least in part funded by their family (hereafter referred to as funding), and the hours per week students spent caring for family members (hereafter referred to as

caring)–and two socioeconomic proxy variables–percent free and reduced lunch (PFRL) at the student's high school, and expected family contribution (EFC). These variables–along with all cognitive and non-cognitive variables from the previous models–were regressed onto students' first year GPA to discover if these demographic factors have a strong impact on students' first year academic success.

Each of these models was built in a stepwise fashion, with each subsequent model building from the previous. Data collection continued after the EFA was performed. Therefore, for this and all subsequent analyses additional students were surveyed, increasing the sample size from $n = 269$ to $n = 301$. Procedures remained consistent across all instances of data collection. Given the entirely voluntary nature of the survey, along with the lack of reporting for several admissions and registrar variables, missing data was present within the dataset. Often times, listwise deletion is used in regression analyses to handle missing data; but this method can introduce bias based on the pattern of missing data and reduces the power of the analyses. Instead, two imputation methods were considered as potential methods for handling missing data: maximum likelihood and multiple imputation. Both were acceptable options, however maximum likelihood imputation in R is unable to handle categorical data such as gender. Since three categorical variables–gender, funding, and caring–were used in this analysis, maximum likelihood was not a valid option. Therefore, multiple imputation was used as the missing data technique as opposed to listwise deletion. Multiple imputation is a technique where missing data are imputed several times, resulting in several different complete-data estimates of all parameters. All complete-data estimates are then combined to get a single estimate for each parameter, as well as reasonable estimates for standard errors (Rubin, 1987). Under missing completely at random and missing at random conditions, multiple imputation performed as well as maximum likelihood, and both performed significantly better than listwise and pairwise deletion in terms of bias and Type I error rates (Newman, 2003; Schumacker & Lomax, 2004). Data missing completely at random means that missingness is not dependent on any other variables. With data missing at random, missingness can be related to the independent variables, but is not related to the dependent variable. Multiple imputation also utilized all data during the analysis, maintaining the maximum possible sample size and reducing bias likely in ignoring missing data. Multiple imputation was completed using the missMDA package in R (Josse & Husson, 2016).

All non-cognitive variables and EFC were standardized, while the cognitive and remaining demographic variables were left unstandardized. It should be noted, however, that standardization was performed on the dataset before imputation, so not all standardized variables in the imputed dataset had a mean of zero and standard deviation of one. Leaving the cognitive variables unstandardized was particularly useful, as it allowed for their coefficient estimates in the model to be expressed directly as GPA or ACT points, as opposed to a unitless standardized value. Keeping these variables unstandardized ultimately made the results easier to translate to an academic context. Gender, funding, and caring were dummy coded, with “female” = 1 and “male” = 0 for gender, “funded by family” = 1 and “not funded by family” = 0 for funding, and “spends no time caring for family” = 1 and “spends time caring for family” = 0 for caring. The dataset was 69% male and 31% female, which is slightly different than the 75/25% male/female split for the institution’s engineering program overall. No interactions between variables were considered, as such relationships were explored in subsequent analyses. Descriptive statistics for all variables can be seen in Table 5.

Table 5: Descriptive statistics for all variables

Variable	Female Mean(SD)	Male Mean(SD)	Total Mean(SD)
First Year GPA	3.30 (0.44)	3.30 (0.52)	3.30 (0.49)
High School GPA	**3.91 (0.15)**	**3.85 (0.20)**	3.87 (0.19)
ACT Score	29.84 (2.41)	29.84 (2.64)	29.84 (2.57)
Test Anxiety	**0.25 (0.68)**	**-0.07 (0.76)**	0.03 (0.75)
Consistency of Interest	0.01 (0.72)	0.00 (0.66)	0.00 (0.68)
Conscientiousness	**0.14 (0.67)**	**-0.08 (0.76)**	-0.01 (0.74)
Study Time	0.06 (0.68)	-0.05 (0.64)	-0.01 (0.65)
Plasticity	0.09 (0.79)	-0.02 (0.73)	0.01 (0.75)
Neuroticism	**-0.16 (0.83)**	**0.07 (0.79)**	-0.01 (0.81)
Funding	0.88 (0.32)	0.90 (0.30)	0.89 (0.31)
Caring	0.94 (0.24)	0.96 (0.20)	0.95 (0.22)
PFRL	0.25 (0.13)	0.23 (0.13)	0.24 (0.13)
EFC	-0.03 (0.67)	-0.07 (0.89)	-0.06 (0.83)

NOTE: Bolded entries have significant mean differences between female and male ($p < .05$)

Cognitive-Only Model

The cognitive-only model included high school GPA, ACT score, and gender as the only independent variables. Both cognitive variables were found to be significant in this model: high school GPA (B = 0.36, SE = 0.15, $p < .05$) and ACT score (B = 0.03, SE = 0.01, $p < 0.01$). Specifically, the model predicted that every one-point increase in ACT score would lead to a 0.03 point increase in first year GPA, while a one point increase in high school GPA would lead to a 0.36 point increase in first year GPA, with all other variables held constant. It should be noted that a one point increase in high school GPA is a much more significant change than a one point increase in ACT score, hence the larger unstandardized effect size of high school GPA even though ACT score has the larger standardized effect. Gender was not found to be significant in the model. Overall, the cognitive-only model was able to explain a significant, albeit small, amount of the variation in first year GPA ($F(3, 297) = 6.09$, $p < 0.001$; $R^2 = 0.06$).

Non-Cognitive Model

The non-cognitive model included six non-cognitive factors in addition to the cognitive variables and gender included in the cognitive-only model. The inclusion of these six non-cognitive variables resulted in high school GPA becoming a non-significant predictor of first year GPA ($B = 0.17$, $SE = 0.14$, p = non-significant [ns]). ACT score became a weaker predictor of first year GPA, but remained significant in this model ($B = 0.02$, $SE = 0.01$, $p < .05$). Of the six non-cognitive variables, five were found to be significant: Test Anxiety ($B = -0.16$, $SE = 0.04$, $p < 0.001$), Conscientiousness ($B = 0.24$, $SE = 0.05$, $p < 0.001$), Study Time ($B = 0.10$, $SE = 0.05$, $p < 0.05$), Plasticity ($B = -0.11$, $SE = 0.04$, $p < 0.01$), and Neuroticism ($B = -0.09$ $SE = 0.04$, $p < 0.01$). The significant non-cognitive factors show a mix of positive and negative effects on first year GPA. For example, a one-point increase in Test Anxiety would result in a 0.16-point decrease in first year GPA, while a one-point increase in Conscientiousness would result in a 0.24-point increase in first year GPA. Only one non-cognitive factor–Consistency of Interest–was found to be non-significant. In total, the non-cognitive model was able to explain significantly more of the variance in first year GPA than the cognitive-only model ($\Delta F(6, 291) = 11.00$, $p < 0.001$; $R^2 = 0.23$).

Non-Cognitive Model with Demographic Variables

In this model, four demographic variables were added to the variables present in the non-cognitive model: funding, caring, PFRL, and EFC. Of these additional variables, only Caring ($B = -0.29$, $SE = 0.12$, $p < 0.05$) was a significant predictor of first year GPA. Specifically, students that spend time each week caring for family members on average have a first year GPA nearly three-tenths of a point higher than students that do not care for family. The five significant non-cognitive variables from the non-cognitive model–Test Anxiety ($B = -0.14$, *SE* = 0.04, $p < 0.01$), Conscientiousness ($B = 0.23$, $SE = 0.05$, $p < 0.001$), Study Time ($B = 0.10$, $SE = 0.05$, $p < 0.05$), Plasticity ($B = -0.10$, $SE = 0.04$, $p < 0.01$), and Neuroticism ($B = -0.09$, $SE = 0.04$, $p < 0.01$)–remained significant. ACT score ($B = 0.03$, $SE = 0.01$, $p < 0.05$) also remained a significant predictor in this model. Neither socioeconomic proxy variable, nor funding, was found to be significant. Overall, this model explained significantly more variance in first year GPA compared to the non-cognitive model, and not enough to make a significant difference ($\Delta F(4, 287) = 2.60$, $p < .05$; $R^2 = 0.26$).

Classroom Specific Models

The final step of the stepwise multiple regression portion of this research was to create a separate regression model using first year GPA in specific classroom settings as the dependent variables: lecture-based, team-based, and liberal arts. Since the non-cognitive model with demographic variables described previously explained the most variation in cumulative first year GPA of the models tested, that model construction was used when creating each of the classroom specific models. The number of actual and imputed grades for each course is shown in Table 6.

Table 6: Number of actual and imputed grades for each course in each classroom setting

Classroom Setting	Course	Number Actual Grades	Number Imputed Grades
Lecture-Based	Calculus 1	180	121
	Calculus 2	225	76
	Physics 1	260	41
Team-Based	Intro to Engineering 1	296	5
	Intro to Engineering 2	297	4
	Chemistry 1	228	73
	Chemistry 2	110	191
	Into to Computer Science	191	110
Liberal Arts	Basic Composition	193	108
	Public Speaking	193	108

For lecture-based classrooms, the average first year GPA was 2.85. In this model, neither of the cognitive factors was found to be a significant predictor of first year GPA in lecture-based classrooms. Three non-cognitive factors, however, were found to be significant. These factors were: Test Anxiety (B = -0.25, SE = 0.06, $p < 0.001$), Conscientiousness (B = 0.26, SE = 0.07, $p < 0.001$), and Neuroticism (B = -0.14, SE = 0.05, $p < 0.01$). Two demographic variables–Funding (B = 0.29, SE = 0.13, $p < 0.05$) and EFC (B = -0.14, SE = 0.05, $p < 0.01$)–were also found to be significant. Overall, this model was able to predict a significant amount of the variation in first year GPA in lecture based classrooms ($F(13, 287) = 5.97$, $p < 0.001$; $R^2 = 0.21$).

For liberal arts classrooms, the average first year GPA was 3.60. Unlike with lecture-based model, in the liberal arts model relatively few of the included variables were found to be significant predictors of first year GPA in liberal arts courses. The only significant non-cognitive predictors were Conscientiousness (B = 0.12, SE = 0.05, $p < 0.05$) and Study Time (B = 0.16, SE = 0.05, $p < 0.01$). For the cognitive variables, only High School GPA was found to be significant (B = 0.35, SE = 0.15, $p < .05$), while for the demographic variables only Caring (B = -0.33, SE = 0.12, $p < 0.01$) was significant. In total, this model was able to predict a significant amount of the variance in first year GPA for liberal arts courses ($F(13,287) = 5.61$, $p < .001$; $R^2 = 0.20$).

For team-based courses, the average first year GPA was 3.43. Similar to lecture-based courses, several non-cognitive factors were significant predictors of first year GPA in team-based courses. These non-cognitive factors were: Test Anxiety (B = -0.15, SE = 0.05, $p < 0.05$), Conscientiousness (B = 0.22, SE = 0.05, $p < 0.001$), Study Time (B = 0.11, SE = 0.05, $p < 0.05$), and Plasticity (B = -0.13, SE = 0.04, $p < 0.001$). Unlike with lecture-based courses, however, ACT score (B = 0.03, SE = 0.01, $p < 0.05$) and high school GPA (B = 0.34, SE = 0.15, $p < 0.05$) were also significant predictors of team-based course GPA. None of the demographic variables was significant in this model. Overall, this model was still able to predict a significant amount of the variation in first year GPA for team-based courses ($F(13, 287) = 7.84$, $p < .001$; $R^2 = 0.26$).

Table 7: Stepwise regression results for the cognitive-only, non-cognitive, and non-cognitive with demographic variables models

	Cognitive-Only Model *(N = 301)*			Non-Cognitive Model (N = 301)			Non-Cognitive with Demographic Variables *(N = 301)*		
Variable	*b*	*SE b*	β	*b*	*SE b*	β	*b*	*SE b*	β
Intercept	0.94	0.61	0	1.93	0.61	0	2.06	0.62	0
High School GPA	0.36	0.15	0.14*	0.17	0.15	0.07	0.18	0.15	0.07
ACT Score	0.03	0.01	0.17**	0.02	0.01	0.12*	0.03	0.01	0.14*
Gender	-0.03	0.06	-0.03	-0.03	0.06	-0.03	-0.04	0.06	-0.04
Test Anxiety				-0.14	0.04	-0.21***	-0.14	0.04	-0.21**
Consistency of Interest				-0.02	0.05	-0.03	-0.05	0.05	-0.07
Conscientiousness				0.18	0.05	0.27***	0.22	0.05	0.33***
Study Time				0.10	0.05	0.14*	0.10	0.05	0.13*
Plasticity				-0.11	0.04	-0.17**	-0.10	0.04	-0.15**
Neuroticism				-0.09	0.04	-0.15**	-0.09	0.04	-0.15**
Caring							-0.29	0.12	-0.13*
Funding							0.10	0.09	0.06
PFRL							-0.14	0.03	-0.07
EFC							-0.04	0.24	-0.04
R^2			0.06			0.23			0.26
F for change in R^2			6.09*			11.00***			2.60*

*$p < .05$, **$p < .01$, ***$p < .001$

Table 8: Regression results for the non-cognitive with demographic variables model for each classroom setting

	Lecture-Based *(N = 301)*			Liberal Arts *(N = 301)*			Team-Based *(N = 301)*		
Variable	*b*	*SE b*	β	*b*	*SE b*	β	*b*	*SE b*	β
Intercept	2.41	0.94	0	2.15	0.64	0	1.47	0.64	0
High School GPA	0.05	0.22	0.01	0.35	0.15	0.14*	0.34	0.15	0.13*
ACT Score	0.01	0.02	0.04	0.01	0.01	0.06	0.03	0.01	0.14*
Gender	-0.10	0.09	-0.06	0.11	0.06	0.11	-0.04	0.06	-0.03
Test Anxiety	-0.25	0.06	-0.26***	0.01	0.04	0.02	-0.10	0.04	-0.15*
Consistency of Interest	-0.05	0.08	-0.05	-0.03	0.05	-0.04	-0.06	0.05	-0.08
Conscientiousness	0.26	0.07	0.26***	0.12	0.05	0.19*	0.22	0.05	0.31***
Study Time	0.06	0.07	0.06	0.16	0.05	0.21**	0.11	0.05	0.14*
Plasticity	-0.11	0.05	-0.11	-0.03	0.04	-0.04	-0.13	0.04	-0.19***
Neuroticism	-0.14	0.05	-0.16**	-0.02	0.04	-0.03	-0.07	0.04	-0.11
Caring	-0.23	0.18	-0.07	-0.33	0.12	-0.14**	-0.23	0.12	-0.10
Funding	0.29	0.13	0.13*	-0.02	0.09	-0.01	0.05	0.09	0.03
PFRL	-0.60	0.36	-0.11	0.24	0.25	0.06	0.07	0.25	0.02
EFC	-0.14	0.05	-0.16**	0.05	0.03	0.08	-0.01	0.03	0.02
R^2			0.21			0.20			0.26
F			5.97***			5.61***			7.84***

*p < .05, **p < .01, ***p < .001

Summary

Several important results were found throughout the stepwise regression portion of this research. Chief among these is that, as expected, cognitive factors alone prove to be rather poor predictors of first year GPA. A number of the non-cognitive factors, on the other hand, were very strong predictors of first year performance. Specifically, Test Anxiety and Conscientiousness had the largest standardized effect sizes of any predictors of first year GPA in any model. In addition, high school GPA went from a significant predictor of first year GPA in the cognitive-only model to a non-significant predictor in the non-cognitive model. This leads to the conclusion that the same variance in first year GPA explained by cognitive variables is also, to some extent, explained by non-cognitive variables. This shared variance explained indicates that cognitive factors mediating the impact of non-cognitive factors on first year performance, as opposed to directly affecting first year performance themselves. Possible mediating variables will be explored in more depth through structural equation modeling. In addition, while Caring was the only demographic variable that was found to be a significant predictor of cumulative first year GPA, the inclusion of all four demographic variables resulted in the regression model able to explain the most variation in first year GPA. A final take-away from the stepwise regression results is that the significant predictors of first year GPA change based on classroom setting. The only variable that was a significant predictor of first year GPA in every classroom setting was Conscientiousness. Other non-cognitive variables, such as Test Anxiety or Neuroticism, were significant only in one or two out of the three classroom settings. As for cognitive variables, ACT score was only significant in the team-based model, while high school GPA was significant in both the team-based and liberal arts models. This shows that no one factor can be targeted to improve the performance of all undergraduate engineering students in every context. Who the students are and where they need to improve are important considerations.

Structural Model Creation

An initial step in structural equation modeling is creating a structural model that hypothesizes the links between latent and observed variables. In order to accomplish this, I designed the structural model using a preexisting theoretical framework. Specifically, structural model development was based strongly on Perna & Thomas' (2008) conceptual model of student success.

This framework consists of four layers, each of which is a context through which student success is affected. These layers, in order from one to four of increasing externality, consist of: Internal Context, Family Context, School Context, and Social, Economic, and Policy context. Within each layer is a set of variables that represent that context. These variables can interact with each other, or with variables in lower layers. However, variables cannot interact with those at higher layers (i.e., layer two can interact with layer one, but layer one cannot interact with layer two). This is due to the fact that higher layers represent broader contexts that influence the more individual contexts of lower layers. Finally, since it is ultimately a student's behaviors and attitudes that lead to success, only layer one variables–those most internal to the student–can directly influence student success. A graphical depiction of Perna and Thomas' model of student success can be seen in Figure 1.

Developing the structural model for this phase of the research was undertaken in three steps. First, a list of variables was selected to represent each layer. Then, the possible interactions between variables within each layer were included. Finally, the interactions between variables across layers were determined.

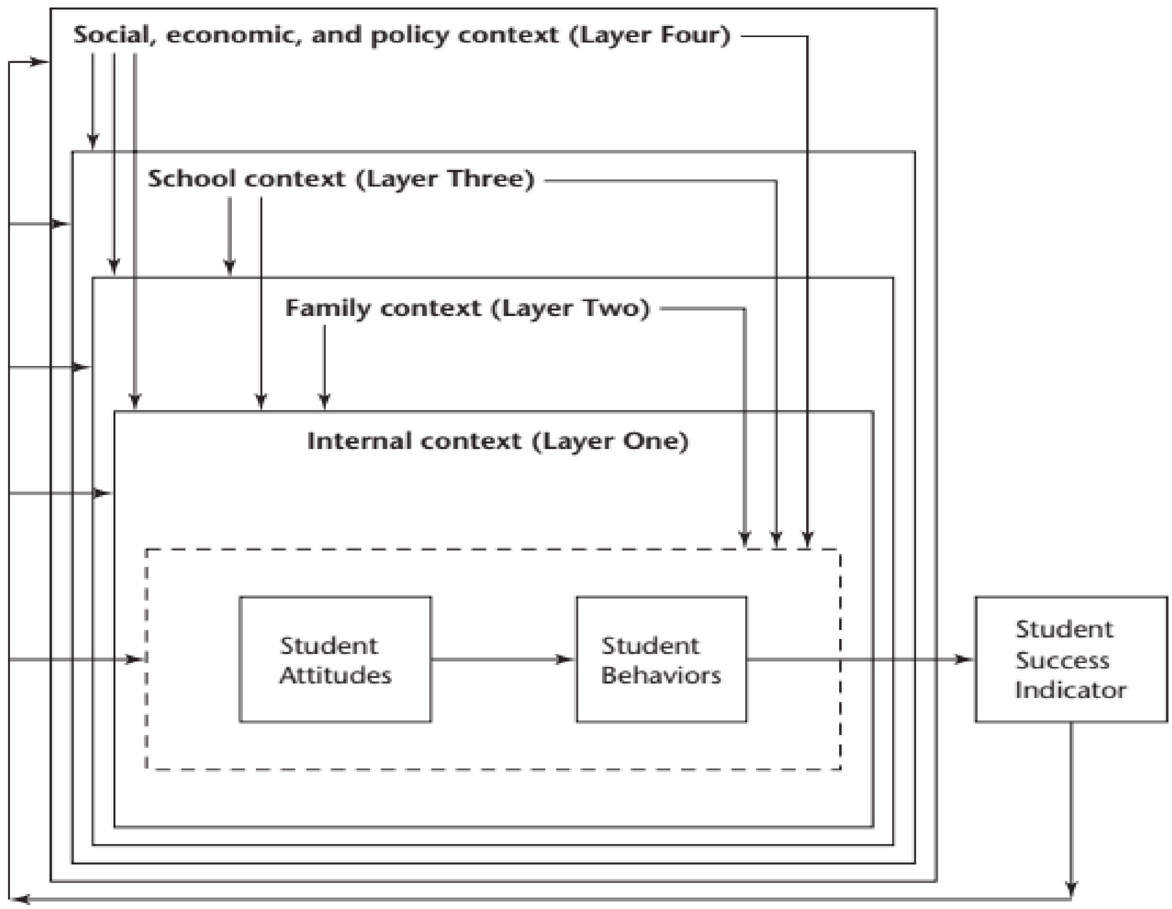


Figure 3: Perna and Thomas' Conceptual Model of Student Success

Layer One–Internal Context

Starting from layer one and working outwards, the internal context variables were determined first. Two sets of variables were used to represent layer one: demographics and non-cognitive variables. These variables affect the student individually and are not part of a larger context and are therefore considered internal per the Conceptual Model of Student Success. The demographic variables were initially going to include gender, ethnicity, and country of origin. However, at this institution ethnicity is only reported for domestic students. If a student indicates that they are international, they may optionally include their country of origin. Given the way ethnicity and country of origin are reported, both variables had too many missing entries to warrant inclusion in the study. Therefore, gender was included as the only demographic variable.

The non-cognitive factors were those determined in the exploratory factor analysis and included in the stepwise regression models. The effect of non-cognitive factors on student success was hypothesized to be moderated by gender, as shown by the indirect pathway from the non-cognitive factors to student success through gender. Hypothesized covariances between all non-cognitive variables were also included, shown by the double-headed arrows connecting each non-cognitive factor. Finally, all layer one variables were hypothesized to have a direct link to student success. While it is expected that the non-cognitive variables will significantly influence student success, the expectation is that demographics will not. However, the direct link will be in place to keep demographics as an important control and mediating variable. The structural model as constructed through layer one is shown in Figure 2.

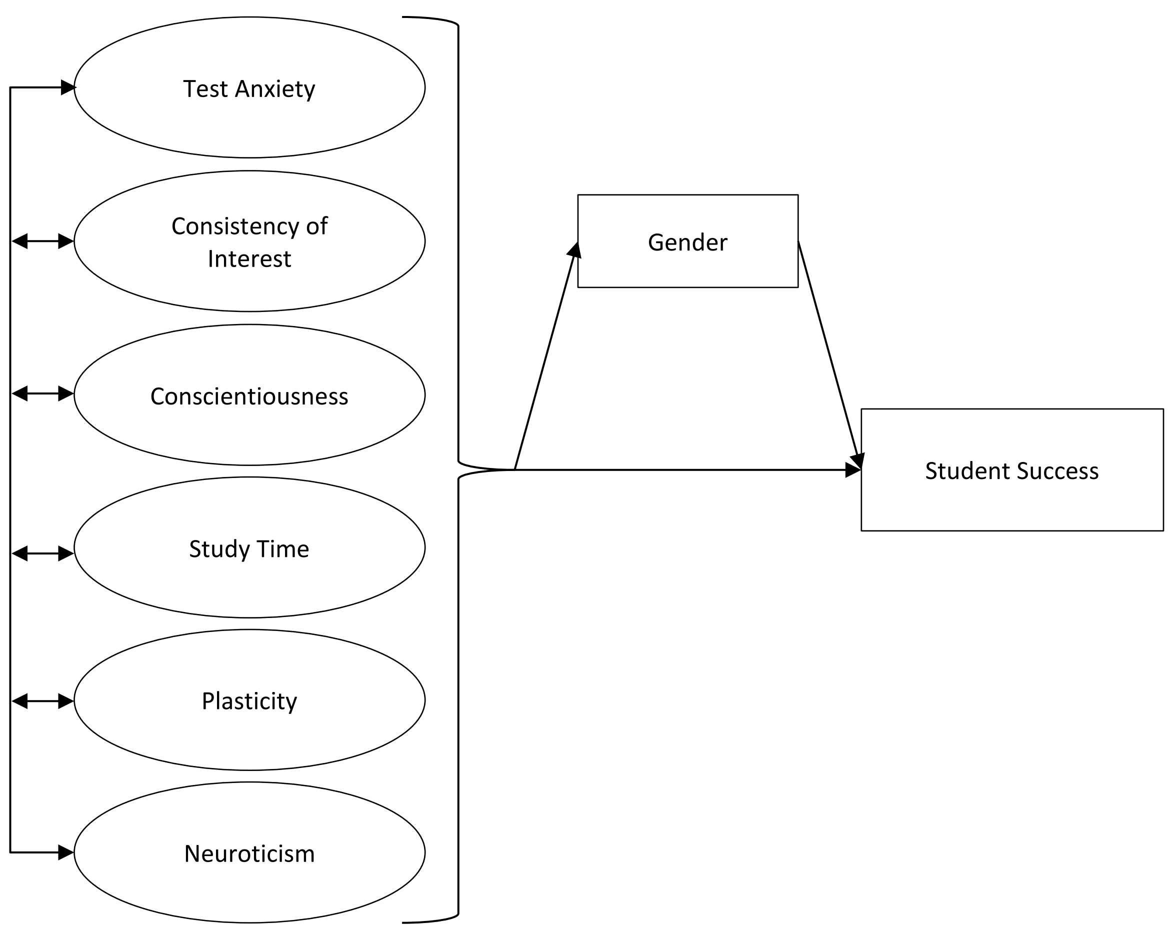


Figure 4: Hypothesized structural model through layer one

Layer Two–Family Context

The layer two variables contained measures that indicated a students' level of family support–one variable for support given by the student and a second variable for support given to the student. These two directions of family support are represented by the Funding and Caring variables seen in the final stepwise regression model. Caring–a binary variable measuring whether students spent time caring for dependent family members–represents the student to family support direction. Funding–a binary variable indicating if a student's family offers financial assistance with tuition payments–represents the family-to-student support direction. Since these two variables represent the entirety of Layer Two, there is a hypothesized covariance between them. There are also hypothesized links between both familial variables and each of the non-cognitive factors in Layer One (the curly bracket indicates a path to all non-cognitive factors). The structural model as constructed through Layer Two is shown in Figure 3.

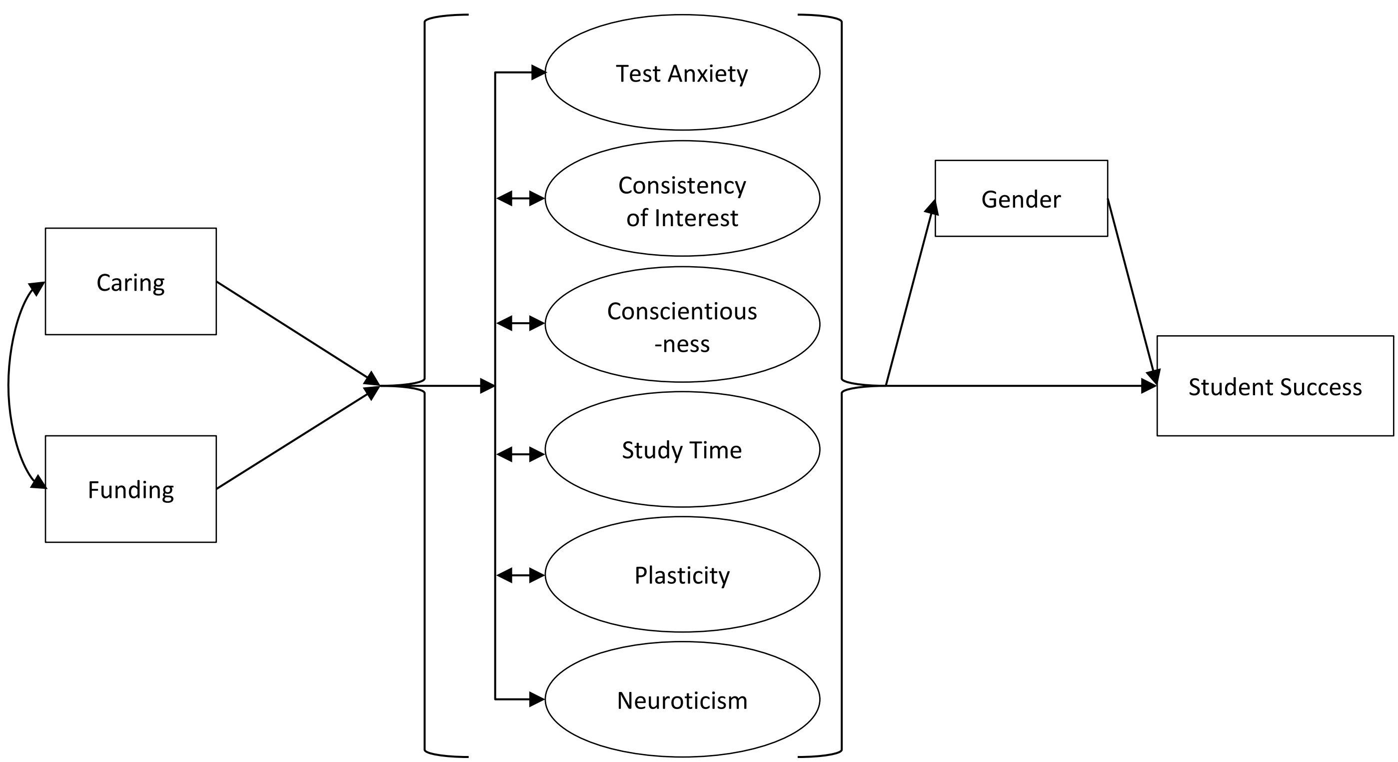


Figure 5: Hypothesized structural model through layers one and two

Layer Three–School Context

Layer Three or school context is depicted by the cognitive predictors of high school GPA and ACT score. As stated previously, these two variables predict a unique portion of academic performance. It is hypothesized that this is due to their college readiness, which can be attributed to their school context. From their position in Layer Three, the cognitive variables are hypothesized to directly affect non-cognitive factors and financial support. The link between the cognitive variables and financial support is in place to account for scholarships and other merit-based awards. A hypothesized covariance will also be in place between the two cognitive variables. In addition to representing the school context, high school GPA and ACT score are also significantly related to intelligence. As such, these two variables are also included in Layer One and given direct paths to student success. This direct path will also be moderated by a direct path to gender. The structural model as constructed through Layer Three is shown in Figure 4.

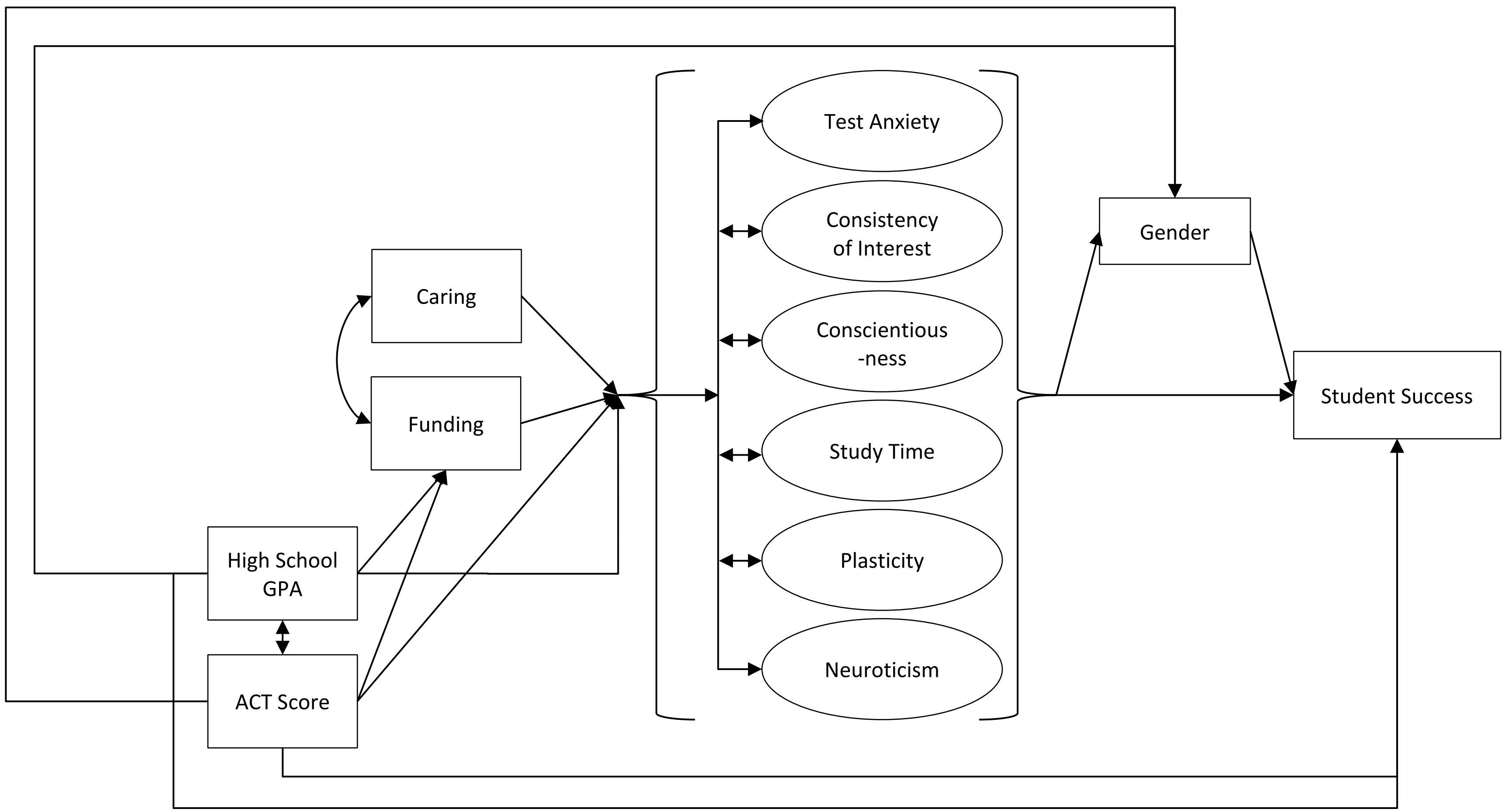


Figure 6: Hypothesized structural model through layers one, two, and three

Layer Four–Socioeconomic and Policy Context

The final layer, social, economic, and policy context, was represented by students' socioeconomic status variables. The variables collected for Layer Four consisted of high school code and expected family contribution (EFC). High school code was used to determine the percent of students on free and reduced lunch at a student's high school (PFRL), which would be used as a proxy for the social setting the students lived in. EFC, on the other hand, would give a more direct measure of their family's economic standing. Both EFC and percent free and reduced lunch were hypothesized to directly affect the Layer Three (cognitive), Layer Two (familial), and Layer One (non-cognitive) variables.

Policy context is being ignored chiefly because there is very little evidence to suggest that state level educational policy has a significant impact on student success (i.e., Rutherford & Rabovsky, 2014). In addition, disentangling the impact of policy differences on state or country level variations in student success would be a challenge given the social, economic, or cultural difference that could easily be conflated with policy differences. Because of these difficulties, and the challenges associated with collecting and quantifying policy data, the policy context is being ignored. The final structural model is shown in Figure 5. Note, all hypothesized links are shown in the proposed structural model, however these hypothesized links do not yet indicate significance.

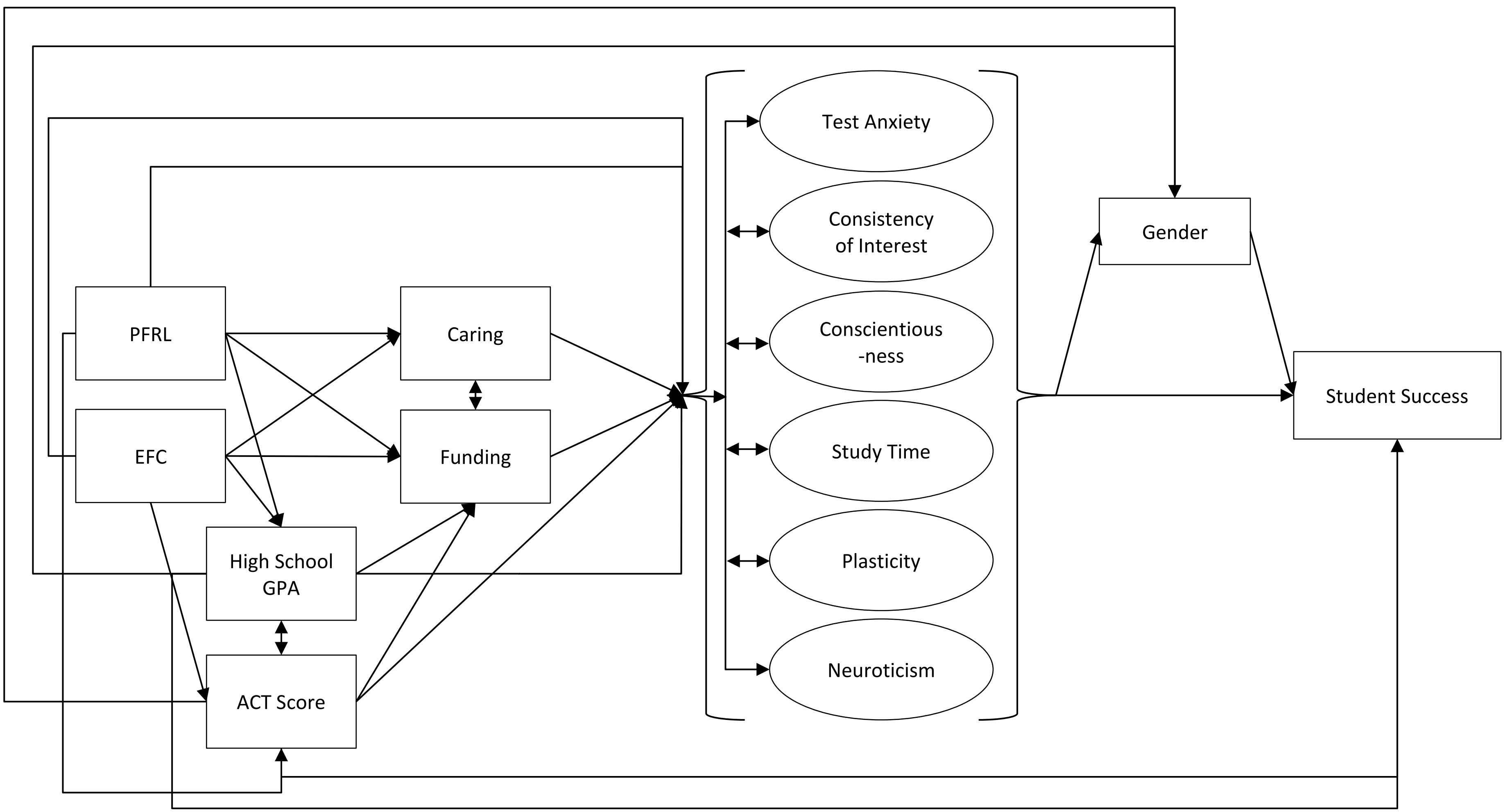


Figure 7: Complete hypothesized structural model

Structural Model Summary

The complete structural model in Figure 5 represents a holistic view of the variables that affect student performance. In addition, the structural model accurately represents Perna and Thomas's Conceptual Model of Student Success. Variables from the four layers or contexts are all included: Internal, Family, School, and Socioeconomic. The variables from the higher layers, or broader contexts, influence those from the lower layers representing contexts more internal to the student. Finally, only those variables from Layer One were given direct paths to student success. This is by no means the only possible model of student success, but it does accurately depict the conceptual model it was built from.

Confirmatory Factor Analysis

The confirmatory factor analysis (CFA) results can be seen in Table 9. Three important values are reported with each latent factor in the CFA: item reliability, construct reliability, and average variance extracted. Each of these measures describes a separate, but important, aspect of the reliability of a measurement model. Construct or composite reliability, as measured by Chronbach's alpha, indicates the degree to which a latent variable is accurately measured by its indicators. Typically, values greater than 0.7 are considered acceptable (Hair et al., 1998), but for constructs with fewer items values as low as 0.6 have been deemed acceptable (Loewenthal, 2001). Item reliability, as measured by the squared multiple correlation, provides information as to how much variance of each item is explained by the factor it belongs to. A cutoff value of 0.5 (i.e., 50% of the variance of an item is explained by the factor) has been suggested (Schreiber, Nora, Stage, Barlow, & King, 2006), but it has also been argued that suggesting a catch-all cutoff value for individual items reliabilities would not be possible (Bagozzi & Yi, 1988). Finally, average variance extracted (AVE) is a measure of the amount of variance that is captured by a construct compared to the variation due to measurement error. An acceptable value for AVE is considered to be greater than 0.5 (Bagozzi & Yi, 1988).

In order to ensure strong reliability for each factor, two items from each of the Consistency of Interest and Study Time factors were removed. As a result, it was found that each factor had acceptable composite reliability. However, the AVE for the Study Time factor remained slightly below the cutoff value of 0.50. Since Study Time was made up of only three items and was used alongside other factors with acceptable AVE, it was decided that Study Time would be used in the SEM as is. The results of the confirmatory factor analysis (Table 9) show that the items hypothesized to constitute a latent factor do, indeed, measure that construct.

Table 9: Confirmatory factor analysis results (* denotes reverse coded items)

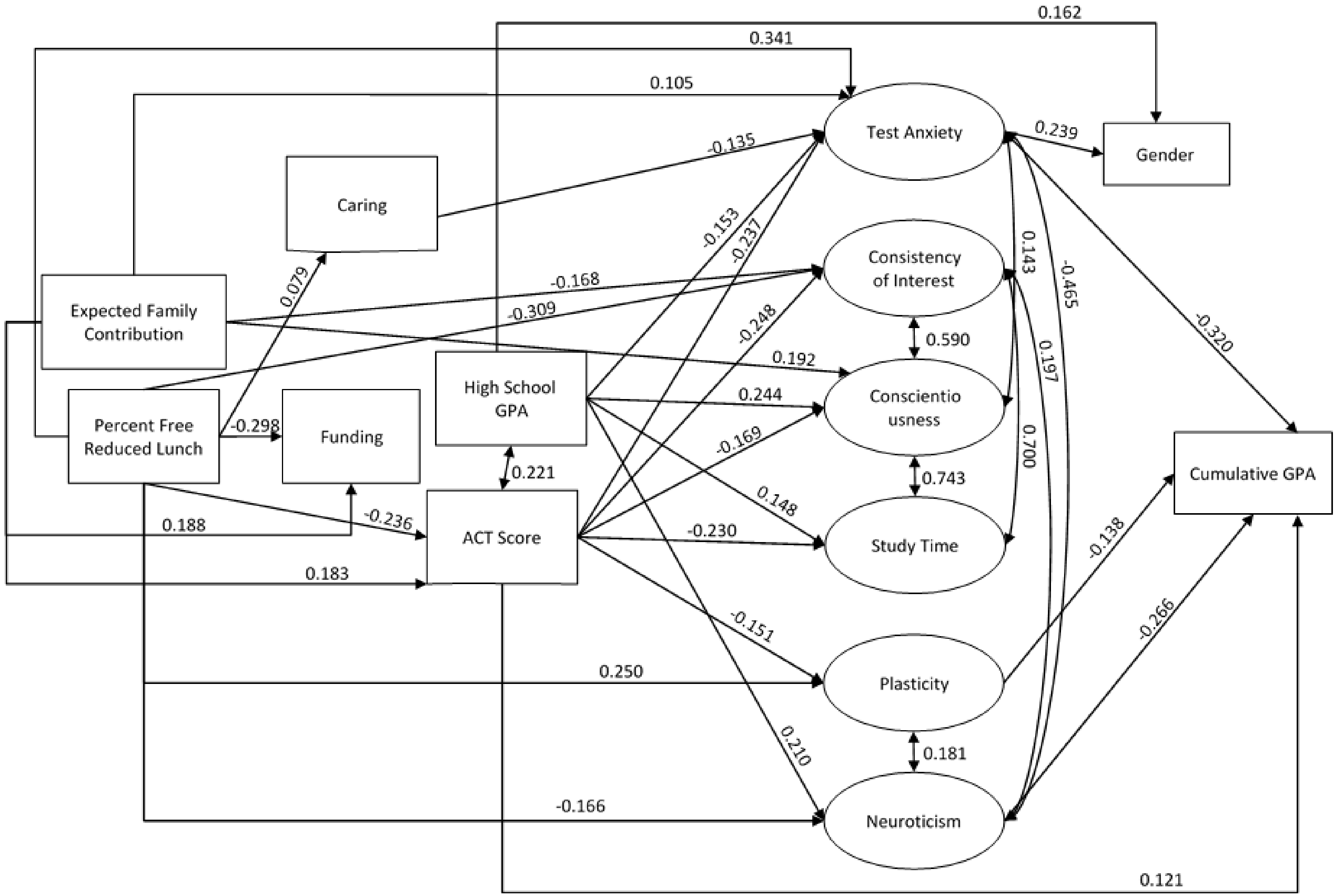
Latent Variable	Item	Estimate	Standard Error	Standardized Estimate	z-value	Individual Item Reliability	Composite Reliability	Average Variance Extracted
Test Anxiety	When I take a test I think about how poorly I am doing compared with other students	1.000	--	0.732	--	0.536	0.863	0.566
	When I take a test I think about items on other parts of the test I can't answer	0.962	0.081	0.708	11.905	0.501		
	When I take tests I think of the consequences of failing	1.106	0.079	0.811	14.047	0.658		
	I have an uneasy, upset feeling when I take an exam	1.139	0.084	0.836	13.568	0.699		
	I feel my heart beating fast when I take an exam	0.885	0.095	0.655	9.339	0.429		
Consistency of Interest	I have been obsessed with a certain idea or project for a short time but later lost interest*	1.000	--	0.649	--	0.421	0.756	0.514
	I often set a goal but later choose to pursue a different one*	1.238	0.133	0.802	9.311	0.643		
	I have difficulty maintaining my focus on projects that take more than a few months to complete*	1.059	0.129	0.689	8.233	0.475		
Conscientiousness	I see myself as dependable, self-disciplined	1.000	--	0.713	--	0.508	0.804	0.517
	I see myself as disorganized, careless	0.843	0.106	0.602	7.952	0.362		
	I am a hard worker	1.041	0.104	0.753	10.006	0.567		

	I am diligent	1.101	0.11	0.796	9.974	0.634		
Study Time	I make good use of my study time for my courses	1.000	--	0.758	--	0.575	0.727	0.477
	I find it hard to stick to a study schedule*	0.947	0.095	0.716	10.009	0.513		
	I make sure I keep up with the weekly readings and assignments for my courses	0.763	0.085	0.581	9.000	0.338		
Plasticity	I see myself as extroverted, enthusiastic	1.000	--	0.922	--	0.850	0.725	0.519
	I see myself as open to new experiences, complex	0.505	0.084	0.465	6.038	0.216		
	I see myself as reserved, quiet*	0.757	0.100	0.702	7.581	0.493		
Neuroticism	I see myself as anxious, easily upset*	1.000	--	0.827	--	0.684	0.675	0.532
	I see myself as calm, emotionally stable	0.743	0.138	0.616	5.397	0.379		

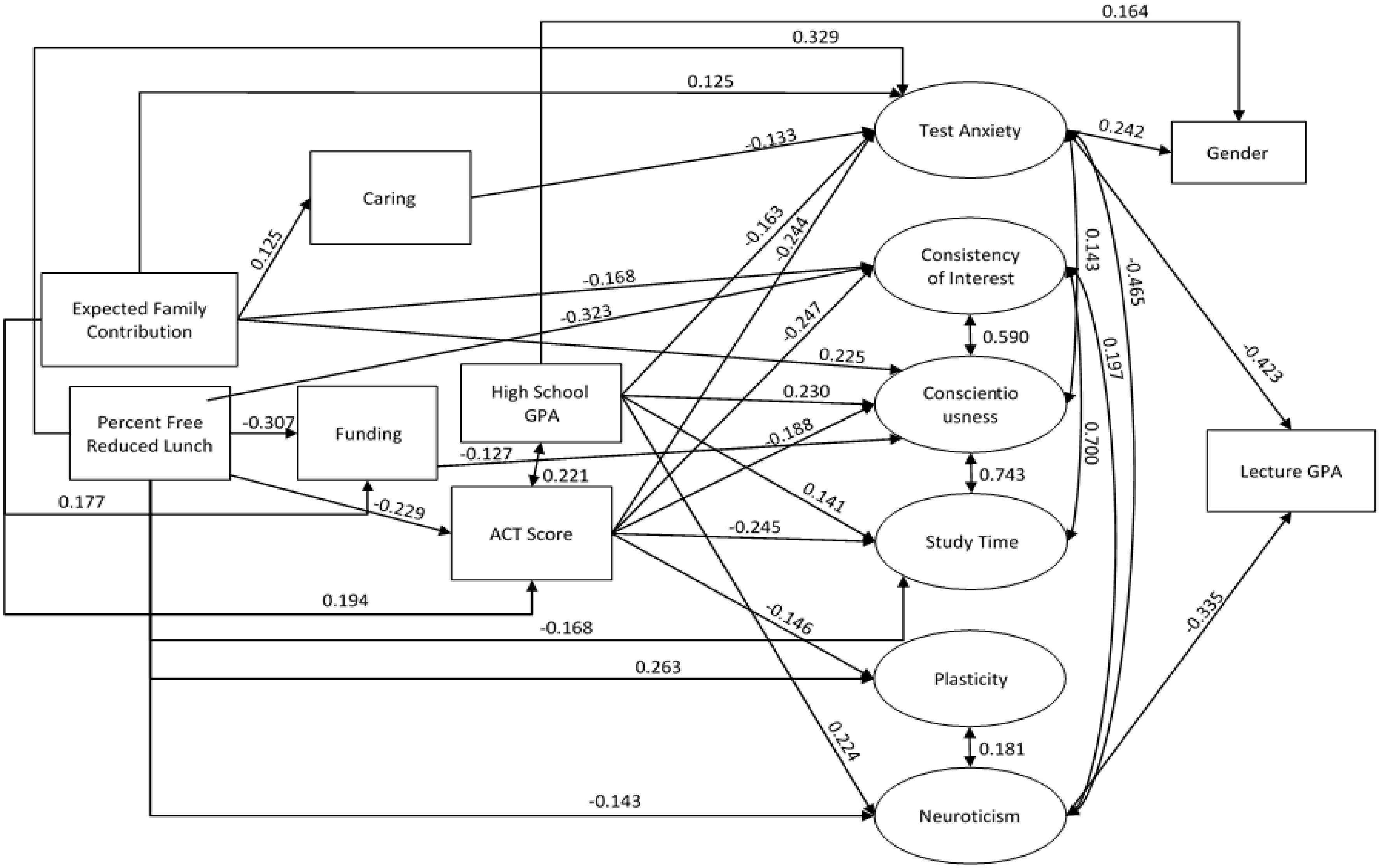
Structural Equation Model

The final step to the quantitative portion of this research was to build the proposed structural model and test the paths between the latent and observed variables. The proposed structural model was created using Perna and Thomas' conceptual model of student success, and its construction is detailed in a previous section. The complete structural model is shown in Figure 5 above. The proposed model was tested using the lavaan package in R (Rosseel, 2012).

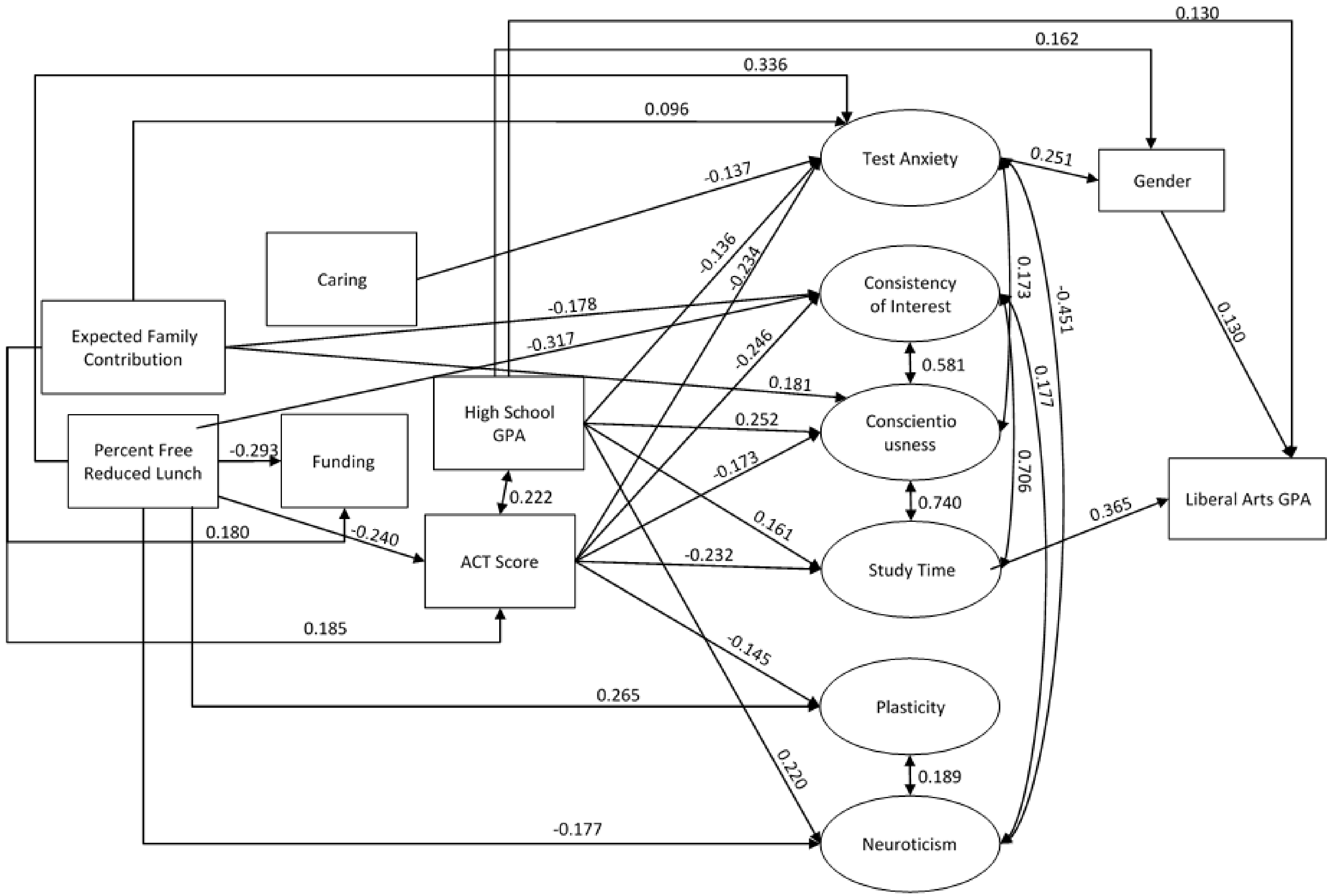
The sample of students in this research was specifically pulled from a first-year engineering classroom, and is made up of academically high performing students. Due to this specific population, the distributions of some of the variables are slightly platykurtic and negatively skewed. To account for this non-normality in the data, the Satorra and Bentler scaling correction was applied during the analysis (Satorra & Bentler, 1994). This correction scales the chi-square test statistic by a factor based on the kurtosis of the data (Bryant & Satorra, 2012), and has been proved to be robust to the violation of the normality assumption (Chou, Bentler, & Satorra, 1991). Using the Satorra and Bentler correction allows for the use of traditional cut-off values when analyzing non-normal data. The same multiply imputed dataset used for the multiple regression analyses was used for the SEM analyses. Multiple imputation was completed using the missMDA package in R (Josse & Husson, 2016). By combining multiple imputation and the Satorra and Bentler scaling correction, both missing and non-normal data are accounted for in the analysis. The proposed SEM model with estimated paths is shown in Figure 6 below. Remaining paths indicate that the relationship is significant at the $\alpha < .05$ level. As with the stepwise regression models, the SEM paths were also estimated with lecture-based, team-based, and liberal arts GPA as the endogenous variables. These classroom specific models can be seen in Figures 7, 8, and 9 for lecture-based, team-based, and liberal arts courses respectively.



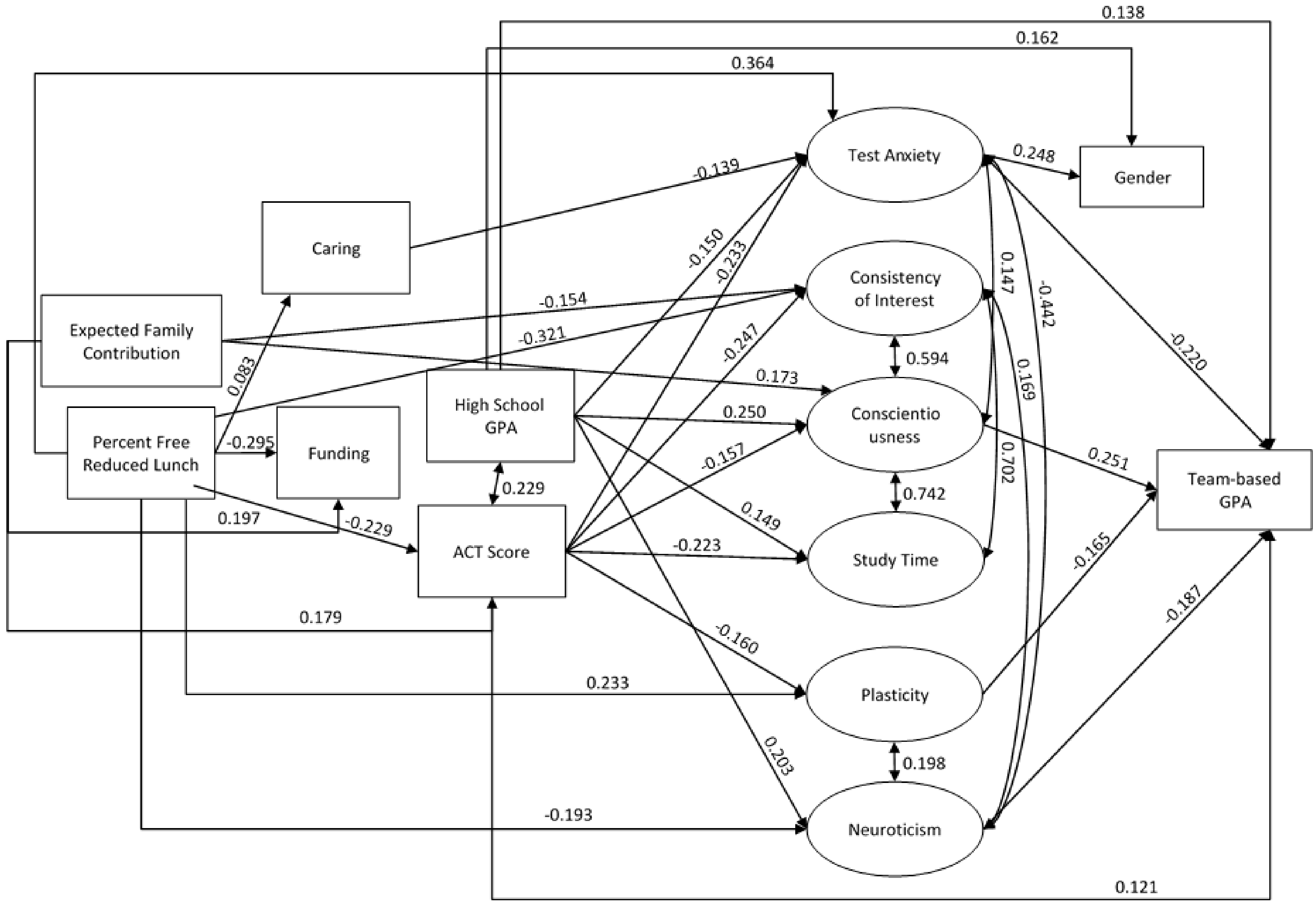
Cumulative GPA Model



Lecture-Based Model



Liberal Arts Based Model



Team-Based Model

The proposed SEM models for each endogenous variable–cumulative GPA, lecture-based GPA, team-based GPA, and liberal arts GPA–were fit and are shown in the figures above. Since the classroom-specific GPAs were calculated via a subset of the courses used to calculate cumulative GPA, including them all in one dataset could violate the missing at random assumption of multiple imputation. Therefore, separate datasets were created for each endogenous variable. Each dataset was imputed individually, and the entire imputed datasets were used to fit each model. Each dataset included 301 unique responses after imputation, and 496 degrees of freedom. For the cumulative and liberal arts datasets, 106 responses were complete prior to imputation. The lecture and team datasets had 101 and 103 complete responses prior to imputation respectively. While this indicates that values were imputed for nearly two-thirds of the responses in each dataset, often only one or two variables were missing for each response out of the thirteen independent variables in each model. Therefore, the data was well below the less-than-75% missing data threshold that is required for multiple imputation to perform well (Newman, 2003).

Before the SEM results can be analyzed, model fit needs to be determined. Model fit measures how similar the predicted data are with the actual data. Good-fitting models are appropriately consistent with the data and their results can be interpreted. Several fit indices were used to assess model fit, including chi-square, root mean square error of approximation (RMSEA), Comparative Fit Index (CFI), and Tucker Lewis Index (TLI). The cumulative GPA model had a chi-square test statistic of 406.98, which was significant at $p < .05$. However, with sample sizes over 200 the chi-square test statistic can become artificially inflated and a significant value does not necessarily indicate a poor model fit (Kenny, 2015; Schumacker & Lomax, 2004). Therefore, other fit measures besides the chi-square were considered. The

RMSEA for the cumulative GPA model was 0.044 with a 95% confidence interval of [0.034, 0.052], indicating a good fitting model based off of the excellent, good, and poor fit cutoffs for RMSEA of 0.01, 0.05, and 0.08 respectively (MacCallum, Browne, & Sugawara, 1996). In addition, the CFI for this model of 0.937 also indicates a good fitting model. CFI values of over 0.90 indicate acceptable fit (Bentler & Hu, 1995). Finally, the TLI of 0.914 for this model also above the acceptability cutoff of 0.90. Therefore, given the RMSEA, CFI, and TLI values in the cumulative GPA model, the proposed model is indeed consistent with the data.

The classroom setting models have very similar fit statistics to the cumulative GPA model. The lecture-based, liberal arts, and team-based models have chi-square test statistics of 416.45, 393.19, and 405.89 respectively, each of which is significant at $p < .05$. The lecture-based model has an RMSEA of 0.045 and a confidence interval of [0.036, 0.054]. The liberal arts model has an RMSEA of 0.041 and a confidence interval of [0.031, 0.050]. Finally, the team-based model has an RMSEA of 0.043 and a confidence interval of [0.034, 0.052]. Each of these values indicates good model fit. The lecture-based model has a CFI of 0.932 and a TLI of 0.902, the liberal arts model has a CFI of 0.943 and a TLI of 0.922, and the team-based model has a CFI of 0.938 and a TLI of 0.915. Similar to the cumulative GPA model, the RMSEA, CFI, and TLI for each classroom specific model indicates good model fit. Therefore, based on these fit statistics, each classroom specific model can be considered a good-fitting model.

Discussion

The quantitative phase of this research was performed primarily to answer research questions one through five. These research questions were:

RQ1: To what extent can items probing non-cognitive factors be grouped into a smaller number of meaningful meta-factors?

RQ2: To what extent do these meta-factors account for variance in the academic performance of first year engineers beyond the variance predicted by cognitive factors alone?

RQ3: To what extent do demographic factors–such as time spent caring for family members–account for additional variance in the academic performance predictions of first-year engineers beyond the variance predicted by the combination of cognitive and non-cognitive factors?

RQ4: How can structural equation modeling be used to create a more sophisticated model of first year engineers' academic performance that includes cognitive, non-cognitive, and demographic factors?

RQ5: How do these predictive models of first year engineers' academic performance differ by classroom setting?

Research Question One: Exploratory Factor Analysis

The initial finding from this phase was derived from the exploratory factor analysis. With this analysis, the original 31 items in the non-cognitive survey specifically targeting non-cognitive factors were examined to determine the underlying factor structure. Given that previous research has shown that several of the non-cognitive factors used in this study load together, the hypothesis was that the same would be found in this dataset. This hypothesis was confirmed, finding that the data used for this research could be grouped into seven higher order factors, six of which had acceptable internal reliability. Two of these six reliable factors–labeled conscientiousness and plasticity–were a combination of items from multiple constructs and were consistent with previous literature. Together these six factors allow for a meaningful understanding of students' non-cognitive profiles. This preliminary step of identifying the six higher order factors facilitated the statistics used in following steps.

Research Question Two: Multiple Regression

The subsequent step of this research was to determine how effective the meta-factors were at predicting the first year performance of engineering undergraduates. To accomplish this, the performance of a regression model with cognitive factors alone was compared to the performance of a model with both non-cognitive and cognitive factors. Given how the incoming engineering student population clustered at the upper end of high school GPA and standardized test scores, those cognitive factors were not expected to be strong predictors of first year performance. The cognitive-only model confirmed this hypothesis. Specifically, the cognitive-only model was able to explain less than 6% of the variance in first year GPA. The non-cognitive model, on the other hand, was able to explain 23% of the variance in first year GPA. This improvement was statistically significant and confirmed the hypothesis for research question two.

Exploring the cognitive and non-cognitive model results in more detail will allow for a better understanding of why these models are significant, as opposed to just knowing that they are. In the cognitive-only model, both high school GPA and ACT score were significant predictors of first year performance. Specifically, the cognitive-only model shows that a one point increase in high school GPA will result in a 0.36 point increase in first year GPA, while a one point increase in ACT score will result in a 0.03 point increase in first year GPA. It should be noted, however, that a one point increase in high school GPA is a much larger change than a one point increase in ACT score. In the non-cognitive model, five of the six non-cognitive factors are statistically significant predictors: Test Anxiety, Conscientiousness, Study Time, Plasticity, and Neuroticism. The only nonsignificant non-cognitive factor was Consistency of Interest. Additionally, non-cognitive factors were found to impact first year GPA both positively and negatively. For example, a one point increase in a student's test anxiety (slightly greater than one standard deviation), results in a 0.14 point decrease in first year GPA. On the other hand, a one point increase in a student's conscientiousness (slightly greater than one standard deviation), results in a 0.18 point increase in first year GPA.

These results exhibit a number of interesting findings. For undergraduate engineering students, non-cognitive factors are much stronger predictors of first year performance than cognitive factors. In addition to the combination of non-cognitive factors adding significant predictive power, non-cognitive factors are also the strongest individual predictors. Only two non-cognitive factors–Consistency of Interest and Study Time–had smaller standardized effect sizes than ACT score, the only significant cognitive factor. Also, changes in every non-cognitive trait except for Consistency of Interest led to non-trivial changes in first year GPA (Table 7). Therefore, not only do the collection of non-cognitive factors in this study allow us to better understand the drivers of student success, most non-cognitive factors are individually more important than any of the cognitive factors.

Examining the differences between the cognitive and non-cognitive models also elicits interesting results. Transitioning from the cognitive-only model to the non-cognitive model caused the high school GPA variable to become non-significant. Similarly, while ACT score remained a significant predictor in both models, it was able to explain less of the variation in first year GPA in the non-cognitive model. The significance of each non-cognitive factor and the non-cognitive model overall is only part of the story. The loss of significance for the cognitive variables indicates that some portion of the variance originally explained by the cognitive variables is also explained by the non-cognitive variables. These results suggest that there may be interactions between variables that are not modeled in the regressions, and consequently that more sophisticated analyses may further illuminate connections in the data.

Research Question Three: Expanded Multiple Regression

Prior to running more sophisticated analyses, additional variables were added to the non-cognitive regression model, creating the non-cognitive model with demographic variables. These demographic variables–caring for family, tuition funding by family, expected family contribution, and percent free and reduced lunch–help capture the factors outside of cognitive and non-cognitive factors that could influence students' academic performance. Specifically, these four demographic variables are used to explain a student's familial and socioeconomic contexts. Only one of these four demographic variables was found to be a significant predictor of student success: caring for family. Specifically, it was found that students that spend any amount of time caring for family members are expected to have a first year GPA nearly three-tenths of a point lower than students that spend no time caring for family. This model was able to explain significantly more variance in first year GPA than the non-cognitive model (R^2 increased from 0.23 to 0.26).

The non-cognitive model with demographic variables produced several results. For one, the only significant demographic variable is representing the familial context. Neither of the socioeconomic context variables is a significant predictor of first-year engineering performance. While this indicates that a student's familial context directly influences first year performance more significantly than their socioeconomic context, all demographic variables may still indirectly affect first year performance. A second finding was that in this model at least one variable from each of the cognitive, non-cognitive, and demographic variables was found to be a significant predictor of first year performance. This indicates that students' performance is influenced through a number of different contexts. No single context–cognitive, non-cognitive, or other–let alone any individual factor–fully grasps the complexity of student academic performance.

Research Question Four: Structural Equation Model

In order to simultaneously analyze the multiple contexts though which students' academic performance are affected, as well as model both direct and indirect influences, structural equation modeling (SEM) was used. The created regression models, as well as previous literature, have shown that no individual factor is sufficient to explain the variation in first year engineers' academic performance. The initial SEM created for this study used cumulative first year GPA as the endogenous variable, and included exogenous variables from four contexts in order to get a holistic view of each student: internal, family, school, and socioeconomic.

Internal Context

The first layer of the SEM represented students' internal context and consisted of gender and non-cognitive factors. Per Perna and Thomas' conceptual model of student success only variables in this context were able to directly affect students' academic performance. Three non-cognitive factors–Test Anxiety, Plasticity, and Neuroticism–had a significant effect on first year GPA. The significant impact of Test Anxiety on performance was expected, as it was individually found to be a significant predictor in the non-cognitive and non-cognitive with demographic variables regression models. More specifically, the SEM estimated that a one standard deviation increase in test anxiety would result in about a three-tenths of a point decrease in first year GPA. This was the single strongest direct pathway to first year GPA. The significance of Neuroticism and Plasticity were also expected and consistent with the regression results. Specifically, a one standard deviation increase in Neuroticism or Plasticity were expected to decrease first year GPA by 0.27 and 0.14 points respectively. Study Time, on the other hand was a weaker predictor in the SEM than it was in the non-cognitive with demographic variables regression model. This reduction in significance is likely because a portion of the variance Study Time explained in first year GPA was shared with the other variables included in the SEM. The inclusion of modeled covariance in the SEM could also account for part of the reduction in variance. The inclusion of more modeled pathways, alongside modeling covariance, was a known difference between SEM and multiple regression. Therefore, these minor reductions in significance were expected. However, the Conscientiousness variable saw a large reduction in significance, which was a more unexpected result. Conscientiousness was the single strongest predictor of first year performance in the multiple regression models, and the strength of that variable was expected to carry over, at least in part, into the SEM analysis. However, in the SEM, the Conscientiousness to first year GPA pathway was non-significant ($\beta = 0.180$, $SE = 0.088$, $p = .09$). Similar to the Study Time variable, this reduction in significance was likely due to the modeling of additional pathways and covariances leading to the introduction of more shared variance. However, the degree to which Conscientiousness' significance dropped indicated that the newly modeled pathways and covariances explained much more of shared variance with Conscientiousness than with other variables. While the initial conclusion to draw could be that Conscientiousness is no longer a significant variable in the explanation of the variance in first year engineers' GPA, the reduction in significance could also indicate that Conscientiousness is an important mediator of other variables' effect on first year GPA.

A deeper look at the modeled covariance reveals that this hypothesis is indeed true. Conscientiousness covaries strongly with three other variables: Test Anxiety (β = 0.151, *SE* = 0.03, $p < .05$), Consistency of Interest (β = 0.687, *SE* = 0.04, $p < .001$), and Study Time (β = 0.699, *SE* = 0.05, $p < .001$). Of these variables, Test Anxiety had a significant path to first year GPA, meaning that changes in Conscientiousness can indirectly affect first year performance. Unexpectedly, however, Conscientiousness seems to be a bit of a double-edged sword. The covariances between Conscientiousness and Test Anxiety and Study Time show that higher levels of Conscientiousness result in higher levels of each of the other two variables. However, since Test Anxiety has a negative path coefficient to first year GPA while Study Time has a positive coefficient, Conscientiousness can have a significant positive and negative indirect effect on first year performance.

Neuroticism has a similarly counterintuitive set of significant covariances. Neuroticism has significant covariances with four other non-cognitive factors: Test Anxiety (β = -0.461, *SE* = 0.04, $p < .001$), Consistency of Interest (β = 0.198, *SE* = 0.03, $p < .05$), Study Time (β = .0186, *SE* = 0.04, $p < .05$), and Plasticity (β = 0.194, *SE* = .05, $p < .05$). While Neuroticism has a directly negative effect on first year GPA, it also has negative covariance with Test Anxiety (also a negative direct effect with first year GPA) and a positive covariance with Study Time (a positive direct effect with first year GPA). Therefore, while reducing Neuroticism would serve to directly improve first year performance, such a change could also increase Test Anxiety and decrease Study Time, effectively indirectly worsening first year performance. The other covariance of note is between Study Time and Consistency of Interest (β = 0.702, *SE* = 0.04, $p < .001$). The combination of direct and indirect effects between the non-cognitive factors and first year performance shows how complex the interplay between the two can be.

The other internal context variable, gender, interacted with first year performance in a less robust way than the non-cognitive factors. As an internal context variable, gender had a direct path to first year GPA in the proposed model, however that path was found to be non-significant. On the contrary, gender was found to be a significant mediating variable between Test Anxiety and first year GPA. Specifically, the path from Test Anxiety to gender was significant (β = 0.225, *SE* = 0.05, $p < .01$), meaning that Test Anxiety's effect on first year GPA is slightly more negative for female students. No other non-cognitive factors had a significant path to gender, indicating that their impact on first year GPA is relatively equal across genders.

Family Context

The family context was represented by two variables: funding and caring. These two variables were binary and captured whether or not a student's tuition was in part funded by their family, and whether or not a student spent time each week caring for family members. Residing in the second layer of the SEM, and per Perna and Thomas' conceptual model of student success, these family context variables were only allowed to affect first year performance indirectly through the layer one variables. As such, both caring and funding were given paths to each of the non-cognitive factors. There were no significant paths stemming from Funding. Caring, on the other hand, was found to have significant paths to two non-cognitive variables: Test Anxiety (β = -0.134, *SE* = 0.17, $p < .01$) and Consistency of Interest (β = 0.129, *SE* = 0.15, $p < .05$). The caring and Consistency of Interest connection seems understandable. Those that spend time caring for family members exhibit an ability to stay dedicated to a single pursuit. The significant path between caring and Test Anxiety, on the other hand, is a bit difficult to interpret. Test Anxiety and caring for family members seem on the surface to be fairly distinct variables, so a direct relationship between the two is unlikely. The significant relationship may, then, be due to unmeasured variables. For example, students spending time caring for family may be non-traditional students caring for children or elderly family members. Non-traditional students have been shown to be on average less worried about class performance, and have better stress coping mechanisms than traditional students (Dill & Henley, 1998; Forbus, Newbold, & Mehta, 2011). Therefore, the significant path between caring and Test Anxiety may be capturing the reduced academic stress experienced by non-traditional college students.

School Context

The third layer in the SEM contains variables from the school context. These variables consisted of high school GPA and ACT score, which were considered cognitive variables in the regression models. These variables were allowed to directly influence all non-cognitive factors in the internal context, as well as funding in the family context. It was found that at least one of the cognitive variables significantly affected every non-cognitive factor. High school GPA had a significant effect on Test Anxiety (β = -0.154, SE = 0.16, $p < .001$), Conscientiousness (β = 0.244, SE = 0.26, $p < .001$), Study Time (β = 0.169, SE = 0.23, $p < .01$), and Neuroticism (β = 0.212, SE = 0.32, $p < .01$). Most of these relationships matched the usual expectation that higher performing high school students will perform better in college. For example, the SEM shows that a higher high school GPA is related to both lower Test Anxiety, higher Conscientiousness, and higher Study Time, all of which would serve to improve first year GPA. The opposite is true, however, with the significant positive path coefficient between high school GPA and Neuroticism. This indicates that a higher high school GPA is connected to higher values of Neuroticism, which in turn would result in a lower first year GPA. Previously, several covariances between Neuroticism and the other non-cognitive variables were suggested to be counterintuitive. With this positive relationship between high school GPA and Neuroticism, there is a possibility that Neuroticism may have been a useful trait in high school but is now a detriment in college. Some researchers argue that the high levels of worry and perfectionism that accompany Neuroticism can lead to better preparation and higher performance in non-arousing situations (Bratko, Chamorro-Premuzic, & Saks, 2006; Matthews, Davies, Westerman, & Stammers, 2000; Zeidner, 1998). This may indicate that, for this higher performing sample of students, high school is non-arousing experience, while college is the opposite.

ACT score was found to have several significant results that were in contradiction with the high school GPA results. For example, ACT score had a significant negative path coefficient with Conscientiousness ($\beta = -0.168$, $SE = 0.02$, $p < .05$) and Study Time ($\beta = -0.196$, $SE = 0.02$, $p < .01$). Both of these results indicate that a higher ACT score is related to lower Conscientiousness and Study Time, both of which would result in lower first year GPA. Other connections with ACT score remain true to expectations. ACT score has a significant negative path to Test Anxiety ($\beta = -0.236$, $SE = 0.05$, $p < .001$), for example, which means that higher ACT scores are in some scenarios indirectly related to higher first year GPA. The relationship with Test Anxiety is consistent with both the high school GPA and previous regression results.

As stated previously, since high school GPA and standardized test score are significantly correlated to general intelligence, they were included in the internal context as an intelligence proxy. From layer one, both of these cognitive factors were allowed to directly affect first year GPA. ACT score was found to have a significant path to first year GPA ($\beta = 0.121$, $SE = 0.01$, $p < .05$), while the high school GPA to first year GPA path was non-significant. Both of these results are consistent with previous literature and the initial regression results. The two cognitive variables also significantly covaried ($\beta = 0.221$, $SE = 0.04$, $p < .05$), meaning that students who entered college with higher high school GPAs also entered with higher ACT scores.

Socioeconomic Context

The final layer in this SEM contained two variables–percent free and reduced lunch (PFRL) and expected family contribution (EFC)–which represented a student's socioeconomic context. From layer four, both of these socioeconomic variables were given paths to all other exogenous variables in the model, but could not directly affect first year GPA. Significant relationships with one or both of the socioeconomic variables were prevalent in every other layer. In layer three, ACT score was significantly related to both PFRL (β = -0.236, *SE* = 1.16, $p < .001$) and EFC (β = 0.183, *SE* = 0.13, $p < .001$), indicating that students from wealthier families and neighborhoods on average performed better on the ACT. This may be because, students from wealthier families or schools may have more opportunities to prepare or the ability to take the exam multiple times. On the contrary, high school GPA was not significantly related to either socioeconomic variable. High schools may be aware of the financial limitations of themselves and their students and can internally compensate for what those limitations may cause.

Both socioeconomic variables also had significant paths to one or both familial variables. PFRL had a significant path to caring (β = 0.079, *SE* = .07, $p < .05$). This shows that students from less wealthy schools are more likely to spend time each week caring for family members. Similar results were found with the funding variable: both PFRL (β = -0.298, *SE* = 0.172, $p < .001$) and EFC (β = 0.188, *SE* = .021, $p < .001$) had significant paths. Matching intuition, students more likely to have their tuition funded by their families were those that came from wealthier families and wealthier neighborhoods.

Relationships between the socioeconomic variables and non-cognitive factors were also common. EFC had a significant path to three non-cognitive factors: Test Anxiety (β = 0.105, *SE*

= 0.04, $p < .05$), Consistency of Interest (β = -0.168, SE = 0.04, $p < .01$), and Conscientiousness (β = 0.190, SE = 0.06, $p < .01$). These paths show mixed indirect effects on first year GPA. Higher EFC relates to higher test anxiety and conscientiousness, which would in turn result in decreased and increased first year GPA respectively. This result may be because higher familial wealth, as seen through EFC, is reflecting familial pressure to perform well. PFRL had significant paths to four non-cognitive factors: Test Anxiety (β = 0.341, SE = 0.33, $p < .001$), Consistency of Interest (β = -0.339, SE = 0.30, $p < .001$), Plasticity (β = 0.250, SE = 0.43, $p < .001$), and Neuroticism (β = -0.165, SE = 0.39, $p < .05$). The relationships to Test Anxiety and Consistency of Interest were similar to, albeit stronger, than the relationships seen by EFC. The relationships to Plasticity and Neuroticism indicate mixed indirect effects on first year GPA. Both Plasticity and Neuroticism have a significantly negative affect on first year GPA, but PFRL is positively and negatively related to each respectively. Specifically, students from wealthier areas on average have higher Neuroticism and lower Plasticity.

Research Question Five: Classroom Specific Models

The fifth and final quantitative research question was to determine how the predictive models of first year GPA differed when cumulative first year GPA was substituted for classroom specific first year GPA. Since it has been established that student learning and performance can be affected by classroom setting, it was hypothesized that the significant predictors of first year GPA in these models would also change with classroom setting. Based upon the results of the multiple regression analyses, this was indeed the case. It was found that the impact of cognitive, non-cognitive, and demographic variables on first year GPA all varied by classroom setting. For example, neither high school GPA nor ACT score were significant predictors of first year GPA in lecture-based classrooms, but both were significant predictors of first year GPA in team-based classrooms. As for the non-cognitive factors, only Conscientiousness was significant in all classroom settings, while the others varied in their significance. Study Time, for example, was significant in team-based and liberal arts classrooms, while Neuroticism was only significant in lecture-based classrooms. The demographic variables had lower effect sizes overall, but varied similarly across classroom setting. Funding and expected family contribution were both significant predictors of first year GPA in lecture-based classrooms, and caring was a significant predictor of first year GPA in liberal arts classrooms.

These results were also supported with the classroom specific SEM models. In each classroom specific model, the effects between all exogenous variables were relatively unchanged compared to the cumulative GPA model. Since only the endogenous first year GPA variable changed between the cumulative GPA and classroom specific models, this similarity was expected. Another similar result was that Conscientiousness was a non-significant predictor in two of the classroom specific models. Only first year GPA in team-based classrooms was significantly affected by Conscientiousness ($\beta = 0.251$, $SE = 0.082$, $p < .05$). First year GPA in team-based courses was affected by the most cognitive and non-cognitive factors, and liberal arts courses the fewest. First year GPA in liberal arts courses, however, was the only endogenous variable significantly affected by gender ($\beta = 0.130$, $SE = 0.06$, $p < .05$). Specifically, this model expects female students to earn GPAs 0.14 points higher in liberal arts courses than their male counterparts. Overall, the classroom specific SEM models lead to the same conclusion as the regression models: predictions of first year GPA vary based on classroom setting.

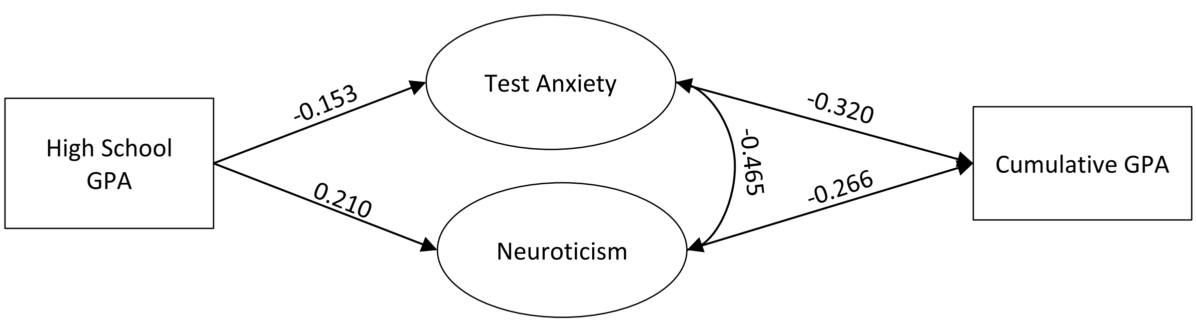
The initial regression models and SEM showed that no single factor–cognitive, non-cognitive, or demographic–was sufficient to explain first year GPA. Instead, a collection of direct and indirect effects from a number of variables best explained undergraduate engineers’ first year performance. However, these classroom specific results show how that collection of direct and indirect effects changes based on what type of performance we are interested in. If performance in lecture-based courses is being examined, then Neuroticism and Test Anxiety are the most important factors. However, if liberal arts courses are of interest, then high school GPA, Study Time, and gender are the significant variables. Ultimately, students in different classroom settings require a different collection of non-cognitive factors to perform well.

Further Insights

The quantitative portion of this research culminated in a structural equation model that illuminates the direct and indirect factors that most strongly affect engineering undergraduates' cumulative first year GPA, as well as their first year GPA in a variety of classroom settings. Given the number of variables and levels included in these models, the results were meaningful and information dense, yet also complex and difficult to decipher. However, when a small group of related paths in these models is considered closely, especially those that may seem counter intuitive on the surface, interesting stories emerge from the data. The following section will, hypothetically, tell a small number of these stories in an attempt to make more meaningful connections between this data and the real world.

Consider the paths between high school GPA, Test Anxiety, Neuroticism, and cumulative first year GPA. These isolated paths are shown in Figure 10 below. Both Test Anxiety and Neuroticism have negative path coefficients to cumulative first year GPA, meaning that more neurotic and more test anxious students perform worse in their first year as an engineering undergraduate. However, the negative covariance between Test Anxiety and Neuroticism indicates that more neurotic students on average also have lower test anxiety. Given the description of Big Five Neuroticism to be individuals more likely to experience anxiety and worry, this result runs counter to the expectation that more neurotic individuals are more anxious. In addition, examining the relationship between these two non-cognitive factors and high school GPA, students with higher Neuroticism scores actually entered engineering with higher high school GPAs. On the other hand, more test anxious students had lower high school GPAs. By considering this group of results together, along with previous literature, it can be hypothesized that more neurotic students may have prepared better for tests in high school, resulting in improved performance and less anxiety about those tests. Therefore, the students with higher Neuroticism had lower Test Anxiety. An additional interesting take-away from this collection of results is, since Neuroticism changes from a positively related to success in high school to a negative predictor of success in college, it may be a particularly detrimental non-cognitive factor for incoming engineering students. Students who previously found success in some aspect of neuroticism, may enter an engineering program and notice that those traits are now harmful. Such a population of students could benefit particularly strongly from academic coaching interventions that improve Test Anxiety.

Figure 12: High school GPA , Neuroticism, Test Anxiety, and cumulative GPA paths isolated from SEM

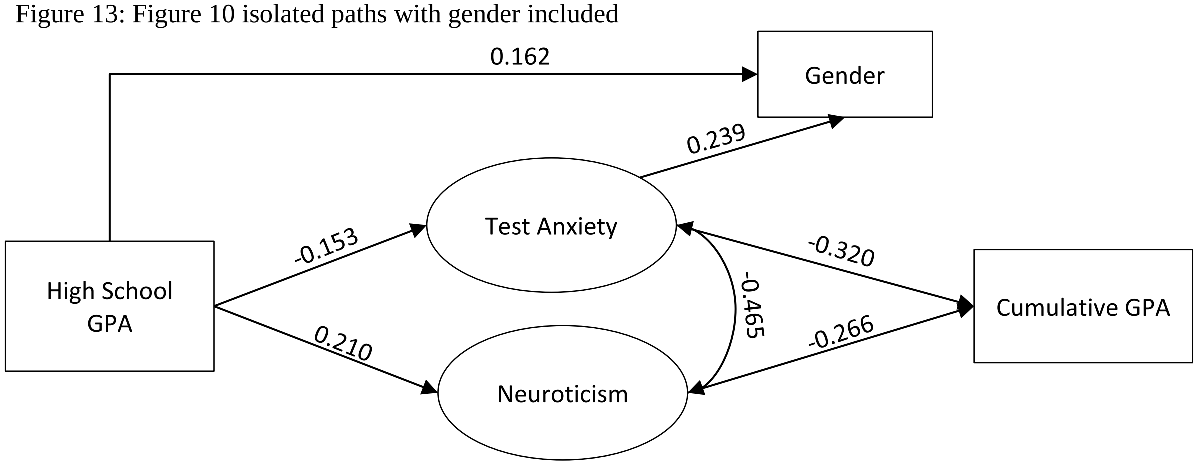


Extending this examination a bit further reveals an additional story. Figure 11 shows the same collection of variables, but with the addition of gender. Only two variables have significant paths to gender, showing that female students have higher high school GPAs and Test

Anxiety. However, the lack of significant paths can reveal just as much. These results show that there is no difference in cumulative first year GPA based on gender. Therefore, female students went from performing betting than their male counterparts in high school, to performing equal to them in college. The other significant path to gender may reveal at least part of the reason for this shift. Female students are on average more test anxious than male students, so the negative affect of Test Anxiety on first year GPA is more prominent for female students than for male. Therefore, the effects of Test Anxiety may be one factor that caused female students in this sample to shift from performing better in high school to performing on average in college.

The goal of this data is ultimately to be able to act on our expanded knowledge of student success to benefit students. Closely examining small sets of variables and considering what significant paths they do or do not have makes it easier to grasp how these variables impact individual students. Using this understanding, academic coaching interventions can more easily be designed for and adapted to a student's individual circumstances.

Figure 13: Figure 10 isolated paths with gender included



Summary

This research used Perna and Thomas' (2008) Conceptual Model of Student Success as a framework to guide the development of the quantitative models examined herein. This conceptual framework posited that student success was affected by variables in four contexts: internal context, family context, school context, and socioeconomic context. Prior to these quantitative analyses, variables were selected to represent each of these contexts. Subsequently, these variables were examined to determine their relationships to each other and directly or indirectly to student success.

The initial finding from these analyses was that three non-cognitive factors—Test Anxiety, Neuroticism, and Plasticity—directly affect the first year GPA of engineering students. The significant relationships between Test Anxiety, Neuroticism, and first year GPA are consistent with previous studies on how personality and anxiety factors affect student success (Chapell et al., 2005; Komarraju et al., 2009). The relationship between Plasticity and student success, on the other hand, neither agrees nor disagrees with results in the literature. There is little consensus on the affect Big Five Extraversion and Openness (which combined to form the Plasticity factor) have on college student success (Conard, 2006; Komarraju et al., 2013; Poropat, 2009).

A second noteworthy finding is that while Conscientiousness was a significant predictor of first year GPA in the multiple regression models, which is consistent with previous research (Komarraju et al., 2009; Poropat, 2009; Trapmann et al., 2007), it did not directly affect first year GPA in the SEM. The SEM allowed for a modeling of indirect pathways and covariances that are not normally examined in the literature. These additional pathways allowed for a more detailed examination of how variables affect each other and ultimately student success. Based on this result, Conscientiousness likely affects student success indirectly through its direct relationships and covariances with other variables. This individually is a novel result that warrants further examination.

These results also validate one of the early assumptions of this research, that cognitive factors would be worse predictors of college performance for high performing high school populations. While high school GPA has regularly been shown to be one of the strongest predictors of academic success in college (Komarraju et al., 2013; Veenstra et al., 2008), for this population it is non-significant. This supports Sawyer’s (2013) finding that high school GPA loses statistical power for high achieving students. Additionally, while both College Board and ACT Inc. suggest that standardized test scores should carry less weight than high school GPA when predicting college GPA (ACT Research, 2008; Kolbrin et al., 2008), these results indicate that for higher performing populations standardized test scores may be the more insightful variable.

Finally, these results indicate important demographic differences between in the cognitive and non-cognitive variables that were included. For example, female students were found to have both higher test anxiety and higher high school GPAs than male students, which is consistent with the literature. In addition, the findings of these quantitative analyses were also consistent with previous research in finding that SES had an impact on standardized test score. However, since this research models demographics alongside additional variables and uses them to explain the variation in first year GPA, additional context is given to how these demographic differences can affect student performance.

QUALITATIVE RESULTS

As was stated earlier, the ultimate goal of this research was to help students become more successful in their engineering studies. The initial, quantitative portion was designed to bring to light those variables that directly or indirectly affect first year GPA. In contrast, this qualitative portion was designed to understand the experiences of those involved in academic coaching interventions aimed at improving a subset of those variables. By accomplishing this, the degree to which academic coaching interventions improve performance or individual non-cognitive factors can be determined, and recommendations can be made to improve such interventions.

To this end, a series of themes were identified from the interviews with students and coaches prior to the coaching sessions, during the coaching sessions, and immediately after the coaching sessions. These themes were compared at each phase across students and coaches, paying particular attention to how their experiences aligned. In addition, since the content of the post-post intervention interviews was focused on sustained behaviors as opposed to intervention experience, the post-post interview results were used specifically to compare with the survey results. The identified themes embody the experiences of students and coaches during each phase of the academic coaching intervention process. More details regarding the content and meaning of the themes in each category will be given in the following sections. A brief demographic breakdown of each participant can be seen in Table 10. Coaches were not asked to report their gender or ethnicity, so that data was not available.

Table 10: Demographic breakdown of all qualitative research participants

Label	Gender	Reported Race/Ethnicity
Student 1	Male	White
Student 2	Male	White
Student 3	Male	White
Student 4	Male	White
Student 5	Male	White
Student 6	Male	White
Student 7	Male	White
Student 8	Male	Black or African American
Student 9	Male	Asian
Student 10	Male	International
Coach 1	Unreported	Unreported
Coach 2	Unreported	Unreported
Coach 3	Unreported	Unreported
Coach 4	Unreported	Unreported
Coach 5	Unreported	Unreported
Coach 6	Unreported	Unreported
Coach 7	Unreported	Unreported

Pre-Intervention

The data regarding the pre-intervention experiences came in equal parts from the students and coaches. The coach's preparation and expectations for each coaching session, and therefore, their addition to the pre-intervention data, came almost entirely from their training. Academic coaches need extensive preparation before entering an academic coaching session so they are able to handle possible challenges they may face. To accomplish this, coaches receive rigorous training prior to conducting any coaching sessions. Academic coach training at this institution runs for two days. The first day covers the history, structure, and goals of the institution's academic coaching system, as well as administrative tasks. The second day covered the general academic coaching workflow, as well as academic coaching frameworks, techniques, and strategies. During day two, coaches are taught methods for effectively building rapport with students, how to structure conversations and ask leading questions during coaching sessions, and how to get students to make guarantees and lay out a plan for their own success. Finally, academic coaches are shown which campus resources students can be referred to if they need other assistance. In addition to these skills, coaches are given a “toolbox” from which they can a pull number of strategies or “tools” that students may find useful. These strategies can be in the form of hand outs, articles, videos, or other various forms of media. Some examples of tools that can be found in this toolbox are the study cycle, and the 5-day study planner. Select training materials and “tools” can be found in Appendix C.

The students, on the other hand, were interviewed prior to the coaching sessions. Throughout the pre-interview the students were given the ability to talk about themselves and voice their expectations for the upcoming academic coaching interventions. The pre-intervention data serves two important roles. First, it highlights an important part of the structure of the intervention by detailing what students and coaches bring into the intervention, both physically and mentally. Second, this data allows for a comparison between the expectations of the coaches and students prior to the actual academic coaching sessions.

Four major themes emerged from the coaches and students from the pre-intervention data: student characteristics, students’ expectations for academic coaching, coaches’ preparation, and coaches’ expectations for academic coaching. The student characteristics and coaches’ preparation represent what each side brings to the academic coaching interventions. For the students, throughout the pre-intervention interview they in part discussed what makes them unique and what about themselves they find to be a benefit or detriment to their engineering studies. Some students described non-academic challenges they faced. These included hurdles such as what Student 2 previously overcame: “All right, so I was born with a severe case of apraxia which is a motor development delay, which for me affected my speech,” or injuries they suffered at school:

> *Coming to [university] was a great feat for me, and I think I even said this [earlier], it hit me like a sack of bricks, or a bench… I was riding my bike and flipped over my bike and hit a bench and went to the ER – Student 1*

Most students also commented on the difference between their high school environment and the environment in college. Most prominently, students noted the increased academic challenge of college. As one student stated:

> *…in high school I didn't really have to study that much. I didn't have to put in that much time… because I knew a lot of the material, or a lot of it wasn't too difficult and I didn't necessarily take the most challenging classes that were offered to me. At [university], I've had to study a lot more.*

Another such difference was the diversity of the engineering program and how that allowed for multiple viewpoints to be brought to their attention. During the pre-interview, Student 2 mentioned:

> *It's very diverse. I like how [university] has a bunch of people from different parts of the world coming together to study engineering. It brings new ideas from different people and new aspects that I've never seen before or been accustomed to.*

These individual characteristics influenced how students experience their undergraduate engineering career. As such, they will likely also play a role in how students experience an academic coaching intervention.

The second pre-intervention theme that emerged was the students' expectations for academic coaching. The concept of academic coaching was new to most students, so during the pre-interview they were given the opportunity to express what they expected to gain from the academic coaching interventions, and how that might benefit them. Two concepts emerged that encompassed a majority of what students thought they would learn during the coaching sessions: improving study habits and improving resource usage. It is not surprising that the participating students expected to improve their study skill during the interventions; the academic coaching label generally carries that connotation. However, there was a difference in whether students perceived improving their study skills to be a positive or negative experience. When discussing expectations during the pre-interview, Student 5 stated: “I imagine […] coaching is where they give you tips, study tips.” While in the same context Student 1 said: “I'm going to be pretty blunt, but I think academic coaching is pretty much somebody yelling at you about … how your studying is bad and trying to make you fix that.”

These quotes show how the students expected to receive the same type of coaching, however, their opinions on how they would experience that coaching differed strongly. One possible explanation for this is that a student confident in their study skills would consider study skills training to be an unnecessary, and therefore negative, experience. The second concept, resource usage, focused on the students’ expectation that the academic coaching intervention would expose them to new and useful methods for seeking help. Student 7 put it plainly when prompted about what they expect to learn through academic coaching: “Use all of your resources. I unfortunately have not [used university specific resources] because I can't find the time.”

While there seemed to be consensus on what the students would learn during the academic coaching interventions, the single most often recurring expectation expressed was what students thought they would gain, improved academic performance. When asked how they thought academic coaching would help them, Student 6 mentioned their main goal: “I'd like to find a way to at least improve my exam scores.” In this simple statement, the student made it clear that their base expectation is to improve their academic performance. Other students, in contrast, made their desire for improved academic performance more implicit. For example, Student 3 described the impact that poor performance could have:

> *And obviously with bad grades you don't do as well in other things such as job interviews, internships, and stuff. I would say [there] is kind of a pressure to do well on those assignments and those classes*

For this student the desire for improved academic performance is still of primary concern. Overall, while students expect to improve their study habits or resource usage, from their perspective the academic coaching intervention should be transactional. They will put in their time and effort and leave with the ability to get better grades in their courses.

In contrast, the academic coaches enter their academic coaching sessions with a different set of expectations. During their training, the coaches are taught that improving student’s academic performance may be the end result of a series of coaching sessions, but the goal of each session is to help students develop skills and improve habits around their academics. Coaches enter sessions with the expectation of setting and working towards a number of small, manageable goals. They do not explicitly work towards improving a student’s academic performance, but allow it to be a result of meeting the goals set during each session. For example, coaches may have students set a goal of creating a weekly planner for their homework and studying, assuming performance will improve organically if students accomplish that goal and sustain the behavior. Throughout the academic coaching interventions, students expected to directly improve their academic performance, whereas coaches expected that improved skills and habits would result in improved performance.

During Intervention

During the interventions the coach and student interacted in three distinct phases. Initially, the students made their concerns known to the academic coaches. These concerns spanned anything from a need to improve study skills to test anxiety to not understanding course material. Depending on the student and the context of the concern, some students , such as Student 4, were confident they knew what they needed to improve on: “It’s silly mistakes, which I kind of brush off and I shouldn’t, because I brush them off, ‘I'll get it right on the exam,’ and then I don't get it right on the exam.” Other students, such as Student 5, only had a general sense of the issue they were facing: “Based off what you said, everything is going good except on the test side, my test taking skills are a little shaky, and you know the tests here, or exams here are very hard.”

Regardless of the students’ conviction, the coach was left with an important decision to make. Based upon the student and their stated concern, the coach had to choose between 1) prescribing a tool from their toolbox, 2) offering personal advice and guidance, or 3) recommending external resources. Often, when the students voiced concerns about their study habits or time management, the coaches would use option 1) prescribing a tool from their toolbox. One such tool used by coaches was the study cycle, as was stated by Coach 3: “Okay, we’ll do study cycle, and I actually do want to do Bloom’s [Taxonomy] with you. ... Have you seen this before, or heard of the study cycle?” As mentioned previously, other such solutions included the 5-day study plan and the weekly task planner. Each solution also came with a specific handout, reference to visual aid, or other form of media. These tools were used by the academic coaches frequently when the students voiced concerns about their study habits or time management skills, which were very common topics discussed during the coaching sessions.

When faced with uncommon or unexpected student concerns, the coaches were required to use option 2) offering personal advice and guidance. For example, when a student mentioned they struggled with test anxiety, their Coach 1 had to provide impromptu advice:

> *If you find out that one question, this is always repeated, try to start your exam with that question. The first question that you solve in the exam, it gives you a confidence boost that, 'Okay. I was able to solve this, and now I can head on to more difficult challenges.'*

Finally, when presented with a concern that fell out of the scope of academic coaching, or if all other options were exhausted without success, the academic coaches would occasionally use option 3) recommending external resources. Occasionally the coaches would describe lesser known help resources to students, but more often than not this option was used either as a last resort, or when the coach did not have the knowledge necessary to assist the student. For example, when a student mentioned they were struggling with certain math concepts, Coach 2 responded with: "There's another thing called COSINE which is by [the] math department which is also a help room, a math help room. This is again free of cost so maybe you want to check that out too."

After consulting with the students and making recommendations, coaches frequently concluded by securing an explicit goal or commitment from the students. During a coaching session, Coach 5 stated their expectation very succinctly:

> *So, I think we need to talk about some commitments here. Because we talked about your study strategy and I've given you my recommendation. You're telling me you're studying at home and I'm giving you, maybe try something else. So, this is what I do with this consultation. I want people to have a goal with this consultation. What do you think is a goal for this consultation…?*

However, students often attempted to make performance related goals, such as getting a certain grade in a course. As a result, coaches had to steer the students towards setting smaller and more manageable goals, such as improving individual behaviors. For example, when Student 7 was prompted to set a goal for the next coaching session, the Student 7 and Coach 6 had the following conversation:

Student 7: *Ideally, I'd like to get an A in every class.*

Coach 6: *Okay. That is ideal. When we talk about goals, we talk about baseline, intermediate and grandiose. I think what you're giving me is the G goal, right? The grandiose goal. Let's maybe take a little bit of a step back, take our foot off the pedal, and let's look at ... It's definitely achievable, but let's start with an intermediate goal first of all, for these classes.*

Student 7: *Yeah, so I've been trying to figure out a schedule more. Incorporating things into my routine that I can do more often so that it becomes a habit. I think that's the biggest thing. That it becomes a habit that I'm studying more and maybe doing more office hours.*

Similar to the pre-interview data, the difference in expectations between the coaches and students persisted into the coaching sessions.

Towards the end of each coaching session, after the students voiced their concerns and the coaches responded, the students had an opportunity to respond themselves. Occasionally the students used this as an opportunity to clarify the coach's recommendation, but more often their response indicated their likelihood to implement it. When a coach recommended that a student form a study group to better learn their course material, Student 1 responded with: "Usually when I meet with my groups, it's to get a project done. It's not really to study. I mean, I'd give it a try, see if it's my cup of tea but probably not." On the contrary, when prompted by their coach to implement a weekly study plan, another Student 8 responded with: "I will definitely try to use it with this upcoming week." This shows how the success of an academic coaching intervention is strongly dependent on the interaction between the student, what they need, and how the coach responds. For a student to successfully implement a coaches' recommendation, what they perceive their needs to be must match the needs their coach addresses. All common student concerns, coach responses, and student responses from the coaching sessions are summarized in Table 11. These themes capture, in large part, the content an average session may contain. Not each of the listed concerns and responses would be present in every session. However, at least one item from each category would be present in most, if not all, coaching sessions.

Table 11: Summary of student concerns, coach responses, and student responses during the intervention

Student Concerns	*Example Quote*	**Coach Responses**	*Example Quote*	**Student Responses**	*Example Quote*
Silly Exam Mistakes	*Well, I didn't do too well on the last exam, and as I mentioned, that was due to a lot of dumb errors*	Reviewing	*Yeah, reviewing it. If you look at some of the stuff that they've done, they are organizing the notes and then writing down the main concepts*	Positive Outlook	*Like I mentioned, I'm definitely going to give these a try*
Lack of Conceptual understanding	*I didn't remember much of calc one so a lot of it, the difficulty comes back from trying to relearn the concepts and again*	Planning	*This is a example of a weekly task planner, and so you can see what they have is they have color coded their subjects*		
Under-performing	*Yeah exactly, and I think my grades don't really reflect how much I actually understand the material*	Resource Usage	*Visit special library hours. We just spoke about this. There are extended hours and there's coffee. Ask if you have questions.*	Negative Outlook	*I'm not really using the time management thing yet*
Academic Performance	*I've been doing a bit mediocre with my exams. I wish that I did better on my exams*	Study Habits	*Don't change other things in your routine… just do something to have fun in between all the studying, but controlled and timed fun.*	Clarifying Coaching	*I do think I can implement this, but I do have a question on self-testing tools. Besides for just the past exams, is there anything else that would be self-testing tools?"*
		Test Taking Skills	*Whenever you're writing your exam and when you're solving a question, you need to think that, "how can I solve this the most correct, the most efficient way in the first attempt itself?"*		

Post-Intervention

Similar to the pre-intervention, the post-intervention is not an explicit part of the academic coaching intervention process. As such, it does not add to the understanding of the structure of the intervention, however it does provide an important glimpse into students' and coaches' reflections about their experiences during the academic coaching intervention. The themes that emerged from this phase were the student's improvements and student's outcomes, as seen from the perspectives of the coach and student.

The first student improvement from the academic coaching intervention was study habits. Each participating student believed that the academic coaching intervention helped them improve their study habits. Specifically, the students cited the 5-day study plan and study cycle as concrete takeaways from their coaching experience. However, the coaches were less likely to suggest that the main benefit of the intervention was any single strategy. Towards this point, when prompted about what they gained from their academic coaching experience, Student 7 said: "Definitely the one we just talked about where I'll split my studying up, I'm definitely going to do that." Yet, when Coach 3 was asked about what one of their students gained they responded with:

> *I think it's like anything. A lot of the help that they come to get is really about habits. The help that we offer, it's not going to be a, "Change this one thing and it will," ... It's not like some click bait amazing thing. It's about changing habits and sustaining that.*

This further exemplifies the disconnect between the students' and coaches' expectations for the academic coaching process. Students expect to gain new habits or strategies during their coaching sessions. As such, simply acquiring a new study strategy, for example, either through their coach's advice or another tool, is enough to meet those expectations. Coaches, on the other hand, are not just expecting to deliver new habits or strategies to students. Instead, they expect to see students attempt to sustain those new habits or strategies, or at least set goals that incorporate that sustained behavior.

On the other hand, with the second student gain–planning–the coaches and students were both content with a simple adoption of an improved planning approach. In the post-intervention interviews, Student 6 stated:

> *My coach really focused on a five-day study plan, which ... I didn't really have any way to study well before an exam, so that really helped me to just ... It helped me to set down an amount of time to study for exams.*

Similarly, when prompted about their student's improved time management, Coach 2 responded with: "[The student] made an elaborate plan. I was really impressed. [The student] had a day-to-day plan…I mean I did not do that in my first year. That was very impressive." Unlike with study skills, coaches were satisfied with their students adopting their proposed planning schemes. What the coaches are recommending seems to have an impact on the extent to which they expect students to implement it. Specifically, it seems that where students have a tangible deliverable–such as a complete study plan–coaches are happy to consider just a completed deliverable as successful implementation. On the other hand, where there is no tangible deliverable–such as with improved study skills–coaches seem to want to see a longer term change in behavior before they consider it successfully implemented.

As for the second theme, student outcomes, the single most common perception by students was that the academic coaching intervention would result in improved academic performance. Student 3 stated: "That translates, in my opinion, to better grades. They're kind of enabling you to, by knowing how to study properly, do better on the test." Other students, however, saw their improved academic performance as a consequence of becoming more efficient. For example, Student 4 stated: “So, at the end of the day maybe you get better grades, but the efficiency is really key.”

Regardless of the reason, however, each student believed that they would be able to improve their academic performance as a result of what they gained during the intervention. The coaches, on the other hand, rarely mentioned whether they believe their students would perform better academically. Their main concern remained the implementation of what their students learned during the coaching sessions, and not the outcomes that were a result of that implementation. Students also made clear whether they found the academic coaching intervention to be an overall positive or negative experience. Overall, most students found academic coaching to be a beneficial experience. The themes that emerged from the post-intervention category are summarized in Table 12.

Table 12: Summary of student's gains and student's outcomes determined post-intervention

Student's Gains	*Example Quote*	**Student's Outcomes**	*Example Quotes*
Planning	*I know what I need to do that he showed me a good way to do it was make a schedule, because I'm bad at studying in advance and getting myself to do it.*	Positive Outlook	*To be honest, I thought they were really helpful.*
		Negative Outlook	*I don't really see myself doing it really at all, but if I see that I have a real need for it, I might go back.*
Study Habits	*I would also say they were helpful in showing me different ways to approach studying, especially for finals.*	Academic Performance	*I want to say they'll improve my academic performance, but it's hard to determine*
		Efficiency	*I definitely went there trying to improve my efficiency.*

Survey Results

Pre-intervention, post- intervention, and post-post-intervention scores for test anxiety and study skills are shown for each student in Table 13. Scores for each variable were measured on a 7-point Likert scale. A higher score on study skills represents better study skills and habits, while a higher score on test anxiety represents a more test-anxious student. For the entire (n = 284) sample of students that took the non-cognitive survey, the mean test anxiety score was 4.31 and the mean study skills score was 4.86. The standard deviations for the entire sample were 1.48 and 0.94 for test anxiety and study skills respectively.

We found that four out of ten participating students saw a reduction in test anxiety (students 1, 4, 6, and 8), four remained roughly the same (students 2, 5, 7, and 10), and two saw an increase (students 3 and 9). For study skills, the results were similar. Four students saw an increase (students 2, 3, 4, and 7), three remained roughly the same (students 1, 6, and 10), and three saw a decrease (students 5, 8, and 9). It should be noted, however, that these are only heuristic categories. According to Cohen (1992), in order to measure a small effect size of 0.2 with a power of 0.8, a sample size of close to 200 would be required. On average, from the pre-intervention to post-intervention, there was a roughly no change in study skills (5.0875 to 5.0125) and a modest decrease in test anxiety (4.10 to 3.64). Finally, every student that took the post-post-intervention survey had a study skills score greater than or equal to their pre-intervention value. This suggests that improved study skills may need to be sustained before the survey instrument can measure a change. Alternatively, the time in the semester when study skills are measured may affect the score. However, it is worth reiterating that these survey results are just illustrative and are not indicative of statistically significant change. A much larger sample would be needed to quantitatively assess the impact of coaching sessions on study skills or test anxiety. These results do, however, provide support to the claims students were making that through coaching there were able to gain improved habits or strategies.

There also seems to be a pattern to how students' study skills and anxiety have changed. As one might expect, the students that saw increased study skills or decreased test anxiety were those that had lower study skills and higher test anxiety before the intervention. That is to say, those students that had more room for improvement seemed to gain more from the interventions, while those that were already confident in their study skills and test anxiety saw some regression or no change at all. The regression may be a remnant of a difficult semester, or a result of the transition from high school to college. This phenomenon may also explain why fewer students overall had improved study skills than test anxiety. On average, students had less room for improvement in study skills than test anxiety going into the coaching sessions. Therefore, since there was less room for students to improve their study skills, less improvement should be expected.

These quantitative observations were also supported with the results from the post-post-intervention interviews. For example, Student 4 showed an improvement in both test anxiety and study skills after the academic coaching intervention, and sustained that change up to the post-post-intervention interview. During that interview, when prompted about the time management skills they learned from the coaching session, Student 4 responded: "Yes I think they're definitely sustainable long term. I think most adults plan their days out before they actually jump into it…Definitely a skill the real world requires." A similar result was seen by Student 2, who noticed and sustained an improvement in their study skills score over the course of several months. When prompted about their sustained behaviors, they called out a specific study skill they learned: "I've kept up with the intensive one hour study sessions. I've been keeping that up for studying."

Table 13: Text anxiety and study skills survey results pre- and post- academic coaching intervention

Student Identifier	**Pre-Intervention**		**Post-Intervention**		**Post-Post-Intervention**	
	Test Anxiety	Study Skills	Test Anxiety	Study Skills	Test Anxiety	Study Skills
Student 1	7.0	6.4	6.2	6.3	7.0	6.4
Student 2	3.2	3.1	3.4	4.3	3.2	4.3
Student 3	1.4	4.8	2.6	5.4	2.6	5.0
Student 4	4.0	4.1	2.0	4.9	2.2	5.0
Student 5	4.6	7.0	4.4	5.4	4.2	7.0
Student 6	3.6	5.6	2.2	5.6	2.6	6.3
Student 7	4.2	4.0	4.0	4.9	4.0	4.3
Student 8	6.6	5.6	3.6	4.4	N/A	N/A
Student 9	2.2	5.5	3.6	4.5	N/A	N/A
Student 10	4.2	4.8	4.4	4.6	2.6	4.9

Discussion

The goal of the qualitative portion of this research was to answer research questions six and seven. These research questions were:

RQ6: What are the experiences of those undergoing and delivering an intervention targeting students' non-cognitive factors, and how do those experiences align with each other?

RQ7: How can these interventions be improved with knowledge of a student's non-cognitive factors and the impact of those factors on student success?

Research Question Six

The focus of research question six was to understand the experiences of those undergoing and delivering the academic coaching intervention, and to determine how well those experiences align. While all involved in academic coaching are engaged in the same discourse of understanding student difficulties and making appropriate recommendations, the students and coaches seem to experience this system differently.

Students

From the onset, students seem to have an expectation that academic coaching sessions will be transactional in nature. Students entered the academic coaching sessions with the mindset that if they put in the time and effort to attend the session and engage with their coach, they will leave with improved skills and habits. For example, during the pre-interviews, students mentioned how they expected academic coaches to *give* them study habits, or *tell* them how to fix their studying. This language insinuates that students see study skills, as well as time management and other habits learned in academic coaching, as strategies that can be imparted to them by their coaches. In addition, it was evident from the students' responses during interviews and coaching sessions that their primary goal was to improve their grades in courses or on individual assignments and exams.

These results suggest that this transactional expectation is, at least in part, due to the fact that students predominantly set performance-based goals for themselves. Given that grades are the outcome of interest for most students, this is a perfectly reasonable goal; however, it means that improved skills and habits are seen as a means to an end as opposed to the end themselves.

Coaches

A problem arises in academic coaching when a student's performance-based goal is at odds with an academic coach's development-based goal. There is nothing wrong with students having performance-based goals or expectations. Grades are, after all, one of the main ways a student's success in college is judged. However, from their training, academic coaches are taught that their role is to help develop students' skills and behaviors, and make improvements where students feel they are struggling. From the perspective of the academic coaches, directly affecting student success is not the main purpose of academic coaching. Instead, coaches' enter academic coaching sessions with a goal of getting students to make small, achievable commitments to changing their behaviors that may ultimately lead students to improved academic success.

Coaches experience this discrepancy between their expectations and their student's expectations fairly directly during coaching sessions. For example, coaches would often attempt to elicit an explicit goal or commitment from their students during each coaching session. If that goal happened to be performance oriented, coaches would have to spend time getting their student to look deeper into what improved skills or habits could help them reach that ultimate, performance-based goal. The following conversation between Coach 6 and Student 6 portrays that experience well:

Coach 6: *Okay, that's cool. So basically if we want to discuss things that you think will help you achieve your goal, like your smart goal of getting a 3.7 what are some of the things you see that you might want to work on.*
The first one you said, led into understanding the material better, right?

Student 6: *Mm-hmm (affirmative)*

Coach 6: *What else do you think can improve on –*

Student 6: *Putting the engineering concepts into practice.*

Coach 6: *Okay.*

Student 6: *Because most of that is just like, they show us how to do something and they give us a situation to put it into practice and so that's where I really struggle.*

Coach 6: *Well, there are a couple of tools we can look at, that can help this main issue here…*
So one thing I wanted to show you is the study cycle. So, this study cycle, in terms of the chemistry class where you're reading a lot, you're trying to understand what you're reading, this will help you sort of grasp the material a little better, right?

In this discussion, the student previously set a goal of getting a 3.7 GPA that semester. The coach had to work backwards form that long-term, performance-based goal to get the student to discover what smaller changes they could make that could allow them to reach that goal. The coach ultimately found a specific are they could address, and made recommendations to the student.

Overall Experiences

Even though students and coaches had different expectations for, and experiences with the academic coaching sessions, by both qualitative and quantitative measures the sessions were successful. Qualitatively, our results show that students almost entirely found the academic coaching sessions to be a positive experience. While few indicated a desire to attend future academic coaching sessions, from the session that they already attended a majority of the participants learned what they considered to be new and improved studying and/or time management skills. Most students were also able to sustain these improved skills into their following semester and believed that these skills were allowing them to perform better in their courses. While improvements in performance were unverifiable, at the very least most students left their academic coaching sessions confident in their ability to study more effectively and efficiently than they were previously.

The success of the academic coaching session is also supported quantitatively. Five of the students in this study had a study skills score below the entire sample average of 4.86 during the prior to the coaching sessions. Of those five students, four saw an improvement in their study skills score of at least one-half standard deviation after the academic coaching intervention, and each sustained some level of improvement into the post-post-intervention interview roughly two months later. One out of the five students saw a marginal decrease in their study skills score between the pre and post-intervention survey, but that score improved to beyond their pre-intervention level in the post-post-intervention survey. The results were similar with test anxiety scores. Three students had higher than average test anxiety (i.e. more test anxious) prior to the intervention, and all three saw a decrease in their test anxiety scores after the intervention. Of those three students, at the post-post-interview one regressed back to their original test anxiety score and one sustained the improvement. The final student did not take the post-post-intervention survey.

In sum, students and coaches entered their coaching sessions with different expectations, and as a result experienced coaching differently. However, over the course of their three academic coaching sessions, those differences were often able to be reconciled. Ultimately, both students and coaches found coaching to be a positive and beneficial experience, and believe the students left with improved habits and better strategies to succeed.

Research Question Seven

Research questions seven encompassed stage three of this research. The goal of which was to determine if knowledge of a student’s non-cognitive factors, and how those factors affected first year performance, would allow for academic coaches to create more effective and personalized academic coaching sessions. Mixed results were found while answering this question. In stage three, four academic coaches were recruited, each of which was assigned one or two of the five participating students. Before students schedule appointments for their first coaching session, each academic coach was given a breakdown of their students non-cognitive factors, how those factors compare to the average of all other students in the sample, and a simplified version of the SEM that shows how a student's non-cognitive factors can affect their performance. Coaches were allowed to use this information in whatever manner they saw fit during their sessions. When prompted during the coach interviews to discuss how they used this information, each coach responded the same way: they ignored it. In addition, each coach indicated that they made a decision to ignore the details on their student's non-cognitive factors in order to avoid biasing their coaching sessions. Coach 5 put it very succinctly: "I tried not to look at that because I don't want to think, oh, they have this type of personality…I didn't look at it because I don't want…those factors to be in [the sessions] at all." However, part of keeping coaching sessions unbiased seemed to be a result of knowing the sessions were being recorded for the sake of research. As Coach 7 mentioned:

> *It was more of like a "Hey, I really don't want this to influence how I talk to [student]." Because I think I'm the type of person who kind of, based on what I hear about a person, I kind of already have this image in my head and I didn't want that [to bias sessions]. I felt like really pure ... quote unquote data would be more, you know, desirable for this kind of study rather than me structuring my questions or my interviews with [student] around my preconceived notions of what type of student they would be.*

Further supporting that point, coaches also made it clear that they would use the knowledge of a student's non-cognitive factors for most of the students they see. When asked specifically if they would find it useful to know about a student's test anxiety or study skills before a session, Coach 5 responded: "I think so. I think so, because at the very least it will help us prepare for the meeting." When asked a similar question, Coach 4 went into much more detail about the use for student's non-cognitive factors:

> *Sometimes I struggle when I look at the board when they make the original appointment, and sometimes they don't put any comments or anything. So, I even reach out to them: "What can you tell me? What do you want to talk about?"* But, *until I seem them in person, I don't know how to prepare for the consultation…But if you have some type of personality or things like that on the [system used by coaches to see students grades and advisor comments], I think you might give me a better idea about how to prepare the consultation. Sometimes people are very resistant to change, then, you know, I can prepare a different way. If they're very acceptable, then I can prepare another way. But, [the current system] doesn't show anything like that…Because, the first time [in a coaching session] they're always intimidated. They don't want to talk…probably not going to give you one hundred percent. But when they come back for the follow up meeting, every time they come back, it changes. So, I think having more information on the student will be better than just the [current system] with the classes.*

In this quote, the academic coach lays out in detail what information they could use, how they could use it, and how they would like to receive it. In the example the coach offers, they call out "resistance to change" as a non-cognitive factor they could use to help prepare their sessions, which could be captured by the Big Five Agreeableness or Openness traits, or other non-measured traits such as mindset. Also, in addition to helping prepare for coaching sessions, this coach alluded to the idea that knowledge of a student's non-cognitive factors would help them build rapport in early sessions, so they can more easily understand what a student needs. Finally, this coach indicated that the most useful way to receive a student's non-cognitive factors would be integrated into the system they currently use to view grade details and advisor notes.

In sum, coaches made an explicit point of ignoring the information about students' non-cognitive factors during their coaching sessions. Therefore, no conclusive answer to research question seven could be found. However, while coaches decided to ignore students' non-cognitive factors while participating in this research, they made it known that such knowledge would be beneficial for them in most contexts. Thus, even though this research was unable to determine how knowing students’ non-cognitive factors could affect academic coaching sessions, this research did determine that there is a large potential impact of such knowledge.

CONCLUSIONS

Improved Interventions

The quantitative and qualitative results of this research suggest, to varying degrees, improvements or alterations that could be made to the academic coaching intervention process. When considered alongside conversations with academic coaches and academic coaching managers, informed and feasible recommendations can be made that have the possibility of improving how well academic coaching benefits student success. These recommendations fall into three broad categories: recruitment, efficiency, and assessment.

Recruitment

One of the most important tasks performed by the academic coaching system is making coaching sessions visible and accessible to the maximum number of students. Accomplishing this allows for recruitment of students into academic coaching sessions that would most strongly benefit from them. Two major barriers are often faced in this recruitment process: determining which students would benefit from academic coaching, and convincing students to attend coaching sessions either of their own accord or once recruited. Determining which students to recruit for coaching sessions is frequently done on a referral basis. Faculty or academic advisors may recognize that a student is struggling and could either suggest to the student that they attend academic coaching, or request that the academic coaching system reaches out to the student themselves. In more extreme cases, such as academic probation, students may be required by their college or university to attend academic coaching. Finally, academic coaches at this institution have the ability to see student grades and number of DFWs (courses where the student received a D, F, or withdrew). With this information, coaches can decide to “cold call” students and recommend that they attend a coaching session to improve their study skills, time management, or test anxiety, with the ultimate goal of improving their grades.

All three of these recruitment methods, however, have two common attributes that can harm both recruitment and attendance: they are reactive, and focus entirely on performance outcomes. A student who is performing well could still benefit from academic coaching, and conversely a student performing poorly is not a guarantee that they can be helped by academic coaching. Academic coaching sessions are designed, administered, and expected to improve students study skills, time management, and test anxiety. Therefore, it is those factors that should be targeted in recruitment as opposed to performance. Similarly, by using these factors in recruitment, students can be prompted to attend coaching before their academic performance is affected by these non-cognitive factors. By measuring and incorporating these non-cognitive factors into the recruitment process, students can be recruited based upon the factors academic coaching is deigned to change, as well as recruited proactively instead of as a reaction to poor performance.

One of the findings in the qualitative portion of this research was also that students and coaches enter academic coaching sessions with different expectations. Students' expectations are performance based, while coaches' expectations are development based. Basing recruitment almost entirely on performance may help to explain why students enter academic coaching with this expectation. By suggesting that students should attend academic coaching because they are performing poorly, the implication is that their performance will increase as a result. However, if non-cognitive factors are included in the recruitment process, then the implication shifts to developing skills instead of improving performance. This small change may be able to mitigate the difference in expectations between students and coaches, making the entire coaching experience more effective.

Efficiency

As was discussed in the qualitative results section, one of the difficulties faced by academic coaching is that most students only attend for one session, and a large portion of that session is taken up by rapport building and understanding the student's needs. Only a relatively small portion of a single session can be dedicated to the academic coach making recommendations, and the student responding to those recommendations and setting goals. Therefore, as they currently stand, academic coaching sessions do not efficiently develop the skills and habits they hope to develop. The most effective solution to this problem, and the solution most vigorously pursued by the academic coaching system, is to convince students to attend at least one follow up coaching session.

It was found that recruiting students for three academic coaching session resulted in the initial stage of each subsequent session was shorter than for the previous session. That is to say, since students and coaches met more frequently, they had to spend less time each session building rapport and discussing the student's concerns. This result strongly supports the goal of the academic coaching system to have students attend multiple sessions. Yet, however effective it may be, meeting that goal will prove a difficult challenge. It has been established, at least at this institution, that the vast majority of student will only attend a single coaching session. A potential reason for this was discussed in the qualitative results: students believe academic coaching to be transactional. Students see academic coaching as a process where they can put in their time and effort and their coach will impart onto them improved skills and habits. With this view, students would see little reason for attending multiple sessions; they can get what they need to improve their performance after attending only one. Altering this view ties back into the recruitment improvements. By changing the perception of academic coaching from benefitting performance to benefitting study skills, time management, and test anxiety, students may be less inclined to see academic coaching as offering a quick fix. If academic coaching were portrayed from the onset as a process aimed at helping those students with worse study skills or more test anxiety, the developmental nature of those skills and habits may become inherent to the entire academic coaching system.

A smaller, but still beneficial improvement that can be made to improve the efficiency of academic coaching would be to further integrate non-cognitive factors. The previous recommendation was to use non-cognitive factors in the recruitment process, but those factors could easily be brought into the coaching sessions themselves as well. If academic coaches had knowledge of the non-cognitive factors of their incoming students, as stated before they could use that knowledge to facilitate more detailed and individualized preparations. These preparations would include some assumptions on what students concerns may be, so they could serve to reduce the amount of time spent discussing those concerns at the front end of the sessions.

A final recommendation, suggested by the academic coaches, was to make the academic coaching space more personal and welcoming. Currently, at this institution, academic coaching occurs either in an open study space, or in smaller conference rooms. Both of these locations are empty, but for tables, chairs, and whiteboards, making the coaching sessions feel somewhat clinical. If coaches were able to claim a space as their own, they would be able to add their own personal touches, making students feel more welcome. If students fell more comfortable and welcomed during their academic coaching sessions, they may also be more open with their coach, making building rapport and discussion concerns a smoother, and ultimately faster, process.

Assessment

A recurring theme throughout these recommendations is that the academic coaching system targets students based on their academic performance, and students have performance based expectations for coaching. Beyond the implications this has for recruitment and efficiency, this performance focus makes the assessing the effectiveness of academic coaching difficult. This issue was touched upon in the qualitative results section; determining what portion of performance changes were due to academic coaching can be complicated since students take different collections of courses across semesters. Just knowing that a student participated in coaching would not allow for the academic coaching system to disentangle what portion of performance change were due to the coaching sessions themselves from the portion due to students being in different courses.

Similar to the previous recommendations, integrating non-cognitive factors into the academic coaching system could improve the assessment of coaches or coaching sessions. However, to improve assessment non-cognitive factors need to be considered at the end of a student's series of academic coaching sessions. Since the goal of academic coaching is to develop habits to improve study skills, time management, and test anxiety, using non-cognitive factors to measure these attributes directly provides a direct way to assess the success or effectiveness of the sessions. In addition, non-cognitive factors directly measuring academic coaching outcomes could be grouped by academic coach as opposed to student to determine how well a specific coaches' style or process works compared to other coaches. Finally, a non-cognitive factor based assessment could allow for more experimentation with new or alternative coaching strategies. By measuring outcome variables directly, skill and habit development for students in traditional coaching sessions could be compared to those in experimental coaching sessions, allowing for an explicit method for determining if alternative strategies are effective.

Improved assessment would allow for the academic coaching system to do more than just determine the effectiveness of their coaches and coaching sessions. Overtime, enough assessment data would be collected that it could be released on aggregate to students. This could immediately accomplish two things. First, it could show students, quantitatively, that academic coaching is an effective way for them to improve their study skills, time management, or test anxiety. Assessment results could also be broken down further to show students how they could see more improvement in their non-cognitive factors by attending follow up coaching sessions. Second, by the academic coaching system framing their assessment explicitly in terms of the outcomes they claim to improve, they can further show students how the purpose of academic coaching is to develop skills and habits, and not to directly improve performance. Ultimately, this could help mitigate the difference in expectations between students and coaches when entering academic coaching sessions.

Summary of Recommendations

In this section, several recommendations were made that could improve academic coaching in three areas: recruitment, efficiency, and assessment. In each of these areas, one recommendation included integrating non-cognitive factors into a stage of the academic coaching process. These recommendations were: 1) Using non-cognitive factors to recruit students for academic coaching sessions directly based upon their study skills and test anxiety, as opposed to their academic performance; 2) Using non-cognitive factors to inform early coaching preparation, ultimately reducing the time in each session dedicated to rapport building and discussing the student’s concerns; and 3) Using non-cognitive factors to directly measure academic coaching outcomes, and subsequently using those outcomes to assess the success of academic coaches and academic coaching sessions.

The recommendation that would likely make the largest impact would also be the most difficult to implement: using non-cognitive factors to recruit students. Accomplishing this would require one of three things to happen: students reflect on their own skills and habits and decide they need improvement, faculty or advisors notice that students are struggling with their study skills or test anxiety and refer them to academic coaching, or non-cognitive surveys are given to incoming freshman students and the results are used to recruit directly. However, distributing a survey to all incoming students would be a difficult and time-consuming undertaking, and the previous academic coaching structure has already shown that relying on referrals and walk-ins for recruitment is not sustainable. Attempting to distribute a non-cognitive survey to all incoming students is a reachable, long-term goal to improve recruitment, but does not improve academic coaching immediately.

Focusing on efficiency and assessment, on the other hand, would allow for sustainable and immediate improvement. Integrating non-cognitive factors into the early stages of coaching can be accomplished by including a short intake survey in the online appointment system. Similarly, the same survey can be sent to students several weeks after their scheduled appointment, giving the academic coaching system two time points with which they can measure improvements. As stated previously, incorporating non-cognitive factors throughout the academic coaching process would also help to mitigate differences in coach and student expectations, and the perception of academic coaching as a quick fix for poor academic performance. In sum, integrating non-cognitive factors into the beginning and end of the academic coaching process, while working towards a long-term goal of administering a non-cognitive survey to all incoming students, would improve academic coaching in recruitment, efficiency, and assessment, while providing maximum benefits to students.

Limitations

There are inherent limitations for both the quantitative and qualitative portions of this research, due to the methodology, data collection, and data analysis techniques. One such limitation is that the structural equation model is based entirely off of Perna and Thomas' conceptual model of student success. Performing SEM requires a theoretical model to guide the construction of the structural model. Therefore, using Perna and Thomas' conceptual model of student success was necessary to successfully completing the analysis. However, this is just one such theoretical model of student success. Other such theoretical models exist, but these results can only speak to the Perna and Thomas model.

In addition, as with all statistical analyses, the results of the quantitative portion of this research cannot make claims of causality. Instead, all results are only correlational. While more sophisticated analyses, such as SEM, can provide a direction to these relationships and tentatively suggest possible causal relationships, it is a common misconception that causality can be determined by using SEM (Bullock, Harlow, & Mulaik, 1994). For example, a common result found was that Test Anxiety has a strong negative relationship with first year GPA. Therefore, while it can be said that students with higher Test Anxiety on average will perform worse in their first year in engineering, the claim cannot be made that Test Anxiety is the reason for their worse performance.

The main limitation inherent in data collection is that, while the collection of non-cognitive factors in this research either directly or indirectly incorporate many important attributes, it is not entirely comprehensive. That is to say, it cannot be claimed that the collection of non-cognitive factors used in this research is inclusive of all non-cognitive factors that can affect first-year engineering performance. A second limitation in data collection is that demographic information was obtained through the university registrar, as opposed to being self-reported on the survey. This impacted the dataset in several different ways. First, since students reported gender only as male or female, students were unable to report a non-binary gender. This may have resulted in an over reporting of male and female students in the dataset, and didn't allow for an exploration of how non-binary gender students' first year performance was impacted by non-cognitive factors. Second, in the university registrar data only domestic students were allowed to report their race/ethnicity. International students were asked their country of origin, but a student's country of origin may or may not match their race/ethnicity. There was a large number of international students in the dataset, meaning that race/ethnicity could not be considered at all in the analyses. Finally, other demographics, such as sexual identity or disability status, were not collected at all.

As far as the qualitative portion of this research in concerned, the main limitation is in the generalization of the results. Steps were taken to recruit students for the academic coaching interventions that represented high, low, and average study skills. While achieving diversity in this aspect this was accomplished, the resulting sample of students was relatively homogenous in terms race and gender. In addition, students were required to attend three academic coaching sessions. This was necessary to collect enough data to gain a complete understanding of the academic coaching process. However, as was discussed previously, this is not indicative of how most students participate in academic coaching. The results of the qualitative analysis were meaningful and added to the knowledge about how academic coaching is experienced, but how the students participating in this research experienced academic coaching may be the same as how other experienced it.

Future Work

Considering the results of this research and the limitations inherent in its design, there are two clear directions for future work: expanding data collection, and implementing improved interventions. These directions for future work compensate for some of the limitations in the original research design, and build upon the results found in this work.

Expanding data collection could take many forms. Simply expanding the sample size would increase the power of the analyses, allowing for additional significant pathways to come to light. Additionally, by including additional and improved demographic questions one of the limitations of this work could be directly compensated for and a better understanding of how different students are affected by non-cognitive factors can be achieved. Finally, a more comprehensive non-cognitive survey could be created and administered that includes improved demographics and additional non-cognitive factors. This will allow for both a better understanding of how non-cognitive factors affect individual students, as well as how a larger number of non-cognitive factors can affect first year GPA.

While this research attempted to quantify the change in non-cognitive factors seen by students after attending academic coaching, the sample size was much too small to make any claims of significance. Future work could expand upon this by incorporating the recommendations made for improving assessment in academic coaching. This could be accomplished by either recruiting students for coaching in a method similar to this research design–which would also serve to improve the diversity of the sample–or by working with the academic coaching system to integrate non-cognitive factors into their academic coaching process. Another direction for future work associated with academic coaching would be to integrate non-cognitive factors into the beginning of the coaching process. While that was attempted in this research, a more directed approach could be taken that eases the concerns of coaches and makes the non-cognitive factors a more explicit focal point of the research.

The goal of this research, the recommendations made for academic coaching, and the suggestions for future work is to better understand and ultimately improve student success in an explicit way. By keeping students at the forefront of research on student success, and constantly considering how new knowledge can be used to benefit students, meaningful strides can be made towards making students more successful in engineering.

APPENDIX A: SURVEY INSTRUMENT

Start of Block: Consent

Q45 **RESEARCH PARTICIPANT INFORMED CONSENT FORM** Study title: The role of non-cognitive and affective (NCA) factors in engineering and computing student academic performance Principal investigator: Dr. Edward Berger (bergere@purdue.edu) Department: School of Engineering Education, Purdue University *Phase 1: non-cognitive trait survey* Please read the following carefully to understand this study. What is the purpose of this study? The purpose of this study is to understand how non-cognitive factors (defined as personality and other innate characteristics and behaviors) impact academic performance of undergraduate engineering students. Understanding this question is important, because it will allow the community of educators to better understand the mechanisms of success and failure among their students. What will I do if I choose to be in this study? · You will be asked to complete a short survey, no longer than 15 minutes, in which we ask you questions about your attitudes, behaviors, and activities during the school year. The survey will be completed online using Qualtrics. · You can agree to participate in the survey by completing the electronic Informed Consent Form that immediately precedes the survey in Qualtrics. · Upon your consent to participate in the survey, you will complete the survey. · During our data analysis, we will connect your survey responses to portions of your academic record, in order to examine relationships among your survey responses and your academic outcomes. These specific data include: grades in courses taken during the freshman year (including course information such as instructor and section number); admission data including SAT/ACT score, high school class rank, and extra-curricular activities; demographic information including gender, race, ethnicity, and country of origin; and socio-economic status data in the form of level of eligibility for financial aid or expected family contribution. · Based upon your responses to the survey, we *may* invite you to participate in another phase of this research that involves other activities. We will fully explain that phase of the research to you if you are invited to participate, and that phase of the research will have its own consent form that fully explains the study and your role in it. How long will I be in the study? Your participation in the study includes completing just one survey of about 15 minutes. We do not anticipate asking you to complete any more surveys at any time in the future. What are the possible risks or discomforts? There is no more than minimal risk, which is no greater than everyday activities. A potential risk associated with the participation in this study is the possibility of breach of confidentiality because your identity will be associated with the survey and academic record data we collect. To minimize this risk, all data will be coded with a unique numerical identifier used to link all the information we collect to each individual. We will perform data analysis only on a de-identified dataset, and all data will be stored on a password-protected, encrypted server managed by Purdue University. Participants are reminded that participation in this study is voluntary and it in no way impacts their grade in any academic class. Are there any potential benefits? There are no direct benefits for completing the survey. Will I receive payment or other incentive? You will not be compensated for participation in this study. Are there costs to me for participation? There are no costs to you for participating in this study. Will information about me and my participation be kept confidential? All digital data files will be stored on a password-protected, encrypted server (the Purdue Data Depot). Only the PI, co-investigators, and departments at Purdue University responsible for regulatory and research oversight will have access to the share-server. Research results will be presented in aggregate form, and all data from individuals will be de-identified before results are reported. At the conclusion of the project, we expect to destroy any original data files containing identity information, and preserve only de-identified datasets to protect identities of participants and enable continued analysis of the de-identified data. What are my rights if I take part in this study? Your participation in this study is voluntary. You may choose not to participate or, if you agree to participate, you can withdraw your participation at any time. You can at any time request the opportunity to review the survey. Who can I contact if I have questions about the study? If you have questions, comments or concerns about this research project, you can talk to one of the researchers. Please contact Edward Berger (765) 496-0193 or bergere@purdue.edu. If you have questions about your rights while taking part in the study or have concerns about the treatment of research participants, please call the Human Research Protection Program at (765) 494-5942, email (irb@purdue.edu) or write to: Human Research Protection Program - Purdue University Ernest C. Young Hall, Room 1032 155 S. Grant St., West Lafayette, IN 47907-2114

Q46 **Documentation of Informed Consent** I have had the opportunity to read this consent form and have the research study explained. I have had the opportunity to ask questions about the research study, and my questions (if any) have been answered. Please choose one option.

- ○ I agree to participate in this study. (1)
- ○ I do not agree to participate in this study. (2)

Skip To: End of Survey If Documentation of Informed Consent I have had the opportunity to read this consent form and ha... = I do not agree to participate in this study.

End of Block: Consent

Start of Block: Ten Item Big Five

BF0
The following are a number of statements containing pairs of personality traits that may or may not apply to you. Please select the response for each statement that best indicates how much you disagree or agree. **You should select how much you disagree or agree based on how much the pair of traits applies to you, even if one characteristic applies more strongly than the other.**

BF1 I see myself as extroverted, enthusiastic

- Disagree Strongly (1)
- Disagree Moderately (2)
- Disagree Slightly (3)
- Neither Agree or Disagree (4)
- Agree Slightly (5)
- Agree Moderately (6)
- Agree Strongly (7)

BF2 I see myself as critical, quarrelsome

- Disagree Strongly (7)
- Disagree Moderately (6)
- Disagree Slightly (5)
- Neither Agree or Disagree (4)
- Agree Slightly (3)
- Agree Moderately (2)
- Agree Strongly (1)

BF3 I see myself as dependable, self-disciplined

- Disagree Strongly (1)
- Disagree Moderately (2)
- Disagree Slightly (3)
- Neither Agree or Disagree (4)
- Agree Slightly (5)
- Agree Moderately (6)
- Agree Strongly (7)

BF4 I see myself as anxious, easily upset

- Disagree Strongly (7)
- Disagree Moderately (6)
- Disagree Slightly (5)
- Neither Agree or Disagree (4)
- Agree Slightly (3)
- Agree Moderately (2)
- Agree Strongly (1)

BF5 I see myself as open to new experiences, complex

- Disagree Strongly (1)
- Disagree Moderately (2)
- Disagree Slightly (3)
- Neither Agree or Disagree (4)
- Agree Slightly (5)
- Agree Moderately (6)
- Agree Strongly (7)

BF6 I see myself as reserved, quiet

- Disagree Strongly (7)
- Disagree Moderately (6)
- Disagree Slightly (5)
- Neither Agree or Disagree (4)
- Agree Slightly (3)
- Agree Moderately (2)
- Agree Strongly (1)

BF7 I see myself as sympathetic, warm

- Disagree Strongly (1)
- Disagree Moderately (2)
- Disagree Slightly (3)
- Neither Agree or Disagree (4)
- Agree Slightly (5)
- Agree Moderately (6)
- Agree Strongly (7)

BF8 I see myself as disorganized, careless

- Disagree Strongly (7)
- Disagree Moderately (6)
- Disagree Slightly (5)
- Neither Agree or Disagree (4)
- Agree Slightly (3)
- Agree Moderately (2)
- Agree Strongly (1)

BF9 I see myself as calm, emotionally stable

- Disagree Strongly (1)
- Disagree Moderately (2)
- Disagree Slightly (3)
- Neither Agree or Disagree (4)
- Agree Slightly (5)
- Agree Moderately (6)
- Agree Strongly (7)

BF10 I see myself as conventional, uncreative

- ○ Disagree Strongly (7)
- ○ Disagree Moderately (6)
- ○ Disagree Slightly (5)
- ○ Neither Agree or Disagree (4)
- ○ Agree Slightly (3)
- ○ Agree Moderately (2)
- ○ Agree Strongly (1)

End of Block: Ten Item Big Five

Start of Block: Short Grit Survey

G0 **Please respond to each of the following statements to the best of your ability.**

G1 New ideas and projects sometimes distract me from previous ones

- Not like me at all (5)
- Not much like me (4)
- Somewhat like me (3)
- Mostly like me (2)
- Very much like me (1)

G2 Setbacks don't discourage me

- Not like me at all (1)
- Not much like me (2)
- Somewhat like me (3)
- Mostly like me (4)
- Very much like me (5)

G3 I have been obsessed with a certain idea or project for a short time but later lost interest

- Not like me at all (5)
- Not much like me (4)
- Somewhat like me (3)
- Mostly like me (2)
- Very much like me (1)

G4 I am a hard worker

- Not like me at all (1)
- Not much like me (2)
- Somewhat like me (3)
- Mostly like me (4)
- Very much like me (5)

G5 I often set a goal but later choose to pursue a different one

- Not like me at all (5)
- Not much like me (4)
- Somewhat like me (3)
- Mostly like me (2)
- Very much like me (1)

G6

I have difficulty maintaining my focus on projects that take more than a few months to complete

- Not like me at all (5)
- Not much like me (4)
- Somewhat like me (3)
- Mostly like me (2)
- Very much like me (1)

G7 I finish whatever I begin

◯ Not like me at all (1)

◯ Not much like me (2)

◯ Somewhat like me (3)

◯ Mostly like me (4)

◯ Very much like me (5)

G8 I am diligent

◯ Not like me at all (1)

◯ Not much like me (2)

◯ Somewhat like me (3)

◯ Mostly like me (4)

◯ Very much like me (5)

End of Block: Short Grit Survey

Start of Block: Motivated Student Learning Questionnaire

MSLQ0 **Please respond to the following items to the best of your ability.**

TA1

When I take a test I think about how poorly I am doing compared with other students

- ○ Very untrue of me (1)
- ○ Untrue of me (2)
- ○ Somewhat untrue of me (3)
- ○ Neutral (4)
- ○ Somewhat true of me (5)
- ○ True of me (6)
- ○ Very true of me (7)

TA2

When I take a test I think about items on other parts of the test I can't answer

- ◯ Very untrue of me (1)
- ◯ Untrue of me (2)
- ◯ Somewhat untrue of me (3)
- ◯ Neutral (4)
- ◯ Somewhat true of me (5)
- ◯ True of me (6)
- ◯ Very true of me (7)

TA3

When I take tests I think of the consequences of failing

- Very untrue of me (1)
- Untrue of me (2)
- Somewhat untrue of me (3)
- Neutral (4)
- Somewhat true of me (5)
- True of me (6)
- Very true of me (7)

TA4 I have an uneasy, upset feeling when I take an exam

- ◯ Very untrue of me (1)
- ◯ Untrue of me (2)
- ◯ Somewhat untrue of me (3)
- ◯ Neutral (4)
- ◯ Somewhat true of me (5)
- ◯ True of me (6)
- ◯ Very true of me (7)

TA5

I feel my heart beating fast when I take an exam

- ○ Very untrue of me (1)
- ○ Untrue of me (2)
- ○ Somewhat untrue of me (3)
- ○ Neutral (4)
- ○ Somewhat true of me (5)
- ○ True of me (6)
- ○ Very true of me (7)

TSE1

I usually study in a place where I can concentrate on my course work

- Very untrue of me (1)
- Untrue of me (2)
- Somewhat untrue of me (3)
- Neutral (4)
- Somewhat true of me (5)
- True of me (6)
- Very true of me (7)

TSE2

I make good use of my study time for my courses

- Very untrue of me (1)
- Untrue of me (2)
- Somewhat untrue of me (3)
- Neutral (4)
- Somewhat true of me (5)
- True of me (6)
- Very true of me (7)

TSE3

I find it hard to stick to a study schedule

- Very untrue of me (7)
- Untrue of me (6)
- Somewhat untrue of me (5)
- Neutral (4)
- Somewhat true of me (3)
- True of me (2)
- Very true of me (1)

TSE4

I have a regular place set aside for studying

- ○ Very untrue of me (1)
- ○ Untrue of me (2)
- ○ Somewhat untrue of me (3)
- ○ Neutral (4)
- ○ Somewhat true of me (5)
- ○ True of me (6)
- ○ Very true of me (7)

TSE5

I make sure I keep up with the weekly readings and assignments for my courses

- Very untrue of me (1)
- Untrue of me (2)
- Somewhat untrue of me (3)
- Neutral (4)
- Somewhat true of me (5)
- True of me (6)
- Very true of me (7)

TSE6

I attend class regularly

- ○ Very untrue of me (1)
- ○ Untrue of me (2)
- ○ Somewhat untrue of me (3)
- ○ Neutral (4)
- ○ Somewhat true of me (5)
- ○ True of me (6)
- ○ Very true of me (7)

TSE7 I often find that I don't spend very much time on my courses because of other activities

- Very untrue of me (7)
- Untrue of me (6)
- Somewhat untrue of me (5)
- Neutral (4)
- Somewhat true of me (3)
- True of me (2)
- Very true of me (1)

TSE8

I rarely find time to review my notes or readings before exams

- Very untrue of me (7)
- Untrue of me (6)
- Somewhat untrue of me (5)
- Neutral (4)
- Somewhat true of me (3)
- True of me (2)
- Very true of me (1)

End of Block: Motivated Student Learning Questionnaire

Start of Block: Background Questions

EDisc What is your intended engineering discipline?

▼Aeronautical and Astronautical Engineering (1) ... None of the above (15)

Fund How are you funding your tuition (select all that apply)?

- ☐ Help from parents (1)
- ☐ Private student loans (2)
- ☐ Federal student loans (3)
- ☐ Scholarships and/or grants (4)
- ☐ Working (part time or full time) (5)
- ☐ Other (6) ____
- ☐ Prefer not to answer (7)

NSEE **How many hours per week do you spend on each of the following?**

NSEE9a

Preparing for class (studying, reading, writing, doing homework or lab work, analyzing data, rehearsing,and other academic activities)

- ○ 0 hours per week (1)
- ○ 1-5 (2)
- ○ 6-10 (3)
- ○ 11-15 (4)
- ○ 16-20 (5)
- ○ 21-25 (6)
- ○ 26-30 (7)
- ○ More than 30 hours per week (8)

NSEE9b

Working for pay **on campus**

- 0 hours per week (1)
- 1-5 (2)
- 6-10 (3)
- 11-15 (4)
- 16-20 (5)
- 21-25 (6)
- 26-30 (7)
- More than 30 hours per week (8)

NSEE9c

Working for pay **off campus**

- 0 hours per week (1)
- 1-5 (2)
- 6-10 (3)
- 11-15 (4)
- 16-20 (5)
- 21-25 (6)
- 26-30 (7)
- More than 30 hours per week (8)

NSEE9d

Participating in co-curricular activities (organizations, campus publications, student government, fraternity or sorority, intercollegiate or intramural sports, etc.)

- ○ 0 hours per week (1)
- ○ 1-5 (2)
- ○ 6-10 (3)
- ○ 11-15 (4)
- ○ 16-20 (5)
- ○ 21-25 (6)
- ○ 26-30 (7)
- ○ More than 30 hours per week (8)

NSEE9e

Relaxing and socializing (watching TV, partying, etc.)

- 0 hours per week (1)
- 1-5 (2)
- 6-10 (3)
- 11-15 (4)
- 16-20 (5)
- 21-25 (6)
- 26-30 (7)
- More than 30 hours per week (8)

NSEE9f

Providing care for dependents living with you (parents, children, spouse, etc.)

- 0 hours per week (1)
- 1-5 (2)
- 6-10 (3)
- 11-15 (4)
- 16-20 (5)
- 21-25 (6)
- 26-30 (7)
- More than 30 hours per week (8)

NSEE9g

Commuting to class (driving, walking, etc.)

- ○ 0 hours per week (1)
- ○ 1-5 (2)
- ○ 6-10 (3)
- ○ 11-15 (4)
- ○ 16-20 (5)
- ○ 21-25 (6)
- ○ 26-30 (7)
- ○ More than 30 hours per week (8)

End of Block: Background Questions

APPENDIX B: INTERVIEW PROTOCOL

Pre/Post/Post-Post interview questions: The role of non-cognitive and affective (NCA) factors in engineering and computing student academic performance

Pre-intervention survey

Participants will complete a short, 16-item "mindset" survey via Qualtrics. The survey will take no more than 10 minutes. They will complete the survey after they have consented to the Phase 2 study.

Pre-interview—immediately before first academic coaching session

Interviewer: "This pre-coaching interview session asks questions in two categories: (i) questions about you in general, and questions about academics (including your preferences about how to learn). There are 8 questions in all, and we expect the interview to take no more than about 30 minutes. We appreciate your willingness to answer these questions, and we encourage you to tell us anything you think is important."

Questions about identity

1. What words best describe what it's like to be a student at Purdue? [Potential clarification: this question is about Purdue in general, and this can be anything you think is important.]
2. How would you describe yourself? [Potential clarification: this can be about demographics, prior experiences, or anything else you think is important about yourself or your experiences.] What advice would you give to students at Purdue about how to be successful in engineering?
3. What is the "Purdue way" of doing things? How would you characterize the undergraduate student culture in engineering? [Potential clarification: is it more competitive or collaborative?] Can you give me an example from your own unique experience?

Questions about academics

4. How do you best learn? What have you learned about how you learn since coming to Purdue?
5. How would you describe someone who is smart? Has this definition changed since coming to Purdue?

6. Can you describe what you think academic coaching is or means? [Potential clarification: can you give me an example of what you think an academic coaching session might look like?]
7. Can you tell me a story about your academics that helps me understand why you think academic coaching may be helpful to you?
8. Do you have any prior experience with academic coaching? If so, can you tell me about it? I'm interested in when you experienced the coaching, the format of the coaching (individual or group?), and your perception of its effectiveness.

Post-interview—immediately after final academic coaching session

Interviewer: "We would like you to reflect on your experience with these academic coaching sessions. These questions ask you about the alignment between the activities with and advice from your academic coach, as compared with your preferences and beliefs about learning. They also focus on your academic actions and outcomes. There are 7 questions in all, and we expect the interview to take no more than about 30 minutes. We appreciate your willingness to answer these questions, and we encourage you to tell us anything you think is important."

Questions about alignment

1. Can you think of two or three specific instances in which the advice given to you by your academic coach really ***resonated with the way you prefer to learn***? Can you explain why/how that advice resonated with your preferences?
2. Can you think of two or three specific instances in which the advice given to you by your academic coach strongly ***conflicted with the way you prefer to learn***? Can you explain why/how that advice conflicted with your preferences?
3. Can you think of any specific suggestions from your academic coach that strongly ***conflicted with your actual practices*** around your academics (behaviors, study habits, etc.)?

Questions about academic actions and outcomes

4. Can you describe one or two specific actions suggested by your academic coach that you expect to sustain throughout the up-coming semester? Why do you think those specific actions are important in terms of your academic success?
5. For those specific actions you just mentioned (in Q4), do you anticipate any challenges to implementing and/or sustaining those behaviors throughout the semester? [Potential clarification: what are 'distractors' or other reasons that could prevent you from sustaining those behaviors?]
6. We are interested in how academic coaching may help students with two important aspects of their academics: task performance (as measured by grades) and task efficiency (as measured by the time you spend to achieve a certain task performance level). Based upon your academic coaching experience, do you think academic coaching will be

beneficial for your task performance, your task efficiency, or both? Can you give me a few examples to help me understand why you think this will be the case?

7. Is there a specific course (or courses) in which you are enrolled next semester for which you think this academic coaching experience may be especially helpful? [Potential clarification: is there anything you've heard about this course (or courses) that worries you academically?] Can you give me one or two examples to help me understand why you think the academic coaching experience may be especially helpful for this specific course (or courses)?

Post-post-interview (several months after the final academic coaching session)

(**<u>Note</u>**: interviewer will need to review previous interview transcripts with each participant in order to 'fill in the blanks' in these interview questions and personalize the questions to each specific participant. These questions about somewhat complicated and conditional, so the interviewer will need to be prepared and agile.)

<u>Interviewer</u>: "We would like you to reflect on your experience with these academic coaching sessions, and its effect on your academics so far this semester. These questions ask you about the activities and behaviors you worked on with your academic coach, and relates them to the academic outcomes you are achieving so far this semester. There are only a few questions, and we expect the interview to take no more than about 30 minutes. We appreciate your willingness to answer these questions, and we encourage you to tell us anything you think is important."

Questions about academic actions and challenges

<u>Interviewer</u>: "First, we would like to understand the challenges you faced this semester in implementing the advice of your academic coach. Those challenges fall into three categories: (i) things you anticipated might be a challenge, and they were; (ii) things you anticipated would be a challenge, but they weren't; and (iii) things that were challenges but that you didn't anticipate. These questions probe those three categories."

1. A few months ago, you told us ________________ about suggestions from your academic coach that you expected to sustain (brief summary of their response to ***Q4-post***). Did you sustain those actions?
    a. (<u>Conditional question if yes.</u>) How easy were they to sustain? What were the challenges to sustaining them and how did you overcome those challenges?
    b. (<u>Conditional question if no.</u>) Why didn't you sustain those actions? What were the challenges and why were those challenges so difficult to overcome?

c. (Condition question if the 'challenges' described ADD A 'NEW' ITEM to their response to ***Q5-post*** about anticipated challenges.) When we asked you about anticipated challenges a few months ago, you didn't mention _______________ (brief summary of the 'new' challenge described in ***Q1.a or Q1.b-post-post***). Why was that such a challenge for you? Why was that challenge so difficult to anticipate? Can you tell me a story about what has changed in your academic or personal experience that makes this challenge so significant and/or difficult to anticipate?

2. Were there other pieces of advice that you initially thought might not be very helpful (that is, you did NOT expect to sustain), but actually turned out to be helpful when you implemented them in a sustained way?
3. (Conditional question only asked if their responses about challenges in ***Q1.a and/or Q1.b-post-post*** OMIT one or more challenges mentioned in ***Q5-post***.) When we talked to a few months ago, you mentioned that ______________ might be a challenge to implementing the advice from your academic coach. Can you tell me how you overcame this challenge?

Questions about academic outcomes

Interviewer: "Now we'd like to discuss academic outcomes."

4. A few months ago, we talked to you about academic outcomes in terms of *task performance* (as measured by grades) and *task efficiency* (as measured by the time you spend to achieve a certain task performance level). As a result of your academic coaching sessions and the advice you received, has either your task performance or task efficiency changed? In what ways? Can you tell me a story or give me an example to help me understand the impact of academic coaching on either of those outcomes?
5. Has either your task performance or task efficiency in one particular course changed the most as a result of your academic coaching experience? [Potential clarification: Or was your change pretty much the same across all your classes?] What are the characteristics of that course, and why do you think it was differentially affected by your academic coaching experience? [Potential clarification: When we say 'characteristics', we mean the course format (lecture, lab, design course, etc.), size (large, small), grading (homework sets and exams, team-based reports, etc.), level of peer collaboration (both in class, for example team quizzes, or out of class), etc.]
6. (Conditional question is response to ***Q5-post-post*** does NOT match response to ***Q7-post***.) When we talked to you a few months ago, you mentioned _______________ (response to ***Q7-post***) as the specific course in which you expected to benefit from the academic coaching experience. Can you give me a few examples of how your academic coaching experience did, and did not, help you improve either your task performance or task efficiency in that course?

Summative questions about coaching experience

Interviewer: "This is the final set of questions about your experience as a whole."

7. Now that you have had this academic coaching experience, as well as some time to implement the advice and see its results, can you describe how you best learn? What have you learned about how you learn as a result of the academic coaching experience?
8. Do you think that the changes you have made as a result of academic coaching are sustainable for you in the long term?
9. How would you describe someone who is smart? Has this definition changed since engaging in academic coaching?
10. What words best describe what it's like to be a student at Purdue? [Potential clarification: this question is about Purdue in general, and this can be anything you think is important.]
11. How would you describe yourself? [Potential clarification: this can be about demographics, prior experiences, or anything else you think is important about yourself or your experiences.] What advice would you give to students at Purdue about how to be successful in engineering?
12. What is the "Purdue way" of doing things? How would you characterize the undergraduate student culture in engineering? [Potential clarification: is it more competitive or collaborative?] Can you give me an example from your own unique experience?

Interviewer: "Thank you so much for your help in this research, and we sincerely hope that the academic coaching experience has been valuable to you."

Post-interview questions for academic coaches: The role of non-cognitive and affective (NCA) factors in engineering and computing student academic performance

Post-intervention interview protocol

Interviewer: "Now that you have completed the academic coaching sessions with the students, we'd like to get your impression about the success of those session. All questions relate to the specific student who is the subject of this set of coaching sessions, rather than your opinion or impressions of academic coaching in general. There are 8 questions in all, and we expect the interview to take no more than about 30 minutes. We appreciate your willingness to answer these questions, and we encourage you to tell us anything you think is important."

Questions about the coaching sessions—mechanics and activities

1. Can you describe what a 'typical' set of academic coaching sessions with a student might look like? We are interested in details such as: (i) how many sessions are typical?; (ii) how long are the sessions?; (iii) what topics are covered in the sessions?

2. In the academic coaching sessions with (student's name), did you discuss or suggest anything atypical? If so, what did you do or suggest?
3. Was the general interaction with (student name) in terms of communication, follow-up, and the logistics of the academic coaching sessions consistent with your part experiences in providing academic coaching to students? If not, can you help me understand how your interactions with this student were different?

Questions about student response to coaching sessions

4. Compared to other students you have coached, did (student's name) participate in the academic coaching sessions (and in between sessions) more actively, less actively, or about the same? Can you tell me a story about your interactions with (student's name) to help me understand your perspective?
5. Do you believe (student's name) took full advantage of the academic coaching sessions? Are there specific observations of or experiences with (student's name) that give you that impression?
6. Compared to other students you have coached, how did (student's name) compare in terms of enthusiasm, commitment, and engagement with your guidance?

Questions about your prognosis for future academic success for this student

7. What specific elements of your coaching advice do you believe (student's name) will implement and sustain into the future? Based upon your experience, what are the typical challenges students face when making changes like this, and do you believe (student's name) can overcome these challenges?
8. One or two semesters from now, do you believe (student's name)'s academic performance and general satisfaction with their Purdue experience will improve, compared to their past performance? Can you help me understand why you feel that way?

APPENDIX C: COACH TRANING DOCUMENTS AND TOOLS

FUEL Model of Coaching

John Zenger and Kathleen Stinnet–"The Extraordinary Coach–How the Best Leaders Help Others Grow"

F–FRAME the conversation

U–UNDERSTAND the current state

E–EXPLORE the desired state

L–LAY out a plan for success

FRAMING THE CONVERSATION

Identify the issue to discuss

"What is the most important thing for us to focus on?"

Determine the purpose/outcome of the conversation

"By the end of our conversation, I would like to ___________"

"What else would you like to make sure that we address?"

Agree on the process for the conversation

"Here's how I thought we could proceed: ____________________. How does that sound?"

ABOUT 15% OF THE INTERACTION (4-8 minutes)

UNDERSTANDING THE CURRENT STATE

Understand the coachee perspective

"How do you see this situation?"

"What is happening?"

"What is working well?"

"What makes this challenging?"

"How might you be contributing to this situation?"

Determine the consequences of not changing

"What impact is this having on you?"

"What are the consequences if this situation does not change?"

"How does this influence your goals?"

"What are the long-term implications?"

Offer your perspective

"Could I share some observations I made?"

"Could I offer some other consequences to consider?

ABOUT 20% OF THE INTERACTION (6-10 minutes)

EXPLORING THE DESIRED STATE

Understand the vision for success

"What would you like to see happen here?"

"What would your ideal situation look like?"

Explore alternative paths of action

"What might be some approaches you can take?"

"What else might work?"

"Could I offer a couple of thoughts? You may want to consider…"

Explore possible barriers

"What are the major barriers preventing this change from happening?"

"Where would the biggest resistance to this change come from?"

ABOUT 50% OF THE INTERACTION (15-20 minutes)

LAYING OUT A PLAN FOR SUCCESS

Develop and agree on an action plan and timelines

"What specific actions will help you achieve your goal?"

"What will the first step be?"

"Who can help hold you accountable?"

"How long would you like this to be a focus for?"

Enlist support from others

"Who can support you moving forward?"

"How can I support you?"

Set milestones for follow-up and accountability

"Let's review the plan"

"Are you interesting in touching base again? When?"

"When do you want to have the first item done by?"

ABOUT 15% OF THE INTERACTION (4-8 minutes)

SURGE Coaching Model

1. Become **Self-aware** about what current behavior is taking place
2. Critically **Understand** how that current behavior effects long-term goals
3. Brainstorm **Reinventions** of their current behavior by improvement or change
4. Make **Guarantees** to themselves and based on reinvented options
5. Plan **Evaluation** opportunities for their guarantees so students can see how those changes affect progress toward their long-term commitments or goals

Self-awareness

Self-awareness refers to the ability to consciously recognize and describe one's own actions. Within the context of the SURGE Coaching model, establishing Self-awareness allows students to define the facts (who, what, where, when) of their behavior.

Understanding

As an extension of Self-awareness, Understanding refers to the student's ability to draw connections between actions and larger, more long-term goals or commitments. Some people may be able to describe their actions, but may struggle to see how those actions affect the future. The Understanding step requires staff to help their students clarify the impact of their actions.

Reinvention

Reinvention refers to the process of defining alternative or improved options that would move a student closer to or better allow a student to maintain progress toward a goal. The process of reinvention requires students to problem solve and think critically, and PSCs facilitate those brainstorming sessions.

Guarantee

Guarantee refers to the students' commitment-making, to themselves, to their PSCs, and/or to others. After the Reinvention step, students have a list of possible actions to take. The Guarantee step asks the students to select one or more of those options and commit to performing the action. Encourage students to make SMART commitments during the Guarantee step.

Evaluation

Evaluation refers to the process of reviewing the qualitative or quantitative outcomes of the Guarantees. Essentially, Evaluation requires students to define a plan for demonstrating or documenting the effects of the behavior. The Evaluation step allows students to assess the effects of their improved actions on progress toward goals or larger commitments.

Examples of evaluation could be visually charting progress on a progress chart, creating and completing a to-do list, demonstrating proof of completion to the PSC or a colleague, etc.

Asking the Right Questions

At the end of the day, we want students to be independently successful. One way of helping students find their own ways to achieve success and autonomy is through questioning. Questioning not only allows the coach to gain information about the students, but also prompts the students to critically think about their own actions. Questioning should be used in conjunction with the SURGE Coaching model to help students work their way from Self-awareness to Evaluation.

Closed-ended Questions

Closed-ended questions, or factual questions, are answerable with one- or two- word responses, and are usually answerable with a simple "Yes" or "No." Use closed-ended questions to identify factual information, to identify the extent of a problem, or to narrow the discussion topic.

Examples:

Did you finish your assignment?

Do you skip class often?

Do you exercise?

Do you think your volunteer activities are taking up too much time?

Open-ended Questions

Open-ended questions require the answerer to elaborate and describe. Use open-ended questions to get to know one another, to encourage students to think for themselves, to elicit more detailed examples, or to motivate students to participate and communicate with you.

Examples:

Why did you decide not to complete this assignment?

What do you do instead when you skip class?

How do you find motivation (or what could motivate you) to exercise?

Can you think of ways to make more time for coursework and still volunteer?

SURGE Coaching Sample Question Bank

Self-awareness:

- What is important to you right now?
- What specific area of your personal, social, or academic life would you like to focus on?
- What impact will it have for you to achieve this goal?
- Where are you now in relation to your commitments or goals?
- What happened this week? Did you complete the commitments you made?

Understanding:

- Why do you think you did/didn't complete your commitments during the last day/week/month/etc.?
- What obstacles have been standing in your way?
- What is helping you meet your commitments?
- What happened when you tried that?
- How do you feel about that?
- If you were going to ask others, how would they describe the situation?
- How's that working for you?
- What would better or perfect look like?
- What do you already know to be true about the situation?
- How much control do you have over this?
- Who else do you know who has already achieved this?
- Is this worth it?

Reinvention:

- What do you want to do differently next time? What must you do differently next time?
- What can you do to change the situation?
- What would happen if …? Have you ever thought about …?
- What do you need to know that you currently don't?
- What else might you do?
- What else can help you get closer to your goal?
- What experience can you use from your past successes?
- What might others do in the same situation?
- What are your options for completing this commitment or achieving this goal?
- Are there any alternatives?

Guarantee:

- What commitments will you make during the next day/week/month/etc.?
- What guarantee(s) will you make to yourself? What guarantee(s) will you make to me?
- Are you ready to start working on this?
- What support do you need and from whom?
- What obstacles are there to meeting these commitments? How will you mitigate these obstacles?
- What resources will you use to help you meet these commitments?

Evaluation:

- When will you know you have completed your commitment (or achieved your goal)?
- How will you document or demonstrate your work or achievement?
- On a scale of 1-5, rate your commitment to performing this action. What could move you up one place?

Figure 14: Academic coaching reading and understanding training material

Figure 15: Academic coaching note-taking training material (part 1)

Note-Taking

Tips & Methods to Improve Your Notes

Good note-taking skills are an essential tool for success that you can use in your courses, student organizations, and career. It is one thing to write down information on paper during lectures, but taking quality notes allows you to process and integrate new knowledge, record the information in your own words and understanding, and organize the new material. Note-taking is more than just an in class activity– for the most benefit, use your note-taking skills before, during, and after class.

BEFORE CLASS

Review the Text: This will give you a heads up of the terms, concepts, and information that will most likely be covered in the lecture. It can also give you an idea of how to structure the information.

Identify Unfamiliar and/or Difficult Content: If you find certain terms, concepts, or information confusing, you will know to take more specific notes during the lecture. You can also be sure to ask questions so that the instructor can clarify the information.

DURING CLASS

Format Your Notes: Find a style of note-taking that works best for YOU and the course. This might be using one style or a combination of styles so that you notes are the best resource they can be!

Record Examples & the Most Important Information: Don't worry about recording down every word the instructor says or your grammar and spelling. Instead, write down the most important information, main ideas/terms, and examples discussed in class.

AFTER CLASS

Review within 24 Hours: To minimize forgetting and maximize information retention, review your notes within 24 hours after your class.

Fill in Gaps: During class, you might not have been able to write down all of the information on a topic or an example you thought of after the lecture– add that information to your notes! This is also a chance to fix any spelling or grammar errors you might have made while quickly recording notes.

Summarize the Information: At the end of your notes for each class, write a short summary or synopsis to what you learned I class. This will help you focus back on the main ideas of the lecture and can serve as a quick review before your next class to help refresh the content covered.

OTHER TIPS

- You can't take notes if you aren't in class or prepared with pencil and paper.
- Try different note-taking methods (examples on back) before deciding which works best for you and each of your courses.
- Add color, graphics, and charts to personalize your notes and draw attention to the important facts, statistics, and terms.

Figure 16: Academic coaching note-taking training material (part 2)

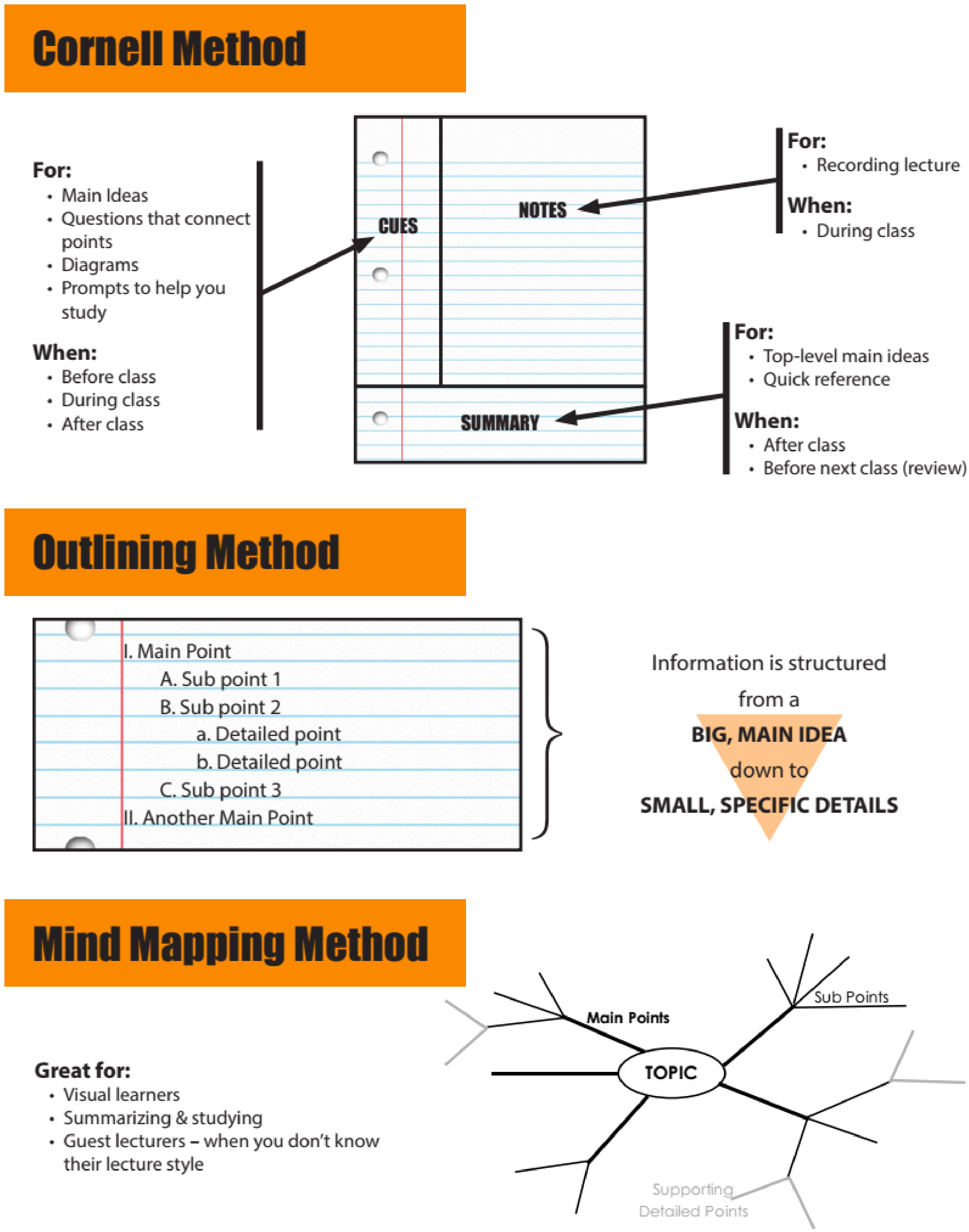


Figure 17: Academic coaching study habits training material

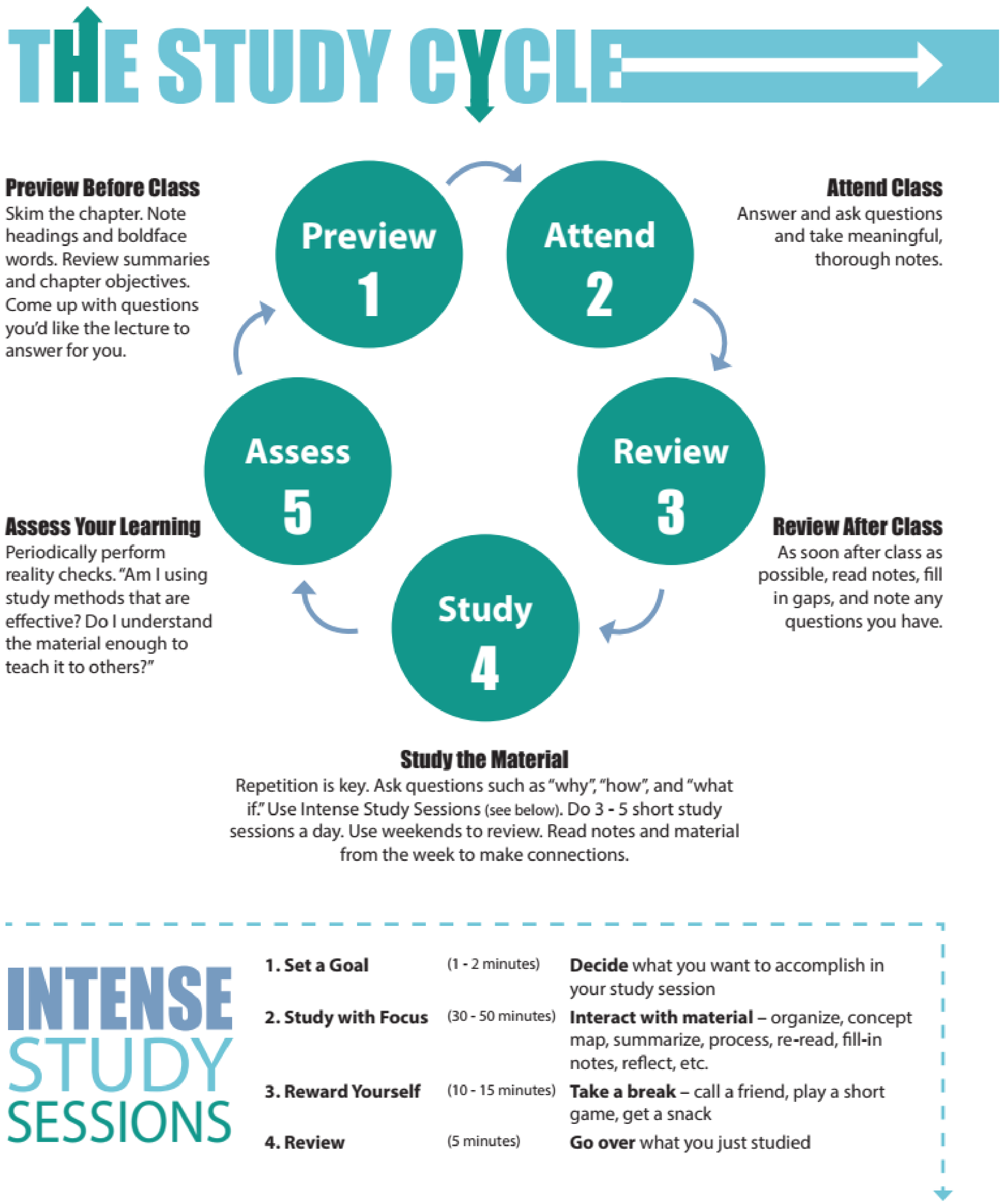


Figure 18: Academic coaching time management training material

TIME MANAGEMENT MATRIX
from Stephen Covey's book "First Things First"

	Urgent	Not Urgent
Important	**I** **(MANAGE)** • Crisis • Medical emergencies • Pressing problems • Deadline-driven projects • Last-minute preparations for scheduled activities	**II** **(FOCUS)** • Preparation/planning • Prevention • Values clarification • Exercise • Relationship-building • True recreation/relaxation
	Quadrant of Necessity	**Quadrant of Quality & Personal Leadership**
Not Important	**III** (AVOID) • Interruptions, some calls • Some mail & reports • Some meetings • Many "pressing" matters • Many popular activities	**IV** (AVOID) • Trivia, busywork • Junk mail • Some phone messages/email • Time wasters • Escape activities • Viewing mindless TV shows
	Quadrant of Deception	**Quadrant of Waste**

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