The Academic Success of College Students with ADHD: The First Year

by

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Table of Contents

Acknowledgments ii

List of Tables viii

List of Figures xi

Abstract xiii

Chapter 1 Introduction 1

1.1 Research Objectives 3

1.2 Research Contributions 3

1.3 Overview of Chapters 4

Chapter 2 Study Framework 6

2.1 Conceptual framework components 7

2.1.1 Pre-college Characteristics and Experiences 7

2.1.2 Organizational Context 11

2.1.3 Classroom Experiences 12

2.1.4 Curricular Experiences 14

2.1.5 Out-of-Class Experiences 17

2.1.6 Academic Success 17

2.1.7 Summary 19

Chapter 3 Literature Review 21

3.1 Disability Models 21

3.2 Attention Deficit Hyperactivity Disorder 23

3.2.1 Executive Function 24

3.2.2 The Brown Model ... 24
3.2.3 Neurodiversity ... 25
3.3 College Students with ADHD ... 26
3.3.1 Strengths ... 27
3.3.2 Challenges ... 27
3.3.3 Inequalities in Higher Education ... 28
3.4 Pre-college Factors of Students with ADHD ... 29
3.5 College Experience of Students with ADHD ... 31
3.5.1 Classroom Experiences ... 32
3.5.2 Curricular Experiences ... 35
3.5.3 Out-of-Class Experiences ... 38
3.6 Academic Success of College Students with ADHD ... 40
3.7 Summary ... 44
3.8 Research Questions ... 45
Chapter 4 Research Methods ... 46
4.1 Data ... 46
4.2 Measures ... 48
4.2.1 Independent, Mediating, and Auxiliary Variables. ... 48
4.2.2 Dependent variables. ... 59
4.3 Missing Data: Briefly ... 62
4.4 Analysis ... 62
4.4.1 Structural Equation Modeling ... 62
4.4.2 Mediation analysis. ... 76
4.5 Limitations ... 78
4.5.1 Sample. ... 78

4.5.2 Data ... 79
4.5.3 Statistical Methods. ... 80
4.6 Summary ... 82
Chapter 5 Results ... 83
5.1 Descriptive Statistics ... 85
5.1.1 Pre-college Characteristics & Experiences. ... 85
5.1.2 Academic Success. ... 86
5.2 Measurement Model ... 87
5.2.1 Indicator Variables. ... 88
5.2.2 Two-Factor Confirmatory Factor Analysis. ... 89
5.2.3 Three-Factor Confirmatory Factor Analysis. ... 95
5.2.4 Summary ... 97
5.3 Structural Equation Modeling ... 101
5.3.1 First-year college grades. ... 102
5.3.2 Creativity. ... 135
5.4 Overall Summary ... 142
Chapter 6 Discussion ... 144
6.1 First-Year Grades ... 144
6.1.1 Pre-college, College, and Academic Success Relationships ... 144
6.1.2 Mediating Role of College Experiences ... 149
6.1.3 Implications for Science, Mathematics, and Engineering ... 150
6.2 Creativity ... 152
6.2.1 Relationships among Precollege, College, and Academic Success ... 152
6.2.2 Mediating Role of the College Experience ... 153
6.2.3 Implications for Engineering ... 153

6.3 Recommendations ... 155
6.3.1 Precursors to Change ... 156
6.3.2 Recommendations for Classroom Instruction ... 158
6.4 Recommendations for Institutional Policies ... 161
6.5 Summary ... 163
Chapter 7 Conclusions ... 165
7.1 First-year grades ... 165
7.1.1 Model Structure. ... 165
7.1.2 Parameter Estimates and Mediation. ... 166
7.2 Creativity ... 166
7.2.1 Model Structure. ... 166
7.2.2 Parameter Estimation and Mediation. ... 167
7.3 Implications ... 167
7.3.1 Theoretical. ... 167
7.3.2 Practical. ... 168
7.4 Future Work ... 168
Appendix A Missing Data ... 170
A.1 Missing Data Mechanism ... 170
A.1.1 Overview of Missing Data. ... 170
A.1.2 Mechanism Exploration. ... 171
A.1.3 Method for Handling Missing Data. ... 177
A.2 Auxiliary Variables ... 178
A.2.1 Auxiliary Variable Screening. ... 178
A.3 Multiple Imputation: Imputation Phase ... 185
A.4 Multiple Imputation Diagnostics ... 188

A.5 Summary 195
Bibliography 197

List of Tables

Table 1. Students' responses, by cohort, to the TFS item about having received an ADHD diagnosis 48

Table 2. Pre-college neurodiversity variables 50

Table 3. Pre-college sociodemographic variables 52

Table 4. Pre-college academic preparation and performance variables 53

Table 5. Pre-college student disposition variables 54

Table 6. Individual Student Experience: Classroom Experience variables 57

Table 7. Individual Student Experience: Curricular Experience variables 58

Table 8. Individual Student Experience: Out-of-Class Experience variables 60

Table 9. Additional variables from the YFCY 61

Table 10. Academic success variables (from the YFCY) 61

Table 11. Distributions of indicator items for academic adjustment, faculty interaction, and sense of belonging constructs 71

Table 12. Students' pre-college characteristics and experiences (n = 45,915) 86

Table 13. Students' first-year academic success (n = 45,915) 87

Table 14. Spearman correlations, r_s, for the three latent variables' indicator variables (n = 32,235; listwise deletion) 89

Table 15. Two-factor latent variable measurement model CFA, standardized 94

Table 16. Three-factor measurement model, standardized solution 99

Table 17. Two-factor, first-year grades SEM (n = 27,410) using ML estimation, unstandardized 105

Table 18. Two-factor, first-year grades SEM (n = 27,410) with ML estimation, standardized . 107

Table 19. Two-factor, first-year grades SEM (n = 43,523) using ML with multiple imputation, unstandardized ... 112

Table 20. Two-factor, first-year grades SEM (n = 28,324) using generalized SEM, unstandardized ... 114

Table 21. Coefficients and 95% CIs for the direct paths of the two-factor, first-year grades SEMs ... 117

Table 22. Three-factor, first-year grades SEM (n = 27,288) using ML, unstandardized ... 120

Table 23. Three-factor, first-year grades SEM (n = 27,288) using maximum likelihood, standardized ... 123

Table 24. Three-factor, first-year grades SEM (n = 43,523) using ML and multiple imputation, unstandardized ... 127

Table 25. Comparison of path coefficients of the three-factor, first-year grades SEMs using ML (n = 27,288) and using ML with multiple imputation (n = 43,523), unstandardized ... 130

Table 26. First-year grades mediation analysis with standard errors (delta and bootstrapped).. 133

Table 27. Generalized SEMs for three models of creativity ... 141

Table 28. Instructional strategies to scaffold students' academic adjustment. ... 162

Table 29. Number of missing and non-missing responses and the fraction of missing responses. ... 173

Table 30. Missing data patterns (with greater than 350 responses) for the model variables within the first-year grades/creativity data set; variables with missing responses are indicated by an “x” ... 174

Table 31. Missing indicator variable for standardized test score (STANDTEST) regressed on independent variables and the dependent variable (first-year grades) ... 175

Table 32. Standardized test score (STANDTEST) regressed on first-year grades model variables ... 176

Table 33. Potential auxiliary variables ... 180

Table 34. Standardized (on y) mean differences between missing and non-missing shown for selected potential auxiliary variables ... 181

Table 35. Semi-partial residuals (standardized on x and y) of selected potential auxiliary variables with model variables with more than 5,000 missing responses ... 182

Table 36. Summary of auxiliary variables and their type ... 183

Table 37. Pairwise correlations model variables and variables extraneous to the model........... 184

Table 38. Extraneous variables included in multiple imputation 187

Table 39. Relative increase in variance (RVI), fraction of missing information (FMI), and relative efficiency (RE) for the 30 imputations based on first-year grades regressed on the model variables 190

Table 40. Summary (fraction or mean and standard deviation) of original and imputed data sets for selected variables.. 193

List of Figures

Figure 1. Conceptual framework, based on the model of Terenzini and Reason (2005) and Reason (2009), for studying the academic success of college students with ADHD 8

Figure 2. Brown's (2009) model of ADHD 25

Figure 3. Bowman and coauthors (2019) structural equation model without the retention outcome 64

Figure 4. Three-factor structural equation model based on the Bowman model (2019) 65

Figure 5. Two-factor structural equation model based on the Bowman model (2019) 66

Figure 6. Model 1 hypothesized structural equation model with the creativity academic outcome 68

Figure 7. The hypothesized two-factor measurement model 73

Figure 8. The hypothesized three-factor measurement model 74

Figure 9. Schematic of mediating relationship of academic success 77

Figure 10. Direct (red) and indirect (lavender) paths in the hypothesized SEM model 77

Figure 11. Two-factor measurement model, standardized 93

Figure 12. Three-factor measurement model, standardized solution 98

Figure 13. Specified two-factor, first-year grades SEM 104

Figure 14. Two-factor, first-year grades SEM (ML estimation), standardized 109

Figure 15. Three-factor, first-year grades SEM using a ML estimator, standardized 126

Figure 16. Mediating (lavender) and direct (red) paths of the three-factor SEM 132

Figure 17. Two-factor, creativity SEM Model 1 138

Figure 18. Two-factor, creativity SEM Model 2 139

Figure 19. Two-factor, creativity SEM Model 3 140

Figure 20. Academic adjustment support provided for students through academic coaching (University of Colorado, n.d.) 163

Figure 21. Trace plots for the estimated mean of standardized test score as a function of iteration for imputation 1 (upper left), 15 (upper right), and 30 (lower) over the 100 burn-in cycles 191

Figure 22. Trace plots of the 100 burn-in cycles for the estimated standard deviation of standardized test scores as a function of iteration for the 1st (upper left), 15th (upper right), and 30th (lower) imputation 192

Figure 23. Density plots of actual standardized test scores (top left) and data from the 1st, 5th, 10th, 20th, and 30th imputation 194

Figure 24. Density of actual average high school grade (top left) and data from the 1st, 5th, 10th, 20th, and 30th imputation 195

Abstract

College students with ADHD commonly share strengths, such as creativity, high energy levels, and resilience, which are advantageous in their future careers. Yet, they often encounter barriers or obstacles in college in their classroom, curricular, and out-of-class experiences and less academic success, such as lower grades and rates of persistence, than their collegiate peers without ADHD. Quantitative studies of the academic success of students with ADHD have not broadly incorporated students' college experiences to understand the role of these experiences on their academic success. This dissertation aims to investigate the role of college experiences on the academic success of students with ADHD to identify targeted aspects of the college environment for change. I ask two research questions.

RQ1. What relationships exist between students' precollege characteristics and experiences, the college experience, and academic success for students with ADHD?

RQ2. What college experiences, if any, mediate the relationship between a pre-college ADHD diagnosis and academic success?

I use Terenzini and Reason's college impact model. It posits that students' pre-college characteristics and experiences and individual student experiences in college (classroom, curricular, and out-of-class) influence their academic success. I conducted structural equation modeling (SEM) of students' academic success in their first year and considered two measures of academic success, first-year grades and creativity. The former provides a traditional measure of academic success, and the latter is a known, yet often undervalued in engineering education,

strength common to many students with ADHD. To estimate these SEMs, I used multi-institutional, longitudinal data (n = 43,523, including 2,082 students indicating they had an ADHD diagnosis) from the Higher Education Research Institute from undergraduate students at four-year higher education institutions in the U.S. The data set has matched responses from students as incoming college students and near the end of their first year.

The first-year grades SEMs indicated that students with ADHD had more difficulty, on average, adjusting to college academics (measured as understanding their professors' expectations, time management skills, and study skills) than their peers without ADHD. They also earned, on average, slightly lower grades (one-fifth of a grade change or approximately 0.1 standard deviation) than their peers without ADHD. Students' academic adjustment (i.e., the ease with which they adjusted to college academics) partially mediated (approximately 33%) the relationship between an ADHD diagnosis and lower first-year grades. Students' interaction with faculty and their sense of belonging had a negligible mediating effect on the ADHD-first-year grades relationship.

For creativity, students with ADHD were more likely to identify as having high levels of creativity (above average or in the top 10% of their peers) than their peers without ADHD. The first-year college experience, measured as their interaction with faculty and sense of belonging, had little effect on their self-rating of their creativity among students with ADHD.

These findings are broadly applicable to higher education administrators, staff, and instructors and can be used to inform higher education instructional practices and institutional policies. They are particularly important within engineering education and, more broadly, science, engineering, and mathematics education, because students with ADHD may choose not to enter these fields or decide not to persist in these majors if they earn lower grades and their strengths are not valued. Based on my findings, I recommend instructional practices that scaffold all students' academic adjustment while deemphasizing its role in first-year grades.

Chapter 1 Introduction

Equity in higher education necessitates a collegiate environment that promotes the academic success of a diverse student body, which will inevitably be neurodiverse. “Neurodiversity describes the idea that people experience and interact with the world around them in many different ways; there is no one "right" way of thinking, learning, and behaving, and differences are not viewed as deficits” (Baumer & Frueh, 2021, para. 1). Neurodivergent students include autistic students, dyslexic students, and students with attention deficit and hyperactivity disorder (ADHD; Cleveland Clinic, n.d.). Higher education instructors, staff, and administrators can best promote the academic success of all students if they are aware of the experiences of specific groups of students, such as students with ADHD, and how these experiences contribute to or hinder academic success.

Multiple achievement disparities (e.g., grades, persistence, and 4-year graduation rates) indicate change in college classrooms and institutional policies is necessary to create a more equitable college environment for a neurodiverse student population. The four-year graduation rates for neurodivergent students, a group that includes students with ADHD, are substantially lower (the University of California Student Experience Survey suggests 21 percentage points lower) than for neurotypical students (i.e., students who are not neurodivergent; University of California Office of the President, 2020).

Students with ADHD account for approximately 6.5% of first-year college students (Eagan et al., 2017). They identify strengths such as creativity (White & Shah, 2011), divergent thinking (White & Shah, 2016), high energy levels, and the ability to hyper-focus on tasks of interest (Delisle & Braun, 2011; Mahdi et al., 2017; Sedwig et al., 2019). They also have differences in executive functioning compared to their peers without ADHD (Brown, 2009). Executive functions enable, for example, regulating attention, organizing, planning, and initiating tasks (Brown, 2009; Diamond, 2013). Students with ADHD encounter challenging experiences in college (e.g., Perry & Franklin, 2006) and on average experience less academic success (e.g., DuPaul et al., 2021) than their peers without ADHD.

Classroom, curricular, and out-of-class experiences often require college students with ADHD to overcome barriers or obstacles to succeed in college (e.g., Perry & Franklin, 2006). For example, lecture-based classes are difficult for students with ADHD because such classes require long periods of sustained attention and note-taking and lower student motivation (Lefler et al., 2016). This instructional method does not align with the learning preferences and strengths of students with ADHD (Lefler et al., 2016). An example of an engineering classroom barrier is "traditional" engineering courses have a limited emphasis on creativity, a known strength of many students with ADHD (Taylor et al., 2020, p. 213). Course assignments, assessments, and projects may not allow students with ADHD who identify creativity as a strength to build on that strength. Barriers can also arise when instructors are unfamiliar with ADHD and unaware of classroom practices to equitably promote the success of students with ADHD (Vance & Weyandt, 2008).

Institutional policies contribute to shaping the college environment and its barriers to the academic success of students with ADHD. For example, many instructors are not provided with opportunities to learn how to create more equitable classroom environments for neurodivergent students (Dwyer et al., 2022). Other examples are limited opportunities for students to participate in bridge programs (Dwyer et al., 2022) or first-year courses or use a learning management system that supports students' academic adjustment.

Identifying barriers long integrated into the traditional college environment and their relationship to academic success is a critical to creating an equitable higher education environment that promotes the academic success of all students (Dwyer et al., 2022). Eliminating these barriers enables us to provide an educational environment where all students have equitable learning experiences that promote their success (Nave, 2019; Nave, 2020; Nave, 2022). However, little research exists on instructional practices and institutional policies for college environments that create these equitable experiences for neurodiverse students. My study aims to broadly identify the relationship between students' college experiences and academic success enabling efforts that target specific areas for change.

1.1 Research Objectives

I aim to recommend changes within higher education to create more equitable higher education environments for students with ADHD. To do this, I investigate the relationships between students' pre-college characteristics and experiences, their college experiences, and academic success outcomes. Furthermore, I identify the mediating role of college experiences on academic success. By identifying the most influential aspects of the college experience, I can tailor recommendations for higher education administrators, instructors, and staff.

1.2 Research Contributions

Research exploring the college experiences of students with ADHD has primarily been qualitative and involved a relatively small number of participants (e.g., Kwon et al., 2018; Lefler et al., 2016; Meaux et al., 2009; Perry & Franklin, 2006; Willis et al., 1995). Although these studies provide in-depth accounts of students experiences, they don't provide a broad view of the experiences of college students with ADHD, nor do they quantify their relationship to academic success. Research investigating the academic success of students with ADHD has primarily been quantitative and involved less than 500 participants with ADHD (e.g., DuPaul et al., 2021; Gormley et al., 2019; Reaser et al., 2007). Furthermore, quantitative research has not jointly explored the role of college experiences and academic success, as is done in this dissertation.

My dissertation research aims to investigate the role of college experiences in promoting or hindering the academic success of college students with ADHD. I explore the role of college experiences (classroom, curricular, and out-of-class) on the academic success of students with ADHD using structural equation modeling (SEM). I employ longitudinal, multi-institutional data (n = 45,915; Higher Education Research Institute, n.d.) from first-year college students, of whom 2,082 (4.5%) had been diagnosed with ADHD. This is the first study on college experiences involving a large number of students with ADHD. Its implications broadly apply to higher education administrators, staff, and instructors. They suggest academic success disparities exist for students with ADHD; however, easing students' adjustment to college academics attenuates these disparities. Based on this, I recommend change within higher education, for instructional practices and institutional policies, that focuses on academic adjustment.

1.3 Overview of Chapters

In Chapter 2, I describe my conceptual framework. In Chapter 3, I summarize the literature focused on the college experiences and academic success of students with ADHD and introduce my research questions. In Chapters 4 and 5, I detail the quantitative methods used to answer my research questions, and in chapter five, I present my results. I close the dissertation by discussing my findings and providing conclusions in Chapter 6 and 7, respectively. Details of how I handled missing data are in the Appendix.

Chapter 2 Study Framework

My study is guided by the conceptual framework in Figure 1 (Carroll et al., 2021; Carroll et al., 2022). This framework is based on Terenzini and Reason's college impact model (2005), which builds on the work of Astin (1993), Tinto (1993), and Pascarella (1985). The college impact model posits that students' *precollege characteristics and experiences* (*sociodemographic traits*, *academic preparation and performance*, and *student dispositions*) are related to their *college experience* (*organizational context* and *individual student experience*) and educational *outcomes* (Terenzini & Reason, 2005).

This model is broad in scope: it considers students' precollege experiences, captures multiple domains of the individual student experience in college (*classroom*, *curricular*, and *out-of-class*), and is designed to study many college outcomes (Terenzini & Reason, 2005). Researchers have employed this college impact model to explore students' "social and personal competence" (Reason et al., 2007, p. 271), ethical development (Finelli et al., 2012), and first-year STEM persistence (Dagley Falls, 2009).

I tailored Terenzini and Reason's (2005) model to study the *academic success* of students with ADHD by (1) adding *neurodiversity* to pre-college characteristics and experiences and (2) defining model components particularly relevant for students with ADHD. For components of the individual student experience (i.e., classroom, curricular, and out-of-class), I follow Reason (2009) and consider findings of studies of the college experience of students with ADHD (e.g., Lefler et al., 2016; Perry & Franklin, 2006). For example, I include variables applicable to the academic success of students with ADHD (e.g., time management and study skills; e.g., Fleming

& McMahon, 2012). Furthermore, I incorporate the strengths of students with ADHD (e.g., Taylor et al., 2020) by including creativity in addition to the more common academic success metrics (e.g., grades; York et al., 2015).

In describing the conceptual framework components in this chapter, I include background information pertaining to all students. The exceptions to this is for academic support and academic success in which I briefly summarize findings pertaining to students with ADHD. For the other framework components and academic success, I summarize background research on students with ADHD in my review of the literature in Chapter 3.

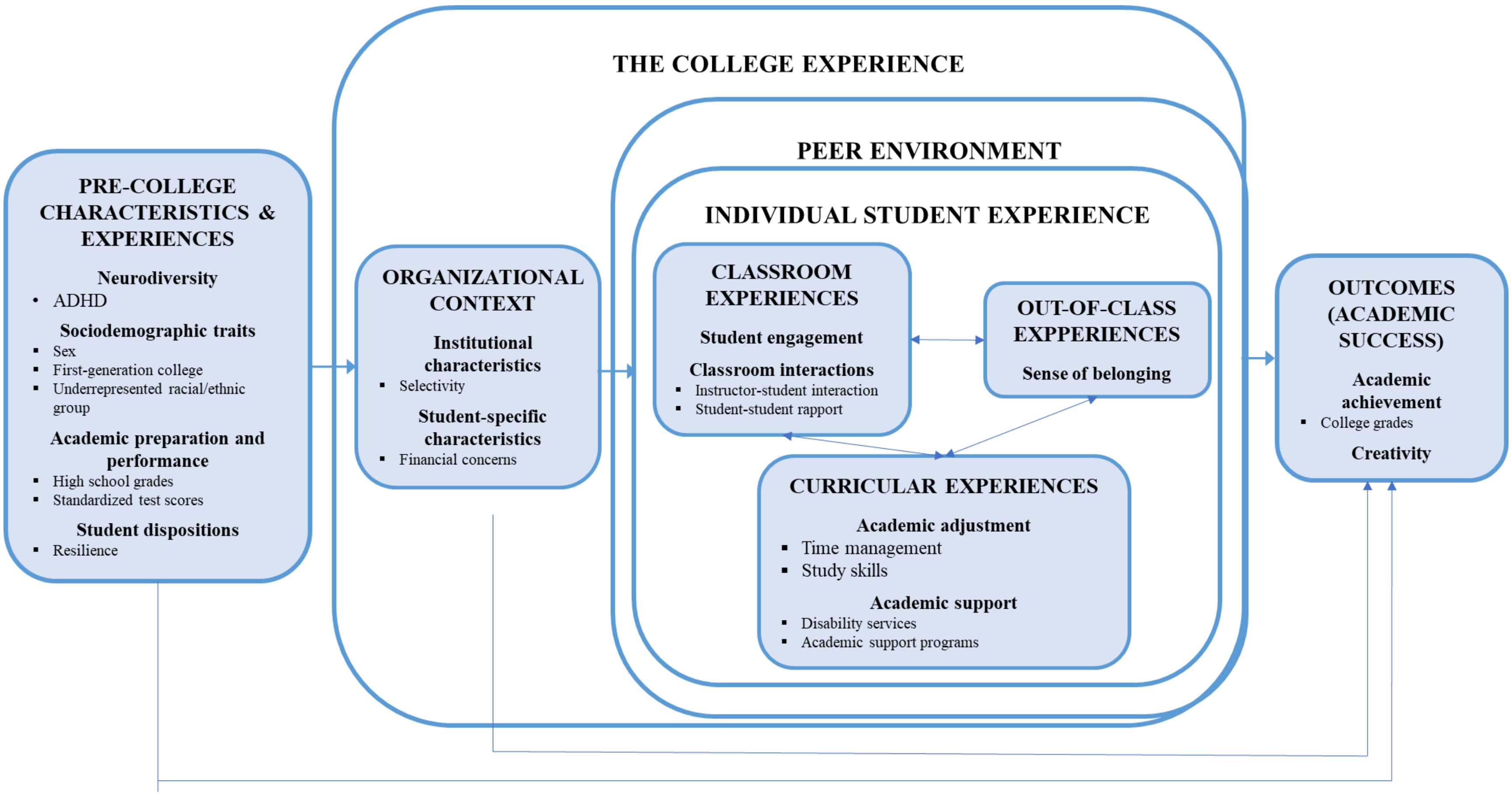
2.1 Conceptual framework components

In this study's framework, *pre-college characteristics and experiences*, directly and indirectly, relate to college students' *academic success*, as shown in Figure 1. Academic success is mediated by *the college experience* consisting of the *organizational context* (institutional characteristics and student-specific characteristics) and the *individual student experience*. Three domains reside within the individual student experience: *classroom* (engagement and rapport), *curricular* (academic adjustment and support), and *out-of-class* (sense of belonging) experiences.

2.1.1 Pre-college Characteristics and Experiences

This section of the model addresses students' experiences before college that influence their college trajectory (Reason, 2009). I include *neurodiversity*, *sociodemographic traits*, *prior academic preparation and performance*, and *student dispositions* as components of pre-college characteristics and experiences.

Figure 1. Conceptual framework, based on the model of Terenzini and Reason (2005) and Reason (2009), for studying the academic success of college students with ADHD



Adapted from Carroll et al., 2021 and Carroll et al., 2022.

2.1.1.1 Neurodiversity.

The experiences of neurodivergent students, including students with ADHD, may differ from their peers (e.g., Lefler et al., 2016). Furthermore, individuals with ADHD are more likely than those without ADHD to have other neurological differences (anxiety disorder, autism spectrum disorder, learning differences; Brown, 2013; Kessler et al., 2006). For example, adults with ADHD have higher odds of having an anxiety (OR = 1.5–5.5) or mood (OR = 1.5–5.5) disorder than adults without ADHD (Kessler et al., 2006). Additionally, many autistic children have ADHD (Rommelse et al., 2010). I specifically include ADHD within neurodiversity in my study's framework to capture whether a student has ADHD because this likely influences their college experiences.

2.1.1.2 Sociodemographic Traits.

Sociodemographic traits (e.g., sex, first-generation college, and underrepresented racial/ethnic group) enable the study of group differences and tailored approaches for supporting college students (Reason, 2009; Terenzini & Reason, 2005). Many researchers have studied academic success and persistence for groups of students differentiated by these sociodemographic traits (e.g., Bettencourt et al., 2020); the relationships are generally complex. For example, Ackerman (2013) found that the interaction between gender and certain student character traits (e.g., math/science self-confidence) correlated with persistence in science, technology, engineering, and mathematics. Thus, I include the sociodemographic trait variables typically included in retention models in this framework, specifically *sex*, *first-generation college*, and *underrepresented racial/ethnic group*.

2.1.1.3 Academic Preparation and Performance.

Students' academic preparation is a well-known predictor of students' collegiate academic success (Reason, 2009); and therefore, it is an essential component of my conceptual framework. Students with higher pre-college standardized test scores, such as the SAT, and high school grades are more likely to earn higher grades in college (e.g., Geiser & Santelices, 2007). I include *high school grades* and *standardized test scores* as a measure of students' academic preparation and performance in this framework.

2.1.1.4 Student Dispositions.

In this framework, I focus student dispositions on non-cognitive factors. Non-cognitive factors are "behaviors, skills, attitudes, and strategies that are crucial to academic performance in their classes, but that may not be reflected in their scores on cognitive tests" (Farrington et al., 2012, p. 4). These factors are distinct from students' content knowledge and academic skills. Recent theoretical perspectives (Farrington et al., 2012) and empirical studies (e.g., Bowman et al., 2019) suggest non-cognitive factors play a role in academic engagement and, therefore, college grades. I include one non-cognitive attribute as measure of student disposition: *resilience*.

Resilience is "a relatively good outcome or functioning, despite experience with adverse situations" (Haktanir et al., 2021) and is a critical factor in college outcomes (Bittmann, 2020; García-Martínez et al., 2022; Haktanir et al., 2021; Yaure et al., 2020). García-Martínez and coauthors (2022) found an indirect relationship between resilience and college grades and hypothesized that students' resilience led to more effort in their studies. Bowman and coauthors (2019) found that non-cognitive factors of academic grit, self-discipline, time management, and self-efficacy influenced students' college grades and persistence. Most similar to resilience, academic grit, defined as “perseverance and passion for long-term goals” (p. 138), was measured using four items focused on “perseverance of effort,” such as “When I get a poor grade, I work harder in that course” (p. 140).

2.1.2 Organizational Context

Organizational context comprises two types of characteristics: institutional and student-specific. These organizational context variables serve as controls in my model because they are not of primary interest in my study.

2.1.2.1 Institutional Characteristics.

I include only *selectivity* as an institutional characteristics in my framework. Selectivity has a significant, positive relationship with persistence; students attending institutions that are more selective in admissions are more likely to persist (Flynn, 2016; Reason, 2009). The relationships between college outcomes and the other institutional variables (e.g., institutional control and institutional type) are complex and difficult to decipher without a more thorough institutional description, including student climate (Flynn, 2016; Reason, 2009).

2.1.2.2 Student-specific Characteristics.

I include *financial concerns* as the single student-specific characteristic in my study’s framework because students experience the financial aspects of attending a given institution differently based on their ability to finance their education. Study findings about the relationship between financial aid and college persistence have varied (Stewart et al., 2015). The relationship between finances and college is complicated; for example, studies have explored the association between family contributions, institutional aid, and unmet need and retention (Olbrecht et al., 2016). By using a measure of a student’s concern about financing their education, I account for the variation that may be induced by its complexity in my statistical model.

I considered Bowman and coauthors' (2019) structural equation model to understand how finances influence college success. In their model, financial means (measured with a three-item scale; the example item provided was "to what degree are you confident that you can pay for next term's tuition and fees"; p. 141) influenced high school GPA, non-cognitive attributes, and social adjustment in college. It also positively but indirectly influenced students' college grades. My study uses a similar simplified financial measure, whether a student has concerns about financing their college education.

2.1.3 Classroom Experiences

Following Reason's description of the college impact model (2009), I include *student engagement* and *classroom interactions* as measures of students' individual classroom experiences. Both of these factors play a role in students' academic outcomes (e.g., Casuso-Holgado et al., 2013; Johnson, 2009).

2.1.3.1 Student Engagement.

Student engagement is a critical factor for the academic success of college students (Astin, 1993; Tinto, 1993; Pascarella, 1985) - it strongly correlates with collegiate academic outcomes (e.g., Casuso-Holgado et al., 2013). Student motivation influences and directs academic-related student engagement behaviors, such as completing homework and studying for exams (Morsink et al., 2022). For example, Casuso-Holgado and coauthors (2013) explored academic engagement, defined as "students' active participation and emotional commitment to learning," and found it positively correlated with grades.

Instructional methods that motivate students, such as active learning, contribute to their engagement (Prince, 2004; Shin & Bolkan, 2021). For example, the positive impact of active learning teaching methods - those that encourage student engagement with course content during class (Prince, 2004) and minimize passive listening and note-taking - on student engagement (Lucke et al., 2017; Seymour & Hewitt, 1997) and academic outcomes (Chi & Wylie, 2014; Freeman et al., 2014; Seymour & Hewitt, 1997; Theobald et al., 2020) for all students is evident. For my study, I include student engagement in my framework.

2.1.3.2 Classroom Interactions.

Both instructors and students play a role in creating classroom environments (Johnson, 2009), and I include both *instructor-student interaction* and *student-student rapport* in my model. Students' interactions in the classroom, either with their instructor or peers, reflect their classroom environment and potentially contribute to or hinder student learning outcomes (Frisby & Martin, 2010, p. 155). Researchers have explored the relationship between instructor-student interactions and student-student rapport and academic outcomes (e.g., Frisby & Martin, 2010).

Students' interaction with their instructors and the rapport they develop is a salient factor in the classroom experiences of college students. It contributes to student motivation (e.g., Estepp & Roberts, 2015; Frisby et al., 2017) and academic outcomes (e.g., Frisby et al., 2017; Lammers et al., 2017; Wilson & Ryan, 2013). In one study, Frisby and Martin (2010) asked undergraduate students to complete an instrument measuring instructor-student rapport with items on interaction and connection with their instructor, classroom connectedness, and affective and cognitive learning. They found that instructor-student interactions positively correlated with students' affective learning (attitudes or emotions toward the course) and students' perceptions of their cognitive (course content) learning. To explain the relationship between instructor-student rapport and cognitive learning, Frisby and Housley Gaffney (2015) hypothesized that "students who perceive positive rapport engage in behaviors that enhance cognitive learning" (p. 341).

Similarly, in a second study, Frisby and coauthors (2017) studied undergraduate students' rapport with their instructors. They found that instructor-student rapport positively correlated with students' state motivation (inherent interest) and perceptions of learning. In a third study, instructor-student rapport predicted course grades of undergraduate students in psychology and psychological statistics courses (Lammers et al., 2017). Instructor-student rapport within the first few weeks of the course predicted 18% of the variance in their course grade. Students reporting declines in instructor-student rapport as the semester progressed earned lower course grades on average than students who reported no changes or improvements in rapport. For my conceptual framework, I include *instructor-student interaction* because of the prior research demonstrating that it is associated with academic achievement and student learning.

The role of student-student rapport in academic outcomes is studied less often than instructor-student rapport. Although student-student rapport contributes to the classroom environment, its impact on academic success is not well understood. Frisby and Martin (2010) found that students' cognitive learning and affect toward the course material positively related to how connected students felt to their class. However, they did not find a statistically significant relationship between student-student rapport and students' affective or cognitive learning. LaBelle and Johnson (2018) explored college student-student confirmation (communicating recognition, endorsement, and acknowledgment of others' value) and found it positively correlated with student motivation and student's perception of their learning. Accordingly, I include *student-student rapport* in my model.

2.1.4 Curricular Experiences

Curricular experiences are another component of students' college experiences and encompass academic adjustment and co-curricular involvement (Reason, 2009). For this research, I do not include co-curricular involvement in curricular experiences because it also relates to students' sense of belonging (Winstone et al., 2022) and is likely captured in the sense of belonging measure in out-of-class experiences. I include *academic adjustment* and *academic support* in my framework.

2.1.4.1 Academic Adjustment.

Academic adjustment to college involves students developing academic skills, such as organization, study skills, and time management, which are instrumental to their academic success (e.g., van Rooij et al., 2017). Other researchers have used academic adjustment latent variables in their models. Van Rooij and coauthors (2017) measured academic adjustment using the 24-item academic adjustment subscale of the Student Adaptation to College Questionnaire (SACQ; Baker & Siryk, 1989) to study three first-year collegiate academic success measures: GPA, credits earned, and intent to persist. They investigated motivational (intrinsic motivation, academic self-efficacy, and degree program satisfaction) and behavioral (time management, study skills, and ability to manage distractions) factors, finding that study behaviors, intrinsic motivation, and satisfaction with their degree program predicted academic adjustment, and academic adjustment predicted credits earned and GPA (van Rooij et al., 2017).

In another study, Bowman and coauthors (2019) used a non-cognitive attributes latent variable similar to academic adjustment and explained by academic grit, time management, self-discipline, and self-efficacy. They modeled the relationship between college GPA and second-year retention and found that non-cognitive attributes (academic grit, time management, self-discipline, and self-efficacy) directly related to social adjustment, college GPA, and second-year retention. Collier and coauthors (2020) confirmed the Bowman model structure, including the relationship between non-cognitive attributes and college GPA, with data from first-year students from a midwestern university.

Bowman and coauthors' (2019) model differs from Terenzini and Reason's (2005) college impact model and my study's conceptual framework in the role of non-cognitive attributes (or academic adjustment). The Bowman model suggests that these non-cognitive attributes (i.e., academic adjustment) influence students' college experience, specifically their social adjustment (social integration and peer connection). In the Bowman model, college experiences (i.e., social adjustment) mediate the relationship between non-cognitive attributes and the academic outcomes of college GPA and retention. In contrast, my conceptual framework suggests academic adjustment (curricular experience) is influenced by students' classroom and out-of-class experiences. College experiences (of which academic adjustment is a part) mediate the relationship between pre-college characteristics and experiences and academic success. In the van Rooij model, there is a path directly from academic adjustment to GPA but no indirect paths between academic adjustment and GPA.

2.1.4.2 Academic Support.

Academic support programs (e.g., first-year seminars; Perry & Franklin, 2006) and services offered by the offices of disability services (e.g., academic coaching; Prevatt & Lee, 2009; Prevatt, 2016) foster academic success of students with ADHD. These programs benefit students' development of academic skills, such as time management, study, and note-taking skills (Reason, 2009). DuPaul and coauthors (2021) found increases in students' GPAs with time in college with participation in academic services for students who have ADHD but do not take medication for their ADHD. This outcome differed, however, for college students taking medication for their ADHD; their GPA decreased with time in college (DuPaul et al., 2021). I include *disability services* and *academic support programs* as measures of academic support in my model.

2.1.5 Out-of-Class Experiences

Out-of-class experiences in Terezini and Reason's (2005, 2009) model incorporates social integration, a concept that includes students' interactions with their collegiate peers and instructors (Tinto, 1993). Social integration is an integral contributor to students' decisions to remain in college (Tinto, 1993) and their sense of belonging in college (Strayhorn, 2012). In my framework, I use *sense of belonging* within out-of-class experiences in my study framework.

2.1.5.1 Sense of Belonging.

Sense of belonging is defined as feeling an important, connected, and valued part of a group, such as a college community (Strayhorn, 2012). Feelings of belongingness are linked to academic success (persistence and grades; Strayhorn, 2012). For example, Hausman and coauthors (2007) found that students' sense of belonging correlated with their intent to persist. They measured students' sense of belonging with a three-item scale (Bollen & Hoyle, 1990) with items focused on belonging, feeling a part of the community, and satisfaction at their institution. Sense of belonging is particularly important for marginalized students (Strayhorn, 2012), such as students with ADHD, and they are less likely to have a sense of belonging in college (Rainey et al., 2018). In the academic classroom, Rainey and coauthors (2018) found that "interpersonal relationships, perceived competence, personal interest, and science identity" are contributors to students' sense of belonging (p. 1).

2.1.6 Academic Success

I include two *academic success* metrics for outcomes in my framework: college grades (as a measure of academic achievement) and creativity. College grades are a more traditional measure of academic success than creativity (York et al., 2015).

2.1.6.1 Academic Achievement.

College grades often serve as a measure of academic success (York et al., 2015). Many studies find college students with ADHD earn lower grades on average than their peers without ADHD (Advokat et al., 2011; Blase et al., 2009; DuPaul et al., 2009; DuPaul et al., 2021; Frazier et al., 2007; Gormley et al., 2019). Researchers have attributed their lower grades to difficulties with executive functioning (DuPaul et al., 2009; Weyandt et al., 2013). Selected studies are summarized in the Literature Review section. In my framework, I include *college grades* as an academic achievement outcome.

2.1.6.2 Creativity.

The process of creating involves both divergent (i.e., idea generation) and convergent (selection of ideas) thinking (Kupers et al., 2018). Researchers have recognized the higher levels of divergent thinking in individuals with ADHD and its connection to creativity (e.g., White & Shah, 2011, 2016; Taylor et al., 2016). I include creativity as a second academic success outcome because enhanced creative and divergent thinking is a known strength of many college students with ADHD (Taylor et al., 2020; White & Shah, 2011; White & Shah, 2016). My motivation for this stems from a recent study (Taylor et al., 2020) that suggests creativity is not reflected in engineering grades. Engineering college students with ADHD scored higher on average than their peers without ADHD on the Torrance Tests of Creative Thinking (a measure of divergent thinking), yet, these higher scores were not associated with higher overall or engineering GPAs. Taylor and coauthors (2020) suggest that the limited emphasis on creative and divergent thinking in engineering education may negatively impact the engineering persistence of creative students (a group of students that may be more likely to include students with ADHD). However, creativity is a sought-after characteristic as students enter their future careers in engineering (e.g., Taylor et al., 2020) and is likely a beneficial attribute for students pursuing other disciplines as well. It is, therefore, an important academic outcome. Therefore, I include *creativity* as a measure of academic success in my project framework.

Wu and coauthors (2020) describe a creativity framework based on the 4P creativity model that integrates *person* (innate characteristics and neurological differences), *process* (cognitive processes in creating), *place* (environment), and *product* (creative result). Research studies have focused on traits of the person, such as gender, personality traits, and motivation, and the place or environment, such as social interaction. Other studies have focused on the process, which includes general creative thinking (Wu et al., 2020). The 4P creativity framework aligns well with Terenzini and Reason's (2005) college impact models' pre-college characteristics and environment (person) and college experience or environment (place) and an outcome.

2.1.7 Summary

My conceptual framework is based on Terenzini and Reason's college impact model (2005). It posits that *pre-college characteristics and experiences* influence students' *academic success* in college both directly and indirectly through their *college experience*. I follow Reason (2009) in including various model components. In pre-college characteristics and experiences, I include neurodiversity, sociodemographic traits, academic preparation and performance, and student dispositions. In organizational context, I include institutional and student-specific characteristics. Within the individual student experience, I include student engagement and classroom interactions in classroom experiences, academic adjustment and academic support in curricular experiences, and sense of belonging in out-of-class experiences. For academic success outcomes, I include academic achievement (college grades) and creativity.

Chapter 3 Literature Review

This literature review provides a picture of the current status of college students with attention deficit hyperactivity disorder (ADHD). In this chapter, I briefly introduce ADHD and review the literature related to the college experiences of students with ADHD. Although I present common strengths of students with ADHD, much of the literature addresses deficits and these students' collegiate challenges, and this is reflected throughout this section.

In terms of presentation, first, I briefly introduce disability models and then describe ADHD and the concept of neurodiversity. Next, I focus on what is known about college students with ADHD, their strengths and challenges, and the inequalities they experience in higher education. Afterward, I summarize the literature on the relationships between pre-college factors and the academic success of students with ADHD and then the college experiences (classroom, curricular, and out-of-class) and the academic success (e.g., grades) of students with ADHD. Lastly, I present the research questions that guide this study.

3.1 Disability Models

Disability models are used by practitioners and researchers and provide a lens for viewing disability (Disabled World, 2022). I introduce these models to familiarize the reader with the differences in the framing of empirical studies found in the literature and the usage of language related to disability. I will focus on two specific disability models, the medical and social models (Goodley, 2011), because they are particularly relevant to my study. The medical and social models of disability provide contrasting viewpoints of disability, such as ADHD and autism, as a deficit that requires treatment versus a difference, respectively (Disabled World, 2022). Understanding the differing viewpoints of the medical and social models helps explain the variation in language used to describe previous research. Throughout the literature review, I present background information using the lens of its source (note that in many cases, I infer the model used based on the language applied).

The medical model places disability at the individual level and focuses on deficits, symptoms, and treatments of those with disabilities (Goodley, 2011). From the medical model perspective, ADHD is a neurodevelopmental disorder that manifests as difficulty with executive function (Brown, 2009). The medical model views neurological differences of individuals with ADHD as deficits that need changing through treatment (Goodley, 2011). A strength of the medical model is that it provides a label that enables students with ADHD to receive medical treatment and request academic accommodations (Goodley, 2011). For example, students with ADHD may receive accommodations for additional time on examinations and lecture notes (Quinn, 2022).

The social model of disability differs from the more familiar medical model because it views disability as originating from societal barriers (Australian Federation of Disability Organisations, n.d.; Dwyer, 2022; Goodley, 2011). From the perspective of the social model of disability, ADHD is a neurological difference, and environmental barriers disable individuals with ADHD. These disabling barriers include *attitudinal*, *environmental*, *institutional*, and *communication* barriers (Australian Federation of Disability Organisations, n.d.). Proponents of this model recommend creating an environment without systematic and physical barriers to provide opportunities to everyone (Goodley, 2011). For example, a classroom designed without systematic barriers for students with ADHD would normalize frequent opportunities for movement, short-duration lectures, and opportunities for hands-on learning (e.g., Lefler et al., 2016). In contrast, a classroom in which students' typical experience is prolonged periods of sitting combined with passive listening to lectures provides systematic barriers for students with ADHD.

The lens through which disability is viewed is often reflected in language usage, and I follow the referenced studies' language usage in summarizing the literature. For example, the language of "diagnosis" is consistent with the medical model, and "difference" is more frequently used with the social model. In this literature review, the discussion of ADHD and the executive function challenges experienced by individuals with ADHD is primarily from the medical model lens; the strengths of college students with ADHD are often presented from the social model viewpoint, and the lenses for college experiences vary.

3.2 Attention Deficit Hyperactivity Disorder

Approximately 9.8% of children and 2.5 to 4.0% of adults in the U.S. have ADHD (ADDitude editors, 2022). Disparities in diagnoses exist for U.S. children across country regions, gender, parental income and education levels, race/ethnicity, and community type (e.g., urban, suburban, rural). Furthermore, the number of adults diagnosed with ADHD increased dramatically in recent years, although there is evidence that it is still underdiagnosed among adults (ADDitude editors, 2022). Chung and coauthors (2019) found that the percentage of adults in their study diagnosed with ADHD doubled from 2007 (0.43%) to 2016 (0.96%) and attributed this to an increase in knowledge about ADHD among adults.

The following subsections provide a brief introduction to ADHD. The first two subsections use the medical model to introduce executive function and the Brown model (2009) of ADHD. Executive functions play a fundamental role in education, and the executive function challenges described in Brown's model provide a basis for later illustrating the challenges experienced by college students with ADHD. The third subsection introduces neurodiversity.

3.2.1 Executive Function

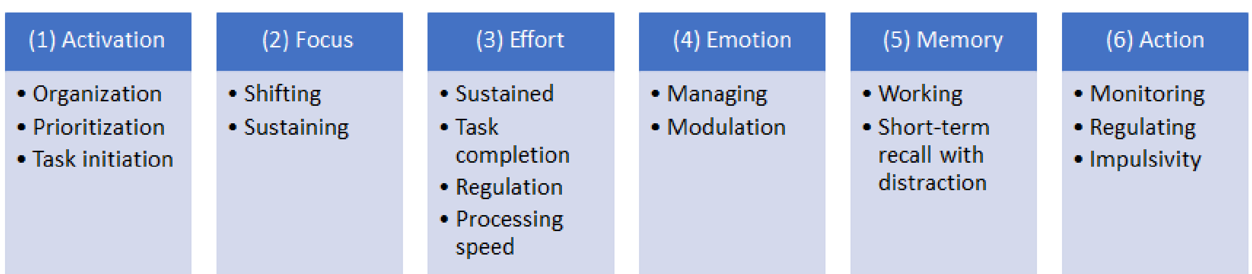
Executive function is the "air traffic control" system of our brain (Center on the Developing Child at Harvard University, 2011, p.1), and its core functions are *inhibition*, *working memory*, and *cognitive flexibility* (Diamond, 2013). Inhibition enables us to control impulses, working memory allows us to "hold and manipulate information in our head over short periods," and cognitive flexibility enables us to change directions when situationally-required (Center on the Developing Child at Harvard University, 2011, p. 2). These functions are the basis of higher-order executive functions such as reasoning, problem-solving, and planning (Diamond, 2013). Individuals with ADHD experience varying degrees of executive function challenges (e.g., sustaining focus and self-regulation), which can make certain aspects of life, such as school, more challenging (ADDitude editors, 2023). The severity of ADHD symptoms varies and influences how ADHD impacts one's life. In transitioning to college, the requirements for students to rely upon these higher-order executive functions increase (Ahrens et al., 2019).

3.2.2 The Brown Model

Brown (2009) defines ADHD as an executive function impairment involving six categories of executive functions: *activation*, *focus, effort*, *emotion*, *memory*, and *action*. These are shown schematically in Figure 2. Brown's model describes the challenges frequently experienced by people with ADHD as difficulty with (1) initiating, organizing, and prioritizing tasks; (2) sustaining and shifting focus; (3) sustaining and regulating effort until task completion; (4) regulating emotions; (5) working memory or the short-term recall necessary for learning; and

(6) regulating actions. These executive-function challenges are context-dependent; individuals find certain situations more challenging than others (Brown, 2009). For example, two college courses on the same instructional material may present vastly different difficulty levels because of the context in which the material is taught and assessed. In one course, the material might be presented in one-hour blocks, lecture notes might not be provided, and tests might be timed written exams. In the other course, active learning might be used multiple times in class, class sessions might be recorded, and the recordings might be provided to students along with lecture notes. Students might have the test time they need and be able to show their understanding in various ways. The different contexts in which students experience the course contributes to their difficulty with the course material.

Figure 2. Brown's (2009) model of ADHD



3.2.3 Neurodiversity

The term *neurodiversity* acknowledges that all people's brains are different, resulting in strengths and challenges (Cleveland Clinic, n.d.; Disabled World, 2022). Neurodiversity emphasizes strengths associated with neurological differences and views such differences as a part of a person's identity. Two additional terms are associated with neurodiversity: *neurodivergent* and *neurotypical*. *Neurodivergent* individuals include people with ADHD and many others whose brains work differently (e.g., autism, dyslexia, dysgraphia, and dyspraxia; Cleveland Clinic, n.d.). A *neurotypical* person is not neurodivergent (Disabled World, 2022).

Substantial controversy surrounds the neurodiversity concept and the social and medical models of disability (Dwyer, 2022). The medical model's deficit focus contrasts neurodiversity, or the idea that diverse brains are a part of someone's identity and are associated with strengths (Disabled World, 2022). Neurodiversity and the social model of disability are similar in that neither aligns with the medical model of disability (Dwyer, 2022). However, Dwyer (2022) notes that the concept of neurodiversity is "evolving" and recommends that neurodiversity take a "middle ground" approach between the medical and social models (p. 75). Neurodiversity's framing of differences, inclusion, and strengths instead of deficits offers advantages for students in the college environment (Independent Educational Consultants Association, 2022). Furthermore, the social model of disability may be a particularly well-suited lens for the college environment because of its emphasis on changes to the environment to provide equitable and inclusive spaces. The strengths and challenges of college students with ADHD are the focus of the next section.

3.3 College Students with ADHD

Many students with ADHD pursue higher education (Green & Rabine, 2012), accounting for approximately 6.5% of incoming first-year college students at baccalaureate institutions (Eagan et al., 2017). Although we know that 63% of students with disabilities do not register as such with their institutions (National Center for Education Statistics, 2022), the percentage of students with ADHD who do not register with their institutions is unknown. We do know, however, that students with ADHD account for approximately 25% of students with disabilities registered with their institution (Weyandt et al., 2013). The following subsections highlight the strengths of individuals with ADHD and describe their challenges in college. The last subsection illuminates disparities in higher education for neurodivergent students.

3.3.1 Strengths

College students with ADHD commonly share many positive attributes that are advantageous for their future careers. For example, college students with ADHD exhibit enhanced levels of creativity (White & Shah, 2011) and divergent thinking (White & Shah, 2016) compared to their peers without ADHD. These characteristics lead to unique problem-solving approaches and drive innovation within science and engineering (Hain et al., 2018; Powell, 2015). Greater resiliency, defined as adaptability under challenging circumstances, is also hypothesized as more likely for college students with ADHD relative to their peers without ADHD (Wilmshurst et al., 2011). Furthermore, adults with ADHD commonly identify high energy levels, courage, and the ability to hyper-focus when engaging in high-interest activities and tasks as strengths (Delisle & Braun, 2011; Mahdi et al., 2017; Sedwig et al., 2019).

3.3.2 Challenges

College students with ADHD have differences in executive functioning that make self-regulation, attentional control, and impulse control more challenging (Barkley, 2002; Wasserstein, 2005). They may struggle with organization, procrastination, and time management (Resnick, 2005). Likely related to these challenges (DuPaul et al., 2009), these students experience less academic success (as traditionally measured by grades) on average compared to students without ADHD (e.g., Blase et al., 2009; DuPaul et al., 2009; Fleming & McMahon, 2012; Frazier et al., 2007). The following section discusses challenges related to students' college experiences.

3.3.3 Inequalities in Higher Education

A growing awareness of the plight of neurodivergent college students, including students with ADHD, is evident at higher education institutions (e.g., University of California Office of the President, 2020) and in research (e.g., Hain et al., 2018). Despite this awareness, garnering a clear picture of neurodivergent students or students with ADHD within the higher education landscape remains difficult. Many studies and surveys aggregate data – they group students with disabilities into a single category or aggregated disability categories, such as specific learning disabilities or cognitive disabilities (e.g., National Center for Education Statistics, 2018). However, the experiences of students with ADHD, their trajectories through college, and the difficulties they encounter differ from other neurodivergent students. Therefore, the opportunity to gain a more in-depth understanding of specific groups of students, such as students with ADHD, is lost.

Furthermore, higher education institutions lack a comprehensive picture of the experiences and academic success of students with ADHD, even within their institutions. Often institutional data resides in different offices and is incomplete (because most students with disabilities do not register with their institution). Qualitative research has primarily focused on the experiences of students with ADHD as opposed to their academic outcomes (e.g., Perry & Franklin, 2006; Lefler et al., 2016), and quantitative studies of academic outcomes are limited (DuPaul, 2021).

A recent University of California (UC) report includes the results of a 2018 Undergraduate Experience Survey on the academic outcomes of neurodivergent college students (University of California Office of the President, 2020). Students from multiple UC campuses completed the survey, which included four-year graduation rates. The survey collected partially disaggregated disability data – neurodivergent students fall into one of two groups, students with a learning disability (examples of speech disorder or dyslexia) and students with a cognitive disability (examples of autism, ADHD, and brain injury). Participating students with a learning or cognitive disability had an expected four-year graduation rate of 58%. In contrast, participating students without a learning or cognitive disability had an expected four-year graduation rate of 79% (University of California Office of the President, 2020). These achievement disparities motivate change in higher education, such as adopting equitable classroom practices and institutional policies.

3.4 Pre-college Factors of Students with ADHD

Two recent studies have begun to explore the relationships between sociodemographic traits and the academic success of students with ADHD to understand if the relationships differ from those of students without ADHD. A longitudinal study (DuPaul et al., 2021) explored these relationships for sex, race/ethnicity, parent education, high school 504 (a formal document outlining school supports for a K-12 student with a disability; Understood, n.d.), and high school IEP (individualized education plan; a formal document with a learning plan and identified services for a K-12 student with a disability; Understood, n.d.) with grades. DuPaul and coauthors (2021) separated college students with ADHD into two groups based on whether they took medication for ADHD (n = 94-99) or not (n = 96-105) and students without ADHD comprised the third group. They found higher levels of parental education positively associated with first-semester GPA for students with and without ADHD. Having an IEP in high school was negatively associated with first-semester GPA for students with ADHD who were not taking medication for their ADHD. Sex, race/ethnicity, and having a 504 plan in high school variables were not statistically significant for any of the three student groups. This study did not include a measure of pre-college academic preparation and only included college experience variables from the Learning and Study Strategies Inventory (LASSI) or that measured behaviors related to executive functions.

In another study, Koch and coauthors (2018) modeled the college persistence of students with disabilities, including students with ADHD as well as those with learning and psychological disorders and depression. In their model, they included sociodemographic traits (gender, race, family income, and first-generation student), full- or part-time/mixed college student status, living arrangements (e.g., off-campus), and academic (peer and faculty/staff contact) and social integration (co-curricular participation) in college. For first-year persistence, they found that male students (*OR* = 1.26, 95% CI: 1.10, 1.46) from low-income families (*OR* = 1.29, 95% CI: 1.08, 1.56) and first-generation college students (*OR* = 1.63, 95% CI: 1.40, 1.90) had a higher likelihood of not persisting through their first year of college. However, in this multivariate regression model, Koch and coauthors (2018) aggregated students with disabilities, and therefore, the unique experiences of students with ADHD are unknown.

Few studies have investigated the relationship between students' pre-college academic preparation and performance and academic success for students with ADHD. However, research from a recent study (Gormely et al., 2019) suggested a potential difference in the relationship between high school GPA and first-year college GPA for students with and without ADHD. They did not include pre-college standardized test scores in their model and found that although high school GPA was statistically significant in predicting first-year college GPA for students without ADHD (*n* = 121), it was not statistically significant for students with ADHD (*n* = 99). It is unclear whether this finding indicates an actual relationship difference; the lack of evidence of a statistical difference may be due to the model's low statistical power resulting from a small sample size.

3.5 College Experience of Students with ADHD

College can be challenging for students with ADHD despite their many strengths (e.g., Fleming & McMahon, 2012; Perry & Franklin, 2006; Prevatt, 2016). In the past ten years, researchers have begun to address the research gap (DuPaul et al., 2009) regarding the college experience of students with ADHD. More recent studies (e.g., Lefler et al., 2016) illuminate supportive and challenging aspects of the college experience faced by college students with ADHD that likely affect students' academic and career success.

In this section, I organized my literature review of the college experiences of students with ADHD in a manner consistent with Terenzini and Reason's (2005) college impact model – classroom, curricular, and out-of-class experiences. I summarize the literature related to the classroom (student motivation and engagement and classroom interaction), curricular (academic adjustment and academic support), and out-of-class (sense of belonging) experiences of students with ADHD.

3.5.1 Classroom Experiences

Students' classroom experiences focuses on students' in-class learning opportunities (Reason, 2009). I emphasize students' motivation and engagement in the classroom and their interactions with both the instructor and other students.

3.5.1.1 Student Engagement.

Academic outcomes are strongly tied to student engagement in the classroom. Students with ADHD may, more often than their peers without ADHD, exhibit behaviors inconsistent with academic engagement. DuPaul and coauthors (2017) examined the academic engagement of more than 5,000 incoming first-year college students with ADHD. Students with ADHD more frequently exhibited, in the past year, behaviors associated with academic disengagement, such as completing homework late or missing class, than their peers without ADHD (DuPaul et al., 2017). However, the students participating in this study primarily reported on their year before college, which may differ from their behaviors in college.

Behaviors typically associated with student disengagement, such as completing homework late, are not the same as students' lack of interest. Instead, such behavior may relate more strongly to motivation (Morsink et al., 2022) or academic adjustment for students with ADHD. Motivation is "a concept that is used to explain behavior, and it generally refers to that what moves us to act, what causes goal-directed behavior" (Morsink et al., 2022, p. 1139). For students with ADHD, motivation is a pivotal precursor to student engagement and academic success (Brown, 2013; Morsink et al., 2022; Perry & Franklin, 2006; Prevatt et al., 2017). Students with ADHD find low motivation contributes to lower-than-possible grades. Students with ADHD in introductory physics courses shared that their grades did not reflect what they could have achieved and attributed their lower grades to low motivation (James et al., 2020).

Traditional instructional pedagogy (i.e., lectures) may not align well with the learning needs or preferences of students with ADHD (Lefler et al., 2016). In contrast, active instructional pedagogies motivate by shifting from passive tasks, such as note-taking and listening to lectures, to engaging students in their learning during class (Powell, 2015; Lefler et al., 2016). Students with ADHD often exhibit an intrinsic motivation to complete high-interest, novel tasks (Prevatt et al., 2017). Highly motivating and "hands on" environments (e.g., those featuring "active" learning or learning by doing) are often preferred by adults with ADHD (Lasky et al., 2016). Although the benefits of active learning for students with ADHD have not yet been specifically studied, students with ADHD participating in Lefler and coauthors' (2016) study found that "any method of breaking up a lecture with discussion, hands-on activities, or videos was extremely helpful" (p. 88). James and coauthors (2020) also recommend instructors provide opportunities to learn actively, such as "student-centered problem solving," and share the relevancy of the course material (p. 193).

3.5.1.2 Classroom Interactions.

Interactions with faculty and peers or social integration have long been recognized as a salient factor in students' college outcomes (Tinto, 1993). These interactions, particularly with instructors and peers in group assignments, can negatively affect coursework and learning for students with ADHD (e.g., James et al., 2020). Inaccurate perceptions (e.g., "laziness") of ADHD potentially influence students' interactions with instructors and other students in their classes (Sedgwick-Müller et al., 2022, p. 13). In contrast to these inaccurate perceptions, experts from the United Kingdom shared, "Instead, they [students with ADHD] tend to work exceptionally hard to overcome their deficits associated with ADHD and still experience academic outcomes that fall below that expected from their general intellectual ability" (p. 14).

Instructor-student interactions and student-student rapport have a considerable impact on the classroom experiences of college students with ADHD. Positive interactions and supportive dialogue with instructors contribute to the academic success and self-confidence of college students with ADHD (Alsopp et al., 2005; Perry & Franklin, 2006). Yet, students with ADHD receive varying levels of support from their instructors, particularly regarding formal accommodations (Alsopp et al., 2005; Perry & Franklin, 2006). Students with ADHD, who have registered with the disability services office at their institution, may receive formal accommodations (e.g., Quinn, 2022), sometimes provided to their instructors in the form of an accommodation letter. In interviews, students shared uncomfortable interactions with instructors regarding their accommodations letter "ranging from negative verbal feedback from a professor to a student perception of body language that communicated disapproval" (Perry & Franklin, 2006, p. 104). Students shared the importance and impact of instructors' reactions to their accommodations letter and the damaging effect of recurring negative interactions on their self-confidence (Perry & Franklin, 2006). They also shared that they experienced more supportive interactions and classroom environments with instructors who were more knowledgeable about ADHD (Perry & Franklin, 2006).

Instructors' perceptions of students with ADHD and their opinions on flexible classroom practices may contribute to negative interactions, although there are few research studies on instructors' perceptions. One study (Vance & Weyandt, 2008) found that 25.7% of professors agreed with the statement "Faculty should not accept alternative assignments or provide copies of lecture notes to students with ADHD," and 29.6% of professors agreed with the statement "A student with ADHD is more stressful to teach than a non-ADHD student" (p. 306). Hopefully, these percentages no longer reflect faculty perceptions, but a link between these perceptions and negative student-instructor interactions would not be surprising.

Students with ADHD may also experience negative classroom interactions with other students. Thompson and Lefler (2016) studied students' perceptions of the likelihood of success in completing an academic task when working with a fictitious partner. One of the fictional partners was described as having ADHD. Another fictional partner was described using behaviors commonly associated with ADHD with the following behavioral description, "I have a difficult time paying attention in class, I'm really disorganized, and I'm easily distracted" (p. 48). Students rated anticipated behaviors, such as equal workload division, finishing the project on time, and even the creativity of their fictional partner more negatively than a control or the partner described as having ADHD but without the behavioral description. Similarly, another study (Canu et al., 2007) found undergraduate students forming groups for a project were less likely to choose to work with a student whose profile described them as a student with ADHD compared to a student whose profile described them as having a medical problem or an "ambiguous weakness (e.g., perfectionist)" (p. 702).

3.5.2 Curricular Experiences

In curricular experiences, I focus on academic adjustment because many students with ADHD do not have well-developed study, organizational, time management, and note-taking skills (e.g., Advokat et al., 2011; Fleming & McMahon, 2012; Lefler et al., 2016; Reaser et al., 2007) and find homework, studying, test-taking, and writing assignments more time-consuming (Lefler et al., 2016; Perry & Franklin, 2017). I also address academic support because of its relationship to developing academic skills such as study skills and time management (DuPaul et al., 2017, 2021).

3.5.2.1 Academic Adjustment.

Executive functioning is generally predictive of academic adjustment in college students (Sheehan & Iarocci, 2019). The additional academic demands students experience in college require skills related to higher-order executive functions, such as planning, organization, time management, and note-taking (Diamond, 2013). Incoming college students have a diverse set of skills and experiences on which to build when adjusting to college academics, and many researchers have focused on the academic adjustment of college students with ADHD (e.g., Reaser et al., 2007). Quantitative studies used established surveys to quantify skill differences between the two populations, whereas qualitative studies arrived at similar conclusions from focus groups and interviews with students with ADHD. They generally identify the executive function components of collegiate academic adjustment (e.g., study skills, time management, and organization) as less developed for students with ADHD compared to their peers without ADHD.

Two instruments – the Learning and Study Strategies Inventory (LASSI; Weinstein & Palmer, 2002) and the College Readiness Scale (CRS; Maitland & Quinn, 2011) – have been used to compare undergraduate students with and without ADHD. Using the LASSI, students with ADHD scored lower on the *Anxiety*, *Motivation*, *Concentration*, *Information Processing*, *Test Strategies*, and *Time Management* subscales than their peers without ADHD (or a learning disability; Reaser et al., 2007). Reaser and coauthors (2007) noted that while these subscales typically predict college grades, this relationship did not hold for students with ADHD.

Using the CRS, which includes 15 items on academic skills, study skills, and time management, undergraduate students with ADHD scored statistically significantly lower than their peers without ADHD on the study skills (e.g., note-taking, preparing for tests, and writing papers) and time management (e.g., scheduling) components (Canu et al., 2021). The first-year undergraduate students with ADHD had difficulty completing their daily and long-term assignments. For all students, Canu and coauthors (2021) noted a strong correlation between high school GPA and college grades, and they suggested that high school GPA may predict students' time management and study skills. They further indicated that a lower high school GPA may reflect that a student did not develop, in high school, the necessary study and time management skills for college (Canu et al., 2021).

Many qualitative studies suggest that deficits in time management and study skills contribute to the lower academic performance of college students with ADHD. For example, Kwon and coauthors (2018) conducted in-depth interviews with college students with ADHD. They found a theme of *unsatisfactory academic performance and achievement*, which students attributed to low motivation and procrastination in completing assignments and studying for exams. The participating students preferred courses of interest and had more difficulty completing courses of little interest to them. In another study, Meaux and coauthors (2009) identified "poor time management and organization skills, difficulty staying focused, failure to complete work on time, poor motivation, poor reading and study skills" as barriers to academic success (p. 251). A third study explored differences in note-taking for students with and without ADHD. Vekaria and Peverly (2018) had students take lecture notes and then gave them 10 minutes to review their notes before writing a summary (without using their notes). They found that participating students with ADHD had more difficulty creating a written summary of the lecture material and slower handwriting speeds but did not identify a difference in the quality of notes between the two student groups (Vekaria & Peverly, 2018). This summary of the more recent literature is consistent with earlier findings of an extensive literature review focused on college students with ADHD (DuPaul et al., 2009):

> *The reasons for their [college students with ADHD] poorer performance are unclear but preliminary findings suggest inadequate academic coping strategies, poor organizational and study skills, time management difficulties, and cognitive impairments such as inattention, intrusive thoughts, and internal restlessness may all have influencing effects.* (p. 246)

3.5.2.2 Academic Support.

Academic support services, such as academic coaching or skill development, promote positive academic outcomes for students with ADHD when tailored to students' individual needs (DuPaul et al., 2017). The programs or services that are particularly beneficial for students with ADHD are those that improve their study, time management, organizational, and note-taking skills (DuPaul et al., 2017). In a study by Perry and Franklin (2006), graduating college students with ADHD noted accommodations such as note-taking and extended testing time as contributing factors to their academic success. Students' opinions about effective support and services vary, suggesting a need for individually-tailored support (e.g., course-specific learning strategies through individualized instruction v. generalized support; Perry & Franklin, 2006). The beneficial nature of academic support programs for students with ADHD for college grades and persistence is not understood because studies have provided mixed results; however, skill-specific instruction is helpful (DuPaul et al., 2021).

3.5.3 Out-of-Class Experiences

Students have a broad range of experiences outside of class (e.g., interacting with friends and engaging in co-curricular activities) unrelated to the curricular aspects of college; such experiences are captured in out-of-class experiences (Reason, 2009). Students' finding a "sense of place" or belonging in college is associated with college persistence (Reason, 2009, p. 670). The social experiences, such as experiencing stigma, and feelings of belongingness of students with ADHD have received little research focus compared to academic success outcomes, such as grades (McKee, 2017). However, Khalis and coauthors (2018) found that college students with ADHD are less likely to develop an attachment to their university than their peers without ADHD. This attachment or sense of belonging is positively associated with college grades. Studies also suggest college students with ADHD express greater concerns about their social relationships and skills (e.g., resolving conflict) than their peers (Blase et al., 2009; Canu & Carlson, 2007; Canu et al., 2008; McKee, 2014; Shaw-Zirt et al., 2005).

3.5.3.1 Sense of Belonging.

Belongingness is a critical aspect of the college experience of students with ADHD and positively associated with college grades and persistence. Khalis and coauthors (2018) found that in transitioning to college, students transferred their dependence from parents to peers, and these peer interactions provided a sense of belonging to their institution. Social acceptance from their peers positively correlated with students' attachment to the university, friendships, and GPA. Students with ADHD symptoms had, on average fewer friendships, a lower attachment to the university, and lower first-year GPAs than their peers without ADHD (Khalis et al., 2018).

A stigma towards behaviors associated with ADHD exists among undergraduate students (Thompson & Lefler, 2016), perhaps making building friendships and an attachment to their institution more difficult (Khalis et al., 2018). In one study, Chew and coauthors (2009) described a college student with ADHD using positive and negative adjectives. Students with and without ADHD similarly "endorsed more negative adjectives than positive adjectives describing a college student with ADHD," consistent with a negative attitude toward ADHD (p. 274). Interestingly, students with ADHD responded to the positive adjectives with less positive attitudes towards individuals with ADHD than students without ADHD. Students with more frequent contact with a student with ADHD provided responses indicating a more positive attitude towards individuals with ADHD, perhaps implying that familiarity may help students recognize the strengths of others (Chew et al., 2009).

In another study, McKee (2017) had first-year college students complete a 10-minute group task of building an as-tall-as-possible block tower. A single group was composed of students with few characteristics associated with inattention, hyperactivity, and impulsivity and students with many of these characteristics. After completing the task, students had more positive initial impressions of the students with similar levels of inattentive, hyperactivity, and impulsivity characteristics as themselves. In other words, students with few traits associated with ADHD preferred (i.e., were more likely to build friendships with) students with few characteristics, and vice versa (McKee, 2017). In a third study, Canu and coauthors (2008) suggested that undergraduate students had a lower likelihood of befriending an individual with ADHD based on their ratings of fictitious profiles of individuals across several domains (ADHD, medical problem, and an "ambiguous weakness" such as a perfectionist; p. 703).

3.6 Academic Success of College Students with ADHD

Researchers have investigated traditional academic success outcomes of college students with ADHD, such as grades and persistence, and less often non-traditional measures of academic success, such as creativity. Grades have been studied most frequently, likely due to the additional challenges of studying persistence (e.g., difficult to differentiate whether a student dropped out of a study vs. dropped out of school). They typically have not included students' individual college experiences in their analyses, nor included college experiences as mediators in academic success models (e.g., DuPaul et al., 2021). Researchers have explored the creative and divergent thinking of college students with ADHD (White & Shah, 2011, 2016), empirically finding students with ADHD had higher levels of creative and divergent thinking compared to their peers without ADHD (White & Shah; 2011, 2016).

3.6.1.1 Grades.

College students with ADHD earn, on average lower grades than their peers without ADHD (e.g., Advokat et al., 2011; Blase et al., 2009; DuPaul et al., 2009; Frazier et al., 2007; Weyandt et al., 2013). Of these studies, I describe three quantitative studies of students with ADHD examining college grades as an outcome. Two of the three studies are more recent and longitudinal, and none of the three incorporate contextual aspects of the college classroom or curricular experiences beyond aspects of academic adjustment.

In one study, Blase and coauthors (2009) conducted a statistical analysis of survey responses from 3,379 undergraduate students, of whom 153 (4.5%) reported currently having ADHD. They included two measures related to students' college experiences: academic concerns ("students' concerns about their academic performance and ability to succeed academically") and social concerns ("students' concerns/satisfaction with their relationships and social life"; p. 300). They found a 0.4 to 0.5 standard deviation lower average GPA of students with ADHD than their peers without a (current or past) ADHD diagnosis (n = 3,153).

In a longitudinal analysis, DuPaul and coauthors (2021) explored both college grades and persistence as well as the LASSI factor scores of approximately 400 undergraduate students over four years of college. They used multiple-group latent growth curve modeling with three groups: students with ADHD not using medication for ADHD (n = 96-105), students with ADHD using medication for ADHD (*n* = 94-99), and students without ADHD (*n* = 190-216). Students without ADHD, on average, had higher LASSI scores (better) on *affective* (managing emotions), *comprehension monitoring* (assessing one's understanding), and *goal strategies* than students with ADHD (taking medication or not). For all four years of college, students without ADHD had, on average, higher GPAs than students with ADHD (taking medication or not). After the first semester, the GPAs of the students without ADHD and students with ADHD taking medication decreased, whereas the GPAs of students with ADHD but not taking medication improved. Despite the comprehensiveness of this study, it did not include information about students' pre-college academics (e.g., high school GPA or standardized test scores) or college experiences, had a borderline adequate college GPA model fit, and a relatively small number of students in each group.

Using first-year data from the same study, Gormley and coauthors (2019) conducted regression analyses on first-year GPA, separately modeling students with ADHD and students without ADHD. Students' use of services ("campus tutoring services" and "academic skill assistance") was the only college experience measures included in their model (p. 1769). In addition to finding that students with ADHD earned, on average, lower GPAs in high school and the first year of college, they concluded that common predictors of college grades differ for students with ADHD compared to their peers without ADHD. They based this on the lack of statistical significance of high school GPA in the model of students with ADHD in comparison with its significance in the regression model of students without ADHD. A disparate interpretation is that the lack of significance of high school GPA for students with GPA arises from the low power of the model - the college GPA regression model had 13 independent variables and used data from only 153 students (ratio of independent variables to responses of less than 12).

3.6.1.2 Creativity

Researchers have found that college students with ADHD have higher levels of divergent thinking and real-world creativity, and hypothesize an association with their lower cognitive inhibition (e.g., White & Shah, 2011). For example, White and Shah (2011) had students with ADHD complete measures of creative achievement, creative style, real-world creativity, and divergent creative thinking. Students with ADHD had statistically significant higher levels of creative achievement (i.e., real-world creativity) and their creative style more often aligned with idea generation, consistent with a divergent thinking. White and Shah (2016) also studied creative thinking using the Unusual Uses Task, a measure divergent thinking, and found that students with ADHD outperformed their peers without ADHD. Mediation analysis indicated inhibitory control drove this difference.

Taylor and coauthors (2020) explored creativity and engineering GPA in college students with ADHD using Torrance Tests of Creative Thinking Figural-test, a measure of divergent thinking that differs from the verbal test used by White and Shah (2011). Taylor and coauthors (2020) found that characteristics of ADHD positively associated with higher levels of divergent thinking. Similarly, in a study of college students, Boot and coauthors (2017) found that characteristics of ADHD positively associated with higher measures of creative achievement, divergent thinking, and self-reported creative behavior. Consistently across these four studies, researchers found higher levels of divergent thinking either associated with ADHD characteristics or were more likely for students with ADHD than their peers without ADHD.

3.7 Summary

College students with ADHD often have more difficulty with executive functions (e.g., working memory, inhibition, and cognitive flexibility; Brown, 2009; Diamond, 2013). Higher-order executive functions, such as organization and time management, are necessary for academic success in college (Ahrens et al., 2019; Diamond, 2013). In transitioning to college, students who have lesser developed college-readiness skills (as is the case for many students with ADHD) experience more difficulty adjusting to college academics (Canu et al., 2021; Reaser et al., 2007).

The college experiences of students with ADHD differ from their peers without ADHD. In the classroom, they experience barriers such as long-duration lectures which require sustained attention and note-taking (e.g., Lefler et al., 2016). The negative stigma associated with ADHD can lead to fewer positive and more negative interactions with instructors and peers, particularly during group work (Canu et al., 2007). Students' curricular experiences are influenced by their difficulty with the academic adjustment to college and less well-developed study and time management skills (e.g., Canu et al., 2021). They are prone to procrastination, leading to incomplete assignments and completing assignments and studying for exams at the last-minute (e.g., James et al., 2020). There is less research on the out-of-class experiences of students with ADHD, although students with ADHD may have a lower sense of belonging than their peers without ADHD (Khalis et al., 2018).

Researchers studying academic success outcomes for college students with ADHD have found that students with ADHD earn, on average, lower grades than their peers without ADHD (e.g., DuPaul et al., 2021). Creativity, a non-traditional metric of college success, is not often investigated as an academic success outcome, although researchers have found that college students with ADHD have higher levels of creative and divergent thinking than students without ADHD (White & Shah, 2011, 2016).

3.8 Research Questions

Through quantitative research, I aim to identify aspects of the college experience associated with the academic success of students with ADHD and focus areas for evidence-based recommendations for college instructors, staff, and administrators to promote a more equitable educational experience.

My study seeks to answer two research questions.

RQ1. What relationships exist between students' precollege characteristics and experiences, the college experience, and academic success for students with ADHD?

RQ2. What college experiences, if any, mediate the relationship between a pre-college ADHD diagnosis and academic success?

Chapter 4 Research Methods

This section describes the data, measures, missing data (briefly), model development, and analysis. Appendix A includes an in-depth description of missing data and the methods I used to handle the missing data appropriately. The University of Michigan IRB has reviewed this study, and it has received a "Not Regulated" determination (HUM00200369).

I want to first comment on the language throughout the remainder of my dissertation. I analyzed secondary data; therefore, the item wording was provided from surveys administered seven to twelve years prior to my receiving it. The language is not bias-free (American Psychological Association, 2023), and items related to neurodiversity are written from the medical model lens (e.g., have received an ADHD diagnosis versus identifies as a student with ADHD). I replicate the survey wording as necessary to accurately describe the items. Furthermore, persistence and retention are frequently used interchangeably in academic success literature; however, more accurately, *persistence* is measured at the student-level, and *retention* is an institutional-level metric. Although I follow the latter convention, the authors of the structural equation model (SEM) described in this section used "retention" (Bowman et al., 2019). Therefore, when referring to their model, I retain their use of the word "retention."

4.1 Data

The Higher Education Research Institute (HERI), in conjunction with higher education institutions across the U.S., administers *The Freshman Survey* (TFS; HERI, n.d.) and *Your First College Year* (YFCY; HERI, n.d.a). Incoming first-year students complete the TFS, which has items focused on "students' background characteristics, high school experiences, attitudes, behaviors, and expectations for college" (HERI, n.d., para. 1). In even years since 2010, the TFS included an item asking students whether they have received a previous ADHD diagnosis (HERI, n.d.b). At the end of their first year, students complete the YFCY survey, including questions about their first-year college experiences and academic outcomes. HERI merges matched responses from these surveys to create longitudinal data.

I requested longitudinal data from the TFS and YFCY through HERI's proposal process (HERI, n.d.c). The combined data set comprised four student cohorts who completed their first year in college in 2011, 2013, 2015, and 2017, and matched (through a HERI student identification number) data from 2010, 2012, 2014, and 2016 TFS surveys. Only students who attended a single institution from when they took the TFS to when they completed the YFCY are included in this data. Transfer students and students who did not continue at the same institution (e.g., dropped out of college) are omitted. It was impossible to determine the extent of the loss of respondents due to dropout or transfer versus not completing the YFCY survey. For this reason, this data set was limited to studying college experiences and only specific measures of academic success (e.g., grades, not persistence). I only included data from students who attended four-year institutions (*n* = 45,915) and excluded data from those who attended two-year institutions because of the small sample size (*n* = 117).

The numbers of respondents who reported not having an ADHD diagnosis, reported having an ADHD diagnosis, or did not respond are displayed in Table 1. Approximately 4.5% or 2,082 of incoming first-year students reported having ADHD, and 4.7% or 2,177 did not respond to the ADHD survey item.

Table 1. Students' responses, by cohort, to the TFS item about having received an ADHD diagnosis

TFS Year	No ADHD diagnosis *n* (%)	ADHD diagnosis *n* (%)	Non-response *n* (%)
2010	16,576 (90.8)	768 (4.2)	917 (5.0)
2012	14,635 (92.5)	668 (4.2)	519 (3.3)
2014	6,020 (88.1)	335 (4.9)	460 (6.7)
2016	4,425 (88.6)	291 (5.8)	281 (5.6)
Total	**41,656 (90.7)**	**2,082 (4.5)**	**2,177 (4.7)**

4.2 Measures

Terenzini and Reason (2005) and Reason's (2009) descriptions of pre-college characteristics and experiences and college experiences guided my selection of HERI variables. All measures used in this study were from TFS or YFCY variables, transformed from TFS or YFCY variables, or TFS or YFCY constructs (HERI, n.d.d). The exact item wording of TFS and YFCY surveys is available on HERI's website (https://heri.ucla.edu/instruments/). The variables and their relationship to my conceptual framework are described in the following text and shown in Tables 2 through 10. Variables screened as potential auxiliary variables (used only for missing data analysis because they are related to variables selected based my conceptual framework) are also included in this section and the associated tables.

4.2.1 Independent, Mediating, and Auxiliary Variables.

A measure of ADHD (in pre-college characteristics and experiences) and measures of students' college experiences (classroom, curricular, and out-of-class) were key independent or mediating variables because this study explored aspects of the college experiences of students with ADHD that are associated with academic success. I included other pre-college characteristics and experiences and organizational context variables but they were not of primary interest.

4.2.1.1 Pre-college characteristics and experiences.

Tables 2 through 5 list pre-college characteristics and experiences variables in four categories: neurodiversity, sociodemographic traits, prior academic preparation and performance, and student dispositions.

4.2.1.1.1 *Neurodiversity.*

The critical variable in this subcategory is self-reported by incoming first-year students on the TFS, and indicates whether they have previously received an ADHD diagnosis (*DISAB2_TFS*; 1=No, 2=Yes; Table 2). I transformed this variable (*ADHD*; 0=No, 1=Yes). A similar survey item was not included in the YFCY.

I requested three additional neurodiversity variables because learning differences play a role in college experiences (Moskal, 2014). They are self-reported measures (Table 2) of having a learning disability (*DISAB1_TFS;* 1=No, 2=Yes), autism spectrum/Asperger's syndrome (*DISAB3_TFS*; 1=No, 2=Yes), or psychological disorder, such as depression (*DISAB6_TFS*; 1=No, 2=Yes). These three measures do not appear in the SEMs. Instead, I screened them as part of my missing data analysis (Appendix A) to determine if they are auxiliary variables (i.e., variables that contain information about missing values).

Table 2. Pre-college neurodiversity variables

Do you have any of the following disabilities or medical conditions?	Variable name	Responses	Transformed variable	Transformed responses
Attention-deficit/hyperactivity disorder (ADHD)	*DISAB2_TFS*	1=No, 2=Yes	*ADHD*	0=No, 1=Yes
Learning disability (dyslexia, etc.)	*DISAB1_TFS*	1=No, 2=Yes		
Autism spectrum/Asperger's syndrome	*DISAB3_TFS*	1=No, 2=Yes		
Psychological disorder (depression, etc.)	*DISAB6_TFS*	1=No, 2=Yes		

4.2.1.1.2 *Sociodemographic Traits.*

Multiple sociodemographic trait variables from the TFS (

Table 3) are included: sex (*SEX_TFS*; 1=Male, 2=Female), financial resources (*INCOME_TFS;* categorical; screened as potential auxiliary variable in missing data analysis), and first-generation college student (*FIRSTGEN_TFS*; 1=No, 2=Yes). I transformed sex to *FEMALE* (0=Male, 1=Female) and first-generation college student to *FIRSTGEN* (0=No, 1=Yes). Additionally, I created a new variable indicating whether a student identifies as part of an underrepresented racial/ethnic group (*URMG*; 0=No, 1=Yes) from the HERI race/ethnicity variable (*RACEGROUP_TFS*; categorical). I assigned students of races/ethnicities other than White or Asian as part of an underrepresented racial/ethnic group. If a student did not respond to the *RACEGROUP_TFS* item as an incoming first-year student, I used the matching data from a similar YFCY survey item (*RACEGROUP*, 1=American Indian/Alaska Native, 2=Asian/Pacific Islander, 3=Black/African American, 4=Latina/o/x, 5=White, 6=Other race/ethnicity, 7=Two or more races/ethnicities).

4.2.1.1.3 *Academic Preparation and Performance.*

My SEMs or missing data analysis used the academic preparation and performance variables from the TFS (Table 4). For SEM, I included students' average high school grades (*HSGPA_TFS*, 1=D, 2=C, 3=C+, 4=B-, 5=B, 6=B+, 7=A-, 8=A or A+) and standardized test scores (*STANDTEST*, range=400-1600). I created *STANDTEST* by adding students' verbal SAT scores (*SATV_TFS*, range=200-800) and math SAT scores (*SATM_TFS*, range=200-800), if available. Approximately half of the students in the data set reported verbal *and* math SAT scores (n = 21,547). For the remaining students who reported an ACT composite score (*ACTCOMP_TFS*, range=1-36; n = 13,721), I converted their ACT scores to SAT scores using an ACT-SAT concordance table provided by ACT (n.d.). The other measures of students' academic preparation served as auxiliary variables (see Appendix A): years of high school math and science (e.g., years of high school math, *YRSTUDY2_TFS*, 1=1 year, 2=2 years, 3=3 years, 4=4 years) and completed math courses (e.g., Algebra II, *MATH1_TFS*, 1=No, 2=Yes). I also transformed years of high school math (*YRSTUDY2_TFS*) to a variable indicating whether a student completed less than four years of high school math (*LESS4MATH*, 0=No, 1=Yes).

4.2.1.1.4 *Student Dispositions.*

For student dispositions, I used four measures of students' self-ratings as incoming first-year students (Table 5). I used self-rating of creativity compared to their peers (*RATE06_TFS*, 1=Lowest 10%, 2=Below average, 3=Average, 4=Above average, 5=Highest 10%), renamed *CREATIVITY_TFS*, in multiple imputation (i.e., filling in missing data). In multiple imputation, I also included the four indicator variables for the HERI academic self-concept construct, defined as "A unified measure of students' beliefs about their abilities and confidence in academic environments" (HERI, n.d.d, p. 5): academic ability (*RATE01_TFS*), mathematical ability (*RATE11_TFS*), intellectual self-confidence (*RATE15_TFS*), and drive to achieve

(*RATE08_TFS*). Each indicator had the same five-point Likert categorical response scale (1=Lowest 10%, 2=Below average, 3=Average, 4=Above average, 5=Highest 10%). Additionally, I included in my first-year grades SEMs a proxy for resilience, accepting mistakes as part of the learning process (*RESILIENT_TFS*, 1=Not at all, 2=Occasionally, 3=Frequently).

Table 3. Pre-college sociodemographic variables

Survey item	Variable name	Responses	Transformed variable	Transformed responses
Your sex	SEX_TFS	1=Male, 2=Female	FEMALE	0=Male, 1=Female
What is your best estimate of your parents' total income last year?	INCOME_TFS	>10 categories of income in $		
First-generation status based on parent(s) with less than 'some college.'	FIRSTGEN_TFS	1=No, 2=Yes	FIRSTGEN	0=No, 1=Yes
Are you:	RACEGROUP_ TFS	1=American Indian 2=Asian 3=Black 4=Hispanic 5=White 6=Other 7=Two or more races/ethnicity	URMG	0 = No, 1 = Yes

Table 4. Pre-college academic preparation and performance variables

Survey item	Variable name	Responses	Transformed variable	Transformed responses
What was your average grade in high school?	HSGPA_TFS	1=D, 2=C, 3=C+, 4=B-, 5=B, 6=B+, 7=A-, 8=A or A+		
What were your scores on the SAT I and/or ACT? ACT Composite	ACTCOMP_TFS	continuous		
What were your scores on the SAT I and/or ACT? SAT Critical Reading	SATV_TFS	continuous	STANDTEST	Range =400-1600
What were your scores on the SAT I and/or ACT? SAT Mathematics	SATM_TFS	continuous		
During high school (grades 9-12) how many years did you study each of the following subjects?				
Mathematics	YRSTUDY2_TFS		LESS4AMATH	0=No, 1=Yes
Physical science	YRSTUDY4_TFS	1=1 year, 2=2 years, 3=3 years, 4=4 years		
Biological science	YRSTUDY5_TFS			
Computer science	YRSTUDY7_TFS			
Please mark which of the following courses you have completed:				
Algebra II	MATH1_TFS			
Pre-calculus/Trigonometry	MATH2_TFS			
Probability and Statistics	MATH3_TFS			
Calculus	MATH4_TFS	1=No, 2=Yes		
AP Probability and Statistics	MATH5_TFS			
AP Calculus	MATH6_TFS			

Table 5. Pre-college student disposition variables

Survey item	Variable name	Responses	Transformed variable	Transformed responses
Rate yourself on each of the following traits as compared with the average person your age. We want the most accurate estimate of how you see yourself.				
Creativity	RATE06_TFS	1=Lowest 10%, 2=Below average, 3=Average, 4=Above average, 5=Highest 10%	CREATIVITY_TFS	Unchanged
Academic ability	RATE01_TFS			
Mathematical ability	RATE11_TFS			
Self-confidence (intellectual)	RATE15_TFS			
Drive to achieve	RATE08_TFS			
How often in the past year did you:				
Accept mistakes as part of the learning process	MNDHAB10_TFS	1=Not at all, 2=Occasionally, 3=Frequently	RESILIENT_TFS	Unchanged

4.2.1.2 Organizational Context.

4.2.1.2.1 *Institutional Characteristics.*

I used two variables characterizing students' higher education institution: institutional selectivity (*SELECTIVITY*, range=662.6-1525) and institutional type (*INSTTYPE*, 1=University, 2=4-year, and 3=2-year). I used *SELECTIVITY* as an auxiliary variable and *INSTTYPE* to exclude students attending a two-year institution (*n* = 117).

4.2.1.2.2 *Student-Specific Characteristics.*

To account for financial aspects associated with higher education attendance specific to each student, I created a measure of whether a student reported "major" concerns about financing college (*CFINANCONCERN*; 0=No, 1=Yes). This measure accounts for first-year students' financial situation, indicating whether they had concerns about financing college either as incoming first-year students or at the end of their first year. I created this measure from the survey item asking, "Do you have any concern about your ability to finance your college education?" (1=None, I am confident that I will have sufficient funds, 2=Some, but I probably will have enough funds, 3=Major, not sure I will have enough funds to complete college) as an incoming freshman (*FINCON_TFS*) and at the end of the student's first year (*FINCON*). I assigned the *CFINANCONCERN* variable a 1 (Yes) if students responded that they had "major" concerns about financing college on either survey and otherwise a 0 (No).

4.2.1.3 Individual Student Experience.

4.2.1.3.1 *Classroom Experiences.*

For classroom experiences, I used indicator variables from two HERI constructs, one measuring student engagement, *academic disengagement*, and one measuring instructor-student interaction, *faculty interaction*. In addition, I included a measure of whether a student frequently felt bored in class (*BOREDCLASS*; 0=No, 1=Yes) transformed from the *ACT04* variable (1=Not at all, 2=Occasionally, 3=Frequently). These variables are listed in Table 6 and are used in handling missing data or SEM.

In multiple imputation, I used student engagement measures from HERI's academic disengagement construct "measures the extent to which students engage in behaviors that are inconsistent with academic success" (HERI, n.d.d, p. 15), and it is comprised of items about students' class behavior (Table 6). Of the five items, three are about class attendance (late, skipped, or fell asleep), and two are about classroom assignments (completion and quality of work).

Within instructor-student interaction, I used measures from HERI's faculty interaction construct that "measures the amount and type of contact students have with faculty that is appropriate for the first year of college, as well as satisfaction with these issues" (HERI, n.d.d, p. 17). It includes items about the frequency of students' interaction with faculty (e.g., office hours and communication). I expect instructor-student interaction and sense of belonging to capture student-student rapport.

4.2.1.3.2 *Curricular Experiences.*

Within curricular experiences, I used indicator variables from the *academic adjustment* construct and a variable, *DISABSERVICES*, measuring students' interactions with their disability resource center (*SERVICES06*, 1=Not at all, 2=Occasionally, 3=Frequently; Table 7).

For *academic adjustment*, I used the four items from HERI's academic adjustment construct about the ease of various aspects of students' adjustment to college academics (HERI, n.d.d, p.16): understand what your professors expect of you academically (*EASY9*; renamed *PROFEXPECT*), develop effective study skills (*EASY6*; renamed *STUDYSKILLS*), adjust to the academic demands of college (*EASY1*; renamed *ADJUSTDEMAND*), and manage your time effectively (*EASY8*; renamed *TIMEMANAGE*). These items had a four-point Likert scale (1=Very difficult, 2=Somewhat difficult, 3=Somewhat easy, 4=Very easy).

4.2.1.3.3 *Out-of-Class Experiences.*

Within out-of-class experiences, I used items from HERI's *sense of belonging* construct (HERI, n.d.d). I also transformed a measure of students' frequency of interacting with friends at their college (*FRIENDS*, 0=Less than once a week, 1= Once a week or more; Table 8), which I used in multiple imputation.

Table 6. Individual Student Experience: Classroom Experience variables

	Survey item	Variable name	Responses	Transformed variable
Academic disengagement construct	Been late to class	ACT05	1=Not at all, 2=Occasionally, 3=Frequently	
	Skipped class	CLSACT18		
	Turned in course assignment(s) late	CLSACT20		
	Turned in course assignments that did not reflect your best work	CLSACT21		
	Fell asleep in class	CLSACT06		
Faculty interaction construct	Interact with faculty outside of class or office hours	INTACT06	1=Never, 2=1 or 2 times/term, 3=1 or 2 times/week, 4=Once a week, 5=2 or 3 times/week, 6=Daily	FACOUT
	Interact with faculty during office hours	INTACT05		FACOFFICE
	Asked a professor for advice after class	ACT01	1=Not at all, 2=Occasionally, 3=Frequently	FACADVISE
	Communicated regularly with your professors	COLACT05	1=No, 2=Yes	FACCOMM
	Satisfaction with the amount of contact with faculty	CMPSAT01	1=Can't rate/no experience, 2=Very dissatisfied, 3=Dissatisfied, 4=Neutral, 5=Satisfied, 6=Very satisfied	FACCONTACT

Table 7. Individual Student Experience: Curricular Experience variables

	Survey item	Variable name	Responses	Transformed variable
Since entering this college, how has it been to:				
Academic Adjustment	Understand what your professors expect of you academically.	EASY9	1=Very difficult, 2=Somewhat difficult, 3=Somewhat easy, 4=Very easy	PROFEXPECT
	Develop effective study skills.	EASY6		STUDYSKILLS
	Adjust to the academic demands of college.	EASY1		ADJUSTDEMAND
	Manage your time effectively.	EASY8		TIMEMANAGE
Since entering this college, how often have you utilized the following services:				
	Disability resource center	SERVICES06	1=Not at all, 2=Occasionally, 3=Frequently	DISABSERVICES

I operationalized out-of-class experiences using the *sense of belonging* construct that "measures the extent to which students feel a sense of academic and social integration on campus" (HERI, n.d.d, p. 20). It is primarily focused on students' sense of belonging related to the college campus instead of the classroom or academic field (Table 8) and comprises four items (I feel I am a member of this college, *COLOPN1*3; I feel a sense of belonging to this campus, *COLOPN14*; I see myself as part of the campus community, *COLOPN27*; If asked I would recommend this college to others; *COLOPN28*; HERI, n.d.d, p. 37). I renamed these variables *MEMBER*, *CAMPUSBELONG*, *CAMPUSCOMM*, and *RECOMMEND*, respectively, and kept their four-point Likert scales.

4.2.1.3.4 *Additional Variables.*

I used three additional variables (Table 9) from the YFCY survey related to student dispositions during the first year of college for handling missing data (see Appendix A): seeks alternative solutions to problems (*INNOVATE*), self-rating of their academic ability (*RATE02*), and intellectual self-confidence (*RATE23*).

4.2.2 Dependent variables.

4.2.2.1 Academic success.

The two academic success measures are listed in Table 10. For college grades, I used students' average grade from the YFCY (*CURRGPA*, "What is your overall grade average (as of your most recently completed academic term)?", categorical). For creativity, I used students' self-rating of their creativity compared to their peers (*CREATIVITY1*, 1=Lowest 10%, 2=Below average, 3=Average, 4=Above average, 5=Highest 10%).

Table 8. Individual Student Experience: Out-of-Class Experience variables

	Survey item	Variable name	Responses	Transformed variable	Transformed responses
Please indicate the extent to which you agree or disagree with the following statements:					
Sense of Belonging	I feel I am a member of this college	COLOPN13	1=Strongly disagree, 2=Disagree, 3=Agree, 4=Strongly agree	MEMBER	
	I feel a sense of belonging to this campus	COLOPN14		CAMPUSBELONG	
	I see myself as part of the campus community	COLOPN27		CAMPUSCOMM	
	If asked, I would recommend this college to others	COLOPN28		RECOMMEND	
	Close friends at this institution	INTACT02	1=Never, 2=1 or 2 times per term, 3=1 or 2 times per month, 4=once a week, 5=2 or 3 times per week , 6=daily	FRIENDS	0=Less than once a week, 1=Once a week or more

[a]Survey wording in 2010 and 2012 = Since entering this college, how often have you interacted with the following people (e.g., by phone, e-mail, Instant Messenger, or in person)

Table 9. Additional variables from the YFCY

Survey item	Variable name	Responses	Transformed variable	Transformed responses
How often in the past year did you:				
Seek alternative solutions to a problem	MNDHAB09	1=Not at all, 2=Occasionally, 3=Frequently	INNOVATE	0=Not at all, 1=Occasionally, 2=Frequently
Rate yourself on each of the following traits as compared with the average person your age. We want the most accurate estimate of how you see yourself.				
Academic ability	RATE02	1=Lowest 10%, 2=Below average, 3=Average, 4=Above average, 5=Highest 10%		
Self-confidence (intellectual)	RATE23			

Table 10. Academic success variables (from the YFCY)

Survey item(s)	Variable name	Responses	Transformed variable	Transformed responses
What is your overall grade average (as of your most recently completed academic term)?				
Overall GPA	CURRGPA	1=I did not receive grades in my courses, 2=D, 3=C, 4=C+, 5=B-, 6-B, 7=B+, 8=A-, 9=A or A+		
Rate yourself on each of the following traits as compared with the average person your age. We want the most accurate estimate of how you see yourself.				
Self-rating of creativity	RATE09	1=Lowest 10%, 2=Below average, 3=Average, 4=Above average, 5=Highest 10%	CREATIVITY1	0=Average or below, 1=Above average, 2=Top 10%

4.3 Missing Data: Briefly

The measures in this study had missing data. The pre-college characteristics and experiences variables had a relatively low fraction of missing responses, whereas the college experience indicators and academic success manifest variables typically had approximately 10% missing responses. I used multiple imputation to fill in missing data (Allison, 2002; Enders, 2022) and provided a detailed description of the application of this method in Appendix A.

4.4 Analysis

4.4.1 Structural Equation Modeling

Structural equation modeling is a causal statistical analysis method that simultaneously models relationships among observed and latent variables (Kline, 2016). Latent variables are constructs that are not directly measured, instead they are indirectly measured by two or more observed or manifest variables. The use of latent variables in SEM enables us to remove the measurement error associated with observed variables. Multiple regression is a SEM in its simplest form (i.e., no latent variables or omitted paths; Bauer & Curran, 2022). Commonly in SEM, there are multiple dependent variables and omitted paths between variables for which no relationship is theorized.

4.4.1.1 Model specification.

The first step in SEM is specifying a model (Kline, 2016). The focus of my study, students with ADHD, drove critical decisions in model specification. I included common strengths of students with ADHD, creativity (White & Shah, 2011, 2016), and challenges of college students with ADHD, executive functioning (e.g., DuPaul et al., 2009) and on-campus social interactions (McKee, 2014).

4.4.1.1.1 *First-year grades.*

I started with Bowman and coauthors' (2019) academic success SEM with outcomes of college grades and persistence because, similar to Terenzini and Reason's (2005) model, it is based on the student retention theories and models of Astin (1993), Pascarella (1985), and Tinto (1993) and includes non-cognitive attributes. The Bowman model (2019) incorporates students' pre-college measures of *high school GPA* and *financial means*, college experience measures of *non-cognitive attributes* and *social adjustment*, and two traditional academic success measures, *college grades* and *retention*. Non-cognitive attributes' indicator variables in the Bowman model are *academic grit*, *time management*, *self-discipline*, and *self-efficacy* and social adjustment's indicator variables are *social integration* and *peer connection* (Bowman et al., 2019).

First, I adapted the Bowman Model (Figure 3) by omitting *retention* because college persistence cannot be measured using the HERI data. Removing *retention* eliminated its associated paths and the measured variable, *commitment to institution*, singularly connected to it.

Next, I adapted the model's latent variables to coincide with available constructs and variables (Figure 4). I replaced financial means with students' concerns about financing college (*CFINANCONCERN*). I selected a closely related HERI construct, *academic adjustment*, to operationalize *non-cognitive attributes*. I chose two closely related HERI constructs to operationalize *social adjustment*, splitting this factor into *faculty interaction* and *sense of belonging*. For the two-factor model (Figure 5), I used the manifest variable, *CAMPUSBELONG*, instead of the *sense of belonging* latent variable, which I used for the three-factor model (Figure 4).

Figure 3. Bowman and coauthors (2019) structural equation model without the retention outcome

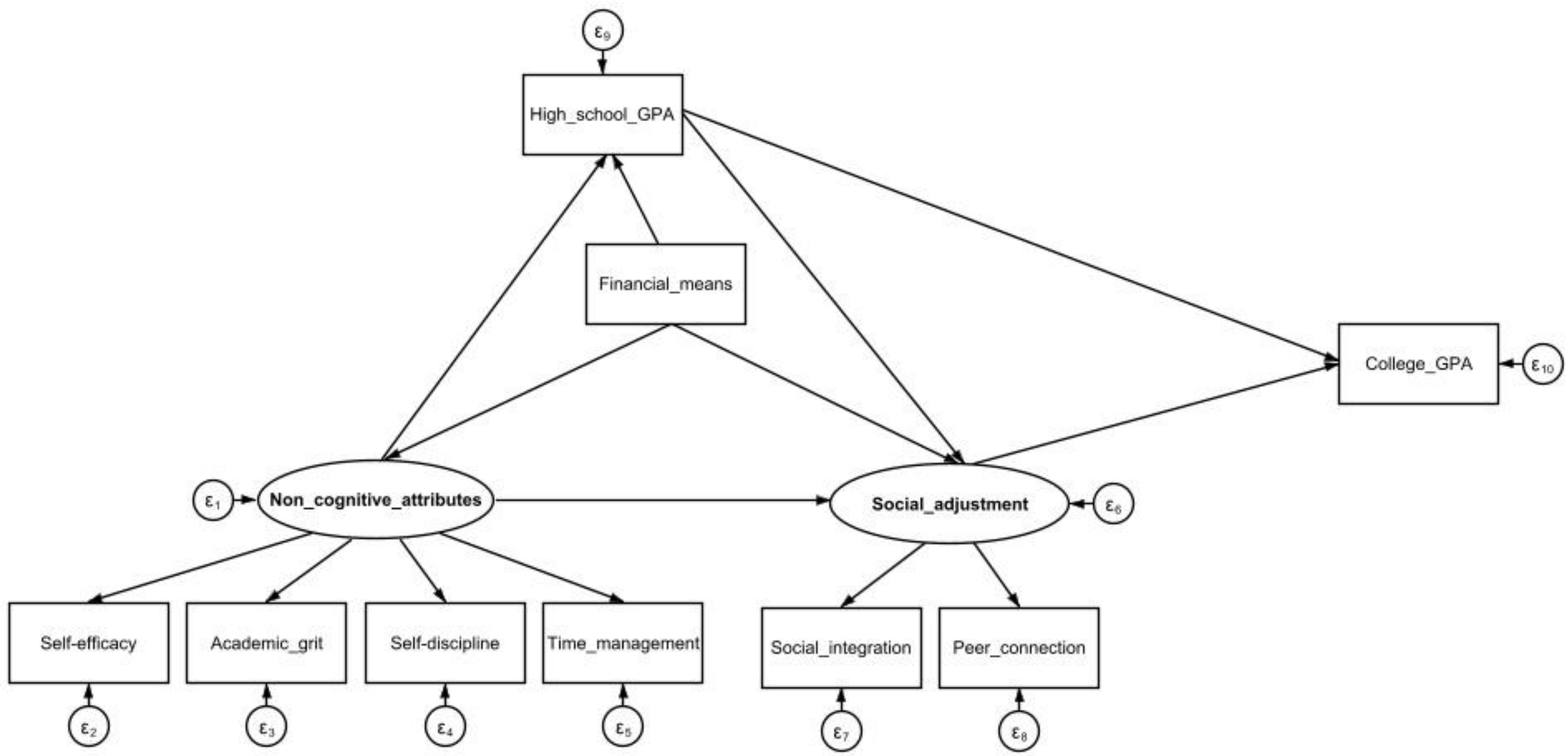


Figure 4. Three-factor structural equation model based on the Bowman model (2019)

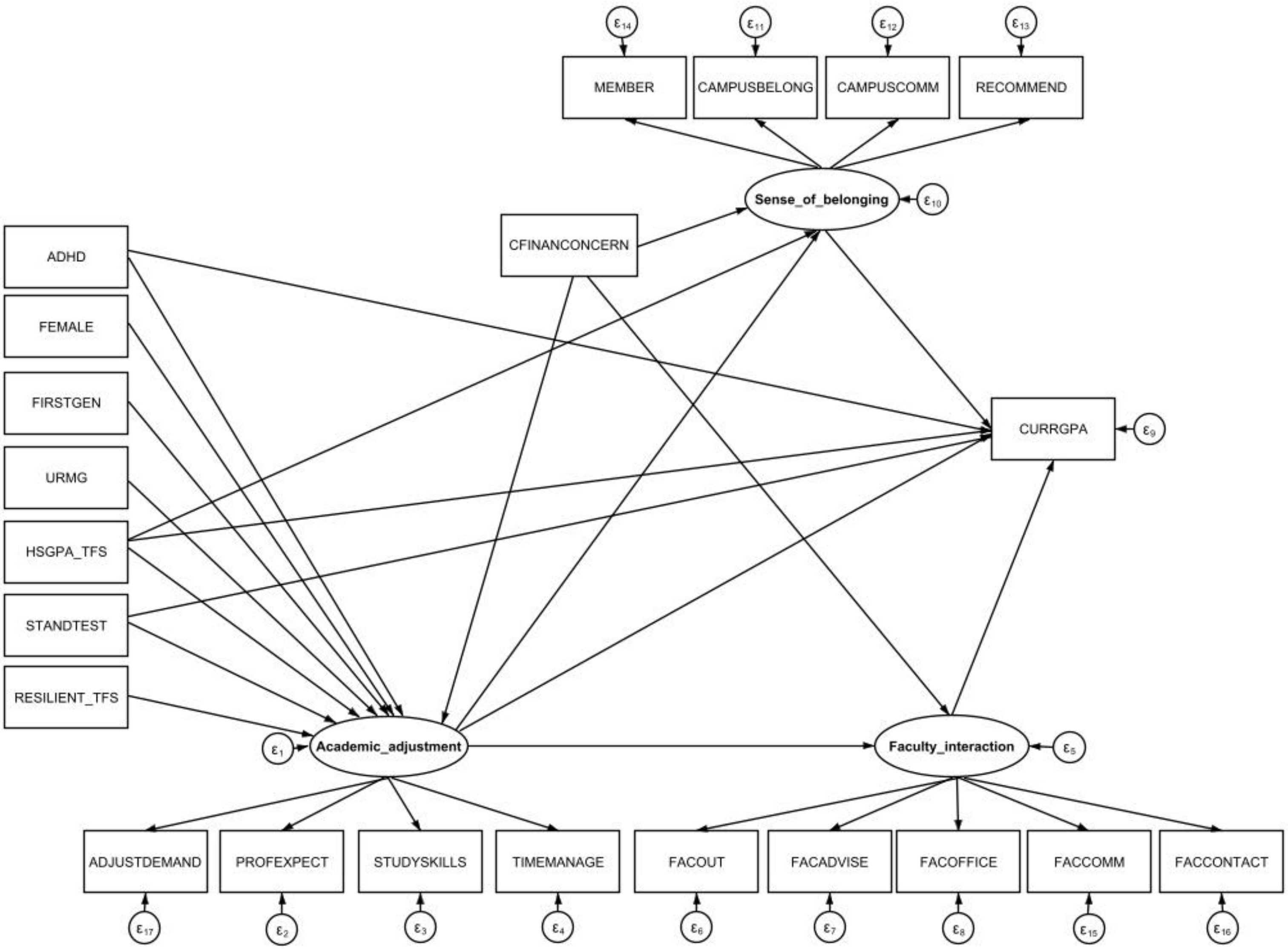
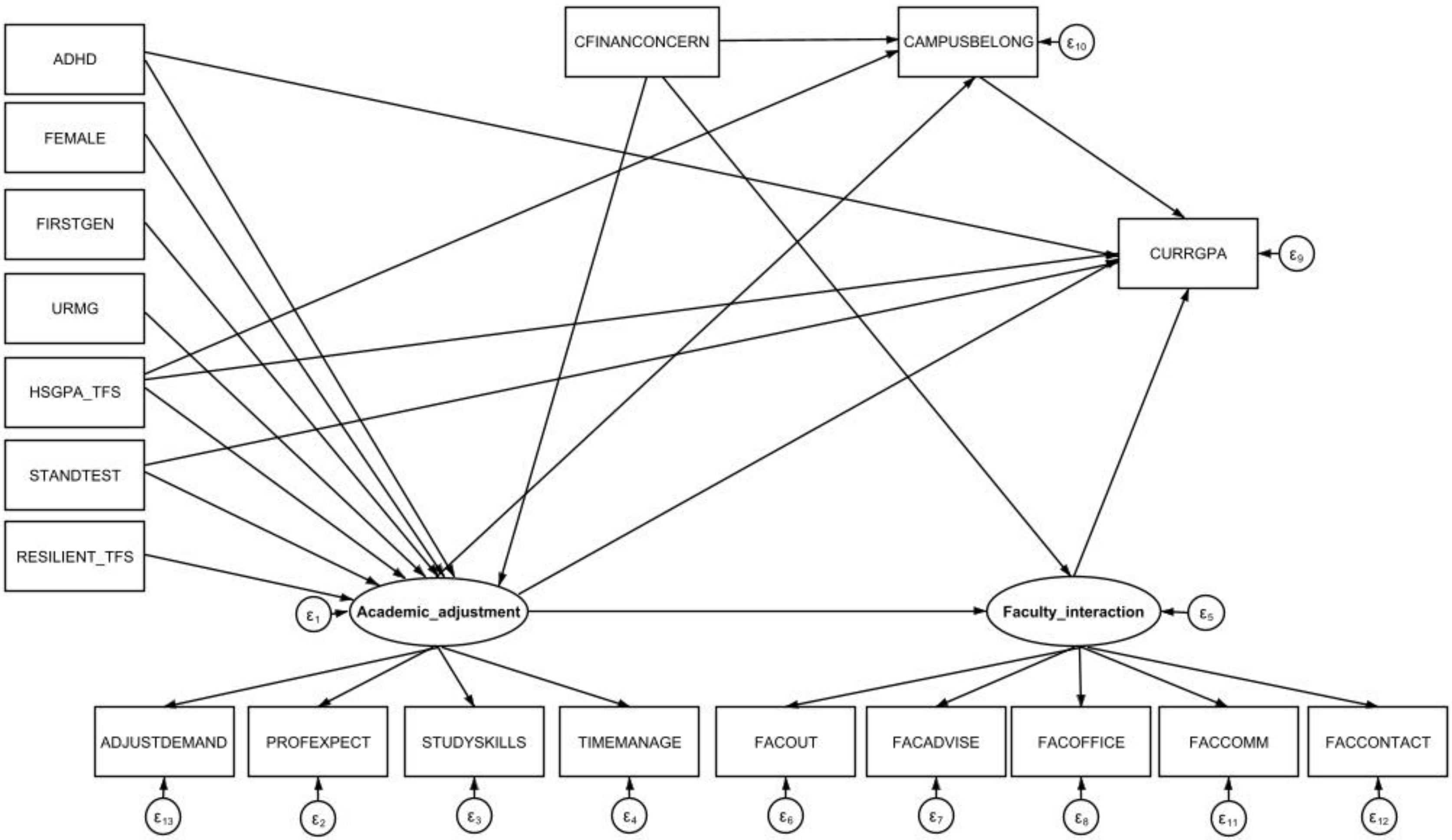


Figure 5. Two-factor structural equation model based on the Bowman model (2019)



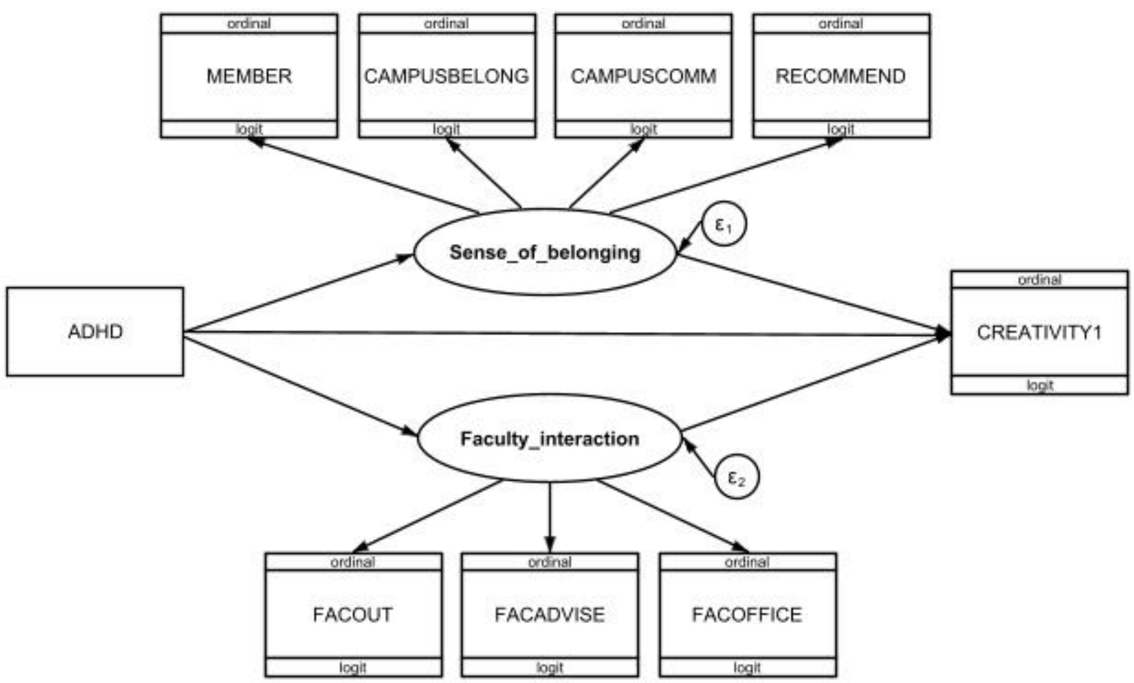
Furthermore, I added pre-college characteristics and experiences variables in addition to *high school GPA* based on my conceptual framework. I added pre-college characteristics and experiences variables: *FEMALE*, *FIRSTGEN*, *URMG*, *STANDTEST*, and *RESILIENT_TFS*, connecting them to *academic adjustment*. I added a path connecting *STANDTEST* to *CURRGPA*, consistent with the other pre-college academic preparation variable, *HSGPA_TFS*. I also included a path from *ADHD* to the academic success outcome variables, enabling mediation analysis.

Lastly, I adapted the model to account for the time progression of HERI variables and structural equation modeling's causal nature (Kline, 2016). I reversed the direction of the path between *academic adjustment*, a college-level factor, and *high-school GPA,* a pre-college variable because students' academic adjustment in college cannot predict their high school GPA. Bowman and coauthors' rationale for predicting high school GPA with a college-level measure was that this measure is expected to remain constant. For many students, pre-college academic adjustment indicators may differ from college indicators because students often receive less parental support in college compared to high school. Therefore, students' time management in high school (and likely the resulting higher grades) may be supported by their parents and not reflective of their time management in college. Parental support may play a substantial role for students with ADHD (Fleming & McMahon, 2012; Stevens et al., 2023). For this reason, using a college-level measure of academic adjustment to predict high school grades is problematic for this study. Instead, I hypothesize high school GPA, in part, predicts college-level academic adjustment, consistent with the hypothesis of Gormley and coauthors (2019). Similarly, I did not include the path from *financial means* (the proxy for this study is concerned about financing college) to *high school GPA*.

4.4.1.1.2 *Creativity.*

I hypothesized SEMs for the academic outcome, *creativity*, starting with my conceptual framework, based on Terenzini and Reason's (2005) college impact model. I explored three models: one included only one of the pre-college characteristics and experiences variables, whether a student had a previous ADHD diagnosis (Model 1), and two included four of those variables (Model 2 and 3; *ADHD*, *FEMALE*, *FIRSTGEN*, *URMG*). Within college experience, I included two college experience latent variables, *faculty interaction* and *sense of belonging*. Figure 6 shows Model 1. Model 2 includes the three other pre-college characteristic variables and Model 3 adds direct paths from all of the pre-college characteristics to the creativity outcome, instead of only a direct path from one pre-college variable, *ADHD*, as in Model 2.

Figure 6. Model 1 hypothesized structural equation model with the creativity academic outcome



4.4.1.1.3 *Specified Measurement Model.*

I employed confirmatory factor analysis (CFA) to assess the underlying structure of the measurement model within my hypothesized SEMs. *Faculty interaction, academic adjustment,* and *sense of belonging* form simple structure (i.e., indicator items load on only one latent factor) two- and three-factor measurement models in the specified SEMs in Figure 4, Figure 5, and Figure 6. Confirmatory factor analysis enabled model fit testing with my empirical data by comparing the model-implied and observed covariance matrices (Bauer & Curran, 2022). This enables a preliminary assessment of how the measurement model fits the experimental data and later the identification of the source of model misspecification (i.e., identifies if the model misspecification arises from the measurement or structural component of the SEM).

The categorical nature of the latent factors' indicator variables had implications for the estimator used in CFA. To use a maximum likelihood estimator, Curran and Bauer (2022) recommend that ordinal variables have at least five response categories, with responses distributed across categories. The *academic adjustment*, *faculty interaction*, and *sense of belonging* indicator variable response distributions are provided in Table 11. The *academic adjustment* indicator variables each had four response categories. "Somewhat difficult" and "somewhat easy" typically had the largest number of responses, with fewer responses in the "very difficult" and "easy" categories. The *ADJUSTDEMAND* indictor variable (skewness = 0.017, zero-normed kurtosis = -0.663) response distribution differed from this trend. Three *faculty interaction* indicator variables had six response categories, with responses distributed relatively evenly across categories and, therefore, could likely be treated as continuous. However, two *faculty interaction* indicator variables had fewer response categories: asked a professor for advice (*FACADVICE;* skewness = 0.000, zero-normed kurtosis = 0.363) and satisfied with the amount of faculty contact (*FACCONTACT;* skewness = -0.913, zero-normed kurtosis = 2.200). The *sense of belonging* indicator variables had four response categories, and the responses tended toward “agree” and “strongly agree.” Skewness values were approximately -0.5 to -0.6 and zero-normed kurtosis values were slightly less than 1. In summary, some of the latent variables’ indicators could be treated as continuous (e.g., *FACOUT* [skewness = 0.606, zero-normed kurtosis = 0.451] and *FACOFFICE* [skewness = 0.561, zero-normed kurtosis = 0.217]), allowing the appropriate use of a maximum likelihood estimator (Curran & Bauer, 2022; Kline, 2016); in contrast, others are more appropriately treated as discrete (e.g., *TIMEMANAGE* and *STUDYSKILLS*).

For CFA, I decided to use maximum likelihood estimation because of (1) the preliminary nature of this step and (2) the availability of Stata’s post-estimation commands. Fit and modification indices are only calculated following the SEM command, not the generalized SEM command (`gsem`, which models discrete outcomes; StataCorp., 2021a). I tested the consistency of the data with two of the hypothesized measurement models: the two-factor model with *faculty interaction* and *academic adjustment* (Figure 7) and three-factor model with *faculty interaction, academic adjustment,* and *sense of belonging* (Figure 8). To do this, I standardized the latent variables by setting the variances to one and the means to zero (Bauer & Curran, 2022).

Table 11. Distributions of indicator items for academic adjustment, faculty interaction, and sense of belonging constructs

Academic adjustment		Very difficult	Somewhat difficult	Somewhat easy	Very easy	
Understand what your professors expect of you academically (*PROFEXPECT*)		465	6,342	22,528	11,516	
Manage your time effectively (*TIMEMANAGE*)		3,788	15,567	15,316	6,160	
Develop effective study skills (*STUDYSKILLS*)		2,017	12,310	19,146	7,381	
Adjust to the academic demands of college (*ADJUSTDEMAND*)		2,077	12,327	17,581	8,852	
Faculty Interaction	Never	1 or 2 times/term	1 or 2 times/week	Once a week	2 or 3 times a week	Daily
Interact with faculty outside of class or office hours (*FACOUT*)	11,353	12,477	9,664	6,079	3,447	975
Interact with faculty during office hours (*FACOFFICE*)	3,984	14,957	12,862	7,121	3,916	1,223
	Not at all	Occasionally	Frequently			
Asked a professor for advice after class (*FACADVISE*)	7,657	25,017	7,657			
	No	Yes				
Communicated regularly with your professors (*FACCOMM*)	11,117	21,814				
	Can't rate/no experience	Very dissatisfied	Dissatisfied	Neutral	Satisfied	Very satisfied
Satisfaction with the amount of contact with faculty (*FACCONTACT*)	256	254	1,466	9,753	19,782	7,296
Sense of belonging		Strongly disagree	Disagree	Agree	Strongly agree	
I feel I am a member of this college. (*MEMBER*)		902	3,741	23,432	11,160	
I feel a sense of belonging to this campus. (*CAMPUSBELONG*)		1,400	5,756	22,905	9,174	
I see myself as part of the campus community. (*CAMPUSCOMM*)		1,048	4,891	24,457	9,130	
If asked, I would recommend this college to others. (*RECOMMEND*)		990	3,166	18,187	17,039	

I considered relative and absolute fit indices in evaluating the overall model fit. I report the chi-square test results; however, because of my very large sample size (n = 27,288 - 43,523), I focus on the fit indices for model evaluation. Generally, a significant ($p < .05$) model chi-square indicates the data does not fit the hypothesized model well, but larger sample sizes increase the chi-squared test statistic (Kline, 2016). For the relative fit indices, I followed general guidelines from Hu & Bentler (1995): Comparative Fit Index (CFI > .90, .95 preferred) and Tucker Lewis Index (TLI > .90 at minimum, .95 preferred). For the absolute fit indices, I used the root mean square error of approximation (RMSEA; <.01 is excellent, <.05 is good, and .08 is moderate; MacCallum et al., 1996) and standardized root mean square residual (SRMR; < .10 preferred; Kline, 2016).

In cases where a model modification aligned with theory, I respecified the model a single change at a time, prioritizing the largest modification indices (MI; Bauer & Curran, 2022) and the expected parameter change (EPC; Kline, 2016; Saris et al., 2009) in combination to identify potential model misspecifications. MIs estimate the change in the model chi-squared statistic if a path between two variables was not omitted (Bauer & Curran, 2022). The unstandardized and standardized EPC estimate the change in the unstandardized or standardized, respectively, parameter if it was not omitted from the model (Whittaker, 2012). Modification indices and EPCs provide empirical information about potential model misspecifications (Kline, 2016). Modification indices of greater than 3.84 are significant (Saris et al., 2009), but based on recommendations by Curran and Bauer (2022), I concentrated on those larger than 10. For EPCs, I prioritized values above 0.1 (for high power; Saris et al., 2009), and particularly those above 0.2 (Kline, 2016).

Figure 7. The hypothesized two-factor measurement model

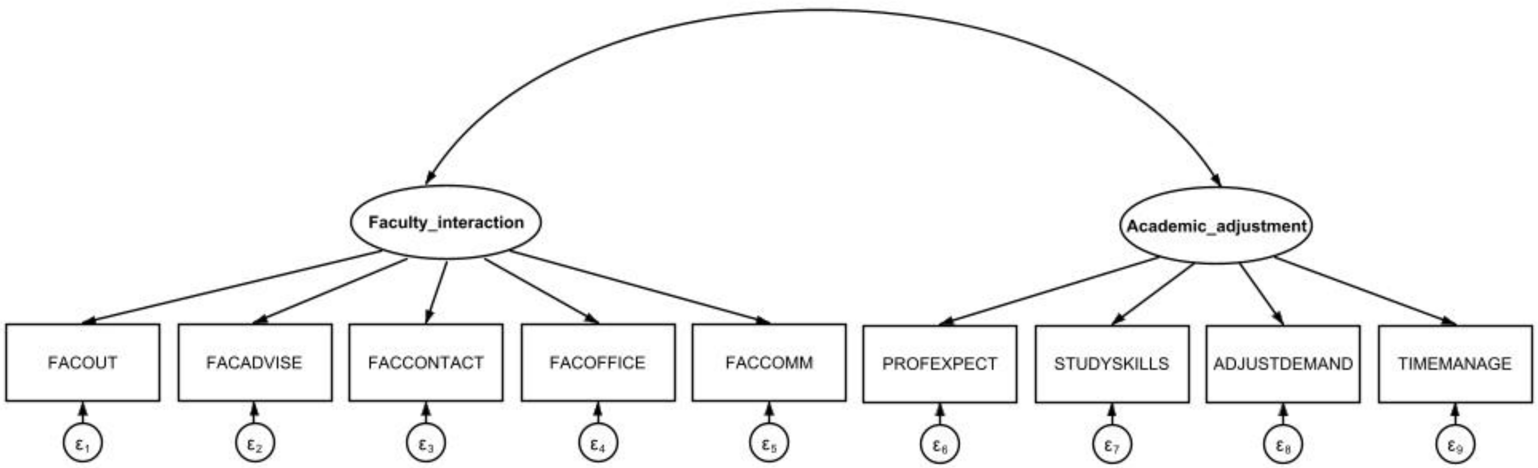
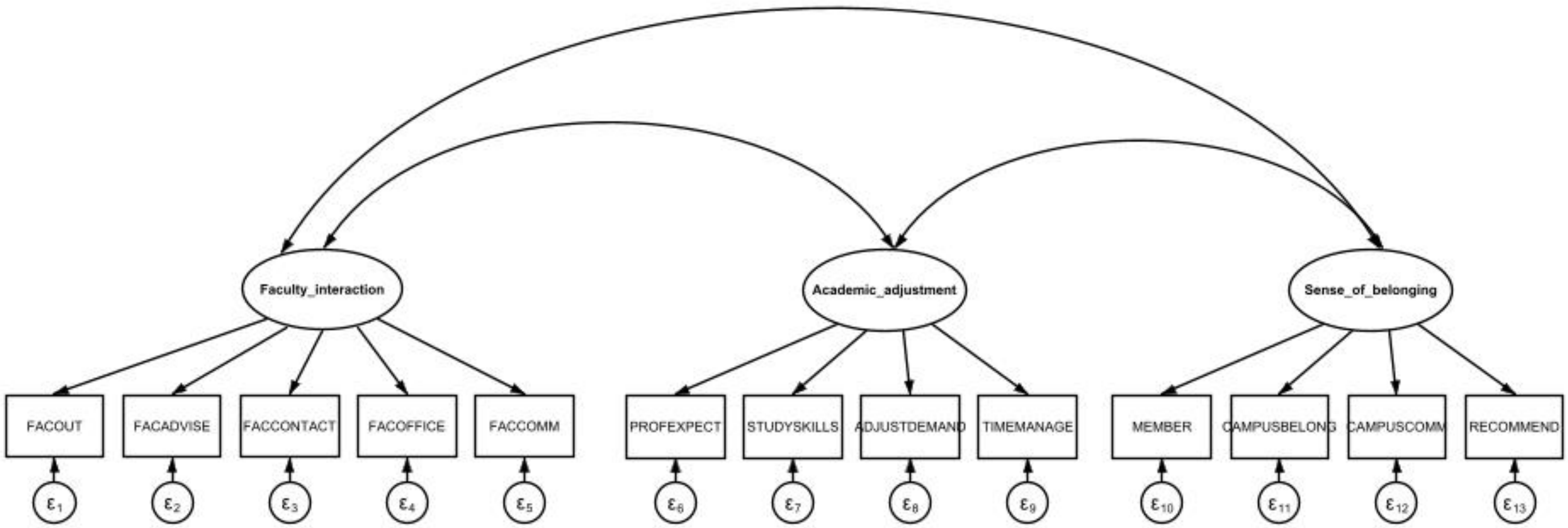


Figure 8. The hypothesized three-factor measurement model



I confirmed the final two-factor and three-factor measurement models using random subsets of the data set (5%, n = 2,296, two-factor model only; 10%, n = 4,592) to assess the magnitude of the ratio of degrees of freedom to chi-square statistic and the significance of the resulting p-values. Additionally, I used these analyses to confirm the relative and absolute fit indices for smaller sample sizes.

After evaluating the fit of the measurement model, I conducted SEM for the two outcome variables, *CURRGPA* and *CREATIVITY1*, following the remaining steps outlined by Kline (2016) and Curran and Bauer (2022): model identification, model estimation, model evaluation, and model respecification.

4.4.1.2 Model Identification.

I used the two-step identification rule to verify that the hypothesized model was identified (Kline, 2016). First, each factor of the measurement component had three indicators and therefore passed the first step of the rule. Second, the path model's structural component was recursive and consequently passed the second step. The two-step rule is a sufficient condition, positively indicating a model is identified (Kline, 2016).

4.4.1.3 Model Estimation.

In model estimation, similar to in CFA, I used a maximum likelihood estimator and set the scale of latent factors by setting the means of the latent variables (α) to zero and the variances (ψ) to one, using Stata's `sem` command (StataCorp., 2021) to build the models depicted in Figure 4 and 6. I also used Stata's `gsem` command and the `ologit` option in estimating the two-factor model to compare a more appropriate method for discrete indicator variables to build the models depicted in Figure 5 and 7.

4.4.1.4 Model Evaluation.

I subjected my hypothesized model to falsification and used the chi-square test and absolute (RMSEA and SRMR) and relative (CFI and TLI) fit indices for evaluation, following previously described procedures (see 4.4.1.1.3 Specified Measurement Model).

4.4.1.5 Model Respecification.

I considered theory, MIs, EPCs, and standardized EPCs in respecifying the model. Similar to model evaluation, I used previously described procedures (see Methods: CFA).

4.4.2 Mediation analysis.

A mediating variable or mediator explains the relationship between an independent and dependent variable (Baron & Kelly, 1986). This relationship is causal in nature, providing an explanation for the mechanism underlying the relationship between an independent and dependent variable. The mediator accounts for the indirect relationship among the variables, and a mediation analysis determines the strengths of these relationships or the degree of mediation. Here, I conduct a mediation analysis in considering the mediating effect of college experiences.

A schematic depicting the mediating relationship (Baron & Kelly, 1986) between college experiences on ADHD and academic success outcomes is shown in Figure 9. The direct and indirect effects of the hypothesized SEM are illustrated in Figure 10. All three indirect paths go through the *academic adjustment* construct. I obtained standardized errors and confidence intervals using the delta and the bootstrap method with 200 replications and a seed of 691 (Bauer & Curran, 2022; UCLA Statistical Methods and Data Analytics, n.d.).

Figure 9. Schematic of mediating relationship of academic success

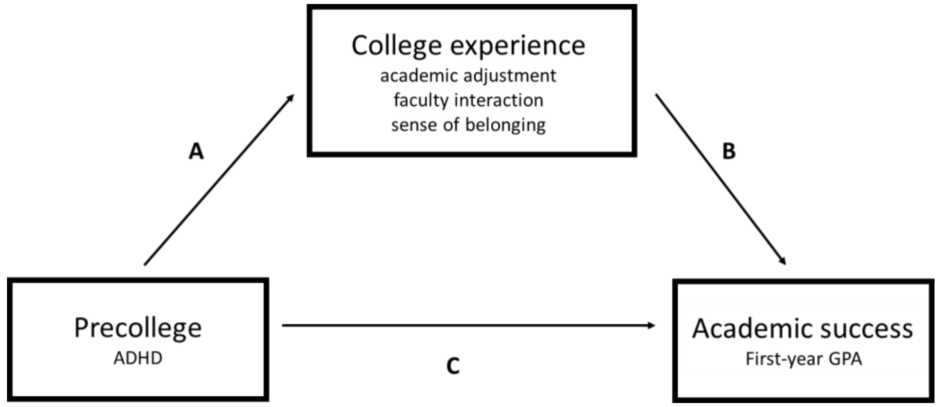
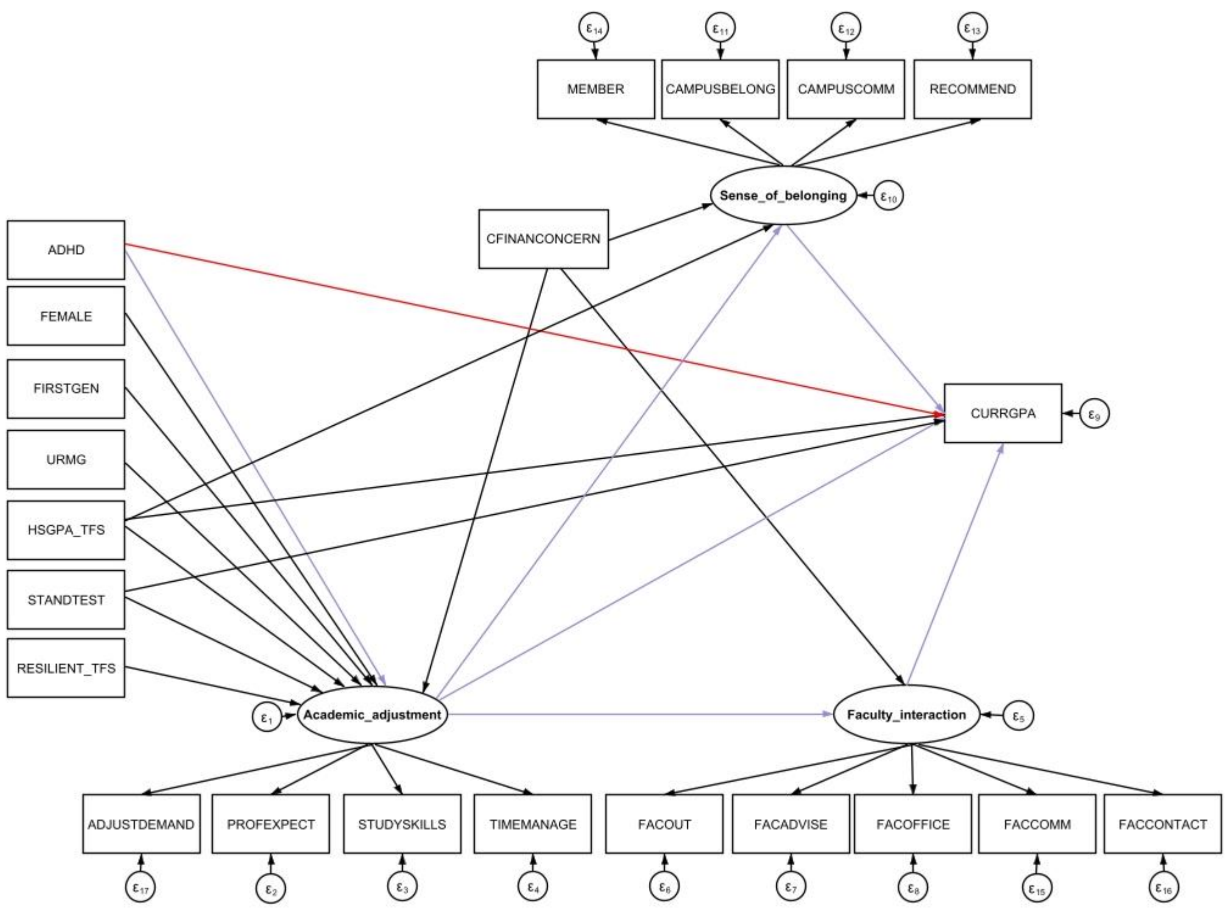


Figure 10. Direct (red) and indirect (lavender) paths in the hypothesized SEM model



4.5 Limitations

There are several limitations within this analysis. They are discussed as they relate to the sample, data, and statistical methods.

4.5.1 Sample.

The sample data may not adequately represent the population of U.S. college students or the participating higher education institutions' student population, limiting the generalizability of these results. First, not all U.S. higher education institutions administer the TFS to their students, and an even smaller fraction of institutions administer the TFS *and* the YFCY (HERI, n.d.a, n.d.b). Institutions of Carnegie classification Large R1: Doctoral Universities (Indiana University Center for Postsecondary Research, 2023) often do not administer both surveys, so students enrolled at those institutions are potentially underrepresented in the data compared to the population of U.S. college students and attend one of a few R1 institutions.

Educational data from the National Center for Education Statistics (NCES; 2016) provides a comparison of the demographics of undergraduate students in this study and the U.S. In this study, female students accounted for 61.1% (n = 29,899) of respondents, and students part of underrepresented racial/ethnic groups accounted for 23.1% (n = 10,624) of respondents. Females are slightly overrepresented in our sample compared to 55.8% of undergraduate female students at four-year institutions in 2012 (Snyder et al., 2014). Students identifying as part of underrepresented racial/ethnic groups are underrepresented in our sample compared to 32.8% of students part of underrepresented racial/ethnic groups at 4-year public and not-for-profit institutions in 2013 (Snyder et al., 2014).

If students with a previous ADHD diagnosis are less likely to complete the TFS and YFCY surveys than students without an ADHD diagnosis, this has the potential to introduce selection bias. The Institute of Education Sciences reported that 19% of undergraduates across U.S. postsecondary higher education in the 2015-2016 school year had a disability of some type (Institute of Education Sciences: National Center for Education Statistics, 2018). It is more difficult to determine the percentage of students with ADHD. In the 2011-2012 school year, college students with ADHD accounted for 21.8% of students with a disability, 27.7% were males and 17.7% were females (Hinz et al., 2017). Assuming these percentages are consistent across years, approximately 4% of college students were students with ADHD (e.g., 19% of college students have a disability, and 21.8% of those have ADHD). This is consistent with the 4.5% of college students diagnosed with ADHD in the data set (Table 1).

4.5.2 Data.

Another limitation of this study is that it does not include persistence as an outcome because HERI data sets are not designed to support studying college persistence. The data in this study does not include students who dropped out of post-secondary school or transferred to another institution during their first year. Students who drop out of school before the end of their first year would not take the second survey (the YFCY), and students who transfer to another institution change student identification (id) numbers. HERI creates longitudinal data by matching student id numbers, preventing the matching of transfer students' responses. Therefore, I only explored the academic success outcomes (first-year grades and creativity) of students who persisted through their first year at the same college at which they began.

Using self-reported measures for ADHD and creativity may also result in limitations. Some students with ADHD may have chosen not to self-report their diagnosis, and others with ADHD may not receive a diagnosis until they are in college or later. Furthermore, students from certain sociodemographic groups are less likely to receive a diagnosis than other students (Chung et al., 2019; Coker et al., 2016; Morgan et al., 2013). Additional factors may influence the academic success of students with ADHD, such as medication use (Henning et al., 2022). One study found that students' use of medication (to treat ADHD) did not associate with higher grades (Advokat et al., 2011) but another study found that it did positively relate to college persistence (DuPaul et al., 2021). Another limitation is that this study uses data from self-reported measures. Students' self-rating of their creativity may not accurately reflect their measured creativity, and they may not accurately report their average first-year grades (*CURRGPA*).

Lastly, the data used in this study does not contain a measure of short-term motivation or instructional practices. Therefore, I could not include short-term motivation in my first-year grades SEMs. Although these measures are not typically included in theoretically-based student retention or academic success models (Bowman et al., 2019; van Rooij et al., 2017), they are potentially relevant for students with ADHD (Morsink, 2022) and without ADHD. Their absence has the potential to result in omitted variable bias or, in other words, bias the regression coefficients (Wilms et al., 2021) and lead to under- or over-estimates of mediation.

4.5.3 Statistical Methods.

Using SEM, I assumed that the measures and constructs were psychometrically valid and reliable. For example, the proxy for resilience (*RESILIENT_TFS*) is a manifest variable indicating whether a student accepts mistakes as part of the learning process but this proxy for resilience is not necessarily a valid measure of resilience. HERI developed the *academic adjustment*, *faculty interaction*, and *sense of belonging* constructs using exploratory factor analysis using a polychoric correlation matrix (n.d.d). Although HERI provides scale scores using item response theory (IRT), recommendations suggest including the original indicator items in SEM instead of conducting path analysis using scale scores (Bauer & Curran, 2022). I addressed this limitation using CFA with my specific data set to verify the constructs and remove poorly functioning items.

I used academic success manifest variables instead of latent variables, and this has the potential to bias coefficients and standardized errors (Bauer & Curran, 2022). The academic success outcomes, first-year grades and creativity, are measured with a single variable and had errors associated with their measurement. However, manifest variables are assumed to be measured without error in SEM. To overcome this limitation, future analyses could include latent variables for academic success instead of manifest variables.

The constructs or latent variables had items with ordinal response scales yet, in some cases, I treated them as continuous. Some of these items are on a 6-point Likert scale and treating them as continuous in an SEM analysis is appropriate (Curran & Bauer, 2022). The response scale of other items was a 3- and 4-point Likert scale or ordinal in nature. In several of my SEM analyses, I treated these variables as continuous by using a maximum likelihood estimator, which may result in biased estimates for coefficients and standard errors (Bauer & Curran, 2022). I addressed this limitation by providing a comparative analysis using Stata's generalized SEM command (`gsem`), which appropriately handles ordinal variables, for the two-factor analysis. This comparison suggested that the path coefficient estimates provided by maximum likelihood are reasonable approximations suitable for mediation analysis; however, the statistical significance of one of the minimally contributing mediating pathways differed.

Lastly, the HERI data set contained missing data, particularly for the college experience and academic success variables. Furthermore, some of the variables with missing data likely were missing not at random (MNAR), which makes handling missing data more complicated

(Allison, 2002). To address this limitation, I thoroughly analyzed the missing data, identified the missing data mechanism, and screened potential auxiliary variables. As recommended by Allison (2002), I filled in missing data using multiple imputation and used auxiliary variables in the multiple imputation process (Enders, 2022). Furthermore, I estimated the SEM parameters multiple way: listwise deletion and with multiply imputed data. In both cases, the SEM parameters were similar in sign and magnitude.

4.6 Summary

In summary, I initially assessed the data and filled in missing data using multiple imputation. For the first-year grades SEMs, I started from the Bowman Model and for creativity SEMs, I started from a model based on my conceptual framework. Then, I assessed the fit of the measurement model and made theoretically-supported modifications. Next, I assessed the fit of the SEMs and again made theoretically-supported modifications. The results are presented in the next section and are organized to correspond with this Methods section. Study limitations include uncertainty regarding whether the data set is representative of U.S. college students, the inability to measure persistence, and the appropriateness of the statistical methods for discrete measures.

Chapter 5 Results

Structural equation modeling (SEM) is a causal analytical method in which a theoretically-based model is specified (hypothesized), and then the model fit to the data is estimated and evaluated (Bauer & Curran, 2022; Kline, 2016). These models can therefore depict the causal nature of the relationships between students' pre-college experiences and characteristics, college experience, and academic outcomes. SEM also enables mediation analysis (Bauer & Curran, 2022) to understand the underlying mechanism or mediating role of students' college experience on academic outcomes.

SEM combines a structural model, such as linear regression or path analysis, with a measurement model, comprised of latent variables that measure underlying, unobservable constructs using multiple observable measures or indicator variables (Bauer & Curran, 2022). Latent variables enable the measurement of constructs, such as *academic adjustment* and *sense of belonging*, that are not directly measurable (Watkins, 2022).

In this chapter, I present the results of multi-step SEM analyses for two academic success measures, *first-year grades* and *creativity*. The first steps in the SEM estimation process are to specify and identify the model (Bauer & Curran, 2022; Kline, 2016), which I described in the Methods section. For first-year grades, I specified two- and three-factor models based on my conceptual framework and the Bowman model (Bowman et al., 2019; Figure 4 and Figure 5). For creativity, I specified a two-factor model based on my conceptual framework and a college impact model (Terezini & Reason, 2005; Figure 6).

I then present my confirmatory factor analysis (CFA) to evaluate the measurement component of these previously specified models. CFA identified several model components that did not fit the data well, so I respecified (i.e., made theoretically consistent, minor changes to) the measurement model based on these empirical findings. I then modified the specified first-year grades and creativity models specified (Figure 4 and Figure 5) to incorporate these changes.

Next, I estimated the models and evaluated the results (Kline, 2016). I considered two-factor and three-factor (latent variable) models for first-year grades, whereas I considered only two-factor models for creativity. The estimation and evaluation steps for the first-year grades and creativity models varied because the appropriateness of the estimation technique depends on the indicator and outcome variable types, continuous or discrete (Kline, 2016). In some cases, I compared the results of several estimation techniques, capitalizing on their strengths and recognizing their limitations. This is described in detail later but summarized here. I used three estimation techniques for the first-year grades two-factor model: (1) maximum likelihood (ML) estimation, (2) ML estimation with multiple imputation, and (3) generalized SEM. I used two estimation techniques for the first-year grades three-factor model (1) ML estimation and (2) ML estimation with multiple imputation. I used a single estimation technique for the creativity model: (1) generalized SEM.

After estimation and evaluation is respecification (Bauer & Curran, 2022), which involves comparing the covariance matrix and the model-implied covariance matrix to empirically identify potential model modifications that would improve the model fit to the data. Modification indices and expected parameter changes enable an empirically-guided reconsideration of theory; respecifying the model must be done carefully and consistent with theory (Bauer & Curran, 2022).

Lastly, I conducted mediation analyses (Bauer & Curran, 2022) using latent college experience variables as mediators for academic success outcomes of first-year grades and creativity. These analyses identify the degree to which different aspects of the college experience (*academic adjustment*, *faculty interaction*, and *sense of belonging*) influenced the relationship between the pre-college characteristic of ADHD and the academic success outcomes.

This chapter is organized in the following manner. First, I summarize the descriptive statistics of students' pre-college characteristics and experiences and academic success outcomes in the data set. Second, I evaluate the data fit with the previously specified measurement model (using confirmatory factor analysis) and respecify the measurement model. Third, I present the SEM (model estimation, evaluation, and respecification) of the first-year grades models and the subsequent mediation analysis of the latent college experience variables. Lastly, I present the model estimation, evaluation, and respecification of the creativity model and the subsequent mediation analysis.

5.1 Descriptive Statistics

5.1.1 Pre-college Characteristics & Experiences.

Table 12 summarizes incoming students' pre-college characteristics and experiences in the data set (n = 45,915). Of these students, approximately 4.5% (n = 2,082) reported a previous ADHD diagnosis, 65.1% (n = 29,899) were females, 13.8% (n = 6,333) were first-generation college students, and 23.1% (n = 10,624) identified as part of an underrepresented racial/ethnic groups. The mean high school grade of these students was between a B+ and an A-, and students receiving an average high school grade between a B and an A+ fell within one standard deviation of the mean. The mean SAT or SAT-equivalent standardized test score was 1233.8, and the standard deviation was 164.3. Additionally, most incoming students responded that they frequently accepted mistakes as part of the learning process (a proxy for resilience; *n* = 24,974), and few answered that they never did (*n* = 937).

Table 12. Students' pre-college characteristics and experiences (n = 45,915)

Neurodiversity	No *n* (%)	Yes *n* (%)	Missing *n* (%)	
ADHD	41,656 (90.7)	2,082 (4.5)	2,177 (4.7)	
Sociodemographic				
Female	15,977 (34.8)	29,899 (65.1)	39 (0.1)	
First-generation college student	38,362 (83.6)	6,333 (13.8)	1,220 (2.7)	
Underrepresented racial/ethnic group	35,032 (76.3)	10,624 (23.1)	259 (0.6)	
Academic Preparation and Performance				
	μ	σ	Min	Max
Average high school grade	6.7	1.2	1	8
Standardized test score	1233.8	164.3	400	1600
Student disposition				
Resilience (accepts mistakes as part of the learning process)	Not at all	Occasionally	Frequently	Missing
	937 (2.0)	18,705 (40.7)	24,974 (54.4)	1,299 (2.8)

5.1.2 Academic Success.

Academic success outcome variables are from responses on the Your First College Year (YFCY) survey students completed at the end of their first year of college. Table 13 provides descriptive statistics for the academic success variables. Most students reported earning a B or higher average grade in college (*n* = 31,474), as measured for the most recently completed term. A few students (*n* = 242) reported not receiving college grades, so I excluded their responses from further analysis. Approximately 13.3% (*n* = 6,098) of students rated their creativity in the top 10% of students.

Table 13. Students' first-year academic success (n = 45,915)

What is your overall grade average (as of your most recently completed academic term)?		*n* (%)
Overall grade average (*CURRGPA*)	I did not receive grades in my courses	242 (0.5)
	D	353 (0.8)
	C	1,226 (2.7)
	C+	2,007 (4.4)
	B-	3,378 (7.4)
	B	7,459 (16.3)
	B+	7,719 (16.8)
	A-	9,109 (19.8)
	A or A+	7,187 (15.7)
	missing	7,235 (15.8)
Rate yourself on each of the following traits as compared with the average person your age. We want the most accurate estimate of how you see yourself.		
Creativity (*CREATIVITY1*)	Average or below	18,226 (39.7)
	Above average	16,682 (36.3)
	Top 10%	6,098 (13.3)
	Missing	4,909 (11.7)

5.2 Measurement Model

SEMs can have a measurement and a structural component, and the measurement component is comprised of latent and indicator variables (Kline, 2016). Separately evaluating the previously specified measurement model fit can help identify the source (measurement or structural) of any SEM model misspecifications (Bauer & Curran, 2022). As a preliminary step to SEM, I explored the fit of the measurement model with two (*academic adjustment* and *faculty interaction*) and three (*academic adjustment*, *faculty interaction*, and *sense of belonging*) latent variables. I first considered the correlation matrix of the 13 indicator variables (i.e., the latent variables' measured variables); second, the estimation and evaluation of the CFA; and third, empirically-guided, theoretically-consistent respecifications of the measurement model. These are all steps before SEM.

5.2.1 Indicator Variables.

Table 11 shows the correlation matrix (using listwise deletion for missing cases) of the 13 indicator variables for the three latent variables of *academic adjustment*, *faculty interaction*, and *sense of belonging*. Weak correlations are those less than .40, moderate between .40 to .59, and strong between .60 and .79 (Akoglu, 2018). Spearman's correlations (r_s) among the four *academic adjustment* indicators ranged from .33 to .64 (weak to strong), and the *sense of belonging* correlations ranged from .48 to .79 (moderate to strong). The five *faculty interaction* indicators had lower correlations (r_s = .24 to .48; weak to moderate). The *FACCONTACT* indicator variable weakly correlated with indicators of constructs other than *faculty interaction* (*PROFEXPECT*, r_s = .29; *sense of belonging* indicators, $r_s \geq .30$), suggesting the inadequacy of this item as a single latent variable indicator.

Table 14. Spearman correlations, r_s, for the three latent variables' indicator variables (n = 32,235; listwise deletion)

	Academic adjustment				Instructor-student interaction					Sense of belonging			
	PROFEXPECT	STUDYSKILLS	ADJUSTDEMAND	TIMEMANAGE	FACOUT	FACADVISE	FACOFFICE	FACCOMM	FACCONTACT	MEMBER	CAMPUSBELONG	CAMPUSCOMM	RECOMMEND
PROFEXPECT	1.00												
STUDYSKILLS	.45	1.00											
ADJUSTDEMAND	.43	.64	1.00										
TIMEMANAGE	.33	.61	.64	1.00									
FACOUT	.06	.08	.06	.06	1.00								
FACADVISE	.06	.09	.06	.05	.34	1.00							
FACOFFICE	.03	.08	.02	.05	.48	.37	1.00						
FACCOMM	.13	.15	.12	.10	.32	.36	.31	1.00					
FACCONTACT	.29	.23	.20	.16	.26	.29	.24	.36	1.00				
MEMBER	.19	.15	.14	.12	.14	.18	.12	.21	.37	1.00			
CAMPUSBELONG	.18	.15	.13	.12	.12	.16	.11	.19	.35	.79	1.00		
CAMPUSCOMM	.15	.13	.11	.10	.12	.16	.12	.18	.30	.66	.67	1.00	
RECOMMEND	.17	.11	.09	.07	.07	.11	.06	.16	.33	.58	.58	.48	1.00

5.2.2 Two-Factor Confirmatory Factor Analysis.

I evaluated the model fit of the specified two-factor (*faculty interaction* and *academic adjustment*) measurement model using CFA with listwise deletion (n = 32,542). The chi-square model test statistic provides "preliminary evidence" of model fit or lack thereof (Kline, 2016) and, for this model, indicated a lack of fit ($\chi^2(26) = 5824.61$, $p < .0001$). However, with high power due to large sample sizes, "trivial differences" can result in a significant chi-square test statistic (Kline, 2016, p. 265). Overall, the fit indices for the two-factor measurement model also suggested a borderline adequate model fit (CFI = .928; TLI = .900; RMSEA = .083, 90% CI [.081, .085], $p_{close} < .001$; SRMR = .061). CFI fell in the adequate range, and SRMR was in the preferred range. However, TLI was at the lower end of the adequate range, and the RMSEA was not within the moderate range.

To empirically identify the model misspecifications suggested by the lack of model fit and to guide theoretically-consistent model respecifications, I used a combination of modification indices (MIs), expected parameter changes (EPCs), and standardized expected parameter changes (SEPCs; Kline, 2016; Whittaker, 2012). When dictated by high MIs and SEPCs (see Methods), and only when consistent with theory (Bauer & Curran, 2022), I freely estimated parameters one at a time (i.e., modified the model by adding paths between variables).

In the specified measurement model, an omitted path from the *academic adjustment* to *FACCONTACT* had one of the largest MIs (1254.95) and a SEPC greater than 0.2 (0.206; EPC = 0.171). The high MI and SEPC indicate an improved model fit with the data with the addition of a path that connects *academic adjustment* and *FACCONTACT*. Adding this path would allow *FACCONTACT* to cross-load on the latent variables, *academic adjustment* and *faculty interaction*. Students' academic adjustment in college is likely related to their satisfaction with the amount of faculty contact; students highly adjusted to college academics may feel more comfortable with less faculty contact or may be more willing to reach out to faculty when academically necessary. I chose to drop *FACCONTACT* from the measurement model because of this cross-loading, plus the availability of four other *faculty interaction* indicator variables. Furthermore, *FACCONTACT* also had the lowest communality (h^2 = .2169) of the *faculty interaction* indicator variables.

I then estimated the respecified measurement model, and the fit improved, $\chi^2(19)$ = 2417.18, p < .0001, with a CFI of .967, and TLI of .951 (now in the preferred range). The RMSEA (.062, 90% CI [.060, .064], p_{close} < .001) shifted into the good range, and the SRMR

(.037) remained in the preferred range. Yet, as evident from the model chi-square test statistic, multiple large MIs remained, indicating additional potential model misspecifications. Allowing the residuals of *FACOUT* (frequency of interaction with faculty outside of class and office hours) and *FACOFFICE* (frequency of interaction with faculty in office hours) to covary had the largest MI (1,115.32) and SEPC (0.561; EPC = 0.474). Because the frequency of students' interactions with faculty during office hours (*FACOFFICE*) and outside of class and office hours (*FACOUT*) may relate to the amount of time the student has available outside of class (e.g., due to family or job responsibilities), I allowed these residuals to covary. This allows the unexplained variance of the two indicator variables to correlate and suggests a common cause or relationship between the two indicator variables distinct from the latent variables underlying construct (Bauer & Curran, 2022).

Estimating the respecified model resulted in $\chi^2(19) = 1375.85$, $p < 0.001$ and preferred fit indices (CFI = .981; TLI = .971; RMSEA = .048, 90% CI [.046, .050], $p_{\text{close}} = .925$; SRMR = .027). However, some MIs, EPCs, and SEPCs remained high, again suggesting additional model misspecification. Covarying residuals of the *academic adjustment* indicator variables' had the four highest MIs: *STUDYSKILLS* and *TIMEMANAGE* (MI = 617.749, EPC = -0.1002, SEPC = -0.4508), *TIMEMANAGE* and *ADJUSTDEMAND* (MI = 426.450, EPC = -0.083, SEPC = -0.323), *PROFEXPECT* and *STUDYSKILLS* (MI = 303.382, EPC = 0.0367, SEPC = 0.1310), and *TIMEMANAGE* and *PROFEXPECT* (MI = 635.063, EPC = -0.0565, SEPC = -0.1771). From these, I chose to drop the *ADJUSTDEMAND* because of the high magnitude of the SEPCs and because it is a more general measure of academic adjustment, not specific to a skill. Three *academic adjustment* indicator variables remained (two are necessary for model identification; Bauer & Curran, 2022).

The fit of the respecified measurement model fit improved (CFI = .991; TLI = .984; RMSEA = .033, 90% CI [.030, .036], p_{close} = 1.000; SRMR = .021), although the chi-square test statistic remained high, $\chi^2(12) = 435.27$, $p < 0.001$. The high MIs were for *academic adjustment* predictive of *FACCOMM* (MI = 191.256, EPC = 0.03928, SEPC = 0.0831) and the covariance of *PROFEXPECT* and *FACCOMM* residuals (MI = 162.724, EPC = 0.018, SEPC = 0.0793). Neither had a SEPC above 0.1. Consistent with these empirically-driven suggestions for model respecification, a theoretical relationship between communicating regularly with professors (*FACCOMM*), understanding professors' expectations (*PROFEXPECT*), and student's academic adjustment is plausible. Because of this potential cross-loading and the theoretical support for the cross-loading, I opted to drop *FACCOM* (h^2 = .3194) from the measurement model, allowing three *faculty interaction* indicator variables to remain.

Estimating the measurement model without *FACCOM* resulted in $\chi^2(7) = 85.32$, $p <$ 0.001 and excellent fit indices (CFI = .998; TLI = .997; RMSEA = .017, CI [.014, .020], p_{close} = 1.000; SRMR = .007). Thus, I did not make further changes. The four remaining MIs exceeding 10 (Bauer & Curran, 2022) indicated adding a covariance among error terms (*PROFEXPECT* and *FACOUT*, MI = 40.201, EPC = 0.0218; SEPC = 0.0328; *PROFEXPECT* and *FACOFFICE*, MI = 36.688, EPC = -0.0186, SEPC = -0.0320; *STUDYSKILLS* and *FACOUT*, MI = 19.174, EPC = -0.0151, SEPC = -0.0420); *TIMEMANAGE* and *FACADVISE*, MI = 20.022, EPC = -0.0085, SEPC = -0.0282). They all had EPCs less than 0.05, so I did not consider further model respecifications.

In the final measurement model, the two latent variables, *faculty interaction* and *academic adjustment*, each had three indicator variables, as shown in Figure 11 and Table 15. *Faculty interaction* predicts the frequency with which students interact with faculty during office hours (*FACOFFICE*), seek advice from faculty (*FACADVISE*), and interact with faculty outside of office hours and class (*FACOUT*). *Academic adjustment* predicts the ease with which students understand their professors' expectations (*PROFEXPECT*), manage their time (*TIMEMANAGE*), and rate their study skills (*STUDYSKILLS*). All indicators had factor loadings of .5 or larger, indicating they were adequate indicator variables (Watkins, 2022) for *faculty interaction* and *academic adjustment*.

Figure 11. Two-factor measurement model, standardized

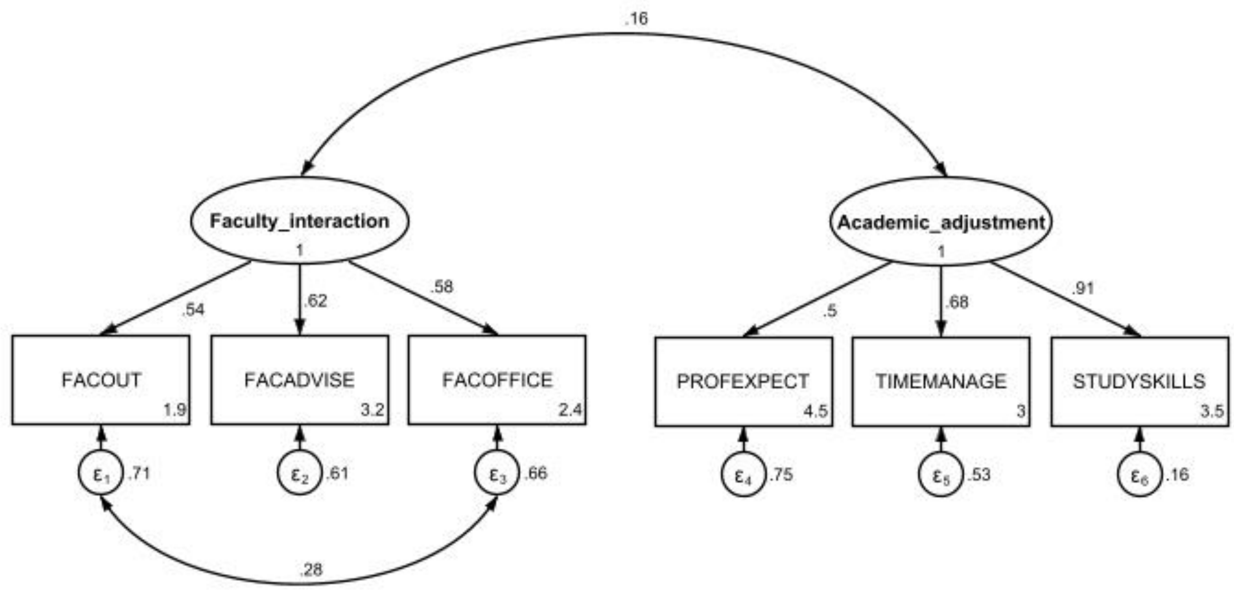


Table 15. Two-factor latent variable measurement model CFA, standardized

	Coefficient	Standard error	z	*p*	95% conf. interval	
ACADEMICADJUSTMENT						
PROFEXPECT	0.501	0.005	110.78	<.001	0.492	0.510
TIMEMANAGE	0.685	0.004	158.45	<.001	0.676	0.693
STUDYSKILLS	0.915	0.005	197.58	<.001	0.906	0.924
FACULTYINTERACTION						
FACOUT	0.543	0.017	32.73	<.001	0.510	0.575
FACADVISE	0.621	0.018	33.83	<.001	0.585	0.657
FACOFFICE	0.582	0.017	33.3	<.001	0.548	0.616
var(e.PROFEXPECT)	0.749	0.005			0.740	0.758
var(e.STUDYSKILLS)	0.163	0.008			0.148	0.181
var(e.TIMEMANAGE)	0.531	0.006			0.519	0.543
var(e.FACOUT)	0.705	0.018			0.671	0.742
var(e.FACADVISE)	0.615	0.023			0.572	0.661
var(e.FACOFFICE)	0.661	0.020			0.623	0.703
var(ACADEMICADJUSTMENT)	1.000	(constrained)				
var(FACULTYINTERACTION)	1.000	(constrained)				
cov(e.FACOUT,e.FACOFFICE)	0.277	0.020	13.86	<.001	0.238	0.316
cov(ACADEMICADJUSTMENT, FACULTYINTERACTION)	0.159	0.007	22.62	<.001	0.145	0.172

The ratio of the model chi-square to the degrees of freedom is high for the final measurement model. It is approximately 12, compared to the more generally accepted range of two to five for acceptable model fits (Hooper et al., 2008). However, the chi-square test statistic, and therefore this ratio, increases with sample size (Bauer & Curran, 2022; Hooper et al., 2008; Kline, 2016). The large sample size is likely a substantial contributor to the large chi-square statistic and this higher-than-expected ratio. In other words, the high ratio does not necessarily indicate a poor model fit but instead results from the sample's high power and ability to identify "trivial" model misspecifications (Kline, 2016, p. 265). For the two-factor measurement model, I attributed the significant *p*-value and high degrees of freedom to the chi-square test statistic ratio to the large sample size (n = 45,915).

For models with high modification indices, a high ratio of degrees of freedom to the chi-square test statistic, or a significant *p*-value, Kline (2016) recommends a more thorough investigation. To more thoroughly investigate this, I conducted a statistical exercise using CFA to explore the role of sample size on the *p*-value and ratio of chi-square to degrees of freedom. I verified my model respecification decisions by conducting CFA using random subsets of 5% (n = 2,296) and 10% (n = 4,592) of the original sample. In both cases, this resulted in two-factor measurement models with a structure identical to Figure 11. The ratios of the degrees of freedom to chi-square test statistic decreased to approximately 1 and 2.5 (p = .0129), respectively. This exercise provided additional support of an adequate SEM fit with the data set.

5.2.3 Three-Factor Confirmatory Factor Analysis.

In specifying the three-factor measurement model, I added the *sense of belonging* latent variable to the two-factor model in Figure 11. Then, I estimated and evaluated the model fit. The chi-square statistic, $\chi^2(31) = 1117.03$, $p < 0.0001$, from the CFA suggested a lack of model fit, whereas the fit indices indicated the opposite (CFI = .992; TLI = .989; RMSEA = .030, CI [.029, .032], p_{close} = 1.000; SRMR = .027). The omitted path between *sense of belonging* and *PROFEXPECT* had the largest MI (591.129) and a SEPC of greater than 0.1 (0.1197, EPC = 0.0821). This suggests that allowing *PROFEXPECT* to cross-load on two latent variables, *academic adjustment* and *sense of belonging*, would improve the model fit. The covariance of the *STUDYSKILLS* and *TIMEMANAGE* residuals exhibited the second-largest MI (469.791) and a very large SEPC (1.767; EPC = 0.3754). This may suggest that *TIMEMANAGE* and *STUDYSKILLS* share variance unrelated to *academic adjustment*, such as a student's lack of interest in their academics. Because of this, I chose to allow the residuals of *STUDYSKILLS* and *TIMEMANAGE* to covary.

After this, I did not further respecify the model because the fit indices suggested an excellent model fit, and the MIs/SEPCs did not dictate further theoretically-supported changes to the model. Figure 12 and Table 16 show the final three-factor measurement model. The chi-square model test statistic, $\chi^2(30) = 614.64$, $p < .001$, is significant, whereas the fit indices suggested a preferred model fit (CFI = .996; TLI = .994; RMSEA =.023, CI [.021, .024], p_{close} = 1.000; SRMR = .013). The largest MI was for the omitted covariance of *PROFEXPECT* and *RECOMMEND* residuals (MI = 205.155, EPC = 0.025, SEPC=0.095), followed by *PROFEXPECT's* cross-loading with *faculty interaction* (MI = 96.283, EPC = -0.0585, SEPC = -0.0852) and *sense of belonging* (MI = 96.284, EPC = 0.1545, SEPC = 0.2252).

Like the two-factor measurement model, I verified the three-factor measurement model respecification decisions with a statistical exercise using a subset of my sample. A CFA with a 10% subsample resulted in the same paths as the model shown in Figure 12. The ratio of the chi-square test statistic to the degrees of freedom was approximately three ($p < .001$). Further decreasing the subsample size (n = 972) resulted in an increased, but still significant, p-value (.0228). This exercise indicates that the high ratio of the chi-square test statistic to the degrees of freedom is attributable to the large sample size, and not a poor model fit.

5.2.4 Summary.

This set of CFAs investigated the fit of the two- and three-factor measurement models of the specified SEMs. After minor model respecifications consistent with theory, the two- and three-factor measurement models fit the data well; the fit indices fell in the preferred range. A thorough analysis of the chi-square test statistic to degrees of freedom ratio suggested an adequate model fit. If the specified two- and three-factor SEMs in the next section exhibit substantial model misspecification, the misspecification originates from the structural component.

Figure 12. Three-factor measurement model, standardized solution

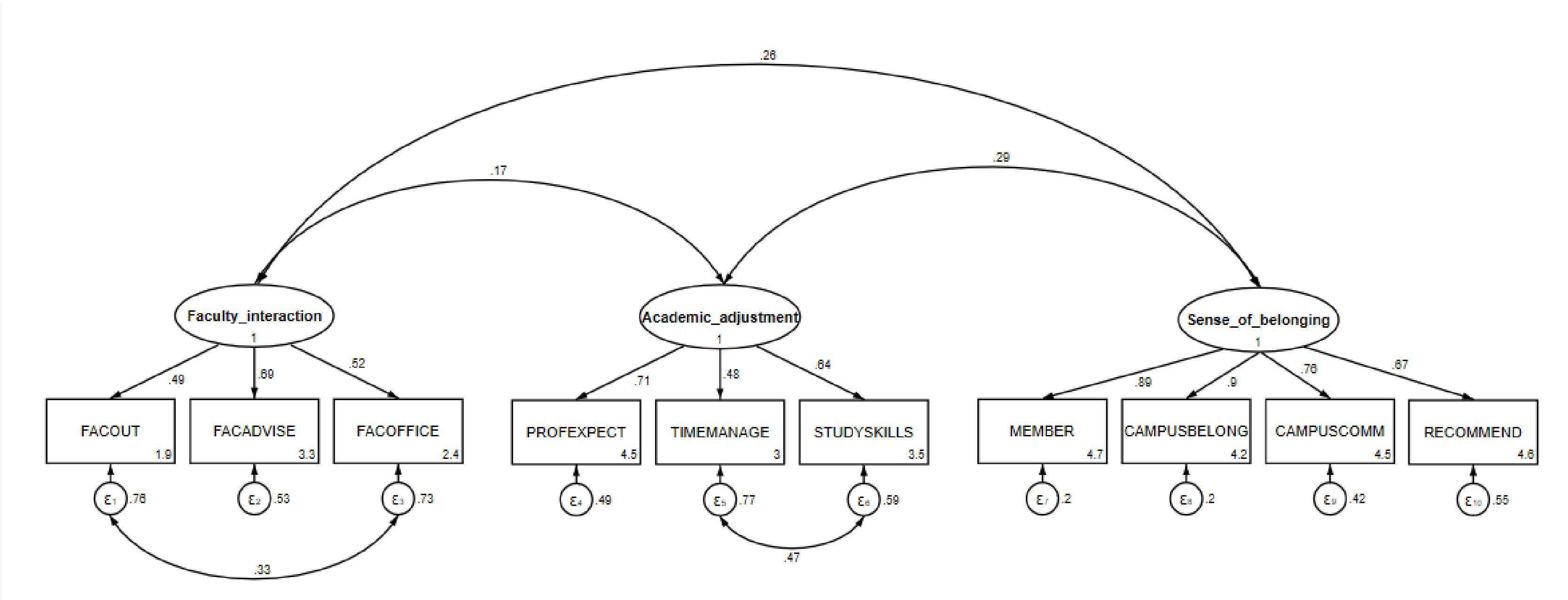


Table 16. Three-factor measurement model, standardized solution

	Coefficient	Standard error	z	*p*	95% confidence interval	
ACADEMICADJUSTMENT						
PROFEXPECT	0.712	0.010	70.36	<.001	0.692	0.731
TIMEMANAGE	0.481	0.008	57.87	<.001	0.464	0.497
STUDYSKILLS	0.643	0.009	68.54	<.001	0.624	0.661
FACULTYINTERACTION						
FACOUT	0.494	0.010	51.06	<.001	0.475	0.513
FACADVISE	0.687	0.012	58.17	<.001	0.663	0.710
FACOFFICE	0.524	0.010	54.15	<.001	0.505	0.543
SENSEOFBELONG						
MEMBER	0.894	0.002	566.75	<.001	0.891	0.897
CAMPUSBELONG	0.896	0.002	573.39	<.001	0.893	0.899
CAMPUSCOMM	0.764	0.002	316.06	<.001	0.759	0.769
RECOMMEND	0.670	0.003	217.65	<.001	0.664	0.676

Table 16, cont. Three-factor measurement model, standardized solution

	Coefficient	Standard error	*z*	*p*	95% confidence interval	
var(e.PROFEXPECT)	0.494	0.014			0.466	0.523
var(e.TIMEMANAGE)	0.769	0.008			0.753	0.785
var(e.STUDYSKILLS)	0.587	0.012			0.564	0.611
var(e.FACOUT)	0.756	0.010			0.737	0.775
var(e.FACADVISE)	0.529	0.016			0.498	0.561
var(e.FACOFFICE)	0.725	0.010			0.706	0.745
var(e.MEMBER)	0.201	0.003			0.196	0.207
var(e.CAMPUSBELONG)	0.197	0.003			0.191	0.202
var(e.CAMPUSCOMM)	0.416	0.004			0.409	0.423
var(e.RECOMMEND)	0.551	0.004			0.543	0.560
var(ACADEMICADJUSTMENT)	1	(constrained)				
var(FACULTYINTERACTION)	1	(constrained)				
var(SENSEOFBELONG)	1	(constrained)				
cov(e.STUDYSKILLS,e.TIMEMANAGE)	0.472	0.008	62.62	<.001	0.457	0.487
cov(e.FACOUT,e.FACOFFICE)	0.331	0.009	36.56	<.001	0.314	0.349
cov(ACADEMICADJUSTMENT,FACULTYINTERACTION)	0.167	0.009	19.56	<.001	0.150	0.184
cov(ACADEMICADJUSTMENT,SENSEOFBELONG)	0.287	0.006	45.47	<.001	0.274	0.299
cov(FACULTYINTERACTION,SENSEOFBELONG)	0.261	0.007	38.70	<.001	0.248	0.274

5.3 Structural Equation Modeling

In this section, I describe the estimation, evaluation, and respecification of SEMs for *first-year grades* and *creativity*, and then I present my mediation analysis. As previously described, the measurement component of SEM exhibited an excellent fit with the data after respecification; therefore, SEM modifications focus on the structural paths. After estimating and evaluating the SEM, I used MIs and SEPCs to identify potential model misspecifications (i.e., model components that do not fit the data well). If supported by theory, I respecified or added a path to the model.

Additionally, I explored further SEM complexities related to how the model is estimated. Stata offers two general SEM methods: structural equation modeling (`sem`) and generalized structural equation modeling (`gsem`; StataCorp., 2021a). These methods are typically used with continuous and discrete endogenous variables, respectively, and they have different methodological limitations and post-estimation options. The `sem` command handles all endogenous variables as continuous but offers powerful post-estimation options (e.g., fit statistics and MIs). The `gsem` command appropriately handles discrete endogenous variables but is more computationally intensive; converging on a solution is difficult with increasing numbers of latent variables; and its post-estimation commands are limited.

In the following sections, I present the estimation, evaluation, and, if applicable, respecification of two- and three-factor SEMs for *first-year grades*. Then, I detail the mediation analysis for multiple two- and three-factor *first-year grades* SEMs. And finally, I describe the estimation and evaluation of two-factor *creativity* SEMs, and then the mediation analysis.

5.3.1 First-year college grades.

In specifying the first-year grades SEM, I incorporated the findings from the two- and three-factor measurement model CFAs into the previously specified two- and three-factor SEMs (Figure 5 and Figure 4, respectively). This resulted in including only three of the four indicator variables for each *academic adjustment* and *faculty interaction* and allowing residuals to covary for two pairs of indicator variables (*TIMEMANAGE* and *STUDYSKILLS*; *FACOUT* and *FACOFFICE*) in the first-year grades SEMs.

I estimated a series of two-factor and three-factor SEMs for *first-year grades* that took advantage of the strengths of different estimation methods. First, I present the results of a two-factor SEM estimated assuming (1) continuous exogenous latent variables (`sem` command using maximum likelihood estimation; ML) with listwise deletion (i.e., incomplete responses are not included in the analysis). I then evaluated the model fit and respecified the model. Next, I present the results of the respecified two-factor SEMs estimated assuming (2) continuous exogenous latent variables (`sem` command with ML) with multiple imputation (i.e., path coefficients averaged across 30 imputed data sets) and (3) ordinal exogenous latent variables (`gsem` command) with "equationwise" deletion (StataCorp., 2021a, p. 49).

Then, I present the results of a three-factor SEM estimated, evaluated, and respecified assuming (1) continuous exogenous latent variables (`sem` command with ML) with listwise deletion. Then, I present the results of that respecified SEM estimated (2) assuming continuous exogenous latent variables (`sem` command with ML) with multiple imputation. Ultimately, the results are similar across all of the estimation methods for the two- and three-factor models.

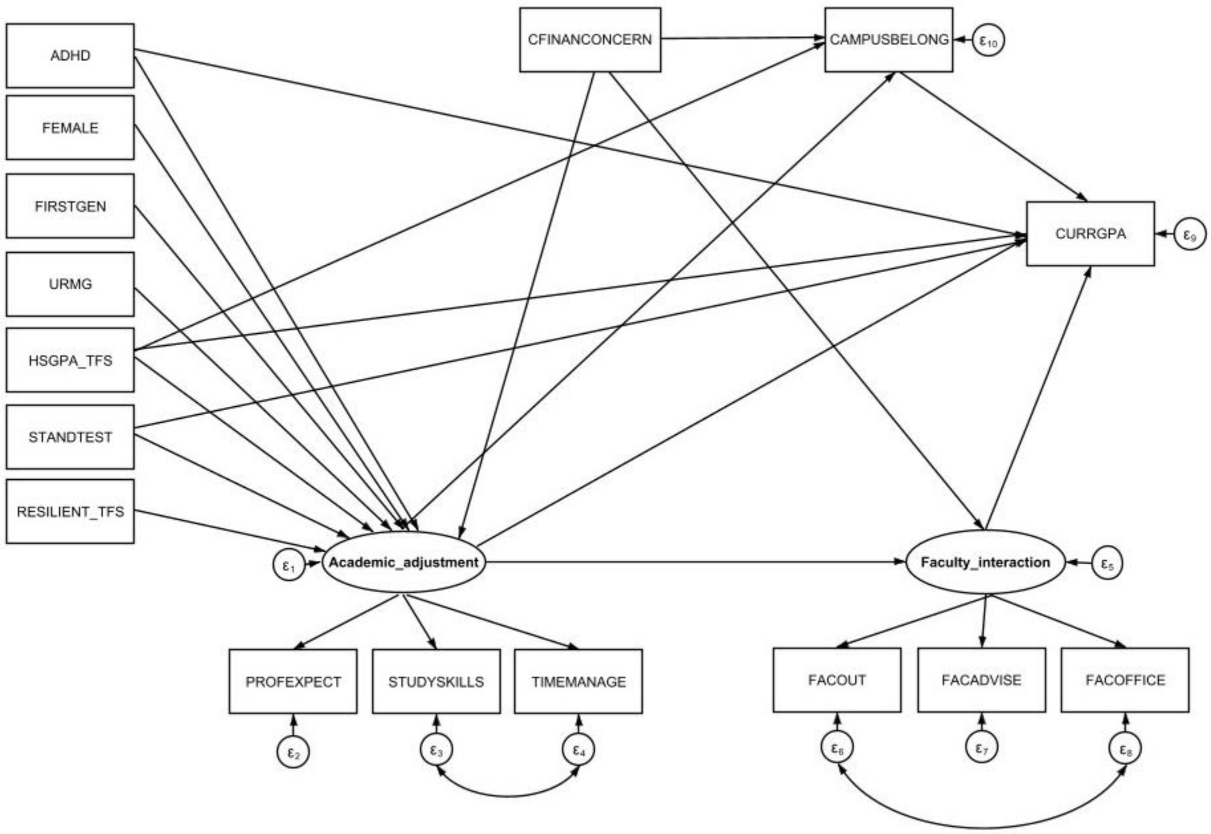
5.3.1.1 Two-Factor Structural Equation Models.

5.3.1.1.1 *SEM Estimation, Evaluation, and Respecification with ML.*

Figure 13 shows the specified two-factor, first-year grades SEM with the modifications from the CFA findings. Estimation and evaluation of a two-factor SEM created assuming continuous, exogenous latent variables with listwise deletion (n = 27,410) exhibited an adequate fit: CFI = .957, TLI = .940, RMSEA = .030, CI [.029, .032], p_{close} = 1.000, and SRMR = .024, and the chi-square, $\chi^2(65) = 2115.23$, $p < 0.001$. The largest MI indicated freely estimating parameters between *faculty interaction* and campus belonging (*faculty interaction* to *CAMPUSBELONG*, MI = 502.39, SEPC = 0.18; *CAMPUSBELONG* to *faculty interaction*, MI = 501.52, SEPC = 0.18; covarying the residuals, MI = 502.39, SEPC = 0.18). I chose to add a path from *faculty interaction* to *CAMPUSBELONG* because there is a theoretical basis for faculty interactions improving students' sense of belonging (Miller et al., 2019).

Model estimation and evaluation after this respecification indicated the model fit had improved, $\chi^2(64) = 1607.201$, $p < 0.001$, and the fit indices fell into the preferred range: CFI = .968, TLI = .954, RMSEA = .030 CI[.028, .031], p_{close} = 1.000, and SRMR = .019. Although the high SEPC indicated an added path between *PROFEXPECT* and *STUDYSKILLS* would have a parameter of 0.32, the MI (89.52) was substantially smaller than the other remaining MIs. I chose not to make further modifications to the model for two reasons: (1) the preferred fit indices and (2) the absence of theoretically-consistent, empirically-driven suggestions for modifications. Table 17 shows the unstandardized SEM results, and Table 18 and Figure 14 show the standardized SEM results.

Figure 13. Specified two-factor, first-year grades SEM



In this final two-factor, first-year grades SEM estimated with maximum likelihood, all direct model paths are statistically significant ($p < .001$). The direct paths to first-year grades (*CURRGPA*) from high school grades (*HSGPA_TFS*), standardized test score (*STANDTEST*), *academic adjustment*, and *faculty interaction* are positive; higher high school grades and pre-college test scores and students' ease of academic adjustment and frequency of interaction with faculty are associated with higher first-year grades. In contrast, students with a prior ADHD diagnosis earn, on average, lower first-year grades. However, the magnitude of this path coefficient is relatively small, 0.218 or one-fifth of a grade change (on an 8-point scale) or 0.13 standard deviations ($\sigma_{CURRGPA}$ = 1.65, therefore, 0.218/1.65).

Table 17. Two-factor, first-year grades SEM (n = 27,410) using ML estimation, unstandardized

Structural	Coefficient	Standard error	*z*	*p*	95% confidence interval	
CURRGPA						
CAMPUSBELONG	-0.068	0.013	-5.38	<.001	-0.093	-0.043
ACADEMICADJUSTMENT	0.651	0.011	60.2	<.001	0.629	0.672
FACULTYINTERACTION	0.059	0.011	5.27	<.001	0.037	0.081
ADHD	-0.218	0.040	-5.45	<.001	-0.297	-0.140
HSGPA_TFS	0.433	0.008	55.34	<.001	0.418	0.449
STANDTEST	0.002	0.000	31.68	<.001	0.002	0.002
_cons	1.769	0.086	20.47	<.001	1.600	1.938
CAMPUSBELONG						
ACADEMICADJUSTMENT	0.121	0.005	22.16	<.001	0.110	0.132
FACULTYINTERACTION	0.126	0.006	22.54	<.001	0.115	0.137
HSGPA_TFS	0.041	0.004	11.16	<.001	0.034	0.048
CFINANCONCERN	-0.137	0.011	-12.9	<.001	-0.158	-0.117
_cons	2.713	0.027	99.13	<.001	2.659	2.766
ACADEMICADJUSTMENT						
ADHD	-0.195	0.035	-5.52	<.001	-0.264	-0.126
FEMALE	0.081	0.015	5.24	<.001	0.051	0.111
FIRSTGEN	-0.144	0.023	-6.29	<.001	-0.189	-0.099
URMG	-0.155	0.019	-8.32	<.001	-0.191	-0.118
HSGPA_TFS	0.086	0.007	12.3	<.001	0.072	0.099
STANDTEST	0.000	0.000	-4.63	<.001	0.000	0.000
RESILIENT_TFS	0.108	0.013	8.13	<.001	0.082	0.135
CFINANCONCERN	-0.382	0.019	-20.63	<.001	-0.418	-0.346
FACULTYINTERACTION						
ACADEMICADJUSTMENT	0.190	0.010	19.17	<.001	0.170	0.209
CFINANCONCERN	0.116	0.020	5.79	<.001	0.077	0.155

Table 17, cont.. Two-factor, first-year grades SEM (n = 27,410) using ML estimation, unstandardized

Measurement	Coefficient	Standard error	*z*	*p*	95% confidence interval	
ACADEMICADJUSTMENT						
PROFEXPECT	0.382	0.005	78.38	<.001	0.372	0.391
TIMEMANAGE	0.512	0.007	70.04	<.001	0.498	0.526
STUDYSKILLS	0.605	0.007	89.96	<.001	0.592	0.618
FACULTYINTERACTION						
FACOUT	0.650	0.016	40.98	<.001	0.619	0.681
FACADVISE	0.412	0.009	45.22	<.001	0.394	0.430
FACOFFICE	0.619	0.014	43.34	<.001	0.591	0.647
var(e.PROFEXPECT)	0.312	0.004			0.305	0.319
var(e.STUDYSKILLS)	0.244	0.007			0.231	0.259
var(e.TIMEMANAGE)	0.450	0.007			0.436	0.464
var(e.FACOUT)	1.303	0.022			1.260	1.347
var(e.FACADVISE)	0.200	0.007			0.186	0.215
var(e.FACOFFICE)	1.009	0.019			0.973	1.046
var(e.CURRGPA)	1.680	0.017			1.647	1.712
var(e.CAMPUSBELONG)	0.470	0.004			0.462	0.478
var(e.ACADEMICADJUSTMENT)	1	(constrained)				
var(e.FACULTYINTERACTION)	1	(constrained)				
cov(e.STUDYSKILLS,e.TIMEMANAGE)	0.098	0.006	15.73	<.001	0.086	0.110
cov(e.FACOUT,e.FACOFFICE)	0.359	0.019	19.41	<.001	0.323	0.395

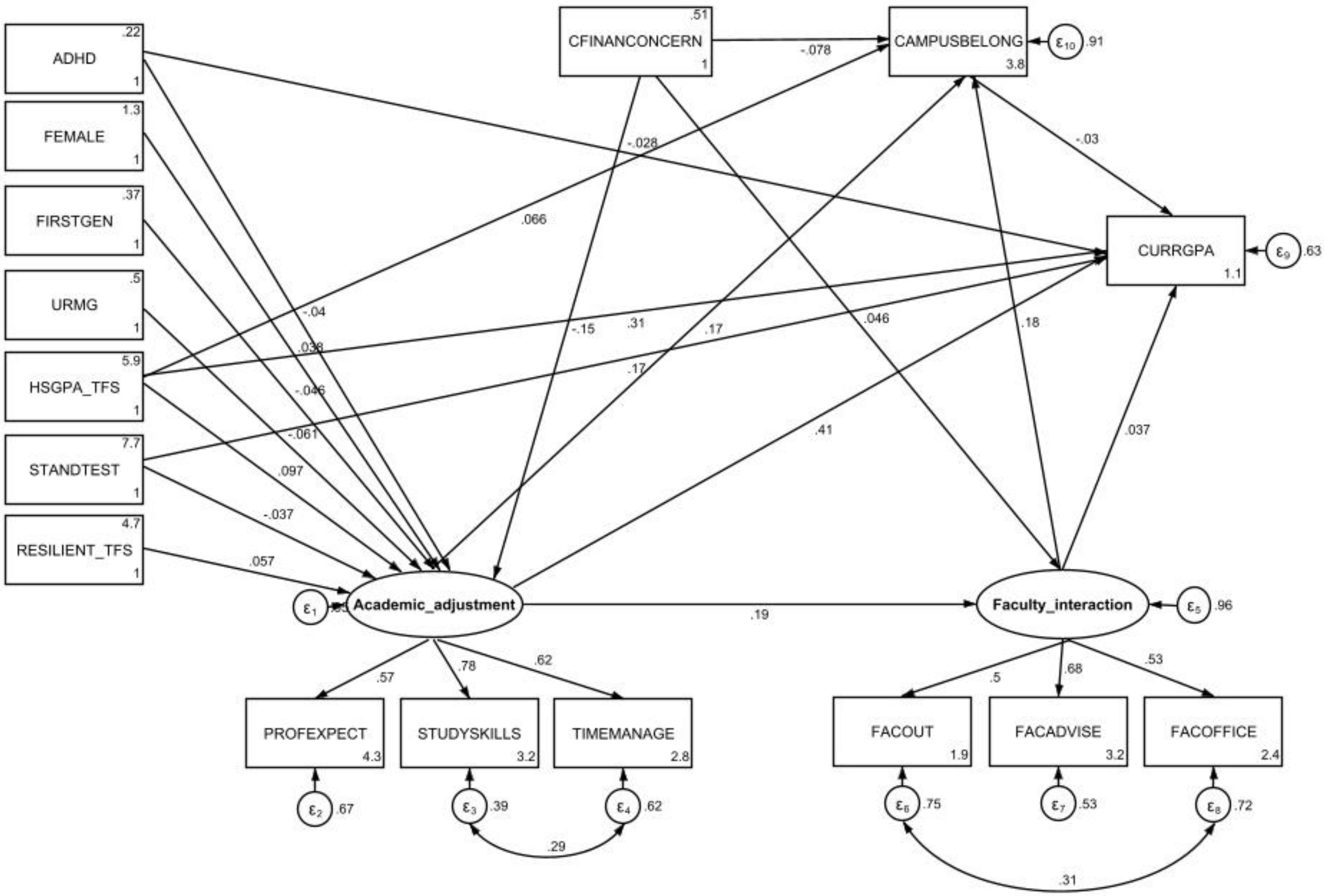
Table 18. Two-factor, first-year grades SEM (n = 27,410) with ML estimation, standardized

Structural	Coefficient	Standard error	z	*p*	95% confidence interval	
CURRGPA						
CAMPUSBELONG	-0.030	0.006	-5.38	<.001	-0.041	-0.019
ACADEMICADJUSTMENT	0.409	0.006	64.01	<.001	0.396	0.421
FACULTYINTERACTION	0.037	0.007	5.28	<.001	0.023	0.051
ADHD	-0.028	0.005	-5.45	<.001	-0.038	-0.018
HSGPA_TFS	0.308	0.005	57.91	<.001	0.298	0.319
STANDTEST	0.173	0.005	32.16	<.001	0.163	0.184
_cons	1.084	0.055	19.7	<.001	0.976	1.191
CAMPUSBELONG						
ACADEMICADJUSTMENT	0.173	0.008	22.4	<.001	0.158	0.188
FACULTYINTERACTION	0.179	0.008	22.88	<.001	0.163	0.194
HSGPA_TFS	0.066	0.006	11.19	<.001	0.054	0.078
CFINANCONCERN	-0.078	0.006	-12.95	<.001	-0.089	-0.066
_cons	3.774	0.043	88.26	<.001	3.690	3.858
ACADEMICADJUSTMENT						
ADHD	-0.040	0.007	-5.53	<.001	-0.054	-0.026
FEMALE	0.038	0.007	5.25	<.001	0.024	0.052
FIRSTGEN	-0.046	0.007	-6.3	<.001	-0.060	-0.032
URMG	-0.061	0.007	-8.35	<.001	-0.075	-0.046
HSGPA_TFS	0.097	0.008	12.39	<.001	0.081	0.112
STANDTEST	-0.037	0.008	-4.64	<.001	-0.053	-0.022
RESILIENT_TFS	0.057	0.007	8.16	<.001	0.043	0.071
CFINANCONCERN	-0.151	0.007	-21.1	<.001	-0.165	-0.137
FACULTYINTERACTION						
ACADEMICADJUSTMENT	0.191	0.010	19.86	<.001	0.172	0.210
CFINANCONCERN	0.046	0.008	5.8	<.001	0.031	0.062

Table 18, cont. Two-factor, first-year grades SEM (n = 27,410) with ML, standardized

Measurement	Coefficient	Standard error	z	*p*	95% confidence interval	
ACADEMICADJUSTMENT						
PROFEXPECT	0.574	0.006	90.73	<.001	0.562	0.586
TIMEMANAGE	0.616	0.008	79.63	<.001	0.601	0.632
STUDYSKILLS	0.782	0.007	108.41	<.001	0.768	0.796
FACULTYINTERACTION						
FACOUT	0.502	0.012	42.33	<.001	0.478	0.525
FACADVISE	0.684	0.014	47.87	<.001	0.656	0.712
FACOFFICE	0.619	0.014	43.34	<.001	0.591	0.647
var(e.PROFEXPECT)	0.671	0.007			0.656	0.685
var(e.TIMEMANAGE)	0.620	0.010			0.602	0.639
var(e.STUDYSKILLS)	0.389	0.011			0.367	0.411
var(e.FACOUT)	0.748	0.012			0.725	0.772
var(e.FACADVISE)	0.532	0.020			0.495	0.571
var(e.FACOFFICE)	0.717	0.013			0.693	0.742
var(e.CURRGPA)	0.630	0.005			0.620	0.641
var(e.CAMPUSBELONG)	0.909	0.004			0.901	0.917
var(e.ACADEMICADJUSTMENT)	0.951	0.003			0.945	0.957
var(e.FACULTYINTERACTION)	0.964	0.004			0.957	0.971
cov(e.STUDYSKILLS,e.TIMEMANAGE)	0.295	0.013	21.92	0	0.268	0.321
cov(e.FACOUT,e.FACOFFICE)	0.313	0.012	27.11	<.001	0.291	0.336

Figure 14. Two-factor, first-year grades SEM (ML estimation), standardized



5.3.1.1.2 *SEM Estimation with ML with Multiple Imputation.*

In estimating the second two-factor, first-year grades SEM, I used multiple imputed data (Appendix A) to include as many responses as possible. In estimation, I dropped responses missing on *FEMALE* (n = 9), underrepresented racial/ethnic group (n = 175), financial concerns (n = 31), and ADHD (n = 2,177) instead of using multiple imputed values. I specified the SEM paths based on the SEM with ML findings shown in Figure 14. Table 19 shows the unstandardized results; all paths are statistically significant (p < .001). The direct path coefficients are similar in direction to the two-factor, first-year grades SEM using ML, but there are minor differences in magnitude. For example, the unstandardized path coefficient from high school grades (*HSGPA_TFS*) to *academic adjustment* is smaller (0.076, 95% CI [0.065, 0.088] v. 0.086, 95% CI [0.072, 0.099]), and the unstandardized path coefficient from *ADHD* to *academic adjustment* is less negative (-0.172, 95% CI [-0.230, -0.115] v. -0.195, 95% CI [-0.264, -0.126]; Table 17; Table 19). The direct path coefficient from *ADHD* to *CURRGPA* remains small and negative (-0.203), indicating slightly lower grades earned on average by students with ADHD.

5.3.1.1.3 *GSEM Estimation.*

I estimated the model using the generalized linear framework to assess changes within first-year grades SEM when estimated using appropriate modeling of ordinal indicator variables (e.g., *TIMEMANAGE*), instead of treating them as continuous (`gsem`; StataCorp., 2021a; Table 9). The a priori model differed slightly from those in Figure 14 and Figure 15 because indicators in generalized models do not have error terms (StataCorp., 2021a). Therefore, in the specified model, the *TIMEMANAGE* and *STUDYSKILLS* and *FACOUT* and *FACOFFICE* residuals cannot covary. In the estimated model, shown in Table 20, the direct paths' coefficients are similar in direction and magnitude to the previous two two-factor SEMs (ML, Table 17; ML with multiple imputation, Table 19). There are differences in the first-year grades generalized SEM results: the path from *CAMPUSBELONGING* to *CURRGPA* is no longer statistically significant (p = .242), and the direct path from *ADHD* to *CURRGPA* is slightly more negative (unstandardized path coefficient; -0.241, 95% CI [-0.319, -0.164] compared to -.218, 95% CI [-0.297, -0.140]), although still relatively small compared to the standard deviation of first-year grades (1.65).

5.3.1.1.4 *Summary.*

Table 21 summarizes the path coefficients and 95% confidence intervals for the direct paths to *CURRGPA* to compare the three estimated two-factor, first-year grades SEMs (ML, ML with multiple imputation, and generalized SEM). All direct paths are statistically significant (p < .001) except for the path from *CAMPUSBELONG* to *CURRGPA* in the generalized SEM (p = .242). The signs of the direct path coefficients are the same in all three models, and the magnitudes are similar. However, the 95% confidence intervals only overlap for a few path coefficients. In the generalized SEM, the *academic adjustment*, *faculty interaction*, and *CAMPUSBELONG* path coefficients are smaller in magnitude, whereas the *ADHD* and *HSGPA_TFS* path coefficients are larger in magnitude. Overall, the three two-factor, first-year grades SEMs are similar regardless of the estimation method.

Table 19. Two-factor, first-year grades SEM (n = 43,523) using ML with multiple imputation, unstandardized

Structural		Coefficient	Standard error	*t*	*p*	95% confidence interval	
CURRGPA							
	CAMPUSBELONG	-0.073	0.011	-6.88	<.001	-0.094	-0.052
	ACADEMICADJUSTMENT	0.629	0.009	66.52	<.001	0.610	0.647
	FACULTYINTERACTION	0.067	0.010	6.84	<.001	0.048	0.086
	ADHD	-0.203	0.033	-6.15	<.001	-0.268	-0.138
	HSGPA_TFS	0.404	0.007	61.37	<.001	0.392	0.417
	STANDTEST	0.002	0.000	34.70	<.001	0.002	0.002
	_cons	2.007	0.073	27.36	<.001	1.863	2.151
CAMPUSBELONG							
	ACADEMICADJUSTMENT	0.126	0.005	27.130	<.001	0.117	0.135
	FACULTYINTERACTION	0.135	0.005	27.030	<.001	0.125	0.145
	HSGPA_TFS	0.042	0.003	13.080	<.001	0.036	0.049
	CFINANCONCERN	-0.141	0.009	-15.560	<.001	-0.158	-0.123
	_cons	2.700	0.023	117.170	<.001	2.655	2.746
ACADEMICADJUSTMENT							
	ADHD	-0.172	0.029	-5.890	<.001	-0.230	-0.115
	FEMALE	0.079	0.013	6.200	<.001	0.054	0.105
	FIRSTGEN	-0.110	0.018	-6.000	<.001	-0.146	-0.074
	URMG	-0.144	0.015	-9.590	<.001	-0.173	-0.114
	HSGPA_TFS	0.076	0.006	13.290	<.001	0.065	0.088
	STANDTEST	0.000	0.000	-6.170	<.001	0.000	0.000
	RESILIENT_TFS	0.112	0.011	10.090	<.001	0.090	0.133
	CFINANCONCERN	-0.356	0.015	-23.630	<.001	-0.385	-0.326
FACULTYINTERACTION							
	ACADEMICADJUSTMENT	0.182	0.008	21.47	<.001	0.165	0.198
	CFINANCONCERN	0.106	0.016	6.500	<.001	0.074	0.138

Table 19, cont. Two-factor, first-year grades SEM (n = 43,523) using ML with multiple imputation, unstandardized

Measurement	Coefficient	Standard error	*t*	*p*	95% confidence interval	
ACADEMICADJUSTMENT						
PROFEXPECT	0.385	0.004	88.28	<.001	0.377	0.394
TIMEMANAGE	0.517	0.006	81.94	<.001	0.505	0.529
STUDYSKILLS	0.612	0.006	102.84	<.001	0.601	0.624
FACULTYINTERACTION						
FACOUT	0.651	0.013	48.87	<.001	0.625	0.677
FACADVISE	0.414	0.008	53.17	<.001	0.399	0.429
FACOFFICE	0.625	0.012	52.23	<.001	0.602	0.649
var(e.PROFEXPECT)	0.317	0.003			0.311	0.324
var(e.TIMEMANAGE)	0.450	0.006			0.437	0.462
var(e.STUDYSKILLS)	0.239	0.006			0.227	0.252
var(e.FACOUT)	1.335	0.019			1.299	1.372
var(e.FACADVISE)	0.202	0.006			0.190	0.215
var(e.FACOFFICE)	1.050	0.016			1.019	1.081
var(e.CURRGPA)	1.688	0.014			1.661	1.716
var(e.CAMPUSBELONG)	0.478	0.004			0.471	0.486
var(e.ACADEMICADJUSTMENT)	1	(constrained)				
var(e.FACULTYINTERACTION)	1	(constrained)				
v(e.STUDYSKILLS,e.TIMEMANAGE)	0.094	0.006	16.58	<.001	0.083	0.105
cov(e.FACOUT,e.FACOFFICE)	0.398	0.016	25.43	<.001	0.367	0.428

Table 20. Two-factor, first-year grades SEM (n = 28,324) using generalized SEM, unstandardized

	Coefficient	Standard error	*z*	*p*	95% confidence interval	
ACADEMICADJUSTMENT						
PROFEXPECT	1.252	0.018	69.66	<.001	1.217	1.288
TIMEMANAGE	2.074	0.029	71.43	<.001	2.017	2.131
STUDYSKILLS	5.155	0.230	22.45	<.001	4.705	5.605
FACULTYINTERACTION						
FACOUT	1.774	0.030	59.22	<.001	1.715	1.833
FACADVISE	1.326	0.023	58.77	<.001	1.281	1.370
FACOFFICE	1.972	0.035	56.73	<.001	1.904	2.040
CURRGPA						
CAMPUSBELONG	-0.014	0.012	-1.17	0.242	-0.037	0.009
HSGPA_TFS	0.441	0.008	57.17	<.001	0.425	0.456
STANDTEST	0.002	0.000	32.39	<.001	0.002	0.002
ADHD	-0.241	0.039	-6.13	<.001	-0.319	-0.164
ACADEMICADJUSTMENT	0.588	0.010	61.69	<.001	0.569	0.607
FACULTYINTERACTION	0.055	0.010	5.43	<.001	0.035	0.075
_cons	1.623	0.083	19.49	<.001	1.460	1.786
CAMPUSBELONG						
CFINANCONCERN	-0.148	0.010	-14.34	<.001	-0.169	-0.128
HSGPA_TFS	0.045	0.004	12.44	<.001	0.038	0.052
ACADEMICADJUSTMENT	0.105	0.005	22.31	<.001	0.096	0.114
FACULTYINTERACTION	0.112	0.005	22.04	<.001	0.102	0.122
_cons	2.711	0.026	103.52	<.001	2.660	2.762

Table 20, cont. Two-factor, first-year grades SEM (n = 28,324) using generalized SEM, unstandardized

	Coefficient	Standard error	*z*	*p*	95% confidence interval	
ACADEMICADJUSTMENT						
ADHD	-0.181	0.031	-5.79	<.001	-0.243	-0.120
FEMALE	0.035	0.014	2.58	0.01	0.008	0.062
FIRSTGEN	-0.119	0.020	-5.82	<.001	-0.159	-0.079
URMG	-0.137	0.017	-8.22	<.001	-0.169	-0.104
HSGPA_TFS	0.083	0.006	13.52	<.001	0.071	0.094
STANDTEST	0.000	0.000	-5.91	<.001	0.000	0.000
RESILIENT_TFS	0.099	0.012	8.30	<.001	0.075	0.122
CFINANCONCERN	-0.327	0.016	-19.98	<.001	-0.359	-0.295
FACULTYINTERACTION						
ACADEMICADJUSTMENT	0.151	0.008	19.18	<.001	0.136	0.167
CFINANCONCERN	0.079	0.017	4.65	<.001	0.046	0.112
var(e.ACADEMICADJUSTMENT)	1	(constrained)				
var(e.FACULTYINTERACTION)	1	(constrained)				
var(e.CURRGPA)	1.764	0.016			1.734	1.796
var(e.CAMPUSBELONG)	0.480	0.004			0.472	0.488

Table 20, cont. Two-factor, first-year grades SEM (n = 28,324) using generalized SEM, unstandardized

	Coefficient	Standard error	z	*p*>|z|	95% confidence interval	
PROFEXPECT						
cut1	-4.723	0.101			-4.921	-4.525
cut2	-1.609	0.085			-1.775	-1.442
cut3	1.678	0.085			1.511	1.845
TIMEMANAGE						
cut1	-2.857	0.142			-3.134	-2.580
cut2	0.575	0.138			0.304	0.846
cut3	3.592	0.142			3.314	3.870
STUDYSKILLS						
cut1	-7.158	0.430			-8.000	-6.315
cut2	-0.215	0.343			-0.887	0.456
cut3	6.922	0.452			6.035	7.809
FACOUT						
cut1	-1.493	0.029			-1.550	-1.435
cut2	0.360	0.027			0.308	0.412
cut3	1.910	0.033			1.846	1.974
cut4	3.398	0.043			3.313	3.482
cut5	5.443	0.065			5.316	5.570
FACADVISE						
cut1	-1.784	0.026			-1.834	-1.733
cut2	2.040	0.027			1.986	2.094
FACOFFICE						
cut1	-3.361	0.046			-3.450	-3.271
cut2	-0.306	0.029			-0.363	-0.250
cut3	1.743	0.035			1.675	1.811
cut4	3.406	0.047			3.313	3.498
cut5	5.500	0.069			5.364	5.637

Table 21. Coefficients and 95% CIs for the direct paths of the two-factor, first-year grades SEMs

	ML	ML with multiple imputation	`gsem`
CURRGPA			
CAMPUSBELONG	-0.068	-0.073	-0.014
	(-0.093, -0.043)	(-0.094, -0.052)	(-0.037, 0.009)
ACADEMICADJUSTMENT	0.651	0.629	0.588
	(0.629, 0.072)	(0.610, 0.647)	(0.569, 0.607)
FACULTYINTERACTION	0.059	0.067	0.055
	(0.037, 0.081)	(0.048, 0.086)	(0.035, 0.075)
ADHD	-0.218	-0.203	-0.241
	(-0.297, -0.140)	(-0.268, -0.138)	(-0.319, -0.164)
HSGPA_TFS	0.433	0.404	0.441
	(0.418, 0.449)	(0.392, 0.417)	(0.425, 0.456)
STANDTEST	0.002	0.002	0.002
	(0.002, 0.002)	(0.002, 0.002)	(0.002, 0.002)

5.3.1.2 Three-Factor SEM.

In specifying the three-factor, first-year grades SEM (Figure 4), I replaced the *CAMPUSBELONG* variable in the two-factor, first-year grades SEM (Figure 5) with the *sense of belonging* latent variable. Like the two-factor SEM and consistent with the CFA findings (Figure 12), I incorporated modifications to the measurement portion of the model. Additionally, I included the path from *faculty interaction* to *sense of belonging* based on the two-factor SEM results (Figure 14). Next, I present estimated two three-factor, first-year grades SEMs, one using ML and another using ML with multiple imputation.

5.3.1.2.1 *SEM Estimation and Evaluation with ML.*

First, I estimated a three-factor, first-year grades SEM using an ML estimator (`sem` command; n = 27,288; $\chi^2(111) = 2397.94$, $p < .001$). Model evaluation suggested an excellent model fit: CFI = .980, TLI = .974, RMSEA = .027 CI[.027, .028], p_{close} = 1.000, and SRMR = .022. Table 22 and Table 23 show the unstandardized and standardized results, respectively. Figure 15 also shows the standardized SEM results. Consistent with the two-factor, first-year grades SEMs, the path coefficients from *ADHD* to *CURRGPA* and *ADHD* to *academic adjustment* are negative (-0.218, 95% CI [-0.297, -0.139] and -0.194, 95% CI [-0.264, -0.124], respectively), and the path coefficient from *academic adjustment* to *CURRGPA* is positive (0.653, 95% CI [0.632, 0.674]).

5.3.1.2.2 *SEM Estimation and Evaluation with ML with multiple imputation.*

I also used the multiple imputed data to estimate, with an ML estimator, the three-factor, first-year grades model. In estimation, I again excluded responses missing on *FEMALE* (n = 9), underrepresented racial/ethnic group (n = 175), financial concerns (n = 31), and *ADHD* (n = 2,177) instead of using multiple imputed values. Table 24 shows the unstandardized results. The magnitudes and signs of path coefficients were similar to the three-factor model with listwise deletion; all paths were statistically significant ($p < .001$).

5.3.1.2.3 *Summary.*

The results of the three-factor, first-year grades SEMs are similar. Table 25 shows the unstandardized path coefficients for both three-factor, first-year grades SEMs. The direct path coefficients to *CURRGPA*, the path coefficients to the three college experience latent variables, and the indicator variables factor loadings are similar among the two models. The 95% confidence intervals of only two path coefficients (path from *academic adjustment* to *CURRGPA* and *HSGPA_TFS* to *CURRGPA*) for SEM estimated with ML and the SEM estimated using ML with multiple imputation do not overlap. The three-factor, first-year grades SEMs are also similar to two-factor, first-year grades SEMs, and this is also evident in the mediation analysis described in the following subsection.

Table 22. Three-factor, first-year grades SEM (n = 27,288) using ML, unstandardized

Structural		Coefficient	Standard error	*z*	*p*	95% confidence interval	
CURRGPA							
	ACADEMICADJUSTMENT	0.653	0.011	59.68	<.001	0.632	0.674
	FACULTYINTERACTION	0.058	0.011	5.04	<.001	0.035	0.080
	SENSEOFBELONG	-0.038	0.009	-4.09	<.001	-0.056	-0.020
	ADHD	-0.218	0.040	-5.42	<.001	-0.297	-0.139
	HSGPA_TFS	0.433	0.008	54.96	<.001	0.418	0.449
	STANDTEST	0.002	0.000	31.53	<.001	0.002	0.002
	_cons	1.581	0.080	19.77	<.001	1.424	1.738
ACADEMICADJUSTMENT							
	ADHD	-0.194	0.036	-5.45	<.001	-0.264	-0.124
	FEMALE	0.082	0.016	5.31	<.001	0.052	0.113
	FIRSTGEN	-0.145	0.023	-6.31	<.001	-0.190	-0.100
	URMG	-0.155	0.019	-8.28	<.001	-0.192	-0.118
	HSGPA_TFS	0.085	0.007	12.13	<.001	0.071	0.099
	STANDTEST	0.000	0.000	-4.62	<.001	0.000	0.000
	RESILIENT_TFS	0.112	0.013	8.31	<.001	0.085	0.138
	CFINANCONCERN	-0.383	0.019	-20.55	<.001	-0.419	-0.346
FACULTYINTERACTION							
	ACADEMICADJUSTMENT	0.192	0.010	19.25	<.001	0.172	0.211
	CFINANCONCERN	0.117	0.020	5.82	<.001	0.078	0.157
SENSEOFBELONG							
	ACADEMICADJUSTMENT	0.201	0.009	22.94	<.001	0.184	0.218
	FACULTYINTERACTION	0.229	0.009	25.57	<.001	0.211	0.246
	HSGPA_TFS	0.075	0.006	13.23	<.001	0.064	0.086
	CFINANCONCERN	-0.243	0.017	-14.64	<.001	-0.275	-0.210

Table 22, cont. Three-factor, first-year grades SEM (n = 27,288) using maximum likelihood, unstandardized

Measurement	Coefficient	Standard error	*z*	*p*	95% confidence interval	
ACADEMICADJUSTMENT						
PROFEXPECT	0.385	0.005	78.66	<.001	0.376	0.395
TIMEMANAGE	0.506	0.007	69.51	<.001	0.492	0.520
STUDYSKILLS	0.598	0.007	89.54	<.001	0.585	0.612
FACULTYINTERACTION						
FACOUT	0.653	0.015	43.58	<.001	0.623	0.682
FACADVISE	0.410	0.008	48.83	<.001	0.394	0.427
FACOFFICE	0.619	0.013	46.21	<.001	0.593	0.645
SENSEOFBELONG						
MEMBER	0.559	0.003	173.9	<.001	0.553	0.566
CAMPUSBELONG	0.601	0.003	172.66	<.001	0.594	0.608
CAMPUSCOMM	0.482	0.003	141.27	<.001	0.476	0.489
RECOMMEND	0.447	0.004	118.73	<.001	0.440	0.455

Table 22, cont. Three-factor, first-year grades SEM (n = 27,288) using maximum likelihood, unstandardized

	Coefficient	Standard error	*z*	*p*	95% confidence interval	
var(e.PROFEXPECT)	0.309	0.004			0.302	0.316
var(e.STUDYSKILLS)	0.251	0.007			0.238	0.265
var(e.TIMEMANAGE)	0.456	0.007			0.442	0.470
var(e.FACOUT)	1.299	0.021			1.259	1.341
var(e.FACADVISE)	0.201	0.007			0.188	0.215
var(e.FACOFFICE)	1.008	0.017			0.975	1.043
var(e.MEMBER)	0.088	0.001			0.086	0.091
var(e.CAMPUSBELONG)	0.104	0.002			0.101	0.107
var(e.CAMPUSCOMM)	0.184	0.002			0.180	0.188
var(e.RECOMMEND)	0.277	0.003			0.272	0.282
var(e.CURRGPA)	1.679	0.017			1.647	1.712
var(e.ACADEMICADJUSTMENT)	1	(constrained)				
var(e.FACULTYINTERACTION)	1	(constrained)				
var(e.SENSEOFBELONG)	1	(constrained)				
cov(e.STUDYSKILLS,e.TIMEMANAGE)	0.105	0.006	17.08	<.001	0.093	0.117
cov(e.FACOUT,e.FACOFFICE)	0.357	0.017	20.70	<.001	0.323	0.391

Table 23. Three-factor, first-year grades SEM (n = 27,288) using maximum likelihood, standardized

Structural	Coefficient	Standard error	*z*	*p*	95% confidence interval	
CURRGPA						
ACADEMICADJUSTMENT	0.410	0.006	63.44	<.001	0.398	0.423
FACULTYINTERACTION	0.036	0.007	5.05	<.001	0.022	0.050
SENSEOFBELONG	-0.025	0.006	-4.09	<.001	-0.037	-0.013
ADHD	-0.028	0.005	-5.42	<.001	-0.038	-0.018
HSGPA_TFS	0.308	0.005	57.49	<.001	0.297	0.318
STANDTEST	0.173	0.005	32	<.001	0.162	0.184
_cons	0.968	0.051	18.98	<.001	0.868	1.069
ACADEMICADJUSTMENT						
ADHD	-0.040	0.007	-5.46	<.001	-0.054	-0.025
FEMALE	0.039	0.007	5.32	<.001	0.024	0.053
FIRSTGEN	-0.046	0.007	-6.32	<.001	-0.061	-0.032
URMG	-0.061	0.007	-8.3	<.001	-0.075	-0.046
HSGPA_TFS	0.096	0.008	12.23	<.001	0.081	0.112
STANDTEST	-0.038	0.008	-4.63	<.001	-0.054	-0.022
RESILIENT_TFS	0.059	0.007	8.34	<.001	0.045	0.073
CFINANCONCERN	-0.152	0.007	-21.02	<.001	-0.166	-0.137
FACULTYINTERACTION						
ACADEMICADJUSTMENT	0.193	0.010	19.96	<.001	0.174	0.212
CFINANCONCERN	0.047	0.008	5.84	<.001	0.031	0.062
SENSEOFBELONG						
ACADEMICADJUSTMENT	0.193	0.008	23.77	<.001	0.177	0.209
FACULTYINTERACTION	0.218	0.008	26.81	<.001	0.202	0.234
HSGPA_TFS	0.082	0.006	13.3	<.001	0.070	0.094
CFINANCONCERN	-0.092	0.006	-14.73	<.001	-0.104	-0.080

Table 23, cont. Three-factor, first-year grades SEM (n = 27,288) using maximum likelihood, standardized

Measurement	Coefficient	Standard error	*z*	*p*	95% confidence interval	
ACADEMICADJUSTMENT						
PROFEXPECT	0.579	0.006	91.29	<.001	0.567	0.592
TIMEMANAGE	0.609	0.008	78.93	<.001	0.594	0.625
STUDYSKILLS	0.774	0.007	107.92	<.001	0.760	0.789
FACULTYINTERACTION						
FACOUT	0.504	0.011	45.32	<.001	0.482	0.526
FACADVISE	0.682	0.013	52.08	<.001	0.656	0.708
FACOFFICE	0.532	0.011	48.29	<.001	0.510	0.553
SENSEOFBELONG						
MEMBER	0.896	0.002	483.56	<.001	0.892	0.899
CAMPUSBELONG	0.894	0.002	480.66	<.001	0.890	0.898
CAMPUSCOMM	0.769	0.003	271.28	<.001	0.763	0.774
RECOMMEND	0.672	0.004	184.75	<.001	0.665	0.679

Table 23, cont. Three-factor, first-year grades SEM (n = 27,288) using maximum likelihood, standardized

	Coefficient	Standard error	*z*	*p*	95% confidence interval	
var(e.PROFEXPECT)	0.664	0.007			0.650	0.679
var(e.STUDYSKILLS)	0.400	0.011			0.379	0.423
var(e.TIMEMANAGE)	0.629	0.009			0.610	0.647
var(e.FACOUT)	0.746	0.011			0.725	0.768
var(e.FACADVISE)	0.535	0.018			0.501	0.571
var(e.FACOFFICE)	0.717	0.012			0.695	0.740
var(e.MEMBER)	0.198	0.003			0.191	0.204
var(e.CAMPUSBELONG)	0.201	0.003			0.194	0.207
var(e.CAMPUSCOMM)	0.409	0.004			0.400	0.417
var(e.RECOMMEND)	0.548	0.005			0.538	0.558
var(e.CURRGPA)	0.630	0.005			0.619	0.641
var(e.ACADEMICADJUSTMENT)	0.951	0.003			0.945	0.957
var(e.FACULTYINTERACTION)	0.964	0.004			0.956	0.971
var(e.SENSEOFBELONG)	0.875	0.005			0.865	0.884
cov(e.STUDYSKILLS,e.TIMEMANAGE)	0.309	0.013	24.19	<.001	0.284	0.334
cov(e.FACOUT,e.FACOFFICE)	0.312	0.011	28.67	<.001	0.290	0.333

Figure 15. Three-factor, first-year grades SEM using a ML estimator, standardized

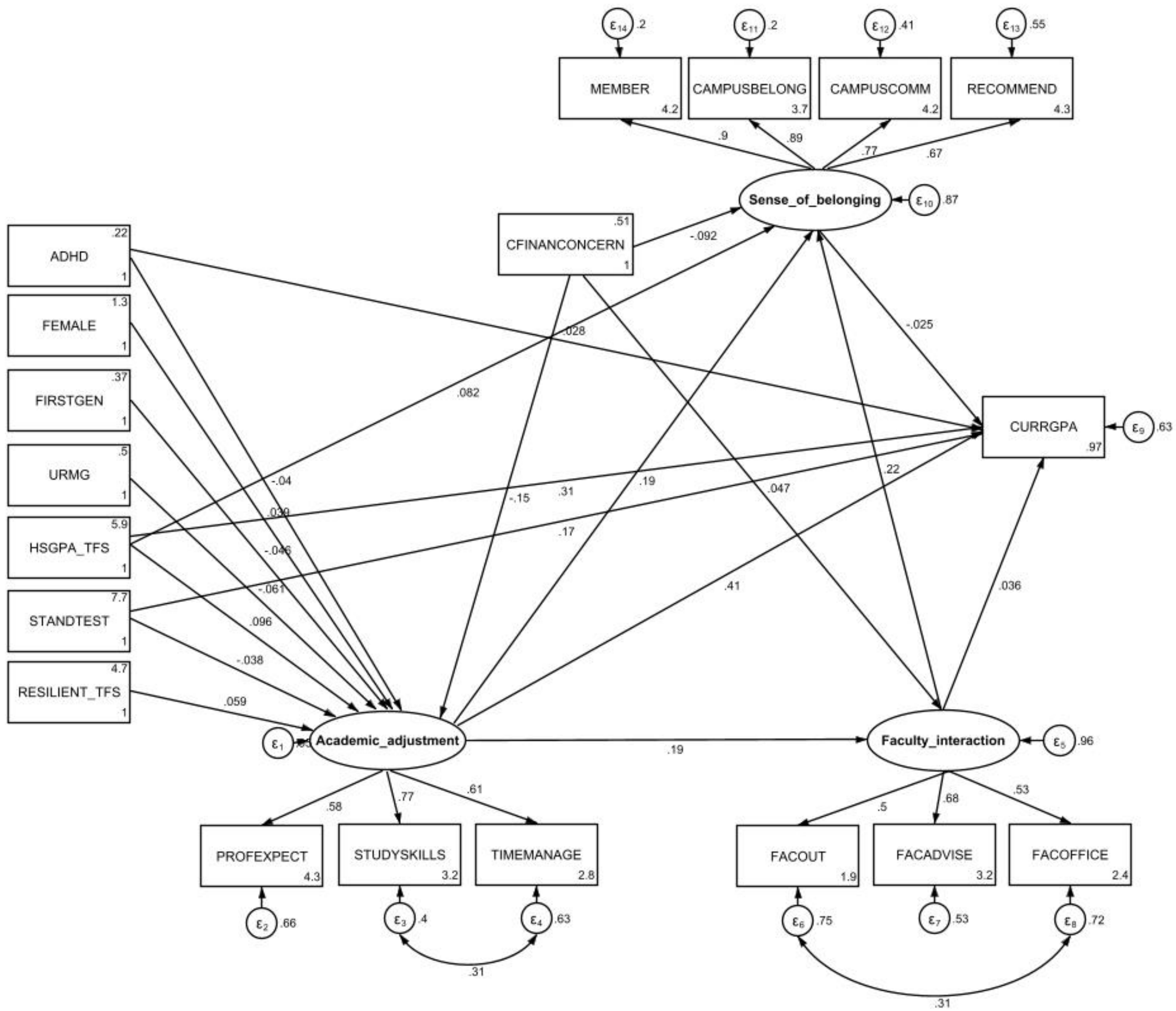


Table 24. Three-factor, first-year grades SEM (n = 43,523) using ML and multiple imputation, unstandardized

Structural	Coefficient	Standard error	*t*	*p*	95% confidence interval	
CURRGPA						
ACADEMICADJUSTMENT	0.632	0.010	66.06	<.001	0.613	0.650
FACULTYINTERACTION	0.067	0.010	6.70	<.001	0.047	0.086
SENSEOFBELONG	-0.045	0.008	-5.63	<.001	-0.060	-0.029
ADHD	-0.203	0.033	-6.13	<.001	-0.268	-0.138
HSGPA_TFS	0.405	0.007	61.26	<.001	0.392	0.418
STANDTEST	0.002	0.000	34.50	<.001	0.002	0.002
_cons	1.805	0.068	26.48	<.001	1.671	1.938
ACADEMICADJUSTMENT						
ADHD	-0.172	0.029	-5.86	<.001	-0.230	-0.115
FEMALE	0.083	0.013	6.43	<.001	0.057	0.108
FIRSTGEN	-0.113	0.018	-6.11	<.001	-0.149	-0.076
URMG	-0.144	0.015	-9.58	<.001	-0.174	-0.115
HSGPA_TFS	0.076	0.006	13.11	<.001	0.064	0.087
STANDTEST	0.000	0.000	-5.97	<.001	0.000	0.000
RESILIENT_TFS	0.114	0.011	10.29	<.001	0.093	0.136
CFINANCONCERN	-0.358	0.015	-23.69	<.001	-0.388	-0.329
FACULTYINTERACTION						
ACADEMICADJUSTMENT	0.183	0.008	21.53	<.001	0.166	0.199
CFINANCONCERN	0.107	0.016	6.56	<.001	0.075	0.139
SENSEOFBELONG						
ACADEMICADJUSTMENT	0.208	0.007	28.06	<.001	0.193	0.223
FACULTYINTERACTION	0.238	0.008	30.68	<.001	0.223	0.253
HSGPA_TFS	0.078	0.005	15.56	<.001	0.068	0.088
CFINANCONCERN	-0.248	0.014	-17.52	<.001	-0.275	-0.220

Table 24, cont. Three-factor, first-year grades SEM (n = 43,523) using ML and multiple imputation, unstandardized

Measurement	Coefficient	Standard error	*t*	*p*	95% confidence interval	
ACADEMICADJUSTMENT						
PROFEXPECT	0.390	0.004	88.36	<.001	0.381	0.398
TIMEMANAGE	0.510	0.006	81.15	<.001	0.498	0.522
STUDYSKILLS	0.605	0.006	102.43	<.001	0.594	0.617
FACULTYINTERACTION						
FACOUT	0.650	0.013	51.61	<.001	0.626	0.675
FACADVISE	0.415	0.007	56.49	<.001	0.400	0.429
FACOFFICE	0.624	0.011	55.12	<.001	0.601	0.646
SENSEOFBELONG						
MEMBER	0.565	0.003	195.66	<.001	0.559	0.571
CAMPUSBELONG	0.608	0.003	201.19	<.001	0.602	0.614
CAMPUSCOMM	0.487	0.003	158.69	<.001	0.481	0.493
RECOMMEND	0.457	0.003	132.25	<.001	0.451	0.464

Table 24, cont. Three-factor, first-year grades SEM (n = 43,523) using ML and multiple imputation, unstandardized

	Coefficient	Standard error	*t*	*p*	95% confidence interval	
var(e.PROFEXPECT)	0.314	0.003			0.307	0.320
var(e.TIMEMANAGE)	0.457	0.006			0.445	0.470
var(e.STUDYSKILLS)	0.248	0.006			0.236	0.260
var(e.FACOUT)	1.335	0.018			1.301	1.370
var(e.FACADVISE)	0.202	0.006			0.191	0.213
var(e.FACOFFICE)	1.052	0.015			1.023	1.082
var(e.MEMBER)	0.091	0.001			0.088	0.093
var(e.CAMPUSBELONG)	0.103	0.001			0.101	0.106
var(e.CAMPUSCOMM)	0.191	0.002			0.187	0.194
var(e.RECOMMEND)	0.288	0.002			0.283	0.293
var(e.CURRGPA)	1.685	0.014			1.658	1.713
var(e.ACADEMICADJUSTMENT)	1	(constrained)				
var(e.FACULTYINTERACTION)	1	(constrained)				
var(e.SENSEOFBELONG)	1	(constrained)				
cov(e.STUDYSKILLS,e.TIMEMANAGE)	0.102	0.006	18.21	<.001	0.091	0.113
cov(e.FACOUT,e.FACOFFICE)	0.399	0.015	27.23	<.001	0.370	0.428

Table 25. Comparison of path coefficients of the three-factor, first-year grades SEMs using ML (n = 27,288) and using ML with multiple imputation (n = 43,523), unstandardized

	Coefficient	
Structural	ML	ML, multiple imputation
CURRGPA		
ACADEMICADJUSTMENT	0.653	0.632
FACULTYINTERACTION	0.058	0.067
SENSEOFBELONG	-0.038	-0.045
ADHD	-0.218	-0.203
HSGPA_TFS	0.433	0.405
STANDTEST	0.002	0.002
ACADEMICADJUSTMENT		
ADHD	-0.194	-0.172
FEMALE	0.082	0.083
FIRSTGEN	-0.145	-0.113
URMG	-0.155	-0.144
HSGPA_TFS	0.085	0.076
STANDTEST	0.000	0.000
RESILIENT_TFS	0.112	0.114
CFINANCONCERN	-0.383	-0.358
FACULTYINTERACTION		
ACADEMICADJUSTMENT	0.192	0.183
CFINANCONCERN	0.117	0.107
SENSEOFBELONG		
ACADEMICADJUSTMENT	0.201	0.208
FACULTYINTERACTION	0.229	0.238
HSGPA_TFS	0.075	0.078
CFINANCONCERN	-0.243	-0.248

	Coefficient	
Measurement	ML	ML, multiple imputation
ACADEMICADJUSTMENT		
PROFEXPECT	0.385	0.390
TIMEMANAGE	0.506	0.510
STUDYSKILLS	0.598	0.605
FACULTYINTERACTION		
FACOUT	0.653	0.650
FACADVISE	0.410	0.415
FACOFFICE	0.619	0.624
SENSEOFBELONG		
MEMBER	0.559	0.565
CAMPUSBELONG	0.601	0.608
CAMPUSCOMM	0.482	0.487
RECOMMEND	0.447	0.457

5.3.1.3 Mediation Analysis.

A mediation analysis identifies the underlying mechanism *mediating* a relationship or, in this case, the degree to which different aspects of the college experience (*academic adjustment*, *faculty interaction*, and *sense of belonging*) influence the relationship between students' pre-college characteristics and experiences and academic success outcomes (Figure 9). SEMs can include single or multiple mediating variables or indirect paths.

Figure 16 illustrates the four mediating pathways connecting *ADHD* to *CURRGPA* (lavender) and the direct path from *ADHD* to *CURRGPA* (red) in the three-factor SEM. The first mediating pathway goes through *academic adjustment*, and the second goes through *faculty interaction* after traveling through *academic adjustment*. The third and fourth pathways go through academic adjustment then through *sense of belonging*, the third traversing *faculty interaction* before *sense of belonging*, to first-year grades (*CURRGPA*). The mediating pathways are similar in the two-factor SEMs except the latter two proceed through *CAMPUSBELONG* instead of *sense of belonging*.

Table 26 displays the coefficients and *p*-values for the mediating paths of the two-factor SEM with ML; the two-factor generalized SEM; and the three-factor SEM with ML. I used the delta method and bootstrapping to calculate standard errors. In all three SEMs, the indirect path coefficient from *ADHD* through *academic adjustment* to *CURRGPA* is statistically significant (p <.001) and is substantially larger than the other three indirect path coefficients. In contrast to the SEMs estimated with maximum likelihood estimation, the indirect paths in the generalized SEM through *CAMPUSBELONG* are not significant at conventional levels (p = .253, p = .254).

The *academic adjustment* college experience variable substantially mediates the relationship between *ADHD* and *CURRGPA*. Table 26 shows the degree of mediation for the three SEMs which ranges from .306 to .367. This means that *academic adjustment* intervenes or partially mediates (~33%) the relationship between *ADHD* and first-year grades (*CURRGPA*), suggesting academic adjustment is an underlying mechanism. In other words, a mediator, or *academic adjustment* in this case, reduces the strength of the direct relationship (Kenny, 2021) between *ADHD* and first-year grades.

Figure 16. Mediating (lavender) and direct (red) paths of the three-factor SEM

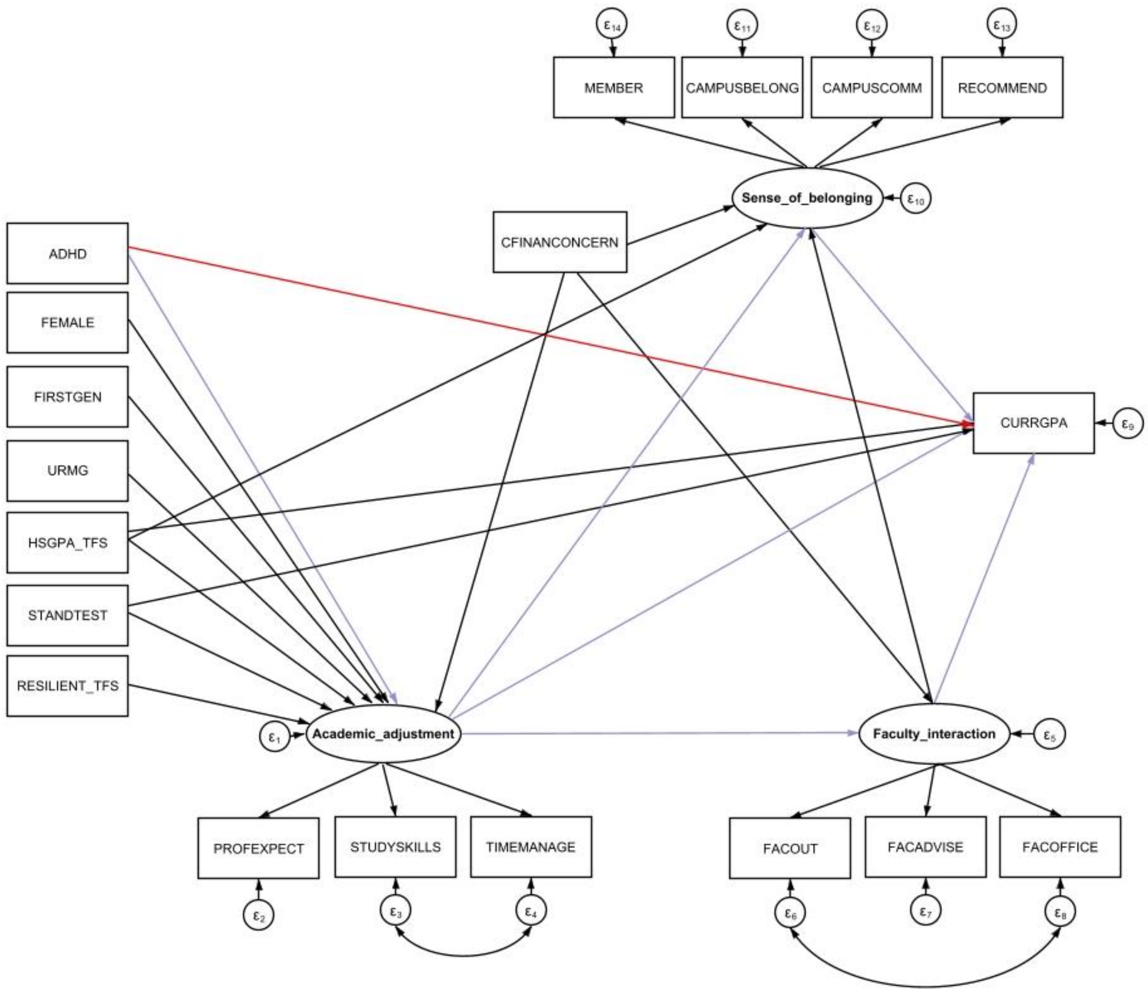


Table 26. First-year grades mediation analysis with standard errors (delta and bootstrapped)

Two-factor indirect (maximum likelihood)	Coefficient	Standard error	z	*p*	95% confidence interval	
Delta						
via academic adjustment	-0.127	0.023	-5.49	<.001	-0.172	-0.082
via faculty interaction	-0.002	0.001	-3.85	<.001	-0.003	-0.001
via campus belonging & faculty interaction	0.000	0.000	3.74	<.001	0.000	0.000
via campus belonging	0.002	0.000	3.68	<.001	0.001	0.002
Mediation via academic adjustment	**.367**					
Bootstrap						
via academic adjustment	-0.127	0.024	-5.2	<.001	-0.175	-0.079
via faculty interaction	-0.002	0.001	-3.84	<.001	-0.003	-0.001
via campus belonging & faculty interaction	0.000	0.000	3.9	<.001	0.000	0.000
via campus belonging	0.002	0.000	3.78	<.001	0.001	0.002
Mediation via academic adjustment	**.367**					
Two-factor indirect (`gsem`)						
Delta						
via academic adjustment	-0.107	0.018	-5.77	<.001	-0.143	-0.070
via faculty interaction	-0.002	0.000	-3.95	<.001	-0.002	-0.001
via campus belonging & faculty interaction	0.000	0.000	1.14	0.253	0.000	0.000
via campus belonging	0.000	0.000	1.14	0.254	0.000	0.001
Mediation via academic adjustment	**.306**					

Table 26, cont. First-year grades mediation analysis with standard errors (delta and bootstrapped)

Three-factor indirect (maximum likelihood)	Coefficient	Standard error	*z*	*p*	95% confidence interval	
Delta						
via academic adjustment	-0.127	0.023	-5.43	<.001	-0.172	-0.081
via faculty interaction	-0.002	0.001	-3.74	<.001	-0.003	-0.001
via campus belonging & faculty interaction	0.000	0.000	3.21	0.001	0.000	0.001
via campus belonging	0.001	0.000	3.15	0.002	0.001	0.002
Mediation via academic adjustment	**.367**					
Bootstrap						
via academic adjustment	-0.127	0.024	-5.27	<.001	-0.174	-0.080
via faculty interaction	-0.002	0.001	-3.63	<.001	-0.003	-0.001
via campus belonging & faculty interaction	0.000	0.000	3	0.003	0.000	0.001
via campus belonging	0.001	0.001	2.85	0.004	0.000	0.003
Mediation via academic adjustment	**.367**					

5.3.1.4 Summary.

Structural equation modeling of first-year grades using a modified Bowman model exhibited excellent fit with the multi-institutional HERI data from undergraduate students at four-year higher education institutions. The five SEM estimation approaches resulted in similar findings. The college experience, specifically *academic adjustment*, influenced first-year grades. It is the key mediator between a previous ADHD diagnosis and first-year grades, exhibiting partial mediation of approximately 33%.

5.3.2 Creativity.

Creativity is a non-traditional academic success measure, yet it is an important characteristic for students in their future careers, particularly in science and engineering (Taylor et al., 2020). I used my conceptual framework based on Terenzini and Reason's (1995) college impact model to specify three creativity SEMs. I specified the models using two latent variables, *faculty interaction* and *sense of belonging*, because theoretically, these are more closely related to creativity outcomes than *academic adjustment*. I compared the three SEMs results using the Akaike information criterion (AIC) and Bayesian information criterion (BIC), indicators of model fit (Long, 1997). Smaller values of AIC and BIC indicate a better fit of the data for that model compared to a model with higher values.

The academic success outcome variable type dictated the SEM estimation method of the creativity SEMs. Creativity (*CREATIVITY1*; students' self-rating of their creativity) had three response categories: average or below (n = 18,226), above average (n = 16,682), and top 10% (n = 6,098). Generalized SEM (`gsem`) appropriately handles ordinal variables, and therefore, I used the `gsem` method to estimate all three creativity SEMs. Next, I describe the specification, estimation, and evaluation for all three models in each subsection. For example, Estimation and Evaluation includes the estimation of Model 1, Model 2, and Model 3.

5.3.2.1 Specification.

Model 1 included only one pre-college characteristic variable, whether a student had received an ADHD diagnosis before college, and two college experience latent variables, *faculty interaction* and *sense of belonging*. Therefore, Model 1 specified a single exogenous variable, *ADHD*, and two latent variables, *faculty interaction* and *sense of belonging,* predicting *CREATIVITY1* (Figure 17). Model 2 included three other pre-college characteristics in addition to *ADHD* (Figure 18). As specified, Model 2 had three additional exogenous variables, *FEMALE*, *FIRSTGEN*, and *URMG,* with paths to the two latent variables, *faculty interaction* and *sense of belonging*, and not *CREATIVITY1*. Model 3 had direct paths from all pre-college characteristic variables to the academic outcome, creativity (Figure 19). In Model 3, all four exogenous variables (*ADHD*, *FEMALE, FIRSTGEN*, and *URMG*) had paths to *CREATIVITY1* in addition to the two college experience latent variables, *faculty interaction* and *sense of belonging*.

5.3.2.2 Estimation and Evaluation.

Table 27 shows the unstandardized coefficients and *p*-values for all three models, along with the AIC and BIC. Model 2's AIC (605811.1) and BIC (606190.8) and Model 3's AIC (605644.8) and BIC (606050.4) were lower than those of Model 1 (AIC = 616949.8; BIC = 617278.4). The small difference between the AIC and BIC of Models 2 and 3 suggests that the additional paths only slightly improved Model 3's fit. A previous ADHD diagnosis, more frequent interaction with faculty, and a greater sense of belonging positively influence students' self-rating of creativity in Model 2. All three paths are statistically significant ($p < .001$) and have positive coefficients. Models 1 and 3 also exhibit positive and statistically significant ($p < .001$) relationships between *ADHD* and *CREATIVITY1*.

5.3.2.3 Mediation.

The college experience latent variables, *academic adjustment* and *sense of belonging*, do not substantially mediate the creativity academic outcome. Stata does not support calculating mediation effects following generalized SEM (StataCorp., 2021a); therefore, the statistical significance and standard errors are not calculated. However, a simple calculation of the mediating path coefficients for the indirect paths through *academic adjustment* (0.047) and *sense of belonging* (-0.011) suggests that they are small in comparison to the *ADHD* to *CREATIVITY1* path coefficient (0.500). The ratios of the path coefficients (e.g., *academic adjustment* to *CREATIVITY1* path coefficient to *ADHD* to *CREATIVITY1* path coefficient) are less than 0.1 or 10% (0.047 to 0.500; -0.011 to 0.500). The *faculty interaction* and *sense of belonging* aspects of students' college experience provide little mediating influence on the students' self-rating of their creativity.

Figure 17. Two-factor, creativity SEM Model 1

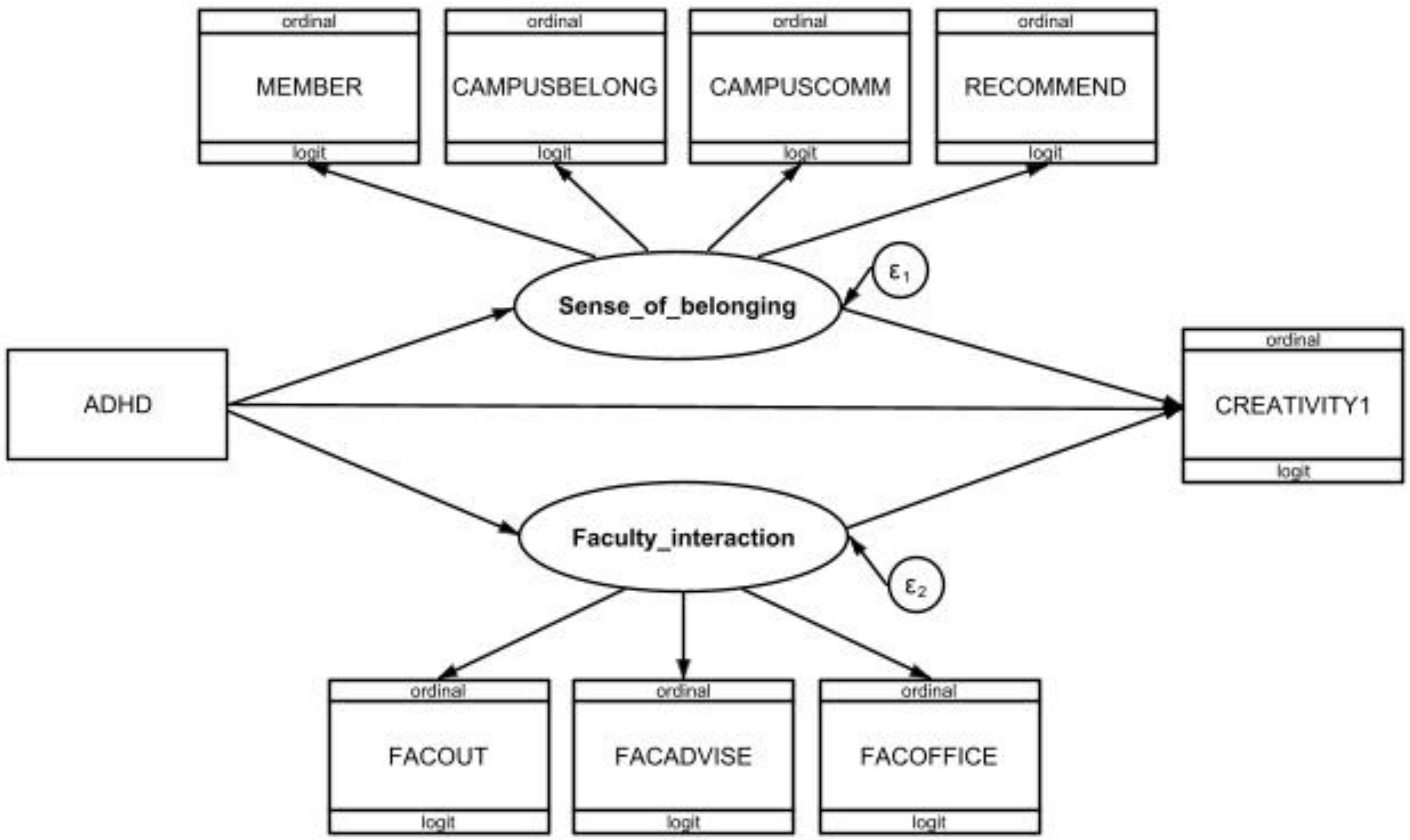


Figure 18. Two-factor, creativity SEM Model 2

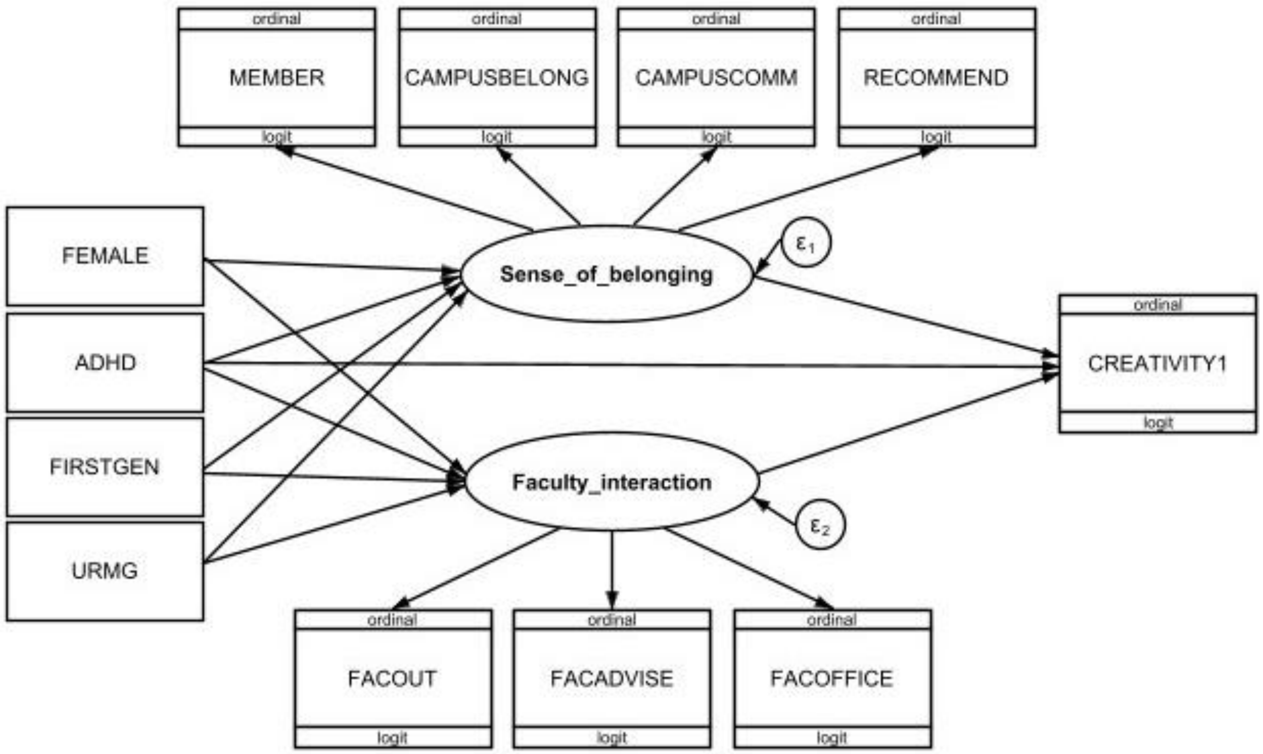


Figure 19. Two-factor, creativity SEM Model 3

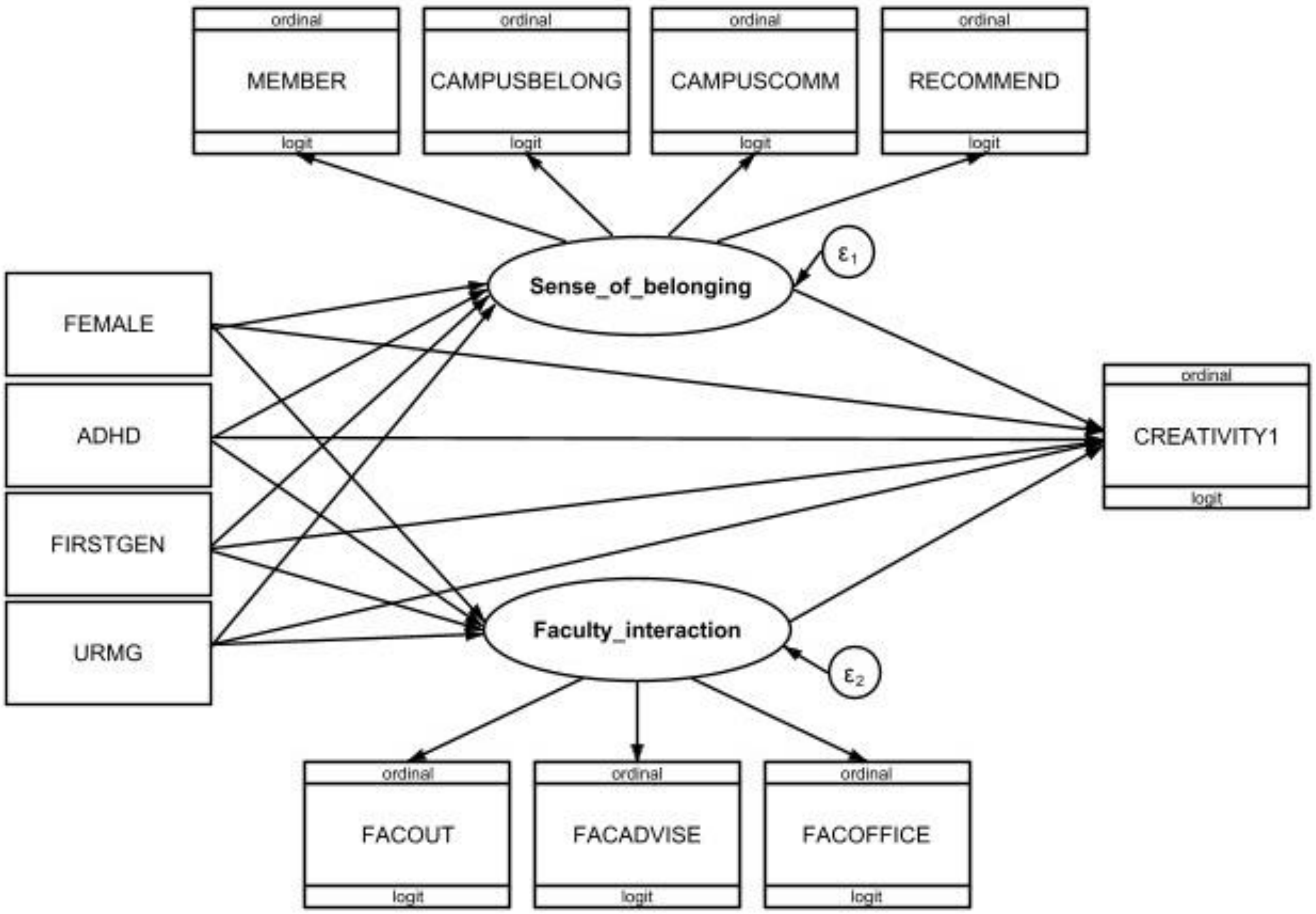


Table 27. Generalized SEMs for three models of creativity

	Model 1	Model 2	Model 3
Measurement model			
FACULTYINTERACTION			
FACOUT	1.817***	1.809***	1.809***
FACADVISE	1.276***	1.276***	1.275***
FACOFFICE	2.029***	2.035***	2.037***
SENSEOFBELONG			
MEMBER	7.011***	6.895***	6.892***
CAMPUSBELONG	5.906***	5.908***	5.909***
CAMPUSCOMM	2.881***	2.875***	2.875***
RECOMMEND	2.154***	2.146***	2.146***
Structural model			
CREATIVITY1			
ADHD	0.496***	0.500***	0.471***
FEMALE			-0.167***
FIRSTGEN			-0.248***
URMG			0.173***
FACULTYINTERACTION	0.251***	0.251***	0.246***
SENSEOFBELONG	0.171***	0.169***	0.175***
FACULTYINTERACTION			
ADHD	0.185***	0.186***	0.187***
FEMALE		-0.073***	-0.069***
FIRSTGEN		0.018	0.024
URMG		0.071***	0.067***
SENSEOFBELONG			
ADHD	-0.052*	-0.066**	-0.066**
FEMALE		0.108***	0.110***
FIRSTGEN		-0.173***	-0.171***
URMG		-0.151***	-0.153***
AIC	616,949.8	605,811.1	605,644.8
BIC	617,278.4	606,190.8	606,050.4

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

5.3.2.4 Summary.

Creativity is an important characteristics of college students for their future careers and is often not considered in models of collegiate academic success. SEMs based on Terenzini and Reason’s (2005) college outcome model indicate that students with ADHD are more likely to identify as having higher levels of creativity than their peers, and their college experience does not substantially mediate this. The college experience, at least *faculty interaction* and *sense of belonging*, had little influence on students’ creativity ratings.

5.4 Overall Summary

I explored two academic success outcomes, first-year grades and creativity, using SEM and conducting mediation analyses. Incoming college students diagnosed with ADHD reported earning a slightly lower average grade (one-fifth of a grade change or approximately 0.13 standard deviations) on average at the end of their first year compared to incoming college students without an ADHD diagnosis, and students’ academic adjustment partially mediated the strength of this relationship. The other college experience latent variables, *faculty interaction* and *sense of belonging*, had minimal influence on this relationship.

In contrast, students with an ADHD diagnosis as incoming college students had higher self-ratings for their creativity at the end of their first year compared to students without an ADHD diagnosis as an incoming first-year student. The SEM indicated that students’ college experience, as measured by the latent variables, *faculty interaction* and *sense of belonging*, did not influence students’ rating of their creativity.

This modeling of first-year grades suggests that changes in students’ college environment/experiences may lead to higher grades for first-year students. In the Discussion section, I discuss changes to the college environment to positively impact students' college experience, specifically focusing on students' academic adjustment in college.

Chapter 6 Discussion

In this chapter I further address and interpret the answers to my two research questions. The implications of my findings are also presented, and they are specifically considered for engineering students. Based on these findings, I make recommendations for higher education policy and practice. Stemming from my findings on the college experiences of students with ADHD, I focus on recommending changes to the college environment that could positively impact student success. I primarily share recommendations and strategies that target the academic adjustment experiences of students with ADHD. These recommendations are based on existing literature related to my findings, and specifically college students' academic adjustment; my dissertation research did not explore the effectiveness of specific recommendations to support students' academic adjustment. Many higher education instructors are already using these recommendations; others may use them to a lesser extent. My findings add to a growing evidence-base regarding the importance of supporting students' academic adjustment to college.

6.1 First-Year Grades

6.1.1 Pre-college, College, and Academic Success Relationships

6.1.1.1 Structural Equation Model.

The Bowman model (2019) provided an excellent starting point for modeling academic success and answering my first research question, *what relationships exist between students' precollege characteristics and experiences, the college experience, and academic success for students with ADHD?* That model is based on the early work on student retention of Tinto

(1993), Cabrera and coauthors (1992), and Pascarella and Terenzini (2005). It includes pre-college measures (e.g., financial means, high school GPA), college-level measures (e.g., non-cognitive attributes, such as academic grit, time management, self-discipline, and self-efficacy; social adjustment; and commitment to the institution), and outcomes (e.g., college GPA and retention). Furthermore, Bowman and coauthors (2019) "intentionally chose not to include direct indicators of academic behavior since these are believed to mediate the link between other noncognitive attributes and academic performance" (p. 139). Additionally, students' academic behaviors or engagement, such as homework completion, are influenced by their classroom environment, particularly for students with ADHD (Morsink et al., 2022). This is a salient factor because my research aim is to identify aspects of the higher education environment to promote academic success for all students, including students with ADHD. Therefore, the Bowman model provided the starting point for the modeling of first-year grades using SEM done in this study.

I made informed modifications to the Bowman model to stay consistent with a causal analysis and incorporate pre-college characteristics and experiences measures. Structural equation modeling is a causal analytic tool and thus requires appropriate time progression (Kline, 2016). In Bowman and coauthors' study (2019), the college-level measure of concerns about financing college predicted high school GPA. However, a student's concerns about financing their college education cannot predict a previously occurring event, such as grades earned in high school. In my HERI data set, financial concern is also a college-level measure of a student's concern about financing college. To address the temporal nature of the variables, I modified the Bowman model by eliminating the path from financial means to high school GPA so that financial concerns predicted only college-level measures (i.e., *academic adjustment*, *faculty interaction*, and *sense of belonging*), and the high-school grades variable was an exogenous variable. Therefore, in my SEM, the financial concerns variable is mathematically (but not theoretically) equivalent to a pre-college exogenous variable. This change allowed me to stay consistent with the time progression of study variables and improved my model's causal analysis and predictive capabilities.

Including additional pre-college measures (e.g., sex, first-generation college student, underrepresented racial/ethnic group, and standardized test score), consistent with my conceptual framework, improves the models' capability to predict academic outcomes. Terenzini and Reason's (2005) and Reason's (2009) college impact model suggests sociodemographic traits and standardized test scores relate to academic outcomes. This addition facilitated the exploration of the college experiences of specific groups of students, such as students with ADHD. The fit of my modified Bowman model and the combined TFS/YFCY data was excellent; thus, the SEM was suitable for investigating the college experiences of students with ADHD.

My SEMs incorporating students with ADHD are also consistent with the academic outcome SEM of van Rooij and coauthors (2018) for first-year students majoring in science, social science, and humanities at research universities in the Netherlands. In their model, self-regulated study behavior, intrinsic motivation, and degree program motivation explained academic adjustment (van Rooij et al., 2018). Similar to my findings, self-regulated study behavior had the largest influence on academic adjustment (although different predictor variables were used) and academic adjustment directly influenced university GPA. Students with greater academic adjustment earned higher grades and this influence exceeded that of secondary school grades. However, it is important to note that the paths for academic adjustment (or non-cognitive attributes, in the case of the Bowman model) and high school or secondary grades differed for my model, the van Rooij model, and the Bowman model.

6.1.1.2 Academic Adjustment and Outcomes.

The negative SEM path coefficient from *ADHD* to *CURRGPA* (in all of the first-year grade SEMs) indicates that students with ADHD, who have received a diagnosis before entering college, earn, on average, lower first-year grades. The sign of the path coefficient is consistent with previous research (Blase et al., 2009; DuPaul et al., 2019; Gormley et al., 2019); however, the magnitude (approximately 0.1 standard deviations or one-fifth of a grade change) is smaller. Blase and coauthors (2019) found students with ADHD earned on average lower grades, 0.4 to 0.5 standard deviations, compared to students without ADHD. DuPaul and coauthors (2021) found students with ADHD earned on average approximately 0.4 points lower on a 4.0 GPA scale. This is equivalent to 0.8 points on an equivalent 8-point scale used in this study. Gormley and coauthors (2019) found students with ADHD (M = 2.91, σ = 0.77, on presumably a 4-point scale) earned on average 0.25 points lower GPAs than their peers without ADHD (M = 3.26, σ = 0.69).

My research extends this prior work because it includes additional factors that influence collegiate academic success. For example, DuPaul and coauthors (2021) did not include a high school measure of academic preparation, such as grades or standardized test scores, in all likelihood introducing omitted variable bias, whereas my model includes both high school GPA and standardized test score. Thus, my findings about college grades account for differences in academic preparation and performance. DuPaul and coauthors (2019) also did not incorporate students' classroom and out-of-class experiences in their model, whereas my first-year grades SEM incorporates the frequency of students' interaction with faculty or instructors and their sense of belonging to their institution. Consistent with Gormley and coauthors (2019), who suggest that high school GPA provides a measure of college-readiness skills such as time management (not included in their model), my first-year grades SEM suggests high school grades predict the ease of students' academic adjustment in college.

My first-year grades SEM is consistent with prior work in that incoming first-year students previously diagnosed with ADHD earn, on average, lower grades during their first year of college than their peers. Although statistically significant, the magnitude of this difference is small, one-fifth of a grade change or 0.13 standard deviations, and is substantially smaller than 0.4 to 0.5 standard deviations found by Blase and coauthors (2009). However, the magnitude of differences in first-year grades are not of primary interest because this study's research objectives focus on the influence of students' college experiences in order to target recommendations for change.

The negative SEM path coefficient from ADHD to academic adjustment indicates students with ADHD have on average more difficulty adjusting to college academics during their first year than their counterparts without ADHD. This is consistent with previous quantitative (DuPaul et al., 2021; Reaser et al., 2007) and qualitative (Kwon et al., 2018; Meaux et al., 2009) research. For example, DuPaul and coauthors (2021) found that students with ADHD scored lower on the LASSI, that is, they had less developed learning and study strategies than their peers without ADHD. Similarly, Reaser and coauthors (2007) found that students with ADHD scored lower on a college-readiness instrument measuring academic skills such as time management and study skills. Qualitatively, students with ADHD expressed similar challenges in interviews with Kwon and coauthors (2018). As discussed in the following section, my findings extend this previous work by illustrating the underlying mechanisms by which aspects of the college experience influence academic success.

6.1.2 Mediating Role of College Experiences

My study's design enabled the investigation of the mediating role of college experiences, answering my second research question, *What college experiences, if any, mediate the relationship between a pre-college ADHD diagnosis and academic success?* Of the four indirect or mediating pathways (lavender paths in Figure 16), only one substantially attenuated the negative direct relationship between ADHD and first-year college grades. The path from ADHD to academic adjustment then to first year GPA partially mediated (~33%) the relationship. The other three mediating paths operated through *academic adjustment* and traversed through *sense of belonging* or *faculty interaction* but they did not substantially mediate the direct relationship between *ADHD* and *first-year grades*. My SEM suggests that understanding professors' expectations, study skills, and time management (indicator variables for the *academic adjustment* construct) influence first-year grades. In other words, students' academic adjustment partially explains the underlying mechanism between ADHD and first-year grades. Although my findings suggest faculty interaction and sense of belonging do not play a critical role in first-year grades, they may play a larger role in later measures of college grades, persistence, and career opportunities following college.

Unfortunately, this model does not incorporate a measure of instructional practices or short-term student motivation, although future research should explore their role in collegiate academic success. Motivation plays a role in academic engagement (Bowman et al., 2019) and if instructional practices in the classroom affect student motivation (e.g., James et al., 2017), these practices may indirectly influence first-year grades. However, measuring short-term motivation is complicated because there are multiple types (Touré-Tillery & Fishbach, 2014) and motivation has the potential to vary over time and across courses. Researchers should consider how to integrate short-term motivation in a SEM studying academic success in future studies.

Despite construct and path differences, the key role of academic adjustment on college grades remained consistent across the three academic success SEM discussed (i.e., this study's SEM, the van Rooij model, and the Bowman model). van Rooij and coauthors (2018) concluded students' behavior outweighed motivational factors in influencing GPA. Although my SEM did not include a motivational measure, the critical role of academic adjustment and study skills coincided and outweighed faculty interaction and sense of belonging. In the Bowman model, the only college level construct that directly influenced college GPA besides non-cognitive attributes was social adjustment (Bowman et al., 2019). Greater levels of social adjustment resulted in lower college GPAs, on average. The key role of academic adjustment on college grades has broad implications for higher education.

6.1.3 Implications for Science, Mathematics, and Engineering

First-year college grades relate to students' persistence decisions in science, technology, engineering, and mathematics (STEM; Dika & D'Amico, 2016; Main et al., 2015; Main et al., 2021; Stinebrickner & Stinebrickner, 2011; Thompson, 2021). Thompson (2021) found students earning higher first-year STEM GPAs are more likely to persist in STEM. Stinebrickner and Stinebrickner (2011) found first-year grades related to students' science and math persistence, and Dika and D'Amico (2016) found first-semester GPA was a statistically significant predictor of students' decision to persist in physical sciences, engineering, mathematics, and computer science majors. Furthermore, first-year grades are associated with students' decisions to switch majors within engineering (Main et al., 2015; Main et al., 2021). Thompson (2021) used social cognitive career theory to explain their findings: "For example, success in a course or field tends to raise a student's self-efficacy, increasing the likelihood that that student will remain on that career path. In contrast, poor experiences, including bad grades, lowers a student's self-efficacy and sense of belonging in that field and lowers the likelihood that he or she will persist." (p. 966)

Certain student groups (i.e., first-generation college students and women) experience greater "grade sensitivity" (Thompson, 2021, p. 965); they are less likely to persist despite earning an equivalent first-year STEM GPA as students belonging to other student groups (e.g., first-generation college students compared to students who are not first-generation college students). Whether students with ADHD experience a heightened sensitivity to grades is unknown as there are not equivalent studies. Regardless, my findings that students with ADHD earn on average slightly lower grades potentially suggest a lower likelihood of persistence in science, mathematics, and engineering.

Furthermore, students experiencing more difficulty adjusting to college academics, particularly developing study skills and time management, may face challenges with instructional practices common in STEM (e.g., lecture and project-based learning in teams). Lecture remains the predominant instructional method in engineering and STEM (Apkarian et al., 2021; Borrego et al., 2010; Cutler et al., 2012; Manduca et al., 2017; Stains et al., 2018; Viskupic et al., 2019), and increases students' need to sustain attention, take notes, and learn the course material outside of class time. For students with less developed study skills and time management skills, such as many first-year students with ADHD, this instructional method makes achieving the learning objectives more difficult (e.g., Lefler et al., 2016).

Furthermore, students with ADHD may experience difficulties in groups or teams (e.g., James et al., 2020), such as in project-based general introductory engineering courses, that are not adequately structured to support students' differences in academic adjustment. An example scenario is if a student does not complete a portion of the project on schedule or understand the instructors' expectations for the project, they may potentially negatively affect their group's grade and perhaps have less positive interactions with peers. Frequent and structured support of group work may lessen the likelihood for this outcome.

More research on STEM instructional practices and the academic success of students with ADHD is necessary. Only a few researchers (James, 2020; Lefler et al., 2016) have explored the role of instructional practices, and these studies are not specific to STEM. I recommend that future work explores the role of STEM instructors' use of (1) instructional practices on students' motivation, learning, and success and (2) explicit structure in team and groupwork for neurodiverse groups of students.

6.2 Creativity

6.2.1 Relationships among Precollege, College, and Academic Success

This study found that students with ADHD are significantly more likely to perceive themselves as more creative than their peers, and previous studies suggest students' perceptions of their creativity are predictive of their creative achievements and divergent thinking ability (e.g., Boots et al., 2017; Furnham et al, 2005). Elementary students' self-rating of their creativity is typically consistent with teachers' rating of the students' creativity (Beghetto, Kaufman & Baxter, 2011). College students' self-rating of their creativity had "high predictive ability" of their scores on a tested measure of creativity (Furnham et al., 2005, p. 137), the Barron-Welsch Art Scale (Barron, & Welsh, 1952). Boot and coauthors (2017) explored the relationship between ADHD symptoms and creativity of college students using self-reported creativity (i.e., an 8-item scale of creative behaviors), creative achievement (i.e., self-reports of achievements), and two established tests of divergent thinking. They found students' self-reports of creative behavior positively correlated with measures of divergent thinking and creative achievement.

I used Terenzini and Reason's (1995) college impact model to model creativity as an academic success outcome (Figure 17), measured as students' self-report of their ability in comparison to their peers. In this model, pre-college characteristics and experiences of having an ADHD diagnosis influences college experiences (specifically, *faculty interaction* and *sense of belonging*). Both pre-college characteristics and experiences of having an ADHD diagnosis and college experiences influence the academic outcome, creativity. For all three creativity SEMs, students with ADHD (diagnosed prior to taking the TFS as incoming first-year students) rated their creativity more highly than their peers without ADHD (as above average or in the top 10% of their peers) at the end of their first year of college. The creativity SEM had direct paths from *ADHD* to *faculty interaction* and *sense of belonging* and *ADHD* to the academic outcome, *creativity*. Furthermore, students reporting a previous ADHD diagnosis as incoming first-year students interacted more frequently with faculty, yet, they had a lower sense of belonging to their college campus than their peers without ADHD.

6.2.2 Mediating Role of the College Experience

The low magnitude of the faculty interaction and sense of belonging college experience indirect path coefficients relative to the direct path coefficient from *ADHD* to *creativity* (ratios of less than 0.1 or 10%) indicates their negligible mediating effect on creativity. The negligible partial mediation through *faculty interaction* and *sense of belonging* suggests that students' college experience during their first year, at least their interactions with faculty and their sense of belonging, do not substantially influence their self-rating of creativity.

6.2.3 Implications for Engineering

My SEMs suggest that students with ADHD are more likely to perceive themselves as more creative than their peers, yet they are more likely to earn lower grades, than students without ADHD. Although my study broadly included first-year college students, its findings are similar to those of Taylor and coauthors (2020) of engineering students with ADHD. They found that ADHD characteristics were associated with lower engineering grades, though not overall grades, and higher levels of divergent thinking, measured using Torrance Tests of Creative Thinking (Torrance, 2008).

My SEMs did not explore the relationship between creativity and first-year grades. The findings of other researchers regarding the relationship among creativity and grades are inconsistent. A meta-analysis suggested a small, positive correlation ($r = .22$) for K-12 students (Gajda et al., 2017); students with higher levels of creativity had greater academic outcomes. Studies of college students are more limited, although there are several that solely focus on engineering. In one such study, Kim (2020) found the creativity of engineering students at a university in Korea increased from their first year to their fourth year. Kim (2020) attributed the students' increases in creativity to the institutional environment and teaching practices at the university.

For engineering, the implications of the finding that students' with ADHD perceive themselves as more creative than their peers, reflect those noted by Taylor and coauthors (2020). Students with ADHD, who on average exhibit higher levels of creative or divergent thinking, may leave engineering if they find their "traditional" engineering education does not value creativity (p. 213). Further, based on my findings that sense of belonging and faculty interaction do not mediate the creativity academic outcome, I recommend researchers instead explore the role of classroom instruction. Instruction that values differences and strengths, such as creativity, is recommended by Chrysochoou and coauthors (2022) and Taylor and coauthors (2020) and may be particularly important in the first-year of college to retain more creative students.

6.3 Recommendations

The importance of academic adjustment for the first-year grades of college students highlights the critical role of the individual student experience for academic success during students' first-year of college. Therefore, in identifying study implications and recommendations, I focus on changes to the college environment or college experiences, and specifically on academic adjustment, that might positively affect academic success. This approach is consistent with my research objectives: identify aspects of the college experience that influence college success and recommend targeted changes to improve the college environment. By incorporating literature findings, I provide suggestions for higher education instructors and institutions to support students' academic adjustment, based on the evidence-based relationships identified in my first-year grade SEMs. Although my dissertation does not provide evidence to support specific instructional or institutional changes, others (e.g., Chrysochoou et al., 2022; Canu et al., 2021; Griful-Freixenet et al., 2017; Shmulsky et al., 2021; Welby, 2022) have suggested specific aspects to support students' academic adjustment.

These recommendations align with Universal Design for Learning (UDL; CAST, 2023). UDL provides three guidelines for teaching (provide multiple means of *engagement*, *representation*, and *action and expression*) that are based on fundamental principles of learning. It strives to optimize all students learning through optimized teaching practices (CAST, 2023). The recommendations in this section highlight specific aspects of UDL that are, based on my research findings, specifically important for first-year grades of students with ADHD.

My recommendations involve instructional change. Instructional change is modeled theoretically as a process in which instructors progress through stages: *unaware*, *aware*, *interested*, and *adopted* (Lund & Stains, 2015). Movement from the first to second stage of the process involves instructors becoming aware of an instructional practice and, in the third stage, instructors gain in-depth knowledge of the practice and decide whether to adopt it. In the final stage, instructors introduce the new instructional practice in their courses (Lund & Stains, 2015). This progression is necessary for sustained instructional change.

I address the first three stages of the instructional change process (*aware*, *unaware*, and *interested*), as precursors to change, and recommend increasing awareness to neurodiversity and a strengths-based approach to instruction. These are discussed prior to providing recommendations related to the fourth stage, *adopt*, in the following subsection. The recommendations focus on creating a supportive environment for students' academic adjustment and suggest classroom strategies related to understanding of their professors' expectations, time management, and study skills.

6.3.1 Precursors to Change

Although instructional strategies and institutional policies play a role in promoting the academic success of a diverse student body, shifting higher education professionals' and students' view of neurodiversity (from *unaware* to *aware* to *interested*) is a critical precursor to instructional change (Chrysochoou et al., 2022; Lund & Stains, 2015; Rogers, 2003). Increased awareness of neurodiversity and the value neurodivergent individuals bring to higher education and their future fields is critical (Chrysochoou et al., 2022). Accordingly, an important precursor to change is instilling an institutional culture that promotes equity and inclusion in classrooms and acknowledges and values differences in students' experiences, strengths, and ways of thinking (Santhanam, n.d.). Additionally, higher education professionals should be aware that students with ADHD are more likely than their peers to also be autistic (Rommelse et al., 2010) or have anxiety or mood disorders (Kessler et al., 2006).

Another precursor to change is developing an institutional culture (or mindset) that approaches education with flexibility and understanding (O'Regan, n.d.) and focuses on strengths (Chrysochoou et al., 2022). An inclusive classroom environment requires flexibility and understanding from higher education professionals and students (O'Regan, n.d.) alike as students play a role in creating an inclusive institutional culture through peer-interactions. Furthermore, a strengths-based approach to education promotes the success of a neurodiverse group of learners (Chrysochoou et al., 2022). "A strengths-based approach toward neurodiversity incorporates an awareness of students' unique abilities rooted in biological/neurological variations…" (Chrysochoou et al., 2022, p. 5). For example, instruction with this approach uses varied and flexible assignments and assessments that value creative contributions (Santhanam, n.d.; the ADHD Academic, 2022; Welby, 2022).

In the following subsections, I offer recommendations for classroom instruction and for institutional policies (i.e., the college environment) that others' have recommended to support students' academic adjustment (e.g., Santhanam, n.d.) with the goal of positively impacting students' first-year college experience. They may also lower the emphasis of academic adjustment on first-year grades. Ideally, these changes could also impact students' four-year academic success since first year grades may remain relatively constant in future semesters. This idea is supported by the findings of DuPaul and coauthors (2021): first-year grades either remained stable or improved in students' subsequent semesters of college for all three groups of students (students without ADHD, students with ADHD taking medication for their ADHD, and students with ADHD not taking medication for their ADHD) – implying that first-year grades are important indicators of students' continuing academic success.

6.3.2 Recommendations for Classroom Instruction

The SEM indicates that students' academic adjustment to college is the primary college experience contributor to first-year grades. The three measured variables of *academic adjustment* examined were students' (1) understanding of their professors' expectations, (2) self-rating of their time management, and (3) self-rating of their study skills. Although entering college with well-developed college-readiness skills like these eases the transition, many incoming students begin college still needing to develop these skills (e.g., Reaser et al., 2007). Higher education should support students in this development and reduce the dependency of learning outcomes and grades on these skills, particularly in the first year.

During the first year, I recommend providing students with multiple and varied opportunities to build their college-readiness skills, consistent with UDL guidelines for sustaining effort and persistence, and self-regulation (CAST, 2023a). Administrators, instructors, and staff should recognize that students are starting college with varying abilities and different opportunities to have developed strategies. Instructors should be cognizant that there are likely students with ADHD in their courses (Santhanam, n.d.). Many of them will not have registered with their institution's disability services office (National Center for Education Statistics, 2022), and thus will not have accommodations. The next three subsections describe specific recommendations for instructors for all students, all of which align with the more general UDL guidelines, and may benefit all students, and especially those with ADHD.

6.3.2.1 Understanding Professors' Expectations.

The classroom provides an excellent opportunity to scaffold students' academic adjustment. One aspect is helping students understand the course expectations. The second column in Table 28 includes strategies instructors can use to support students in understanding the expectations for their courses. For example, instructors can design courses with clear structure (Shmulsky et al., 2021) and use direct and written communication to convey this structure (Santhanam, 2019; Santhanam, n.d.). For example, providing a shortened, single-page version of the course syllabus with key information, such as assignment due dates and assessment dates can provide students with more explicit structure (Welby, 2022). Instructors can also clearly and directly communicate learning objectives (Welby, 2022) and their standards and expectations for course assignments, projects, and assessments (Santhanam, 2019; Santhanam, n.d.; Shmulsky et al., 2021). Written directions, a grading rubric, and assignment, paper, or project examples, located in a single location, can accompany assignments, projects, and assessments (the ADHD Academic, 2022). Further, large assignments can involve multiple drafts or stages, at each of which specific, written feedback is provided (Griful-Freixenet et al., 2017). This gives students multiple opportunities to understand assignment expectations and improve their grades.

6.3.2.2 Time Management.

Instructors can also support students' time management skills in the classroom (third column in Table 28). For shorter-term, daily, or weekly assignments, instructors can schedule consistent due dates with consistent reminders that correspond with a relevant time or date, such as the start of class (Shmulsky et al., 2021; the ADHD Academic, 2022). For example, if there are weekly assignments, design the course so they are due each week on the same day and at the same time. This enables students to develop a regular weekly routine for studying and homework and aid in remembering due dates. Instructors can scaffold longer-term assignments (the ADHD Academic, 2022), not only helping students manage their time but also modeling how students might break a large assignment into more manageable parts, an often more difficult task for students with ADHD than their peers without ADHD (Canu et al., 2021). Scaffolding can also improve motivation and engagement (Belland et al., 2013). Instructors can also support students in scaffolding their own longer-term assignments. By requiring students to submit a plan and timeline for completion, students have the opportunity to practice partitioning assignments or projects into smaller steps and managing a schedule for completion.

Group work provides an additional opportunity to support students' time management. Scaffolding students' time management can also apply to group work and should occur prior to students beginning work (Santhanam, n.d.). Instructors can provide structure for group work by requiring students to plan and provide the written organization of the division of tasks among group members and schedules for its completion (Santhanam, n.d.).

6.3.2.3 Study Skills.

First-year courses provide an excellent opportunity for instructors to aid students in developing study skills (fourth column in Table 28). Instructional practices such as active learning enable more student learning in class (e.g., Theobald et al., 2020), and they reduce the need for traditional study skills, such as taking and reviewing notes. Additionally, instructors can encourage students to study actively and on multiple occasions (Dolin, 2022; The Learning Center, n.d.). Active studying, which includes problem-solving, self-quizzing, and drawing concept maps, is associated with more effective learning than passive activities, such as reviewing notes and reading and highlighting text (The Learning Center, n.d.). Additionally, instructors can dedicate class time to connect with other students to create groups for later study and attach exam wrappers as a cover sheet on exams, where students can preemptively evaluate and then reflect on their exam readiness (Lovett, 2013).

6.4 Recommendations for Institutional Policies

Institutions should also develop policies to support students' academic adjustment and success. An example of a beneficial policy is one that provides academic coaching for all students who feel they would benefit from it. Academic coaching provides broad support related to academic development, as shown in Figure 20 (University of Colorado, n.d.). Institutions can offer first-year courses aimed at promoting students' academic adjustment and success to all students (e.g., University College, n.d.). They can also require instructors to record lectures, enabling students to access the information multiple times (Chrysochoou et al., 2022). Institutions can also provide faculty development opportunities to facilitate cultural change and support faculty in promoting students' academic success (Carroll et al., 2022). Faculty development opportunities may promote an improved understanding of neurodiversity and the plight of neurodivergent college students.

Table 28. Instructional strategies to scaffold students' academic adjustment.

	Understand professors' expectations	Time management	Study skills
Course design	Provide a one-page summary of your syllabus	Build consistent structure into course	Provide class time for students to create study groups
	Create and communicate a clear course structure	Schedule consistent assignment due dates (day, time)	Schedule frequent quizzes to encourage multi-occasion studying
Instruction	Communicate learning objectives		Use active learning in class
Assignments & projects	Provide written directions, examples, and a rubric	Scaffold long-term assignments and projects, divide project into parts with intermediate due dates	Use a single, central location for storing assignment, examples, rubric, etc.
	Provide multiple opportunities for feedback and revisions	Build in flexibility in due dates	Encourage active studying out of class & provide examples or activities
		Send consistent email reminders	
Assessments	Provide examples of previous exams		Encourage studying on multiple occasions
			Use exam wrappers for students to preemptively and reflective self-assess their exam preparation
Group work	Provide feedback on students' written plans and division of labor	Written plans and division of labor	

Note. Strategies from Welby (2022), Shmulsky et al. (2021), Santhanam (2019), the ADHD Academic (2022), Griful-Freixenet et al. (2017), Canu et al. (2021), Dolin (2022), The Learning Center (n.d.), and Lovett (2013).

Figure 20. Academic adjustment support provided for students through academic coaching (University of Colorado, n.d.)

6.5 Summary

Structural equation modeling of first-year grades suggests that students diagnosed with ADHD before their first year of college, on average, rate themselves as less adjusted to the academic demands of college and earn, on average, lower grades. They are also more likely to identify as having higher levels of creativity. My modeling did not find, however, that students' first-year college experience influenced their creativity self-ratings.

My results indicate that academic adjustment partially mediates the academic success of students with ADHD, which has implications for higher education administrators, staff, instructors, and students. As theorized by Lund and Stains' (2015) instructional change model, a necessary precursor to these recommended instructional and institutional changes is shifting the culture of higher education and its view of neurodiversity. Instructional strategies in the classroom and institutional policies can support all students’ academic adjustment. Students’ understanding of their professors’ expectations and development of time management and study skills can be promoted in the classroom. Furthermore, institutions can create policies that promote the academic success of incoming college students with varying levels of college-readiness skills.

Chapter 7 Conclusions

Most of the research studies on the college experiences and academic success of students with ADHD suggest these students encounter a challenging college experience and less academic achievement than their peers without ADHD (e.g., Canu et al., 2021; Gormely et al., 2019; Lefler et al., 2016). Few studies explore the relationship between these challenging college experiences and students' academic outcomes, particularly none with this large of a data set. The primary goal of my dissertation was to understand the role of the college experience on the academic success (i.e., first-year grades and creativity) of students with ADHD and, based on these findings, recommend changes to the higher education environment that positively impact first-year students.

To explore the relationships between students' pre-college characteristics and experiences, college experiences, and academic success of students with ADHD, I estimated structural equations models (SEMs) for first-year grades and creativity using multi-institutional, longitudinal data from four cohorts of first-year college students (n = 43,523). The models incorporated a common strength of students with ADHD, creativity, as an academic success outcome and a known challenge, academic adjustment, as part of the college experience.

7.1 First-year grades

7.1.1 Model Structure.

I specified first-year grades SEMs based on theoretical student retention models, specifically Terenzini and Reason's (2005) college impact model and Bowman and coauthors'

(2019) models' integration of non-cognitive attributes. The SEMs exhibited an excellent fit with the data used in this study providing supportive evidence for the model structure, and particularly the incorporation of non-cognitive attributes in a student retention model (Bowman et al., 2019). The SEMs indicate that students' academic adjustment influences their college experiences (i.e., faculty interaction and sense of belonging) and academic success (i.e., first-year grades). Furthermore, students' pre-college characteristics and experiences influence their collegiate academic adjustment and first-year grades.

7.1.2 Parameter Estimates and Mediation.

Students diagnosed with ADHD prior to the time that they are incoming college students rated their academic adjustment (understanding of professors' expectations, time management, and study skills) lower than their peers. Additionally, they earned, on average, slightly lower first-year grades than their peers. Students' academic adjustment partially mediated (approximately 33%) the relationship between a pre-college ADHD diagnosis and first-year grades, further reducing the gap in first-year grades between students with ADHD and their peers without ADHD. In other words, academic adjustment attenuates the magnitude of the relationship between ADHD and first-year grades. Students who more easily adjust to college academics earn higher first-year grades than students who experience a more difficult time adjusting to college academics. Furthermore, students' academic adjustment positively influences their frequency of interaction with faculty and their sense of belonging.

7.2 Creativity

7.2.1 Model Structure.

To model students' creativity as an collegiate academic outcome, I specified my SEM based on Terenzini and Reason's (2005) college impact model. The models included selected pre-college characteristics and experiences (e.g., ADHD), and the college experiences (i.e., faculty interaction and sense of belonging) mediate the relationship between pre-college characteristics and experiences and academic success (i.e., above average or top 10% ratings of creativity). The models that incorporated additional pre-college characteristics best fit the data.

7.2.2 Parameter Estimation and Mediation.

In contrast to first-year grades, students with ADHD are more likely to rate their creativity higher (above average or in the top 10%) than their peers without ADHD at the end of their first-year of college. The frequency of their interaction with faculty and their sense of belonging during their first year of college had a negligible mediating effect on this relationship.

7.3 Implications

7.3.1 Theoretical.

The theoretical implications of my findings suggest that academic adjustment in college (or non-cognitive attributes, as included by Bowman et al., 2019) are a critical component of collegiate academic outcome models of first-year grades. In this study, the academic adjustment construct plays a larger role in first-year grades than either sense of belonging or faculty interaction. The critical role of academic adjustment is consistent with the findings of Bowman and coauthors (2019) and van Rooij and colleagues (2017). Furthermore, students' academic adjustment is strongly predictive of their study skills and time management.

7.3.2 Practical.

The mediating role of academic adjustment on first-year grades has implications for classrooms and institutional policies recommendations in higher education for all students including those with ADHD. These recommendations involve instructional change, which theories posit is a staged process with initial stages related to awareness and a decision to adopt the change (Lund & Stains, 2015). As precursors to suggested instructional strategies, and consistent with Chrysochoou and coauthors (2022), I recommend higher education administrators, staff, and students develop an increased awareness of neurodiversity, a inclusive institutional culture, and a strengths-based approach to instruction.

Recommendations for instructional strategies to support students' academic adjustment are particularly applicable to instruction in first-year courses (but would likely benefit all courses). They focus on easing students' academic adjustment to college through (1) scaffolding academic adjustment skills (understanding professors' expectations, time management, and study skills) and (2) deemphasizing academic adustment skills in first-year college grades. The former provides students entering college with different opportunities to build these skills and additional time to build these skills while supported by scaffolded opportunities. One way of accomplishing the latter is through instructional methods, such as active learning, that promote student learning during class (e.g., Prince, 2004) and encouraging active studying (Dolin, 2022).

7.4 Future Work

This study provides a first-step and a framework for designing future research studies to explore the academic success of college students and may help guide future studies on the academic success of neurodivergent students. The implications of my findings and my recommendations for higher education highlight the need for further work. First, I recommend researchers further explore the role of college experiences, while incorporating instructional practices, on the academic success of students with ADHD as well as other neurodivergent students. My SEMs illustrate the critical role of academic adjustment for both students with and without ADHD. However, they do not include measures of short-term (or course-specific) motivation, which is influenced by instructional practices (e.g., Lefler et al., 2016), and influences academic engagement (Morsink, 2022). Second, I recommend that researchers study, using qualitative and quantitative methods, how recommended instructional strategies from the literature contribute to students' academic adjustment to college. For example, some strategies, such as scaffolding larger assignments, may have a greater affect than others. These research findings would allow instructors to prioritize changes to their courses based on those with the greatest influence.

Appendix A Missing Data

A.1 Missing Data Mechanism

Missing data, a common challenge encountered in quantitative research, is classified based on the mechanism by which it is missing: missing completely at random (MCAR), missing at random (MAR), and missing not at random (MNAR; Allison, 2002; Enders, 2010; Enders, 2022; Rubin, 1976). In MCAR data, every item response has an equal probability of being missing; missingness is not related to observed or missing values. MAR data exhibits systematic missingness associated with observed data but not missing values. In MNAR data, missingness is related to observed values and missing responses' (unknown) values. The best practice is to determine the missing data mechanism for each model (e.g., first-year grades and creativity; Enders, 2022). Hypothesis testing can identify MCAR data; however, differentiating between MAR and MNAR data is more difficult since the actual values of the missing data are unknown (Allison, 2002; Enders, 2010; Enders, 2022).

A.1.1 Overview of Missing Data.

The first step in understanding missingness is developing an overview of the missing data. The regressors for the first-year grades and creativity models for these two outcomes are listed in Table 29, along with the number of missing observations and the fraction of missing responses. Altogether, 18,909 of the 45,915 (41%) responses have some degree of missingness. The most frequently missing variables are shaded. Standardized test score (*STANDTEST*) has the largest number of missing responses (*n* = 10,703 or 23.3%), followed by first-year grades

(*CURRGPA*; n = 7,477 or 16.3%). Many college experience indicator variables have more than 10% missing responses. The academic adjustment (i.e., understands professors' expectations, study skills, time management, and adjust to the demands of college) and the sense of belonging (i.e., feel a member of this college, feel a sense of belonging to this campus, and part of the campus community) indicator variables have approximately 5,000 to 7,000 missing responses, accounting for 11 to 15% of the respondents.

Patterns of missing responses (Table 30) are also important to identify. Approximately 59% of responses are complete. The second most common missing data pattern is respondents missing only the standardized test score (n = 7,305, 15.9%). Other missing data patterns account for less than 5% of responses.

A.1.2 Mechanism Exploration.

To determine whether the data in the first-year grades or creativity data set is MCAR, I ran a series of regressions on missing data indicators (M_y; variables with an indicator of zero if a value is missing and one if there is a response) for the model variables with more than 5,000 missing responses (10.9%; shaded gray in Table 29). These regressions provide evidence that the probability that a response is missing is related to observed responses, suggesting the non-responses are not MCAR.

Table 31 shows regression results for the standardized test score missing data indicator ($M_{STANDTEST}$) for the first-year grades model. Multiple model variables (i.e., sex, first-generation college student, underrepresented racial/ethnic group, high school GPA, study skills, frequency of interactions with faculty during office hours, feel a member of campus, and first-year grades) have significant p values ($p < .05$), providing evidence that respondents with these characteristics have a higher probability of a non-response on standardized test score. This is particularly evident for high school GPA (*HSGPA_TFS*; $t = -24.36$, $p < .0001$); students with lower high school GPAs are more likely to have missing responses on the standardized test score variable. These regressions are inconsistent with MCAR data, yet they cannot differentiate between MAR and MNAR data (Allison, 2002; Enders, 2022).

Enders (2022) recommends considering standardized mean differences (b_{StdXY}; third column of Table 31) of greater than 0.2 effect size (small effect size threshold; Cohen, 2013) as evidence against MCAR data. Accounting for other model variables, none of the model variables exceed this 0.2 small effect size threshold for the standardized test score missing indicator (Table 31). In contrast to the regression results previously described, the standardized mean differences do not provide evidence against the data being MCAR.

Strong relationships among model variables (one regressor is predictive of another regressor) benefit the multiple imputation process because these relationships help fill in missing data (Allison, 2002). To gather information on these relationships, I ran a series of regressions for each model variable regressed on the dependent variable (e.g., first-year grades, *CURRGPA*; creativity, *CREATIVITY1*) **and** the independent model variables. The standardized test score regression results (Table 32) indicate that the first-year grades, sex, and high school GPA variables are highly correlated with the standardized test score variable (*STANDTEST*; e.g., first-year grades, *CURRGPA*, $t = 26.10$, $p < .0001$; sex, *FEMALE*, $t = -28.04$, $p < .0001$; high school GPA, *HSGPA_TFS*, $t = 29.80$, $p < .0001$). The high t values ($t > 10$) indicate highly significant relationships. Strong relationships among other regressors and the regressor with the most missing data (*STANDTEST*) are essential to impute missing data for this variable. This follows for other variables with larger amounts of missing data.

Table 29. Number of missing and non-missing responses and the fraction of missing responses.

Variable	Missing responses	Fraction of responses missing	Non-missing responses
Precollege Characteristics and Experiences			
ADHD	2,177	0.047	43,738
Sex	39	0.001	45,876
First-generation college	1,220	0.027	44,695
Underrepresented racial/ethnic group	259	0.006	45,656
High school GPA	610	0.013	45,305
Standardized test score	10,703	0.233	35,212
Resilient	1,299	0.028	44,616
College Experience			
Concerns about financing college	74	0.002	45,841
Understands professors’ expectations	5,064	0.110	40,851
Study skills	5,061	0.110	40,854
Time management	5,084	0.111	40,831
Adjust to demands of college	5,078	0.111	40,837
Interact with faculty outside of class/office hours	1,920	0.042	43,995
Seek advice from faculty	5,614	0.122	40,301
Interact with faculty during office hours	1,852	0.040	44,063
Feel a member of this college	6,680	0.145	39,235
Feel a sense of belonging to this campus	6,680	0.145	39,235
Part of the campus community	6,389	0.139	39,526
Academic success			
First-year grades	7,477	0.163	38,438
Self-rating of creativity	4,909	0.107	41,006

Note. The shaded variables have 5,000 (10.9%) or more missing responses.

Table 30. Missing data patterns (with greater than 350 responses) for the model variables within the first-year grades/creativity data set; variables with missing responses are indicated by an "x"

	Precollege		College experience				Academic success	
n (%)	ADHD	Standardized test score	Academic adjustment indicators	Faculty interaction indicators	Seek faculty advice only	Sense of belonging indicators	First-year grades	Creativity
27,006 (58.8)								
7,305 (15.9)		x						
2,099 (4.6)			x		x	x	x	x
1,239 (2.7)			x	x	x	x	x	x
849 (1.8)	x							
676 (1.5)							x	
586 (1.3)		x	x		x	x		
526 (1.1)						x	x	x
379 (0.8)	x	x						

Table 31. Missing indicator variable for standardized test score (STANDTEST) regressed on independent variables and the dependent variable (first-year grades)

$M_{STANDTEST}$	*t*	*p* value	b_{StdXY}
Pre-college Characteristics and Experiences			
ADHD	-0.96	0.336	-0.005
Sex	14.18	<0.001	0.075
First-generation college	9.87	<0.001	0.054
Underrepresented racial/ethnic group	9.39	<0.001	0.051
High school GPA	-24.36	<0.001	-0.144
Resilient	0.44	0.659	0.002
College Experiences			
Concerns about financing college	-0.90	0.367	-0.005
Understand professors' expectations	-1.04	0.300	-0.006
Time management	1.54	0.124	0.011
Study skills	2.53	0.011	0.019
Adjust to demands of college	-1.86	0.063	-0.015
Interact with faculty out of class/office hours	0.04	0.970	0.000
Seek advice from faculty	1.23	0.218	0.007
Interact with faculty during office hours	3.83	<0.001	0.024
Feel a member of this college	-3.30	0.001	-0.030
Feel sense of belonging to this campus	0.69	0.492	0.006
Part of the campus community	-0.37	0.712	-0.003
Academic Success			
First-year grades	-5.03	0.000	-0.032

Table 32. Standardized test score (STANDTEST) regressed on first-year grades model variables

	t	p	b_{StdXY}
Pre-college Characteristics and Experiences			
ADHD	7.18	<0.001	0.038
Underrepresented racial/ethnic group	-25.41	<0.001	-0.137
Female	-28.04	<0.001	-0.148
First-generation college	-26.29	<0.001	-0.141
High school GPA	49.80	<0.001	0.292
Resilient	-0.44	0.657	-0.002
College Experiences			
Concerns about financing college	-15.26	<0.001	-0.082
Understand professors' expectations	-0.05	0.959	0
Study skills	-6.93	<0.001	-0.053
Time management	-12.87	<0.001	-0.094
Adjust to college demands	8.91	<0.001	0.07
Interact with faculty out of class/office hours	1.32	0.186	0.008
Seek advice from faculty	-1.62	0.104	-0.009
Interact with faculty during office hours	-12.73	<0.001	-0.079
Feel a member of this college	0.66	0.509	0.006
Feel sense of belonging to this campus	0.60	0.547	0.006
Part of the campus community	-1.28	0.201	-0.01
Academic Success			
First-year grades	26.10	<0.001	0.168

If the data is MNAR, the missingness is related to missing and observed values (Allison, 2002; Enders, 2010). In this study, there are theoretical reasons to hypothesize that the missing data mechanism is MNAR. An example of this reasoning to suggest MNAR data in this study is that students with lower pre-college standardized test scores may be less likely to respond to the survey item about their standardized test scores. Classifying the data sets as MAR or MNAR requires additional consideration beyond the described analysis providing evidence against MCAR data (Allison, 2002; Enders, 2010; Enders, 2022). Most likely, the missing data mechanisms in first-year grades and creativity data sets are a combination of MAR and MNAR.

A.1.3 Method for Handling Missing Data.

Whether the data is MAR or MNAR, the common practice of dropping entire responses with missing data can result in non-response bias (i.e., biased coefficients and standard errors; Allison, 2002; Enders, 2010; Enders, 2022). Other methods, such as multiple imputation, used to fill in missing data, are more appropriate, and ideally, for MNAR data, Allison (2002) recommends modeling the missing data mechanism. However, modeling the missing data mechanism is often not practical because of the absence of information on the actual values of the missing responses (Allison, 2002). Fortunately, multiple imputation is relatively robust to MNAR data (Allison, 2002).

Therefore, I used multiple approaches to handle missing data. Lacking the necessary information to model the missing data mechanism, I used multiple imputation with auxiliary variables (discussed in the next section) to fill in incomplete responses prior to structural equation modeling (SEM). I compare these results using multiple imputation with SEM results from which responses with missing values are dropped. Furthermore, I include a discussion of the potential implications of my decisions regarding missing data and the potential for introducing non-response bias in the limitations section.

A.2 Auxiliary Variables

Auxiliary variables are available variables that are not included in the theoretically-based SEM. However, they should be included in handling missing data because they contain information about missing values (Enders, 2022). I introduced the variables that I include as potential auxiliary variables in the Methods chapter in the tables of pre-college characteristics and experiences and college experiences variables (Table 2–9). Other potential auxiliary variables are only included in this Appendix. To identify auxiliary variables, I used the inclusive analysis strategy Enders (2022) described, based on the work of Collins and coauthors (2001). Its primary focus is identifying auxiliary variables for model variables with the largest amount of missing data (e.g., *STANDTEST*).

There are three types of auxiliary variables: Type A, Type B, and Type C (Collins et al., 2001; Enders, 2022). Type A variables correlate with a model variable and its missingness (Collins et al., 2001). Type B variables correlate with a model variable but do not correlate with the missingness of that variable. Type C variables predict the missingness of a model variable but do not correlate to that model variable. Type A and B variables should be included in the multiple imputation (to avoid non-response bias and increase power, respectively; Enders, 2022). Type C variables do not improve the imputation and are omitted.

A.2.1 Auxiliary Variable Screening.

I analyzed 19 variables (Table A5) extraneous to the first-year grades and creativity models to determine whether they were auxiliary variables and, if so, their type. I selected potential auxiliary variables to screen based on their theoretical relationship to model variables. For example, for many students, parent's total income last year (*INCOME_TFS*) likely relates to students' concerns about financing college (*CFINANCONCERN*).

Following Enders (2022), I first considered the relationship between potential auxiliary variables (Table 33) and missing data indicators for model variables with more than 5,000 missing responses (highlighted in gray in Table 29). To do this, I determined standardized (on y) mean differences by regressing potential auxiliary variables on each missing indicator variable. In contrast to Type B variables, Type A and C variables have a standardized mean difference greater than 0.2 (i.e., Cohen's, 2013, small effect size; Enders, 2022). Table 34 includes the standardized mean differences for select variables (which include those with a standardized mean difference greater than 0.2) from Table 33. Three potential auxiliary variables (completed Algebra II, *MATH2_TFS*; completed AP Calculus, *MATH6_TFS*; and academic self-rating at the end of the first college year, *RATE02*) had standardized mean differences of greater than 0.2, indicating they are either Type A or C auxiliary variables.

I explored the relationships between potential auxiliary variables and model variables for the first-year grades and creativity models. Again following Enders (2022), I analyzed semi-partial correlations (after controlling for other model variables) with potential auxiliary variables for each model variable with more than 5,000 incomplete responses. Variables with semi-partial correlations larger than 0.3 are either Type A or B, providing information about the incomplete model variable beyond that provided by the other model variables (Enders, 2022). Semi-partial correlations are shown for the first-year grades model in Table 35, and none exceeded the 0.3 threshold. For the creativity model, only students' self-reported creativity as an incoming college student (*CREATIVITY_TFS*) exhibited a semi-partial correlation of greater than 0.3 (r_{sp} = 0.566) with students’ self-reported creativity at the end of their first year (*CREATIVITY1*). The three potential Type A auxiliary variables (i.e., with standardized mean differences greater than 0.2; *MATH2_TFS*, *MATH6_TFS*, and *RATE02*) did not have any semi-partial correlations larger than 0.3, indicating they are Type C variables.

Table 33. Potential auxiliary variables

Pre-college	
DISAB01_TFS	Learning disability (e.g., dyslexia)
DISAB03_TFS	Autism spectrum disorder
DISAB06_TFS	Psychological disorder (e.g., depression, anxiety, PTSD)
YRSTUDY2_TFS	Years studying mathematics
YRSTUDY4_TFS	Years studying physical science
YRSTUDY5_TFS	Years studying biological science
YRSTUDY7_TFS	Years studying computer science
MATH1-TFS	Completed Algebra II
MATH2_TFS	Completed pre-calculus/trigonometry
MATH3_TFS	Completed probability and statistics
MATH4_TFS	Completed calculus
MATH5_TFS	Completed AP probability and statistics
MATH6_TFS	Completed AP Calculus
INCOME_TFS	Parents' total income last year
LESS4MATH	Completed less than four years of math
CREATIVITY_TFS	Self-rating of above-average creativity
First-year of college	
INNOVATE	Alternate solutions to problems
RATE02	Self-rating of academic ability
RATE23	Self-rating of self-confidence (intellectual)

Table 34. Standardized (on y) mean differences between missing and non-missing shown for selected potential auxiliary variables

	Potential auxiliary variables							
Model variables	MATH2_TFS	MATH6_TFS	INCOME_TFS	LESS4MATH	INNOVATE	RATE02	RATE23	CREATIVITY_TFS
Pre-college Characteristics & Experiences								
Standardized test score	**-0.214**	**-0.293**	-0.198	0.180	-0.045	**-0.361**	-0.190	0.029
College Experiences								
Professors' expectations	-0.085	-0.061	0.027	0.021	0.018	**-0.226**	-0.070	-0.004
Study skills	-0.074	-0.071	0.038	0.021	0.009	-0.146	-0.034	-0.010
Time management	-0.007	-0.071	0.032	0.021	0.016	-0.178	-0.034	-0.006
Adjust to college demands	-0.075	-0.067	0.036	0.022	0.013	-0.134	-0.022	-0.007
Seek faculty advice	-0.062	-0.060	0.035	0.028	0.034	-0.120	-0.033	0.000
Feel a member of this college	-0.020	-0.055	0.010	0.044	0.040	-0.102	-0.034	0.000
Feel sense of belonging to this campus	-0.065	-0.062	0.008	0.042	0.033	-0.106	-0.041	-0.001
Part of the campus community	-0.060	-0.055	0.024	0.040	0.045	-0.085	-0.021	-0.003
Academic Success								
First-year grades	-0.079	-0.074	0.023	0.051	0.059	-0.110	-0.042	0.014
Creativity	**-0.214**	-0.065	0.040	0.025	0.005	**-0.252**	-0.003	-0.011

Table 35. Semi-partial residuals (standardized on x and y) of selected potential auxiliary variables with model variables with more than 5,000 missing responses

	Potential auxiliary variables			
Model variables	MATH2_TFS	MATH6_TFS	RATE02	CREATIVITY_TFS
Standardized test score	.192	.290	.182	.020
Professors' expectations	.001	-.003	.053	-.016
Study skills	-.001	-.001	.032	.004
Time management	.001	.006	.002	-.011
Study skills	-.001	-.001	.032	.004
Adjust to college demands	-.002	-.014	.069	.029
Seek faculty advice	-.022	-.054	.036	.061
Feel a member of this college	-.012	-.005	.027	.002
Feel sense of belonging to this campus	.000	-.001	-.008	.004
Part of the campus community	.039	.014	.008	.012
First-year grades	-.028	.000	.247	-.003

Table 36 summarizes the auxiliary variables and their types. Results shown in Table 34 and Table 35 indicate that variables measuring whether a student completed Algebra II (*MATH2_TFS*) and Calculus (*MATH6_TFS*) are Type C for the standardized test score model variable. Similarly, students' self-rating of their academic ability at the end of their first year (*RATE02*) is a Type C variable for both standardized test score (*STANDTEST*) and students' self-rating of their creativity at the end of their first year of college (*CREATIVITY1*). The only Type B variable is a student's self-rating of their creativity as an incoming student (*CREATIVITY_TFS*) – it exhibited a semi-partial correlation of greater than 0.3 with creativity self-rating at the end of their first year of college (*CREATIVITY1*). Therefore, it should be included in the imputation process to improve power (Enders, 2022). I did not identify any Type A auxiliary variables.

Table 36. Summary of auxiliary variables and their type

	Auxiliary variables			
Model variables	MATH2_TFS	MATH6_TFS	RATE02	CREATIVITY_TFS
Standardized test score	**C**	**C**	**C**	
First-year grades				
Creativity			**C**	**B**

Another approach used to decide whether to include a variable extraneous to the model in multiple imputation is the strength of the correlation between an extraneous variable and a model variable (UCLA: Statistical Consulting Group, n.d.). Table 37 shows the pairwise correlation coefficients for select extraneous and model variables. Students' self-rating of their academic ability (*RATE02*) correlated with standardized test score (*STANDTEST*; r = .37) and first-year grades (*CURRGPA*; r = .50), exceeding the recommendation for inclusion (r > .40; UCLA: Statistical Consulting Group, n.d.). Students' pre-college estimate of their parent's income (*INCOME_TFS*) correlated with their concerns about financing college during their first year (*FINANCECONCERN*; r = -.22), although it does not meet the .4 threshold. Despite having a lower correlation than the threshold, I included parents' income (*INCOME*) and intellectual self-confidence (*RATE23*) in the multiple imputation because of their theoretical connections to a student's ability to finance college and self-efficacy, respectively.

Table 37. Pairwise correlations model variables and variables extraneous to the model

	Self-rating of academic ability (*RATE02*)	Self-confidence (intellectual) (*RATE23*)	Standardized test score (*STANDTEST*)	First-year grades (*CURRGPA*)	Parent's income (*INCOME_TFS*)	Concerns about financing college (*CFINANCONCERN*)
Self-rating of academic ability	1					
Self-confidence (intellectual)	.48	1				
Standardized test score	.37	.16	1			
First-year grades	**.50**	.22	.30	1		
Parent's income	.13	.07	.19	.07	1	
Concerns about financing college	-.11	-.08	-.17	-.12	-.22	1

A.3 Multiple Imputation: Imputation Phase

In the multiple imputation process, I included the first-year grades and creativity model variables and the 22 extraneous variables shown in Table 38. I used the indicator variables related to student engagement in conceptual framework (i.e., HERI *academic disengagement* construct), that were not used in the SEMs, in multiple imputation. I also used all of the *faculty interaction* and *sense of belonging* indicator variables; institutional selectivity, *SELECTIVITY*; alternative solutions to problems, *INNOVATE*; frequently bored in class, *BOREDCLASS*; accepts mistakes as part of the learning process on the YFCY, *RESILIENCE1*; interacts with disability services, *DISABSERVICES*; and frequently interacts with friends, *FRIENDS*).

I conducted multiple imputation (i.e., filled in missing responses) using Stata's (StataCorp., 2021) multiple imputation by chained equations (MICE; StataCorp., 2021a). MICE allows individualized imputation models for each variable (StataCorp., 2021a). For example, a binary model is most appropriate for whether a student reports an ADHD diagnosis (*ADHD*). An ordinal model is the proper choice for the ordered study skills (*STUDYSKILLS*) variable. MICE also allows truncated regression for variables with a minimum and maximum value (StataCorp., 2021a).

I designated the univariate method (StataCorp., 2021a) for each variable based on its type (Table 38): binary variables employed the `logit` command, and ordinal variables the `ologit` option. For continuous variables, I used ordinary least squares regression for institutional selectivity (*SELECTIVITY*) and truncated regression for high school GPA (*HSGPA_TFS*; min. 1, max. 8), first-year grades (*CURRGPA*; min. 2, max. 9), and standardized test score (*STANDTEST*; min. 590, max. 1600). For high school and current GPA, I selected the minimum and maximum values based on the lowest and highest possible item response. For standardized test score, I selected the maximum value based on the highest possible SAT score and the lowest based on a value at which 99.999% of the standardized test scores were above.

I conducted multiple imputation with 30 imputations using 100 burn-in cycles (i.e., stabilization cycles before the draw), a seed of 1, and augmented the data to avoid perfect prediction. Stata's `augment` option adds "a few extra observations to the data set (with small weight) so that no prediction is perfect" (White et al., 2010, p. 394).

Table 38. Extraneous variables included in multiple imputation

		Missing responses	Fraction of missing responses	Type
Pre-college Characteristics and Experiences				
	Self-rating of creativity	1,554	0.03	ordinal
	Self-rating of academic ability	1,578	0.03	ordinal
	Self-rating of mathematical ability	1,591	0.03	ordinal
	Self-rating of self-confidence (intellectual)	1,630	0.04	ordinal
	Self-rating of drive to achieve	1,568	0.03	ordinal
College Experience				
	Institutional selectivity	302	0.01	continuous
Academic disengagement	Adjust to academic demands of college	5,078	0.11	ordinal
	Frequency late to class	5,721	0.12	ordinal
	Frequency skipped class	8,995	0.20	ordinal
	Frequency of turning in a course assignment(s) late	8,949	0.19	ordinal
	Frequency of turning in course assignments that did not reflect your best work	9,046	0.20	ordinal
	Frequency fell asleep in class	9,071	0.20	ordinal
Faculty interaction	Satisfaction with communication with faculty (not asked in 2017)	12,984	0.28	ordinal
	Communicated regularly with your professors	7,108	0.15	binary
Sense of belonging	Recommend this college to others	6,533	0.14	ordinal
	Alternative solutions to problems	4,611	0.10	ordinal
	Frequently bored in class	5,587	0.12	binary
	Interacts with disability services	5,138	0.11	binary
	Interacts frequently with friends	1,949	0.04	binary
	Self-rating of academic ability	4,890	0.11	ordinal
	Self-confidence (intellectual)	4,926	0.11	ordinal
Academic success				
	Accepts mistakes as part of the learning process	4,508	0.10	ordinal

A.4 Multiple Imputation Diagnostics

Imputation diagnostics suggest the adequacy of 30 imputations with 100 burn-in cycles for multiple imputation. Table 39 provides three diagnostic measures (*relative increase in variance,* RVI*; fraction of missing information,* FMI*;* and *relative efficiency*, RE; *UCLA: Statistical Consulting Group, n.d.*) for each model variable based on a first-year grades multiple regression. Stata does not provide these diagnostic measures following SEM because SEM of multiply imputed data is currently not supported.

The RVI is a measure of the increase in variance due to missing data; it considers the amount of missing data for a variable and that variable's correlation with other model variables (UCLA: Statistical Consulting Group, n.d.). Variables with high RVIs are most difficult for multiple imputation; they have a large amount of missing data or are not highly correlated with other variables (UCLA: Statistical Consulting Group, n.d.). Likely due to the relatively large amount of missing data, standardized test score has the highest RVI (.4173), meaning 41.73% of the variance stems from missing data. The variables for ADHD (RVI = .3050) and first-generation college (RVI = .2775) have the next largest RVIs. This is likely because they do not highly correlate with other model variables and are more difficult to impute.

The FMI is another measure of the variance occurring due to missing data (UCLA: Statistical Consulting Group, n.d.). The largest FMI (.2986) was for STANDTEST, followed by ADHD (.2366), meaning that 29.86% and 23.66% of the sampling variance resulted from missing data. Generally, the imputations should equal or exceed the largest FMI (*UCLA: Statistical Consulting Group, n.d.*). Standardized test score (STANDTEST) has the largest FMI (.2986), suggesting 30 imputations is adequate. To further determine the adequacy of 30 imputations for standard error replication, I used Von Hippel's (2018) formula,

$$M = 1 + \tfrac{1}{2}\,(FMI / CV(se))^2$$

where *M* is the number of imputations, *FMI* is the fraction of missing information (i.e., variance resulting from missing data), and *CV(se)* is the coefficient of variation. Allowing for a coefficient of variation of 5% with an *FMI* of .2986 requires 19 imputations, again suggesting the adequacy of 30 imputations. For 30 imputations, the *CV(se)* is less than 4% (3.92%).

Lastly, the RE provides the efficiency of the 30 imputations compared to an infinite number of imputations (*UCLA: Statistical Consulting Group, n.d.*). For my analysis, RE is larger than .99 for all model variables.

I also determined the sufficiency of 100 burn-in cycles from trace plots (*UCLA: Statistical Consulting Group, n.d.*). Trace plots for the mean (Figure 21) and standard deviation (Figure 22) of standardized test score are shown for three imputation cycles (1, 15, and 30); they indicate convergence within the 100 burn-in cycles. The means and standard deviations quickly flatten out indicating they are almost immediately stable (UCLA: Statistical Consulting Group, n.d.).

Table 39. Relative increase in variance (RVI), fraction of missing information (FMI), and relative efficiency (RE) for the 30 imputations based on first-year grades regressed on the model variables

	RVI	FMI	RE
Pre-college Characteristics and Experiences			
ADHD	.305	.237	.992
Underrepresented racial/ethnic group	.247	.200	.993
Female	.095	.087	.997
First-generation college	.278	.220	.993
High school GPA	.205	.172	.994
Standardized test score	.417	.299	.990
Resilient	.134	.119	.996
College experience			
Concerns financing college	.177	.151	.995
Understands professors expectations	.173	.149	.995
Study skills	.157	.137	.996
Time management	.248	.201	.993
Adjust to demands of college	.211	.176	.994
Interaction with faculty outside of class/office hours	.143	.126	.996
Seek advice from faculty	.252	.203	.993
Interact with faculty during office hours	.063	.059	.998
Feel member of this college	.183	.156	.995
Feel sense of belonging to this campus	.151	.132	.996
Part of the campus community	.166	.143	.995

After multiple imputation, I compared summary statistics for key variables (i.e., those with the greatest percentage of missing responses) across imputations (Table 40). Overall, the imputed fractions and means are similar across the imputed data sets. For standardized test score (*STANDTEST*), the mean of the original data set, 1233.8, was slightly higher than the consistent imputed data set means, approximately 1216. A lower mean of the standardized test score in the imputed data sets is unsurprising for MAR or MNAR data; students with lower test scores may be less likely to report them. Similarly, the number of students reporting an ADHD diagnosis is higher in the imputed than in the original data set. Students with an ADHD diagnosis may be less likely to respond to the survey item about an ADHD diagnosis if they are concerned that responding may potentially disclose this to their institution.

I further considered the distributions and kernel densities of imputed variables, particularly those with larger fractions of missing data, in assessing the adequacy of the imputation. The density graphs of standardized test scores (*STANDTEST*; Figure 23) of the incomplete data set resemble the distributions of the imputed data sets. This is similarly observed for average high school grade (*HSGPA_TFS*; Figure 24). This is further indication of the adequacy of multiple imputed data sets.

Figure 21. Trace plots for the estimated mean of standardized test score as a function of iteration for imputation 1 (upper left), 15 (upper right), and 30 (lower) over the 100 burn-in cycles

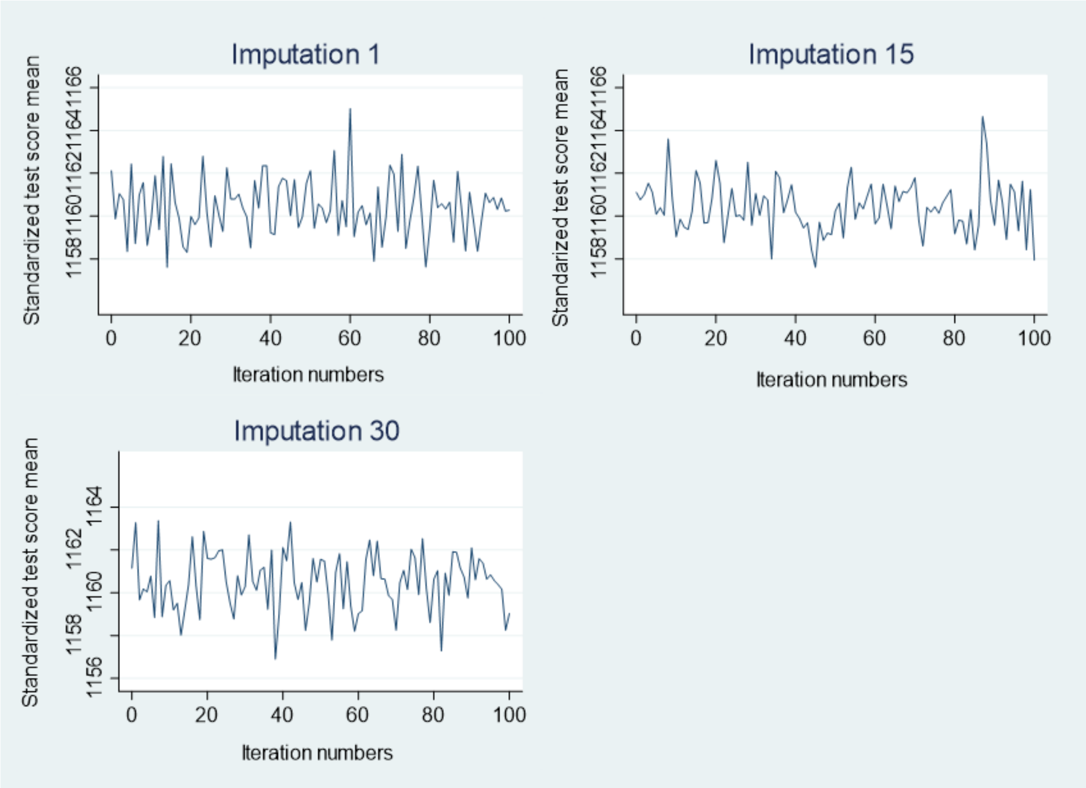


Figure 22. Trace plots of the 100 burn-in cycles for the estimated standard deviation of standardized test scores as a function of iteration for the 1st (upper left), 15th (upper right), and 30th (lower) imputation

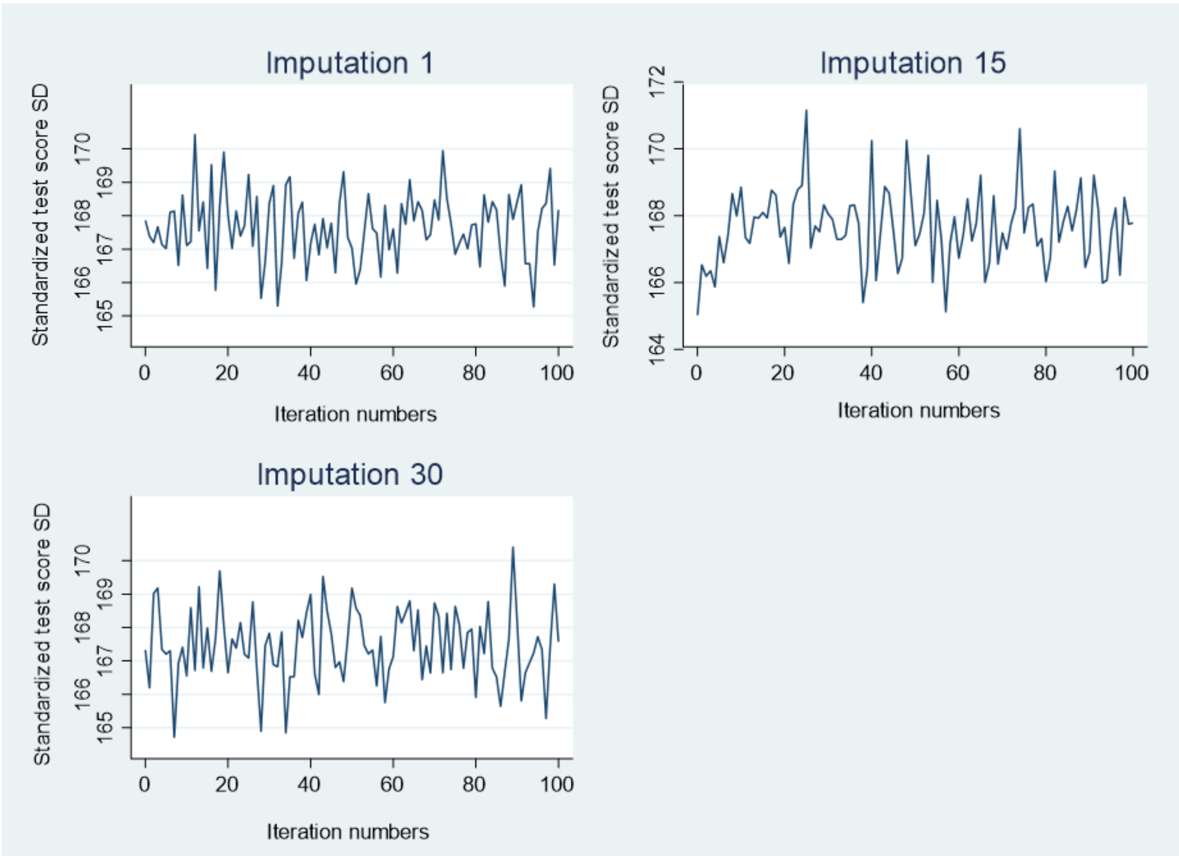


Table 40. Summary (fraction or mean and standard deviation) of original and imputed data sets for selected variables

		Imputation cycle					
	Original	1	5	10	15	20	30
ADHD							
ADHD (number)	2,082	2,236	2,226	2,228	2,224	2,220	2,249
ADHD (fraction)	0.049	0.049	0.049	0.049	0.048	0.048	0.484
Creativity							
Average or below (fraction)	0.397	0.444	0.443	0.444	0.444	0.444	0.444
Above average (fraction)	0.363	0.407	0.409	0.407	0.408	0.407	0.407
Top 10% (fraction)	0.133	0.149	0.148	0.149	0.148	0.149	0.149
Fraction missing	0.107						
Standardized test score							
Mean	1233.8	1216.6	1216.1	1216.7	1216.1	1216.3	1216.3
SD	164.3	168.1	168.4	167.4	168.2	168.1	168.1
First-year grades							
Mean	6.7	6.7	6.7	6.7	6.7	6.7	6.7
SD	1.2	1.2	1.2	1.2	1.2	1.2	1.2

Figure 23. Density plots of actual standardized test scores (top left) and data from the 1st, 5th, 10th, 20th, and 30th imputation

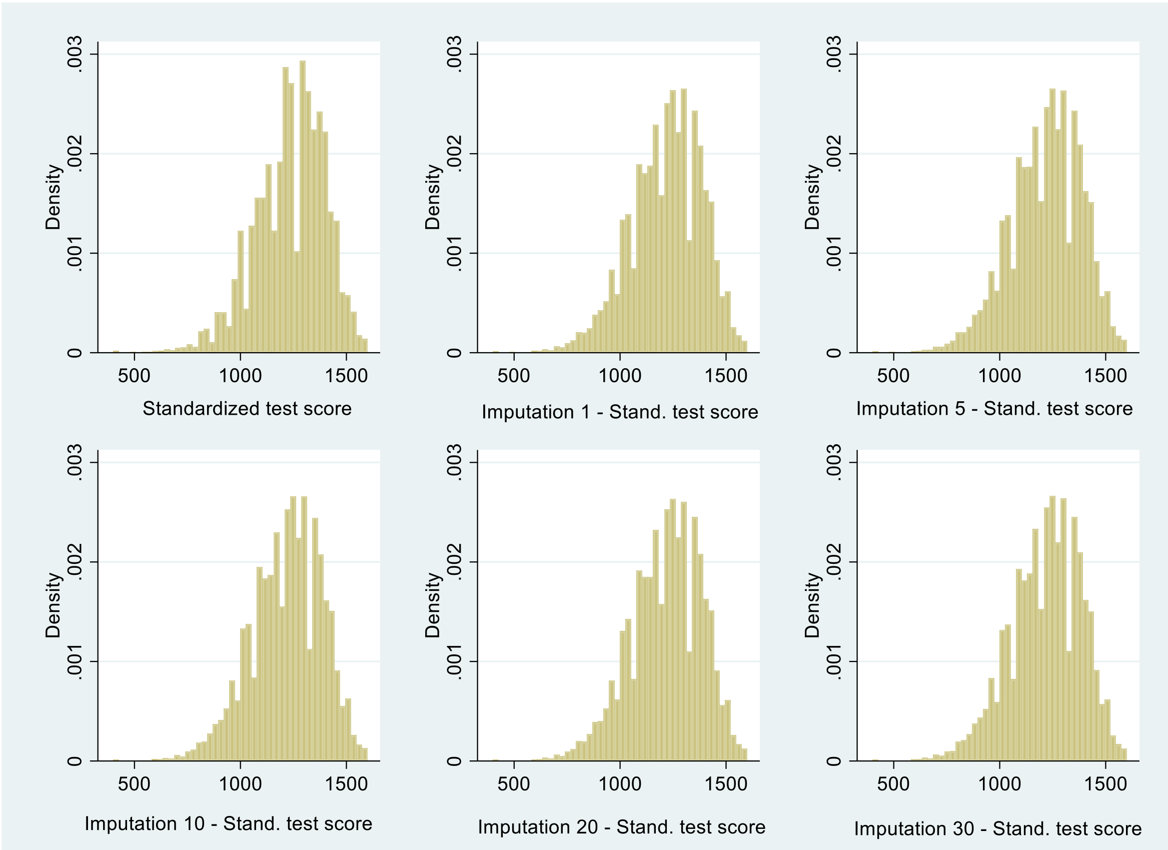
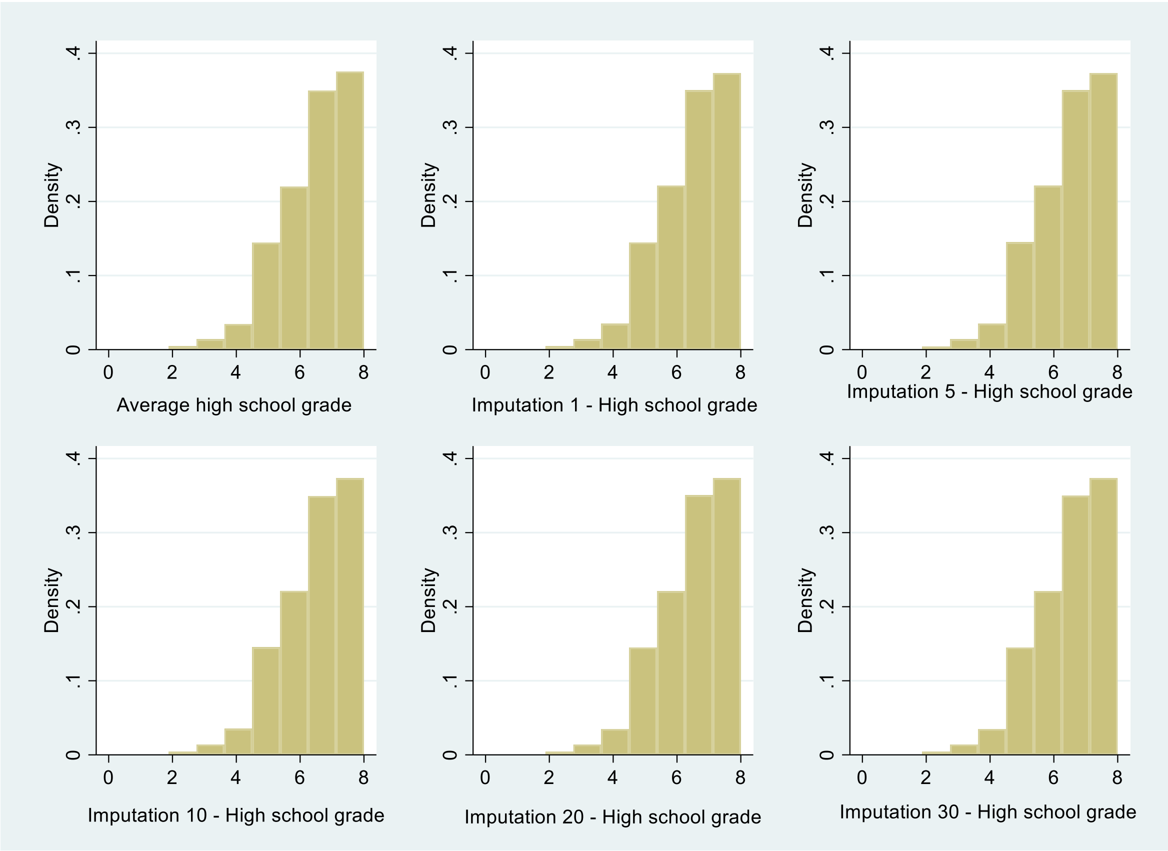


Figure 24. Density of actual average high school grade (top left) and data from the 1st, 5th, 10th, 20th, and 30th imputation



A.5 Summary

The missing data in this study is not missing completely at random (MCAR). Respondents with certain characteristics (e.g., first-generation college students) are more likely to have missing responses on some regressors (e.g., standardized test score and first-year grades). Furthermore, respondents with specific characteristics (e.g., ADHD) are more likely to have missing responses for items asking about that characteristic. Because the data is not MCAR, dropping respondents with missing responses results in the data set no longer containing representative data. For example, it shifts to respondents with higher standardized test scores and first-year grades with no ADHD diagnosis. Statistical analysis of this subsample may lead to bias coefficients and standardized errors.

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