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Christina Gramatikova
Claremont Graduate University

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First-Year Effects and Persistence Decisions:

A Moderated Mediation Model of Coping, Self-Efficacy, and Locus of Control

By
Christina Gramatikova

Claremont Graduate University and San Diego State University
2022

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Approval of Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Christina Gramatikova as fulfilling the scope and quality requirements meriting the degree of Doctor of Philosophy of Education.

Dr. David E. Drew, Co-Chair
Claremont Graduate University
Professor of Education

Dr. Marissa C. Vasquez, Co-Chair
San Diego State University
Assistant Professor of Community College
Leadership/Postsecondary
Educational Leadership

Dr. Gwen E. Garrison, Member
Claremont Graduate University
Associate Professor of Education

Dr. Aaron Iffland, Member
San Diego State University
Lecturer, College of Education

Dr. Marilee Bresciani Ludvik
University of Texas Arlington
Professor and Chair, Educational Leadership
and Policy Studies

Abstract

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by

Christina Gramatikova
Claremont Graduate University: 2022
San Diego State University: 2022

The purpose of this study was to estimate the effects of a theoretical model encompassing psychological theories underlying student retention in postsecondary education. New conceptual operationalizations were applied to elaborate Bean and Eaton's theoretical model of student retention. The influences of student entry characteristics, environmental interactions, psychological processes, attitudes, and intentions toward persistence were assessed using a repeated measures, longitudinal design. Within the framework, persistence is an endogenous variable based on actual re-enrollment into subsequent semesters.

Three student samples were drawn from a large urban research university in California. Survey data collected from a first-year seminar and the National Survey of Student Engagement (NSSE) and were used to test pathways of Bean and Eaton's conceptual framework. The data were analyzed through Structural Equation Modeling (SEM) and moderated mediation considering the following dichotomized groups: male/female, underrepresented/non-underrepresented students, first-generation/non-first-generation students. Analysis of first-time freshman cohort data revealed that the hypothesized model is supported across all three samples in 2018, 2019, and 2020.

The results reveal that measures of locus of control, self-efficacy and coping were found to indirectly predict persistence into the second year and third year of college, while measures of academic interactions, academic integration, social integration, and institutional fit were directly

predictive of persistence. Path level differences between first-generation students and non-first-generation students were found in the 2019 cohort in the relationships between past behavior and faculty academic interactions, and normative beliefs and classroom interactions. None of the other grouping variables yielded moderating effects. The fit statistics for three models are within the acceptable range, with the 2020 SEM model producing the best fit. The 2018 model, which included NSSE independent variables and assessed persistence into the third year, had the most explanatory power.

Across all three cohorts, both classroom and faculty academic interactions exerted the strongest indirect effects on persistence. The results from this study provide strong support for the indirect effects of coping strategies, locus of control, and self-efficacy on both social and academic integration. Moreover, quality of student interactions with other students, academic advisors, faculty, student services and administrative staff is influenced by normative beliefs as a function of self-directedness and autonomy. The findings supported evidence that programs that influence students' coping strategies can encourage self-efficacy, which in turn reinforces academic interactions and indirectly influences academic integration, social integration, institutional fit and persistence.

High Impact Practices (HIPs) such as first-year seminars and learning communities may enhance faculty and classroom academic interactions, and ultimately academic and social integration leading toward persistence. Faculty academic interactions and classroom academic interactions also facilitate social integration leading toward persistence. Overall, this study highlights a need for a better understanding of these interactions in order to help institutional administrators develop services and programs to better meet the needs of students, particularly in an era of teaching and learning in an online environment.

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Chapter 1 Introduction

Statement of the Problem

Student enrollment in higher education increased 27% between 2000-2017 (NCES, 2019), yet sizable dropout rates for American Indian/Alaska Native, Hispanic, and Black college students indicate enduring disparities in student retention (NCES, 2019). Research suggests that inequities in college student retention and graduation rates have remained stagnant and uneven across racial and ethnic student subgroups over the last few decades, and that differences between degree attainment proportions have not diminished over time (NCES, 2019; Tinto, 1993). Historical trends indicate that up to 70% of African American students do not obtain a degree within 6 years, compared to 42% of White students (Kunda, 1999). Further, some federally funded colleges have been shown to graduate less than 10% of students, and more than half of those institutions do not graduate students within 6 years (Erickson, 2020). It is notable that these challenges persist despite evidence indicating that instructional and programmatic interventions have been shown to contribute to increased student success and retention rates (National Survey of Student Engagement, 2018; Erickson, 2020; Pascarella & Terenzini, 2005; Mayhew et al., 2016; Bresciani Ludvik, 2019). Despite decades of research, there is still a critical need to identify and understand student success factors as well as institutional interventions that contribute to student success and persistence toward graduation.

Significance of the Study

The relationship between student persistence and academic performance is still inadequately understood when multiple student and environmental characteristics are taken into account. For example, studies assessing the impact of grade point average (GPA) on college dropout have produced mixed results for first-year freshman (Adebayo, 2008). Research suggests that up to 45% of dropout decisions that occur within the first two years of college are explained by grade performance (Stinebrickner & Stinebrickner, 2014), and that differences in grade performance particularly drive disparities in educational attainment for racial/ethnic minority students (Farrington et al., 2012). However, Adebayo (2008) and Ting (1998) reveal that cognitive measures such as standardized test scores and high school percentile rank are not adequate predictors of grade performance for high-risk students (e.g., first-generation, ethnic minorities). Instead, non-cognitive variables account for a greater proportion of variance (29% vs. 19%) in grade performance for those high-risk student populations in the first two years of college (Ting, 1998).

While the research literature often broadly treats persistence toward degree completion as a function of student achievement, fewer empirical investigations focus on persistence as a function of behavior. Behavior is an underlying dimension of engagement, along with affect and cognition (Kahu, 2013), and is a result of attitudes and beliefs (Ajzen, 1991). In practice, an understanding of the conditional effects of psychological and behavioral dimensions on student persistence can provide new insights to help higher education institutions improve the quality of support services and overall education. Further, consistent patterns of how psychological and behavioral variables translate to persistence are difficult to discern for racial and ethnic student subgroups when assessed in aggregate. Addressing this research gap of multiple predictors through moderated mediation would prove valuable in informing effective programs and interventions that target academic behaviors through psychosocial constructs.

Therefore, the purpose of this study is to examine the role of psychological factors and engagement indicators on students' first year persistence through a longitudinal samples using the model developed by Bean and Eaton (2000) as a conceptual framework. The psychological processes examined in this study include self-efficacy, coping behavior, and locus of control.

From a policy standpoint, there exists a profound shift in the higher education landscape toward academic capitalism, which often leaves the needs of students unmet in the face of prioritization of monetary gains (NSSE, 2018; Hagood, 2019). For example, there is a growing body of research on performance funding policies in higher education, which establish financial incentives and accountability mechanisms. The intent behind adoption of financial incentives tied to institutional outcomes is to encourage institutions to shift behaviors and/or implement new student support services (Hagood, 2019). Therefore, considering the mediating psychological processes that lead to student persistence outcomes merits further attention. Policymakers would benefit from a better understanding of student needs in order to improve creation and implementation of student success initiatives that would help promote an equitable learning environment, especially for underserved student populations (e.g., Adebayo, 2008; Ting, 1998; Bresciani Ludvik, 2020).

This study is important for several reasons. First, it incorporates measures from both psychological and sociological frameworks, examined in a predictive sequence, in order to promote understanding of student persistence. More importantly, this investigation will explore conditional indirect effects across demographic subgroups (i.e., ethnicity, gender, first-generation) in order to assess how the predictive model functions, and whether it remains constant across successive cohorts. Second, this investigation represents a movement to improve student success models. Spady (1970) synthesized the theoretical necessity for an interdisciplinary model of college student attrition, and Pascarella and Terenzini (1991, 2005) have similarly recognized that empirical frameworks drawing from both sociological and psychological roots can enhance theoretical validity. Third, this research contributes to the growing body of literature that examines variables influencing persistence toward degree completion, and whether those variables can be controlled directly by the institution. Isolating conditional indirect effects across demographic subgroups could be beneficial for developing the analytical model as a tool to identify areas for additional resources allocation in the first year of college (Tinto, 2006).

Considering the dearth in evidence substantiating psychological models of college student persistence, this study aims to deliberately test the theoretical validity of Bean and Eaton's psychological model of college student retention. Retention and persistence are terms that are often used interchangeably in the research literature; however, one distinction is that persistence refers to year-to-year reenrollment, whereas retention suggests student enrollment within the same institution overall (Mayhew et al., 2016). Both are relevant in the current context, and one of the aims of this study is to explore the role of psychological factors on students' first year persistence through repeated measures. The other is to examine group differences based on gender, first-generation status, and ethnicity through moderated mediation.

Preacher et al. (2007) define moderated mediation as conditional indirect effects in regression and path-analytic analyses. Conditional indirect effects are of interest when researchers want to understand how and when effects occur based on individual differences across groups (e.g., race/ethnicity, first-generation). There is a need to examine conditional indirect effects through this theoretical model in order to determine how the psychological processes work in subgroups of the population, and if those processes only apply for certain types of students.

Theoretical Rationale

The theoretical framework for this study is Bean and Eaton's 2000 Psychological Model of College Student Retention. This model incorporates three of the aforementioned psychological theories, attribution: locus of control, coping theory, and self-efficacy theory. Building on the prior works of Bean (1982;1985;1990), Bandura (1997) and Fishbein and Ajzen (1975), the theories are combined in a predictive sequence that is interdependent on environmental influences including academic interactions, social interactions, and interactions external to the institution. While each of these theories alone could not explain the extraordinarily complex persistence or withdrawal behaviors, together they form a multidimensional framework that helps to illuminate how attitudes lead to intentions and successive persistence behaviors in the college setting.

The Bean and Eaton model presupposes that this reciprocal feedback loop leads into academic and social integration. Following the flow of the model, these types of integration may lead to positive or negative attitudes toward the students' institutional fit and commitment. Subsequently in the model, institutional fit and loyalty attitudes may lead to persistence intentions. As Ajzen (1991) explained, intentions are the strongest predictors of behaviors, and have two precursors: attitudes and normative beliefs. Accordingly, Bean and Eaton's model has incorporated normative beliefs as a student entry characteristic, as well as attitudes toward behaviors (see Figure 1).

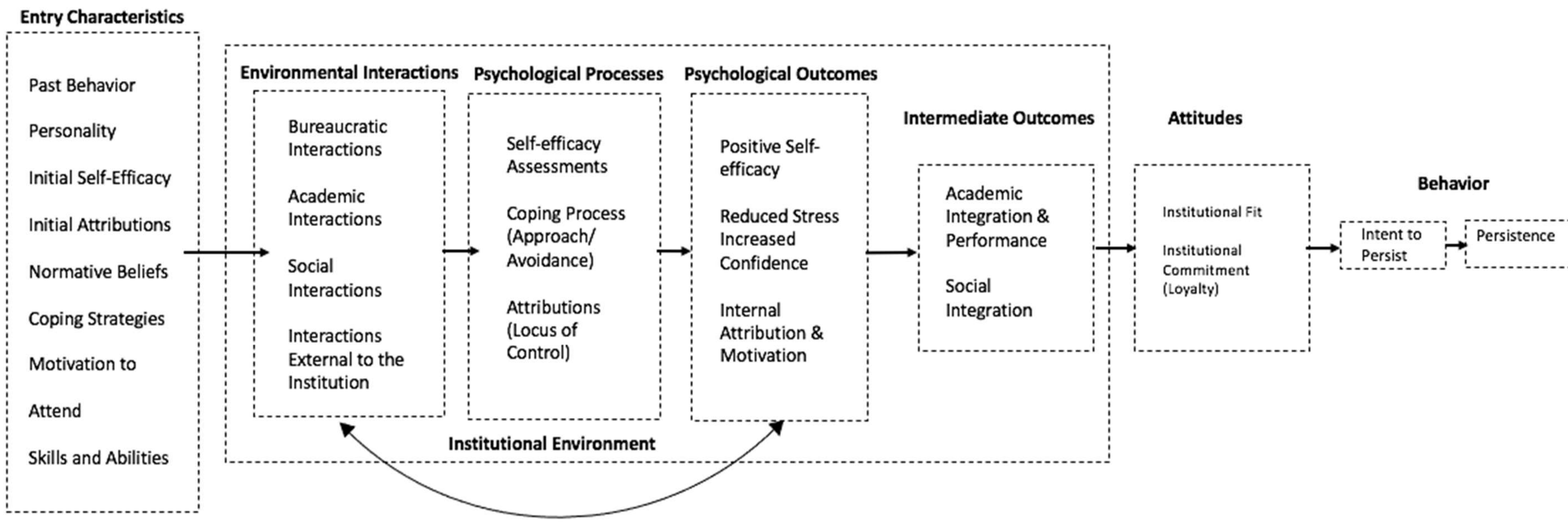
Research Questions

The purpose of this study is twofold. One of the aims is to explore the role of psychological factors on students' first year persistence through repeated measures. The other is to examine group differences based on gender, first-generation status, and ethnicity. The overarching questions guiding this study are: “How well does the theoretical model explain the first-year student persistence process,” and “Which factors in the model are most important?” The research questions include:

1) Which psychological processes (self-efficacy, coping, attributions: locus of control) account for the most variance in the persistence outcome?
2) How do student engagement indicators affect the persistence of students within the semester of their initial college enrollment?
3) Does the model differ based on group differences including gender, first-generation status, and ethnicity? Specifically:
    a. Is the psychological process of persistence moderated by gender, first-generation status, or underrepresented group identification?

Figure 1

A Psychological Model of College Student Retention



Note. Adapted from *Reworking the Student Departure Puzzle* (p. 57), by J. Braxton, 2000, Vanderbilt University Press.

Data and Analysis Overview

This study uses data collected from a first-year university seminar (USEM) survey and the National Survey of Student Engagement (NSSE) in combination with an institutional dataset containing student records. The USEM dataset is based on student experiences gathered from course participation and assessments at two timepoints during their first semester (pre-and post-test). The USEM questionnaire includes about 148 items with post-test follow up matched to the initial response, while the NSSE survey includes about 39 questions. The combined dataset began tracking the Fall 2018 cohort, and student responses were aligned to their NSSE Spring 2019 participation. Subsequent USEM assessments were administered to the Fall 2019 and Fall 2020 student cohorts. This study utilizes follow-up data summarizing student re-enrollment through Spring 2021. The final endogenous variable in the Fall 2018 cohort is a dichotomous persistence measure indicating whether a student persisted into the Fall 2020 term. Similarly, the final endogenous variable in the Fall 2019 and Fall 2020 cohorts is a dichotomous measure of whether or not a student persisted into the subsequent Spring term.

All data were analyzed using SPSS and AMOS statistical software. The analytical approach that will be used is structural equation modeling (SEM). This technique combines factor analysis, correlation, and multiple regression (Tabachnick & Fidell, 1996). Specific aspects of the research questions will be addressed as follows: Research questions (1) and (2): direct and indirect effects, and amount of variance accounted for by variable(s) and factors; Research question 3) Multigroup analysis; 3a) Moderated mediation (Preacher et al., 2007). Therefore, the first and second research questions will be a test of direct and indirect effects and will be addressed through two-step SEM for parameter estimation, as well as R^2 statistics. The third research question will be addressed through multiple group modeling as described by Tabachnick and Fidell (1996) and Byrne (2010).

Means and standard deviations of items will be presented, and the first step in the analysis will be to build a measurement model using the data. Once the measurement model is correctly specified, the second step will be to build the structural model (theory). As part of the first step, assumptions of SEM will be checked including: multivariate normality, multicollinearity, and sample size. During this model specification phase, exploratory factor analysis (EFA) will be performed to refine the factors that represent the data for each of the scales (Hair et al., 2014). At this stage, items with low factor loadings will be removed. Cronbach's alpha will be calculated to assess the reliability of the constructs. Convergent validity will be evaluated through the amplitude of loadings on a single factor above .5 (Hair et al., 2014), and discriminant validity through lack of major cross loadings or correlations.

Next, the confirmatory factor analysis (CFA) will be calculated in AMOS and any redundant items inflating the chi-square value will be removed. After the data screening, EFA, and model fit issues have been addressed, configural, scalar, and metric invariance will be checked for each multi-group analysis (e.g., gender, underrepresented group, first-generation status). Convergent validity will be observed based on average variance extracted (AVE) above .5, and discriminant validity will be assessed by comparison of the AVE to the square of the correlations between constructs (Hair et al., 2014). CFA reliability will be assessed through the construct reliability (CR) value above .7 as recommended by Hair et al. (2014). Prior to building SEM structural model as part of step 2, multivariate outliers and multicollinearity diagnostics will be examined.

Study Overview

This study consists of five chapters. The current chapter establishes the research territory and student persistence niche. Chapter Two outlines the relevant literature supporting student persistence and retention models in postsecondary education, as well as how they are shaped by moderating and mediating influences. A rationale for the psychological model of college student retention is presented in this context. Chapter Three provides a description of the study participants, methods, and procedures. It contains information describing the university seminar freshman year survey data set, as well as the measures used to construct latent variables. Findings from the SEM analyses are presented in Chapter Four. Finally, interpretations of findings alongside previous research are presented in Chapter Five.

Chapter 2 Literature Review

Foundational Research

The development of empirical models of college student departure, attrition, and retention models are most frequently based off of Tinto's (1975) interactionalist theory of student departure. Tinto relates student departure decisions to Durkheim's theory of suicide by comparing the integration process in college environments more broadly to individual integration into society, citing the negative repercussions of misalignment between personal and societal values, leading to withdrawal. In Tinto's terms, voluntary withdrawal is a type of coping to offset the incongruency between student values and those held by the institution. Of critical importance then are the structural and normative domains of academic and social integration, as well as the tradeoffs that occur between the two within the institution of higher education. In that sense, institutional departure and persistence toward degree completion are two sides of the same coin and stem from a continual assessment of whether the costs of college attendance outweigh the benefits of persistence toward degree attainment. Tinto discusses at length the various individual characteristics leading to departure including family background, ability, as well individual attitudinal differences. All of these characteristics including grade performance, have been shown to contribute to either withdrawal or persistence decisions. Overall, the interactionalist theory takes into account that it is the institutional characteristics (e.g., resources, facilities, personnel) that place limits on students' academic and social integration, and that students "must come to grips" (Tinto, 1975, p. 111) with these limiting institutional characteristics. It's worth noting that the departure/persistence literature combines distinct yet related perspectives: that the integration tradeoff process is largely one based on individual perceptions of reality and personality characteristics, and that the institution is accountable for asymmetric student integration.

Bean (1980) and Tinto (1975) heavily emphasize the influences of goal commitment and institutional commitment toward student departure in higher education, however; Bean applied an organizational model of employee turnover to explain related mechanisms at play in student attrition. Bean also goes one step further to describe the differential influences of organizational determinants and intervening variables on dropout for males and females. For example, subsets of the independent variables, institutional commitment, academic performance, campus organizations, transfer opportunity, development, routinization, goal commitment, communication, centralization, and housing accounted for 21% of the variance in female student attrition, and only 12% for male students. Institutional commitment was the most important predictor of dropout for both genders; however, contrary to expectations, satisfaction with being a student was significantly and positively related to dropout for males. Satisfaction only had a moderate indirect effect on dropout for females. The homogenous sample of college freshman used in this study possibly limits generalizability to more diverse racial and ethnic populations. Nevertheless, Bean's (1980) study has important implications for understanding different persistence and withdrawal patterns through an employee turnover perspective, where turnover is related to student departure at institutions of higher education. While the indirect effects of personality dispositions and larger patterns of structural inequalities were not considered as part of Bean's (1980) conceptual lens, he concluded that postsecondary institutions should offer programs that apply those processes and strategies that have positive effects on institutional commitment and satisfaction. Based on the study findings, Bean reasoned that institutions must provide opportunities for students to develop “personal, intellectual, and creative, and inter-personal skills” (Bean, 1980, p. 28).

Whereas prior student success frameworks had focused on resources, instructional, and individualized techniques to optimize student learning, Astin (1984) reinforced the importance of student participation into the academic experience in terms of overall energy investment (e.g., time on task, effort) (Astin, 1984). Following this viewpoint, students are not passive recipients of instructional strategies or organizational programs. Rather, enhanced student involvement as facilitated by the institution, leads to outward behaviors that are precursors to achievement and persistence. According to Astin, the behavioral manifestation of motivation through involvement is critical for student development and learning. Therefore, behavioral indicators of overall student involvement are directly related to student departure. This extends the focus of prior theories of student departure into those particular forms of involvement or engagement that the institution can facilitate based on an understanding of diverse student entry characteristics.

Astin (1993) advanced the Input-Environment-Outcome (IEO) framework, which is another powerful model that is commonly used in examining how college affects students through inclusion of student background characteristics to understand the college environment influence on student outcomes. The model contends that student development outcomes can be understood through observing the influence of the college environment while controlling for student inputs. Inputs are defined as personal qualities the student brings to the educational context, while the environment is represented by the students’ experiences of the campus climate and educational practices and programming. Assessing the latter is a significant challenge since it encompasses a broad array of external influences, such as the classroom environment, courses, teaching practices, organizations, cocurricular activities, counseling, and other social interactions

(Astin & Antonio, 2012). However, Astin's IEO framework allows for the disentangling of the effects of multiple student inputs and the college environment on student outcomes. The student involvement theory as integrated within the IEO framework, therefore shifts the focus from sociological interactionalist perspectives to the student experience.

College Student Persistence and Engagement

Student engagement research has been particularly influenced by developmental theories from psychology, sociological perspectives, and college impact models. Rooted in the works of William Spady, Alexander Astin, and Vincent Tinto, engagement is not a unitary construct but a collective term for behaviors, processes, and activities leading to successful college outcomes (NSSE, 2018).

Tinto's (1975) research of personal, demographic or environmental influential factors of student persistence appropriately frames the discourse for psychological explanations of student departure from higher education. Tinto argued for a unified model consisting of individual entry characteristics, institutional and social characteristics that conceptualize and predict dropout rates. He proposed that student integration into academic and social systems is most influential when predicting student departure. However, applying Tinto's model to nontraditional students and different types of colleges and universities has yielded mixed results (Deil-Amen, 2011; Braxton & Lien, 2000), and revealed the overlapping and contested influence of academic and social integration (Braxton, Sullivan & Johnson, 1997). Due to these inconsistencies, the social and academic integration components of Tinto's framework should be revisited in elaboration of Bean and Eaton's model.

Building off of Tinto's theory, Bean and Eaton's (2000) model identified important behavioral variables for student persistence and interactions between academic and environmental influences. Bean and Eaton supplemented Tinto's interactionist model with relevant social psychological dimensions that directly and indirectly lead to academic and social integration. Additionally, the theoretical model implied directional causality in that attitudes and (leave/stay) intentions lead to persistence behaviors (Bean 1980; Eaton & Bean, 1995). Given the directionality, positive outcomes associated with the psychological processes influence attitudes toward institutional commitment, institutional fit, and lead toward persistence.

The model posits that individual entry characteristics are first influenced by environmental factors such as institutional bureaucratic interactions, academic interactions, social interactions, and interactions external to the institution. Next, psychological processes are influenced by the institutional environment, through attitude-behavioral dynamics. The three theories guiding psychological outcomes are coping behavioral theory in terms of approach or avoidance, self-efficacy theory, and attribution or locus of control theory (Bean & Eaton, 2000). Student outcomes based in these behavioral progressions will then influence academic or social integration, as per Tinto's model construction. Subsequently the intent to persist would directly affect persistence behavior.

The foundational theories described (e.g., Tinto, 1975; Bean, 1980; Astin, 1984; Bean & Eaton, 2000) form a thematic synthesis of factors contributing toward visible student outcomes in the form of persistence. These student success models can be reframed collectively to explain the extent to which those internal student dispositions below the surface are outwardly transformed into visible behaviors or indicators of educational and personal growth (Bresciani Ludvik, 2019; Kuh et al., 2018), and how the institution facilitates that process. Practically then, institutional emphasis can be placed on how students utilize resources that the college environment provides (Kuh, 2001).

Contrasting Studies and Elaboration of Interactionalist Frameworks

Spady (1970) recognized that it is precisely this type of analytical-explanatory interdisciplinary framework that is scant in the retention literature. Spady also established that important safeguards must be implemented to develop an interdisciplinary systematic examination. First, when varying definitions of college student attrition are taken into account, inferences that are made about the dropout process and population parameters are often discrepant (e.g., Panos & Astin, 1968; Knoell 1960; Trent & Medsker, 1968). Varying results from these studies indicate that a consistent definition of attrition or dropout should be applied when comparing attrition and graduation across institutions. Second, the issue of inconsistent attrition outcomes findings is closely linked to the student background variables taken into account when estimating college dropout. That is, family background and interactions, as well as attitudinal presets heavily influence the dropout process, and should be controlled for when measuring student attrition. Students' educational background and aspiration goals, gender-based differences in growth mindset, and norm-referenced decision-making greatly contribute to attrition outcomes. Similarly, interpersonal relationships and the institutional environment also play a role in this explanatory model. Therefore, Spady's vision for an interdisciplinary model includes considerations for consistent measurement of an outcome variable, inclusion of student background characteristics, psychosocial processes, and a means for taking into account college experiences occurring in the environmental interactions.

Spady's point that the varying operational definitions of attrition outcomes considered by numerous studies contribute to discrepant results also applies to other variables from traditional sociological models. For example, Munro (1981) revisited Tinto's (1975) theory of student departure from higher education and the various influences on persistence. Tinto's (1975) research of personal, demographic, and environmental influential factors of student persistence framed the logic of the multivariate relationships and path analysis for Munro's study. The variables that were used in Munro's study were SES, ethnicity, aptitude, locus of control and self-esteem, high school grades, perceived parental aspirations, educational aspirations, academic integration, social integration, goal commitment, institutional commitment, dropout decisions, and persistence in institution. The study sample size was determined by including students entering 4-year colleges in the Fall of 1972 from the National Longitudinal Study of the High School (NLS) population. Munro found that the variables related to academic integration were more influential to persistence in higher education, in contrast to Tinto's theory which posited that academic and social integration exert roughly the same influence on dropout. In the reduced path model, goal commitment had the highest percentage of direct effect (i.e., 26%) on persistence. Moreover, perceived parental aspirations had the strongest effect on student goal commitment and educational aspirations. Munro's findings only partially support Tinto's, and account for only 14% of the variance in student departure.

In another multi-institutional study using Cooperative Institutional Research Program (CIRP) data for freshman entering college in the Fall of 1971, Pascarella and Chapman (1983) found that the influences of academic and social integration were mostly indirect and that academic integration was more influential for 2 and 4-year commuter institutions. Between the two integration measures, only social integration was found to have a modest direct influence persistence at 4-year residential institutions, and these effects were not present in the commuter samples. A comparison of findings between Munro (1981) and Pascarella and Chapman's (1983) show different patterns when corroborating the relationship between academic integration and institutional commitment. While in Munro's study academic integration measures were significantly related to institutional commitment, this same relationship was diminished in Pascarella and Chapman's study and academic integration was not directly predictive of persistence. Results from disaggregation by institutional type suggest that academic integration is more important for commuter institutions than for residential institutions, and that institutional commitment is more important for residential institutions, where it indirectly functions through social integration.

Other single-institutional studies have found the academic integration construct to be inconsistently applicable to institutional commitment and persistence (Braxton, & Lien, 2000). This is noteworthy in that institutional commitment is often the strongest predictor of persistence or withdrawal behaviors (Bean, 1980). Braxton and Brier's (1989) single-institutional study using CIRP data from a commuter university showed that academic integration was significantly predictive of institutional commitment but not persistence. In contrast, a longitudinal study using the CIRP data from a private residential university found that academic integration was not significantly predictive of institutional commitment and persistence as measured by intent to reenroll (Milem & Berger, 1997). In Milem and Berger's study, academic integration for the first-year freshman sample was significantly and positively predicted by Fall perception of institutional support, Spring involvement with peers, and Spring involvement with faculty. The strongest of these influences was involvement with faculty. Though both Braxton and Brier (1989) and Milem and Berger (1997) confirmed the strong association between institutional commitment and persistence, the contrasting findings of the contested academic integration construct indicate that these relationships are not static. In light of the dynamic relationships between students' attitudes and behaviors and interactions with faculty and peers, further disaggregation and expansion of these analyses is warranted.

Braxton and Lien (2000) propose that the academic integration construct has been problematic and has yielded inconsistent results across single and multi-institutional studies due to its misspecification. As previously mentioned, Tinto (1975) explained integration measures in terms of structural and normative dimensions. However, based on those definitions, the normative component of academic integration does not account for the congruency of values between the student and institution. Instead in traditional interactionalist frameworks, academic integration is only represented in part by the student's intellectual development and grade performance. Consequently, Braxton and Lien suggest that this normative dimension of academic integration is incomplete, unless it incorporates student values and beliefs relative to interaction with faculty and comfort with the field of study and institutional offerings. It is recommended then that future studies incorporate measures of intellectual isolation into the overall academic integration construct, or omit academic integration as a measure altogether (Braxton & Lien, 2000).

More recently, researchers have made connections between these suggested indicators of academic integration and institutional activities intended to encourage student engagement and sense of belonging (e.g., Kuh, et al., 2018). As a result, traditional perspectives of academic integration have been elaborated in terms of course offerings and high impact practices (HIPs) intended to reduce intellectual isolation. One strategy to resolve the viability of the academic integration construct in future studies is to incorporate measures designed to address academic normative incongruence through connections with faculty as well as campus organizations. Models testing the validity of academic integration can utilize psychometrically validated process indicators relating to the overall concept of involvement (e.g., Kuh, 1997), as well as constructs foundational to the dispositional attributes related to learning and persistence (Kuh, et al., 2018). The next section of research explores those dispositional attributes broadly aligned to retention outcomes as framed by the Bean and Eaton (2000) theoretical framework.

Social and Emotional Influences

This study seeks to examine the role of psychological factors and engagement indicators on students' first year persistence in a context much broader than that of conventional student integration (Tinto, 1987) and attrition theories (Bean, 1980). While Bean and Eaton's (2000) theoretical framework recognizes the importance of the interaction between student background characteristics, the environment, and multiple psychological and sociological processes, its core focus is on those aspects of behavior that promote learning, academic achievement, and persistence. Therefore, an analysis and application of the model would be incomplete without a discussion of the types of competencies that drive the observed variability of behavior.

Cognition and emotions are inextricably linked and form the developmental experiences individuals bring to learning (Cantor et al., 2019). Hence cognitive functions such as learning, memory, and decision making are not only influenced by emotion, but in some cases are emotional processes (Immordino-Yang & Damasio, 2007). When applying Bean and Eaton's (2000) theoretical framework through this lens, nearly all of the processes that explain persistence behavior are dynamic social and emotional influences that form the foundation for learning, particularly those involved in behavior based on appraisal of information. Because the *Psychological Model of College Student Retention* is based on the theory of planned behavior (Ajzen, 1991), competencies from the neuroscience literature including executive function (EF) and social and emotional learning (SEL) are heavily recruited in the overall framework. For example, there is agreement in the literature that self-regulation is linked to goal-directed behavior (Bandura, 1991), and self-regulatory mechanisms to EF skills (Zelazo et al., 2016).

Furthermore, EF is understood as both automatic (e.g., physiological process) and intentional (e.g., inhibitory process) (Zelazo et al., 2016). Goal-directed behavior such as learning is then both socially conditioned and supported or undermined by emotions (Bandura, 1991; NAS, 2018)

EF and SEL influences form the dynamic interplay of processes underlying behavior and are present throughout students' educational careers and the life span (NAS, 2018). Specifically during the critical transition between high-school and college, students typically struggle with adjusting to increased academic workloads, applying new study habits, and maintaining and forming relationships (Parker et al., 2005). In spite of these difficulties, expanding student knowledge in application of SEL competencies such as stress management, adaptability, and interpersonal skills have been linked to higher first-year semester GPA (Wyatt & Bloemker, 2013).

A quasi-experimental study of 11 first-year seminars at a private East Coast university also showed that where SEL competencies were taught for three years from 2008-2010, students had a higher pre/post growth rate in self-management skills, interpersonal abilities, flexibility with perspective taking, and emotional awareness skills. Additionally, GPAs for the experimental groups were significantly higher across two years than those in the comparison groups (Wang et al., 2012). These results were apparent after controlling for students' standardized test scores and high school GPAs (HS GPA). Multiple study findings converge to indicate that stress management, a coping behavior, and study habits, a self-regulating behavior, influence academic achievement in the first year of college (Parker et al., 2004; 2005). What is unknown however, is how first-year persistence is impacted by SEL influences and how the college environment supports SEL through a sociocultural context. Bean and Eaton (2001) explore the effects of first-year retention programming on prominent SEL influences, and three prominent psychological theories embedded in these SELs are featured in their (2000) model. Therefore, aligning interpersonal competency measures to first-year persistence outcomes through this model can serve as a valuable resource for institutions (Breschiani Ludvik, 2020).

Theoretical Framework

Coping Behavior Theory

According to Folkman and Lazarus (1984) coping can be defined as a purposeful style of behavior or cognitive effort that is enacted in an internal or external stressful encounter. Lazarus (1966) outlines three forms of coping approaches individuals may exhibit under stress: action, reappraisal, or apathy toward the stressor. In an academic environment, the actions that students take can be in the form of a proactive approach to strengthen individual ability, or they can be avoidant. Through the first approach, an appraisal or evaluation of the stressor guides the action. That is, there is an assessment of success or failure, and a subsequent exploration of the environment for cues to take toward improvement, e.g., preparation, training, vigilance (Lazarus, 1966). This approach is characterized by making an effort toward meeting goals and could take the form of comprehension monitoring and studying in anticipation of a threat (in the form of an exam). The second adaptive reaction is avoidance and can take the form of thinking about something else or joking. The third reaction is an apathetic response toward a helpless condition and is most often linked to depression.

Bean and Eaton (2000) apply coping theory in the psychological model of college student retention primarily through the conceptual application of adaptational processes leading to integration and institutional fit. Since coping is based in adjustment and adaptation processes (Folkman & Lazarus, 1984) where adjustment is how an individual acclimates to an environment, and adaptation is a subset of activities an individual uses to cope with situations, then this set of behaviors is closely related to institutional assimilation. From this perspective, coping can also be viewed as acquired behaviors an individual uses in order to integrate academically and socially (Eaton & Bean, 1995). Therefore, successful integration would result from adjustment behaviors that are based in strategies or behaviors used to increase competence and confidence (Eaton & Bean, 1995). As contextualized in retention research, this person-environment shift can lead toward institutional fit.

In this context, the literature on coping suggests a number of potential pathways through which coping functions, including influences of perceived controllability, personality dispositions, and social resources alongside the coping process. While previous research on coping focuses primarily on stress resolution, the benefits of positive affect as a type of coping mechanism (Folkman & Moskowitz, 2000) are also directly relevant to student outcomes (Pennebaker et al., 1990). Folkman and Moskowitz (2000) note that positive affect can occur alongside negative affect during stressful times and can serve as a buffer against depression. Thus, it’s important to consider the positive affect dimension of the coping process, as it potentially sheds light on how coping is experienced differently by student subgroups (i.e., gender, ethnicity) and may function jointly with other strategies only when they are held constant (Aldridge & Roesch, 2008; Lewis & Frydenberg, 2004). For example, the coping strategies Mexican American adolescents use have been shown to fluctuate daily, and planning and problem solving were frequently reported approaches (Aldridge & Roesch, 2008). Thus, positive affect is a type of coping strategy students may exhibit prior to entering college (i.e., pre-college entry characteristics), and therefore should be incorporated as measure when coping processes and persistence decisions are examined in student retention models.

Struthers et al. (2000) studied the mediating effects of student coping strategies and motivation on achievement using a Student Coping Scale (SCOPE). Three hundred and twelve students were surveyed, and the analytic sample included of 203 university students enrolled in various disciplines. The findings revealed that there was a significant relationship between stress and Emotion Focused Coping (EFC) and Problem Focused Coping (PFC). The results also showed a weak association between EFC and motivation, and non-significant path between both EFC and PFC and grades. There was however a significant relationship between motivation and grades, and the overall structural equation model fit was acceptable and was supported by a nonsignificant chi-square value (Struthers et al., 2000). While these findings provide meaningful insights, they are also influenced by gender, as well as first-generation status, as Mayhew et al. (2016) suggest. Thus there is value in exploring the moderating influences for students who are experiencing ongoing negative emotions such as stress, inadequacy and uneasiness stemming from both attributions and coping strategies.

Coping and Moderating Influences. In a study of 26 public and private institutions including both commuter and residential colleges, Nora et al. (1996) found that stressors such as financial need, family obligations, and working off-campus impacted minority and nonminority students differently. The study also found that there were differences between men and women in terms of how social integration and interactions with faculty impacted persistence. For example, the need for financial aid was negatively related to persistence only for white students, and faculty interactions was only significantly related to persistence for females. Additionally, familial responsibilities such as having children and working away from campus were negatively related to persistence only for minority students. These findings align with conclusions from Brower (1992) in that task focus or motives for attending college significantly impact fit with the institutional environment. If the institutional environment does not conform to student's focus and needs, then there's less of a chance of social and academic integration, and ultimately persistence. Given the differential effects on persistence between males and females as well as students of different ethnic backgrounds (Nora et al., 1996), it is plausible that the coping strategies different student subgroups employ are complex and nuanced. This supports the conceptual perspectives of Lazarus (1966) in that student coping approach sets the stage for decisions whether or not further sacrifice toward degree completion is warranted.

In a study of first-generation ethnic minority college freshman, Phinney and Haas (2003) found that college self-efficacy was the only significant predictor of successful coping, even when assessments of grade goals, confidence, demographic information, and social support were considered. Narratives from 30 students attending an urban commuter institution were analyzed for stressful incidents and self-reported coping efforts across 90 journal entries. Analyses between the self-reported coping success and student survey responses indicated that there were no significant differences between coping success, gender, ethnicity, and parental education. That is, students who experienced low success in coping and high success in coping did not differ on any of the demographic characteristics other than their self-reported self-efficacy assessments. While student enrollment in number of units and hours worked per week varied, these variables were unrelated to their self-reported success in coping with college stressors and adjustment difficulties. Social support emerged as an influential predictor of coping success and converged with findings from the surveys. The study suggests that social support is intertwined with sense of self-efficacy, and while the effects are difficult to disentangle, these variables play a significant role in college achievement and persistence for first generation students.

Pizzolato (2004) extends findings from Phinney and Haas (2003) into different classifications of self-regulatory and supported coping strategies students employ. Pizzolato (2004) explored high-risk first-year college students' use of self-authorship in this context. High-risk students are those categorized as academically predisposed to attrition (e.g., first-generation students, students from low SES backgrounds, or students of color enrolled in a predominantly white institution) (Schreiner et al, 2011). The self-authorship concept was used as a means of understanding the way coping strategies were adopted by the 35 student participants. Self-authorship involves an individual's integration of knowledge and empowerment through interaction with multiple diverse perspectives and settings. While some students used avoidance strategies and independent self-regulatory coping, others relied on external support. In some cases, those students who sought conversational social support, e.g., talking through feelings to gain emotional clarity, also applied Problem Focused Coping (PFC). This finding echoes prior empirical work from Struthers et al. (2000) that Problem Focused Coping and Emotion Focused Coping are significantly related, and that there is a positive relationship between PFC and motivation. Through a grounded theory approach, Pizzolato (2004) provides specific support consistent with that research. The data discussed illustrate that high-risk students engage in supported coping strategies to create meaning-making on their own, which leads to motivation (e.g., Struthers et al., 2000) and commitment (Phinney & Haas, 2003).

Self-Efficacy Theory

Bandura (1997) defined self-efficacy as individuals' "beliefs in their capabilities to produce desired effects by their actions" that influence events in their lives (p. vii). Positive self-efficacy and optimism are shown to influence better performance in students in the form of GPA, while low efficacy beliefs can lead to negative beliefs and failure (Coutinho & Neuman, 2008).

Research has shown that self-efficacy is strongly linked to academic performance and student persistence (Bean & Eaton, 2000).

Mone et al. (1995) tested a set of hypotheses to determine whether task self-efficacy is a stronger predictor of exam performance and personal goals than self-esteem, and if that relationship remains constant over repeated measures. Mone and colleagues theorized that measures of self-esteem and self-efficacy will more accurately predict exam performance than recent measures of test scores on the same subject. They also hypothesized that students' personal goals and recent exam performance will be more strongly predictive of recent self-esteem and self-efficacy scores, than self-esteem and self-efficacy assessments taken at an earlier time (i.e., distal measures). This study assessed the effects of measurement timing using grade self-efficacy, self-esteem, student grade goals, and student exam performance. Response patterns from a sample of 215 university students enrolled in a management course were analyzed using hierarchical and moderated regression. The study found that self-efficacy was predictive of exam performance in multiple trials of measurement before the course exams, but that self-esteem was not. Support was also found for the proposition that personal goals and exam performance were consistently predictive of self-efficacy over time. There were no statistically significant differences between the effects of goals and performance on proximal or distal measures of self-efficacy or self-esteem. These findings coincide with other literature which reports that students generally perform to their expectations.

Building on these findings, grade performance has been shown to be influenced by the students' particular task orientation, such as achievement or affiliation. So, while self-efficacy is significantly predictive of performance, success in the predominant task focus can lead to persistence. Brower (1992) proposed that the fit between a student's predominant focus, and the extent to which the environment provides opportunities compatible with that focus, directly influences college student persistence. In a longitudinal study using a sample of 311 students enrolled as first year freshman, Brower (1992) revealed that life-task/environment compatibility significantly improved the prediction of persistence into the second year. That is, significant unique variance emerged, beyond Tinto's traditional integration model. Additionally, the study demonstrated that the timing of when a student chooses to focus on achievement, affiliation, and personal identity matters. For example, persistence as measured by the number of semesters of enrollment college, was significantly predicted by focus on friends in the second semester, and less focus on identity concerns in the first semester. Those findings were particularly true for achievement-oriented students. As Brower suggests, ultimately integration in Tinto's terms should be measured by the second half of this equation, i.e., how the compatibility between student focus and the institution shapes the environment.

This concept of the compatibility between individual orientations, needs and congruence to the environment is strikingly similar to the career decision making dynamics Lent et al. (1987) proposed. Multiple regression was employed to examine the effects of self-efficacy, interest congruence, and consequence thinking in this study using a sample of 105 undergraduate students enrolled in a career planning course. Consequence thinking is defined as weighing the pros and cons of various decisions using a balance sheet method. And congruence is a measure of fit between occupational interests and interests of others in the environment. Regression analyses were employed to predict the outcome measures: grades, persistence, perceived career options, and career indecision (Lent et al., 1987). Self-efficacy added the most unique variance beyond measures of ability for all dependent variables except career indecision. In the case of career indecision, congruence added the most amount of unique variance, while self-efficacy was the most significant predictor.

Given that numerous studies have confirmed the significant effects of self-efficacy on academic outcomes, it is worthwhile to relate those findings to attributional variables to ascertain the impact on persistence. For example, attributional predispositions help us to understand why perceived stressors in achievement contexts can be countered by self-efficacy beliefs through internal locus of control. Considering these attributional dimensions, Amirkhan (1998) assessed coping strategies for various stressful life events in a large-scale community study in Southern California. For the first part of the study, questionnaires were distributed to a sample of 679 community participants. Results from this study confirmed that attributions predict both distress and coping behavior, and that coping behavior also directly predicts distress. Another finding suggested that the "classification along the controllability dimension is crucial to the predictive power of an attribution" (Amirkhan, 1998, p. 8). This prompts the question, do attributions have a significant effect on self-efficacy, or do attributions only affect coping behaviors, which in turn can be influenced by efficacy beliefs? Furthermore, do attributions have direct effects on persistence behaviors, both directly and indirectly through coping behaviors? The directionality of influences is unlikely to be resolved; however, it may be valuable to focus on stronger influences for certain subsets of students.

Self-Efficacy and Moderating Influences. Task-specific orientations may lead students to selecting certain coping strategies and behaviors toward integration and persistence. Using data from the Educational Longitudinal Study (ELS), Wood et al. (2015) found that self-efficacy is task-dependent particularly for African American men enrolled in a two-year college setting. Analyses were framed by Bean and Eaton's psychological model of college student retention in terms of entry level self-efficacy and subsequent influences on academic integration outcomes for first-year college students. Academic integration outcomes were assessed for a sample of roughly 212,703 African American male college students. The study found that math self-efficacy was predictive of students' interactions with academic advisors, and academic integration as measured by use of library resources, whereas English self-efficacy was not. Specifically, math self-efficacy accounted for 22% of the variance in the faculty interaction academic integration outcomes when control variables such as parental income, education, and high school grades were taken into account. One of the key takeaways from this is study is that by reinforcing math self-efficacy through targeted programming, students will not only have the skills to meet their goals, they may in turn be integrated academically through interactions with faculty and campus resources. According to the Bean and Eaton's conceptual framework, this process ultimately leads to persistence and retention.

Salinas and Llanes (2003) found that there is a disproportion of Mexican American men to women persisting and graduating from higher education (37% vs. 63%), and Aguayo et al. (2011) partially attribute these troubling statistics to the effects of acculturation and enculturation on student self-efficacy. Aguayo et al. (2011) used acculturation and enculturation measures to independently assess the influence of student heritage culture orientation (enculturation) and mainstream culture orientation (acculturation) on a sample of college 408 students. The study found that enculturation significantly predicted college performance as measured by GPA for first-generation Mexican American students but did not predict academic performance for second-generation students. Additionally, main effects of acculturation and enculturation orientations on GPA were not found; however, both significantly predicted self-efficacy. Post-hoc analyses revealed that self-efficacy was not a significant predictor of GPA for first-generation Mexican American students but was significantly predictive of academic performance for second-generation students. Thus, contradictory outcomes were uncovered for generational status through the indirect effects of self-efficacy on GPA. These findings demonstrate both generational and cultural differences in the relationship between self-efficacy and achievement. Since these relationships are precursors to retention and graduation, it's important to incorporate the moderating influence of cultural identification in student success models.

Salinas and Llanes (2003) further examined the relationship between academic performance and persistence for Mexican American college students using a sample of 1,425 students enrolled in a 10-year period spanning between 1992-2002. Ex post facto analyses showed that persisting students (those who had not received a degree throughout the assessment period) had lower overall scores on the ACT and lower high school percentage ranking when compared to non-persisting students and graduates. Further, the difference in college GPA between persisting and non-persisting students was greater than the difference in GPA between persisting students and graduates. Salinas and Llanes (2003) attribute the differences in college GPA and graduation outcomes to academic and social integration in the first six semesters of college. That is, persisting students had GPAs below 2.0 for the first six semesters of college, as opposed to graduate students and transfer graduates, who all had GPAs above 2.0 in the first six semesters. Interestingly, non-persisting students, i.e., those who dropped out before graduation also had an average GPA greater than 2.0 in the first six semesters. This study further reinforces the findings that student background characteristics and prior academic experiences initially influence engagement, and ultimately integration and persistence toward graduation. This pattern was most evident across Mexican American student subgroups (Salinas & Llanes, 2003; Aguayo et al., 2011).

Attribution Theory: Locus of Control

Attributional theory is particularly influential an achievement and persistence contexts as it incorporates dimensions of locus, control, and stability (Weiner, 1985). Specifically, the locus and controllability dimensions are applicable to perceived causes of success (Astin, 1984). That is, individuals ascribe causality based on internal factors (e.g., ability, effort) and external factors (e.g., luck, task difficulty), and whether those factors are controllable and stable. Locus of control is a predominant motivational factor in this higher order attribution context (Rotter, 1966). Internal locus of control is the intrinsic belief that an individual has the ability to influence external events and outcomes. Contrastingly, an individual with external locus of control may believe specific outcomes are attributable to fate or luck. Internal and external locus of control have been shown to influence academic performance and integration (Bean & Eaton, 2000; Perry et al., 1993).

According to Coleman et al. (1966) the student attitude factor, analogous to locus of control, has a stronger relationship to academic achievement than all institutional factors combined and has been found to be inversely related to achievement measures for African American, Hispanic, and Native American students, with adverse effects attenuating with greater school integration. Though the concept of fate control has not been elaborated from a sociological perspective since Coleman et al. (1996), it continues to evolve through the literature developing the locus of control construct.

Locus of control plays a critical role in the contextual effects of college for students of different races, genders, and generational status (Mayhew et al., 2016). For example, in a multi-institutional study of 18 four-year colleges that participated in the National Study of Student Learning (NSSL) Pascarella et al. (2004) found pronounced differences in effects between first-generation and non-first-generation students' locus of control over a 3-year period. In the second and third year of enrollment, academic interactions significantly predicted internal academic locus of control for first-generation students, but not for those students with parents who obtained moderate to high postsecondary education. And in the third year, extracurricular involvement was positively related to first-generation students' internal locus of control, but was negatively related to internal locus of control for those students whose parents obtained moderate and high postsecondary education. An opposing relationship surfaced for first-generation students involved in volunteer work, (i.e., it negatively predicted internal locus of control). On the other hand, volunteer work positively predicted internal locus of control for those students whose parents obtained moderate to high postsecondary education. Pascarella et al. (2004) hypothesize that different models of college success may apply for first-generation students since the evidence indicates that certain extracurricular influences weaken internal locus of control over the years. Additionally, Pascarella et al. (2004) argue that colleges have programmatic control over how they affect these outcomes, and ultimately persistence.

Based on the literature delineating the conditional effects of self-efficacy and internal attributions and locus of control, it is clear that persistence outcomes are often the result of a combination of motivational and academic coping behaviors (e.g., Struthers et al., 2000). Additionally, individuals are likely to identify with these influences differently based on whether they think effort and ability are controllable (Astin, 1984). Individual perceptions of ability and effort may also be based on other influential factors like parental education (e.g., Pascarella et al., 2004) and perceived parental aspirations. For example, in Munro's (1981) study, locus of control exhibited a modest direct effect on perceived parental aspirations, and was not significantly related to any other variables in the reduced path model. The only two variables related to locus of control were ethnicity and gender, the latter of which was inverse relationship. From Munro's study, it therefore follows that locus of control exerts an indirect effect on goal commitment that functions through perceived parental aspirations, and eventually does influence persistence, while it is experienced differently by gender.

Locus of Control and Moderating Influences. In a study of approximately 3,066 freshmen across two successive cohorts in 2000-2001, Gifford et al. (2006) observed differences in GPA and retention in students depending on their self-reported locus of control score. The analyses found that male students were more oriented toward internal locus of control than females, and that first-year cumulative GPA was significantly predicted by internal locus of control and ACT scores. These two variables accounted for seven percent of the variance in GPA, and follow up t-tests confirmed that those students who persisted into their sophomore year had higher GPAs than those who did not. Therefore Gifford et al. (2006) suggest that student persistence into the second year of college is at least partially influenced by locus of control orientation. And while pre-college entry examinations contribute to first year academic achievement, and retention, it's important to investigate whether locus of control directly and reliably predicts persistence into the second year. It's worth noting that these analyses were not disaggregated further into student ethnicities, and that locus of control may function differently based on student racial/ethnic backgrounds and cultural stressors.

Similar to Gifford et al. (2006), Grimes (1997) found that students who persisted into subsequent semesters had higher GPAs. However, differences in persistence were found when academic readiness scores were disaggregated by ethnicity for this sample of 140 first year community college students. For example, those students who reported an internal locus of control rated higher on college readiness scores, but college readiness was not always predictive of college retention. Specifically, when compared to Caucasian students, African American students reported lower college readiness scores in math, reading, and writing but did not demonstrate greater attrition (Grimes, 1997). This study suggests that at-college experiences and quality interactions may be more important in influencing the persistence trajectories for underrepresented student groups. Further, the analysis of the effects of locus of control (Gifford et al., 2006; Grimes, 1997) provide converging evidence that the effects on persistence may vary with different moderating variables such as race, ethnicity, and gender.

A more detailed discussion of the moderating effects of culture and ethnicity links locus of control and social relationships and/or peer support. Using nationally representative samples of 8th and 10th graders from the Early Childhood Longitudinal Study (ECLS) and the National Education Longitudinal Study (NELS), Kang et al. (2015) found that the relationship between locus of control and peer acceptance is stable across adolescents of different racial and ethnic subgroups. That is, internal locus of control was significantly predictive of peer acceptance for Caucasian, Asian, Hispanic, and African American 8th and 10th graders, but this relationship was more pronounced for Caucasian students consistently over datasets and timepoints. So, while the literature broadly links internal locus of control with higher academic achievement, Kang et al. (2015) demonstrate that there are constant and stable relationships between internal locus of control and peer acceptance related to individualistic and collectivist cultural values. Cooperative vs. competitive and individualistic ways of learning may benefit some students more than others, particularly when peers are involved. It follows then that the relationships between locus of control, academic achievement, and persistence may be influenced by cooperative and individualistic learning styles.

The interactive relationships between cultural values and locus of control continue to exert an influence on student persistence throughout the first years of college and may lead to psychological distress, if there is an overreliance on peer acceptance (Llamas et al., 2018). In a study of Latinx 137 college freshman at a large West Coast university, Llamas et al. (2018) found that locus of control and social support mediated the relationship between intragroup marginalization and psychological distress. That is, the stressful effects of interpersonal marginalization by members of one's own ethnic or cultural group, predicted an external locus of control orientation, which in turn had an impact on greater psychological distress. This aligns with findings from Llamas and Consoli (2012) that intragroup marginalization is negatively related to resilience and thriving in a college setting. Consequently, an internal or external locus of control predisposition is an unobservable characteristic that influences both college adjustment and persistence (Llamas & Consoli, 2012), particularly when there is social reliance on individuals from one's heritage culture. These studies provide evidence of the moderating effects of cultural background variables and stressors that can be used to understand the associations between locus of control and college persistence. Internal locus of control is not simply an indicator of academic achievement, more complex and intervening relationships are involved in the college environment.

Malleable Learning Dispositions

As the studies on self-efficacy, locus of control and coping, suggest that students bring their individual dispositions to the college environment, which in turn can be fostered and developed by the institution. So while persistence toward degree completion and grades are visible indicators of student success, the underlying attitudes, dispositions, and resultant behaviors can be influenced by the college experience (Kuh, et al., 2018).

One way of visualizing these attitude-behavior linkages and underlying processes is through Bean and Eaton's (2000) framework. As mentioned previously, the *Psychological Model of Student Retention* is more broadly situated within the SEL and EF literature (e.g., Zelazo et al., 2016) due to its representation of self-regulating attributes (i.e., self-efficacy, coping strategies, locus of control) leading to goal directed behaviors (i.e., integration, commitment). In this context, Bean and Eaton's theory provides the framework to ask: which learning dispositions are identifiable, and lead to persistence outcomes during a student's first year in college? Educators and campus leaders can adapt their approach at this critical point in time through an awareness of how the SEL constructs can be intentionally influenced for certain subsets of students.

Learning dispositions such as self-efficacy, locus of control, and coping strategies have been found to be malleable and interrelated. For example, coping strategies are closely related to planning and regulation of emotion. Nielsen and Knardahl (2014) propose that coping behavior profiles can be clustered into three significantly different categories, and that these categories have been found to be stable over time: active coping, disengaged coping, and low coping. Their study examining a sample of 4,328 respondents across 91 Norwegian organizations surveyed over two years showed categorical transitions between coping groups was common (e.g., high transition). Correlational analyses between the 14 coping strategies indicated that the strongest association was between the self-regulatory behavior planning, and active coping ($r = .49$, $p < .0001$). Additionally, an analysis of transition between groups at baseline and follow-up demonstrated that 31.7% of low coping strategy respondents moved to the engagement coping category, and 28.7% of the disengaged coping respondents moved to the engagement coping category. So while there was categorical stability between coping strategy clusters, the actual coping strategies themselves were more malleable. Based on these findings, Nielsen and Knardahl (2014) reason that it's possible to change counterproductive coping behaviors.

The idea that coping behaviors are more situationally based and evolve rapidly based on changing actions and encounters is echoed in Stewart and Schwarzer's (1996) study, which found that coping strategies are highly idiosyncratic over both time and across situations. Stewart and Schwarzer (1996) used an earlier version of the COPE inventory applied by Nielsen and Knardahl (2014) in a longitudinal study examining the coping behaviors of first-year medical students. In Stewart and Schwarzer's study, retest correlations along with factor analysis of the structure showed a three-factor solution that is unstable, accounting for 45-54% of the total variance. Significant correlations were found between grades and planning coping behaviors, as well grades and acceptance coping behaviors. However due to moderately low retest correlations overall, Stewart and Schwarzer (1996) concluded that measurement instruments must be improved in order for researchers to be able to assess the predictive validity of dispositional versus situational coping strategies. Stewart and Schwarzer's research has implications for the current study in that it reveals coping strategies are dynamic dispositional states in an academic context.

Vrugt et al. (1997) explored the relationship between self-efficacy, malleability beliefs, and exam performance for a group of freshman students. The first of their experiments showed that self-efficacy magnitude was significantly related to exam performance, and personal goals. The second experiment in the study revealed that those students with lower self-efficacy beliefs tend to attribute poor exam performance to lack of talent, and that this pattern is present for both students of high and low ability. Further, performance and mastery orientations as represented by the measure malleability beliefs, were related to higher exam performance for students of higher ability. The ability measure was not found to be related to greater exam performance for those students categorized as having low malleability beliefs. Considering this finding then, the malleability beliefs factor is a key component of exam performance, regardless of ability. The findings from this study suggest that self-efficacy beliefs can be strengthened based on student attributions. It's quite possible that induced self-regulatory behaviors such as study strategies and effective problem solving can affect malleability beliefs, and thus performance (Vrugt et al., 1997). Though this study directly elaborates the effects of self-efficacy on performance, it directly reveals the malleable quality of individual coping strategies and locus of control.

Phillips and Gully (1997) also found that performance and learning goal orientations directly affect self-efficacy beliefs and exam performance for undergraduate students. Learning goal orientation was synonymous with mastery orientation as cited by Vrugt et al. (1997) and had a positive effect on self-efficacy, while performance goal orientation had a negative effect on self-efficacy. Internal locus of control was positively and significantly related to learning goal orientation and was not significantly related to performance goal orientation. Together with ability and locus of control, performance and learning orientations accounted for 20% of the variance in self-efficacy. Conclusions from Vrugt et al. (1997) and Phillips and Gully (1997) converge in support of the proposition that self-efficacy and performance and learning goal orientations are malleable beliefs, with the latter study illustrating that this relationship may function through internal locus of control. The implications of these studies are significant since they identify specific pathways through which self-efficacy can be enhanced, (e.g., educators can encourage learning or mastery orientation beliefs in students, and cultivate an environment in which maladaptive beliefs are not supported).

The results from these studies indicate that individual differences in the notion of causality are related to student helplessness and mastery orientations (Perry et al., 1993), and that performance and mastery orientations are synonymous with the term growth mindset. Anderson et al. (2016) report that growth mindset interventions have proven to be effective across diverse K-12 and postsecondary education contexts. For example, interventions specifically targeting African American college student attitudes about intelligence have had positive effects on grades just after three sessions. Additionally, interventions targeting reflection on core values have been shown to reduce the achievement gap between African American and White students by up to 40% in middle school settings (Anderson et al., 2016).

Locus of control has been found to be malleable in K-12 settings, specifically in the form of interventions emphasizing autobiographical writing and discussions focusing on goal setting (Anderson et al., 2016). And in postsecondary education settings, locus of control has been found to function through self-efficacy beliefs that can be molded through growth mindsets (Vrugt et al., 1997; Phillips & Gully, 1997). These findings imply that individual goal setting and environmental mastery are characteristic of the internal attribution concept, and therefore appropriately frame the discourse for the effects of locus of control on college persistence and success outcomes through Bean and Eaton's conceptual framework.

Findings from this section should be interpreted from the broader context of structural barriers to student success. The relationships between the malleability of growth mindsets, self-efficacy beliefs, and locus of control do not exist in isolation. In the broader social context within which these interactions occur, locus of control is closely intertwined with the concept of powerlessness (Anderson et al., 2016). The experience of powerlessness and alienation is also central to Tinto's (1975) theory of college student departure and antithetical to integration.

Consequently, the review of learning dispositions that influence achievement and persistence would be incomplete unless it is connected to actionable institutional practices aimed at ameliorating the perception of personal powerlessness.

Chapter 3 Research Design and Methodology

Overview

Consistent with prior student retention research that commonly applies path analytic and regression techniques to enhance the theoretical validity of student integration and attrition models (Johnson et al., 2014; Brown et al., 2008; Pascarella et al., 2004; Sandler, 2000; Struthers et al., 2000; Berger & Braxton 1998; Milem & Berger 1997; Nora et al., 1996; Braxton et al., 1995; Brower, 1992; Cabrera et al., 1992; Braxton & Brier 1989; Lent et al., 1987; Terenzini & Wright 1987; Bean 1985; Bean & Metzner, 1985; Bean 1983; Pascarella & Chapman 1983; Bean 1982; Munro, 1981; Bean, 1980; Pascarella & Terenzini, 1980), this study employs a structural equation model statistical approach to understand patterns of persistence through Bean and Eaton's (2000) theoretical framework.

The strength of the relationships between the latent constructs and the attitudes, intentions, and behaviors are of great interest in the current investigation; therefore, meaningful effects will be assessed through mediation. Moderated mediation through regression is particularly applicable for jointly examining the psychological mediating processes: self-efficacy, locus of control, and coping processes, alongside moderating variables. The moderating variables can be different contexts, groups and values representing subgroups of the population. While prior studies have analyzed indirect effects on persistence through similar latent constructs, they have either focused more on the environmental mediating influences, and have dichotomized the overall model by ethnicity (e.g., Johnson et al., 2014), or have applied non-simultaneous mediation analysis (e.g., Llamas & Morgan, 2012). However, simultaneous mediation through SEM with bootstrapping is preferred over non-simultaneous mediation because iterative bootstrapping can provide more reliable estimates (Preacher et. al., 2007).

Furthermore, a more complex moderated mediation model can explain more of the observed behavior across student samples.

Research Design

This study will use a quantitative, longitudinal research design using responses from online questionnaires. The dependent variable will be persistence, a one item dichotomous enrollment variable. The independent variables are past behavior, normative beliefs, coping strategies, motivation to attend, bureaucratic interactions, academic interactions, social interactions, interactions external to the institution, self-efficacy assessments (pre and post measures), coping process (pre and post measures), locus of control (pre and post measures), academic integration, social integration, and institutional commitment.

Sample and Procedures

Three independent samples were drawn from three separate cohorts of first-year undergraduate students at a public, research university in California in 2018, 2019, and 2020. The university has a total enrollment of approximately 32,000 of which about 28,000 are undergraduates. Cohort 1 was drawn from approximately 5,680 first-time students entering the Fall 2018 semester. A freshmen year survey was administered to 4,583 first-year students enrolled in a university seminar at the beginning and at the end of the Fall 2018 semester, of which 1,225 responded; a response rate of approximately 27%. Of those students, only students who completed the pre- and post-assessment will be chosen for this inquiry (n = 335). In the Spring 2019 semester, the National Survey of Student Engagement (NSSE) was distributed to 6,255 first-year status students of which 1,716 responded; a response rate of approximately 27%. Of these students, 565 responded to both the NSSE and 2018 freshman seminar surveys. Of those students, 183 had both pre and post-test freshmen year survey scores, and this is the final sample for analysis. The NSSE sub-sample of student is only available for Cohort 1.

Cohort 2 was drawn from approximately 5,210 first-time students entering the Fall 2019 semester. A freshmen year survey was administered to those first-year students enrolled in a university seminar at the beginning and at the end of the Fall 2019 semester, of which 2,574 responded; a response rate of approximately 49%. Of those students, only students with complete information on pre- and post-test measurements will be chosen for this inquiry (n = 763).

Cohort 3 was drawn from approximately 4,798 first-time students entering the Fall 2020 semester. A freshmen year survey was administered to those first-year students enrolled in a university seminar at the beginning and at the end of the Fall 2020 semester, of which 2,362 responded; a response rate of approximately 49%. Of those students, only students who completed the pre- and post-assessment will be chosen for this inquiry (n = 416).

This study employs a cross-validation strategy as discussed by Cudeck and Browne (1983) to assess the theoretical validity of competing models; with one model incorporating NSSE engagement indicators (Cohort 1), while the comparison models do not (Cohorts 2 and 3). According to Browne and Cudeck (1989), the aim of cross-validation is to determine whether the model is applicable to similar samples from the same population. For competing models, one sample can be used as a calibration sample, and validation samples can used to estimate comparative cross-validation coefficients (Browne & Cudeck, 1989).

Sample Selection

The demographic variables for the Fall 2018 cohort are presented in Table 1 The final sample of 183 students for analysis consisted of 75.4% (n = 138) female and 24.6% (n = 45) male students. The ethnicity distribution comprised of 17.5% (n = 32) Asian, 2.2% (n = 4)

African-American, 36.6% (n = 67) Hispanic/Latino, 1.1% (n = 2) Hawaiian/Other Pacific Islander, 7.7% (n = 14) Multiple Ethnicities, 28.4% (n = 52) White, 4.2% (n = 8) International, 4.4%, and 2.1% (n = 4) students who were categorized under Other/Not Stated. Those students categorized as underrepresented according to the Integrated Postsecondary Education Data System (IPEDS) definition are students of within African American/Black, Hispanic/Latino, and Native American/American Indian groups. According to that definition, the analytic sample consisted of 38.8% (n = 71) underrepresented students, and 41% (n = 75) first-generation students.

Table 1

Descriptive Statistics for Fall 2018 Survey Sample and NSSE Sample

	Respondents		Final Sample	
Race/Ethnicity [a]	*n* =1,225	%	*n* = 183	%
Asian	211	17.2	32	17.5
Black or African American	45	3.7	4	2.2
Hispanic or Latino	378	30.9	67	36.6
International	41	3.3	8	4.4
Native Hawaiian or Pacific Islander	3	0.2	2	1.1
Other or Not Stated	27	2.2	4	2.2
Two or more races, Non-Hispanic	90	7.3	14	7.7
White	414	33.8	52	28.4
Underrepresented Group [a]				
White, Asian, Native Hawaiian, Pacific Islander, Two or More Races, Unknown	786	64.9	112	61.2
Black/African American, Hispanic/Latino, and American Indian/Native American	426	35.1	71	38.8
Gender [a]				
Female	816	67.3	138	75.4
Male	396	32.7	45	24.6
Age [a]				
≤ 17	152	12.5	31	16.9
18-19	1053	86.9	152	83.0
≥ 20	7	0.6	-	-
First Generation [a]				

	Respondents		Final Sample	
One or more parents attended college	769	63.6	108	59.0
Parents did not attend college	441	36.4	75	41.0

Note. [a] Missing values not included.

The demographic variables for the Fall 2019 sample are presented in Table 2. The final sample of 763 students for analysis consisted of 64.5% (n = 492) female and 35.5% (n = 271) male students. The ethnicity distribution comprised of .1% (n = 1) American Indian/Alaskan Native, 20.8% (n = 159) Asian, 1.6% (n = 12) African-American, 35.9% (n = 274) Hispanic/Latino, 8.9% (n = 68) Multiple Ethnicities, 28.8% (n = 220) White, 3.1% (n = 24) International, 4.4%, and .7% (n = 5) students who were categorized under Other/Not Stated. The analytic sample consisted of 37.6% (n = 287) underrepresented students, and 42.7% (n = 326) first-generation students.

Table 2

Descriptive Statistics for Fall 2019 Survey Sample

	Respondents		Final Sample	
Race/Ethnicity [a]	*n* = 2,574	%	*n* = 763	%
American Indian or Alaskan Native	6	0.2	1	0.1
Asian	407	15.8	159	20.8
Black or African American	112	4.4	12	1.6
Hispanic or Latino	847	32.9	274	35.9
International	87	3.4	24	3.1
Native Hawaiian or Pacific Islander	5	0.2	-	-
Other or Not Stated	39	1.5	5	0.7
Two or more races, Non-Hispanic	201	7.8	68	8.9
White	864	33.6	220	28.8
Underrepresented Group [a]				
White, Asian, Native Hawaiian, Pacific Islander, Two or More Races, Unknown	1603	62.4	476	62.4
Black/African American, Hispanic/Latino, and American Indian/Native American	965	37.6	287	37.6
Gender [a]				
Female	1605	62.5	492	64.5
Male	963	37.5	271	35.5

Age [a]				
≤ 17	266	10.4	83	10.9
18-19	2416	89.1	675	88.5
≥ 20	16	0.5	5	0.7
First Generation [a]				
One or more parents attended college	1578	61.4	437	57.3
Parents did not attend college	990	38.6	326	42.7

Note. [a] Missing values not included.

The demographic variables for the Fall 2020 sample are presented in Table 3. The final sample of 416 students for analysis consisted of 62.7% (n = 261) female and 37.3% (n = 155) male students. The ethnicity distribution comprised of .2% (n = 1) American Indian/Alaskan Native, 17.3% (n = 72) Asian, 3.1% (n = 13) African-American, 24.0% (n = 100) Hispanic/Latino, .2% (n = 1) Hawaiian/Other Pacific Islander, 7.7% (n = 32) Multiple Ethnicities, 42.8% (n = 178) White, 2.6% (n = 11) International, 4.4%, and 1.9% (n = 8) students who were categorized under Other/Not Stated. The analytic sample consisted of 27.4% (n = 114) underrepresented students, and 25.7% (n = 107) first-generation students.

Table 3

Descriptive Statistics for Fall 2020 Survey Sample

	Respondents		Final Sample	
Race/Ethnicity [a]	*n* = 2,362	%	*n* = 416	%
American Indian or Alaskan Native	5	0.2	1	0.2
Asian	331	14.0	72	17.3
Black or African American	88	3.7	13	3.1
Hispanic or Latino	679	28.8	100	24.0
International	36	1.5	11	2.6
Native Hawaiian or Pacific Islander	4	0.2	1	0.2
Other or Not Stated	41	1.7	8	1.9
Two or more races, Non-Hispanic	188	8.0	32	7.7
White	972	41.2	178	42.8
Underrepresented Group [a]				
White, Asian, Native Hawaiian, Pacific Islander, Two or More Races, Unknown	1572	66.6	302	72.6
Black/African American, Hispanic/Latino, and	772	32.7	114	27.4

American Indian/Native American				
Gender [a]				
Female	1476	62.5	261	62.7
Male	868	36.7	155	37.3
Age [a]	2344	99.2	416	100.0
≤ 17	259	11.0	50	12.0
18-19	2071	87.7	361	86.8
≥ 20	14	0.5	5	1.2
First Generation [a]				
One or more parents attended college	1652	69.9	309	74.3
Parents did not attend college	692	29.3	107	25.7

Note. [a] Missing values not included.

These tables present comparison data to assess sample representation to respondents from the overall cohorts. Sub-sample distributions of race/ethnicity, gender, underrepresented students and first-generation status were representative of the overall respondent samples.

Measures

The study will use two surveys over three time points to elaborate the theoretical model. The first-year freshman survey consists of topical areas including metacognitive awareness (MAI), psychological wellbeing (PWB), sense of belonging (SOB), and leadership (TGLQ), and was administered in the Fall 2018- 2020 semesters (three years). The questionnaire is presented in Appendix A. The second survey, the NSSE instrument, includes engagement indicators representing the campus environment and was administered only to the 2018-2019 student cohort.

Subscales and items directly applicable to Bean and Eaton’s model were selected from the following scales:

Psychological Wellbeing

Ryff’s (1989) classification of psychological well-being dimensions guided the process for selecting indicator items to reflect Bean and Eaton’s theoretical process. The psychological well-being (PWB) questionnaire draws on the conception of well-being grounded in the works of Maslow, Erikson, and Jung (Mayhew et al., 2016) and reflects student reported responses on a 6-point Likert scale and from 1 (strongly disagree) to 6 (strongly agree). This scale collects information on perceptions of autonomy, environmental mastery, personal growth, positive relations, purpose in life, and self-acceptance. Out of the 42 items representing this scale, 20 were reverse coded to avoid reverse-polarity.

Metacognitive Awareness

The metacognitive awareness inventory (MAI) consists empirically validated items representing knowledge about cognition and regulation of cognition as described by Schraw and Dennison (1994). The MAI can be further broken down into three subcomponents of knowledge about cognition: procedural knowledge, declarative knowledge, and conditional knowledge. Additionally the regulation of cognition category in this survey consists of five subcomponents: planning, comprehension monitoring, debugging strategies, and evaluation. MAI scores were derived from alternative responses to items with 1 (true) and 0 (false) for all 43 questions.

Sense of Belonging

The revised 26-item sense of belonging (SOB-R) measure of college student sense of belonging and provides measures of: perceived peer support, perceived classroom comfort, perceived isolation, and perceived faculty support as validated by Hoffman et al. (2004). The SOB items are written from the perspective of a college student specifically developed for freshman seminar and learning community contexts. The SOB items are rated on a 5-point Likert scale according to the likelihood of student identification with a statement from 1 (completely untrue) to 6 (completely true).

Leadership Questionnaire

The Timm and Gates (2018) leadership questionnaire includes dimensions of confidence in personal and academic vision alignment, conflict/challenge resolution, and confidence in cultural strengths. This questionnaire includes 14 items representing leadership dimensions in a collegiate setting, and reflects student reported responses on a 6-point Likert scale, ranging from 1 (strongly disagree) to 6 (strongly agree).

National Survey of Student Engagement

In recent decades, scholars have directed considerable attention to student engagement and time on task to better understand effective teaching and learning and increase institutional accountability and transparency (Kuh, et al., 1997; Kuh, 2001, 2009). First launched in 2000, and significantly updated in 2013, NSSE combines measures of Engagement Indicators (EIs) and High Impact Practices (HIPs) to inform policy implementation toward student learning outcomes. EIs are the 10 major benchmarks measured by NSSE: Higher-Order Learning, Reflective & Integrative Learning, Learning Strategies, Quantitative Reasoning, Collaborative Learning, Discussions with Diverse Others, Student-Faculty Interaction, Effective Teaching Practices, Quality of Interactions, and Supportive Environment (NSSE, 2018). HIPs are enriching undergraduate experiences such as: first-year experience seminars, community-based projects, research with faculty, internships, study abroad programs, and capstone experiences (Finley & McNair, 2013).

As previously considered, an explanation of processes that lead to academic and social integration is uninterpretable unless combined with actionable process indicators (NSSE, 2018). Therefore, the current model elaborates the previous psychological model and combines it with key items validated to measure campus interactions from the NSSE. In this study, engagement indicators representing the campus environment will be used to elaborate the Bean and Eaton model due to Berger and Braxton's (1998) claim that organizational attributes such as the campus' administrative processes are a source of social integration. Despite this evidence, virtually no studies specifically examine the effects of bureaucratic interactions on student outcomes such as self-efficacy, coping, and internal attribution to explain retention.

Quality of interactions is a measure of student interactions with other students, academic advisors, faculty, student services staff, and administrative staff and offices, and responses are rated in terms the degree of quality; 1 (poor) to 7 (excellent). Supportive environment is a measure of how much the institution supports students in non-classroom related activities and events. This includes supporting students' overall well-being, offering tutoring services, social events, and facilitating student management of non-academic responsibilities. Responses are rated in terms the degree of supportive emphasis in each area; 1 (very little) to 4 (very much).

Operational Definition of Variables

The structural model is adapted from the Bean and Eaton (2000) causal model using the following theoretical substitutions. This section will operationally define the latent and measured variables of interest. A detailed description of the indicators of each of the latent variables is presented in Appendix B.

Entry Characteristics

The first set of variables in the hypothesized model correspond to the student entry characteristics in the psychological model of college student retention. Entry characteristics will be represented by four latent variables (factors): past behavior, normative beliefs, coping strategies, motivation to attend. Past behavior will be a latent variable with indicators from Ryff's self-acceptance scale, environmental mastery scale, and purpose in life scale, as derived from

Ryff (1989) and Ryff and Keyes (1995). Normative beliefs will be indicated by Ryff's autonomy scale, and coping strategies will be indicated by the planning scale from the MAI validated by Schraw and Dennison (1994). Motivation to attend will be indicated by items from Ryff's personal growth scale and purpose in life scale. Pre-college skills and abilities as will be represented by the measured variables incoming HS GPA and scholastic aptitude test (SAT) composite score. The means and standard deviations of these measured variables are presented in Table 6.

Environmental Interactions

The second set of variables in the hypothesized model represent environmental interactions and act as mediators toward persistence. Environmental interactions will be represented by four latent variables: bureaucratic interactions, academic interactions, social interactions, and interactions external to the institution. Bureaucratic interactions will be measured by the Quality of Interactions Scale subscale from NSSE. Academic interactions will be indicated by two subscales: 1) Sense of Belonging: Perceived Classroom Comfort; and 2) Sense of Belonging: Empathetic Faculty Understanding (Hoffman, et al., 2002). The third latent mediator, social interactions, will be indicated by items from Ryff's positive relations and environmental mastery scales (Ryff, 1989; Ryff & Keyes, 1995). The fourth latent variable, interactions external to institution, will be measured by the NSSE Supportive Environment Scale.

Psychological Processes and Psychological Outcomes

The third set of variables in the hypothesized model represent psychological processes, and act as mediators toward persistence. Psychological processes will be represented by three latent variables: self-efficacy assessments, coping process (approach/avoidance), and locus of control. Self-efficacy assessments will be represented by two subscales: 1) MAI: Declarative

Knowledge, Procedural Knowledge; and 2) MAI: Conditional Knowledge (Schraw & Dennison, 1994). Coping process will be indicated by three subscales: 1) MAI: Comprehension Monitoring 2) MAI: Debugging Strategies, and 3) MAI: Evaluation (Schraw & Dennison, 1994). And locus of control will be associated with three indicators, including items from Ryff's environmental mastery, positive relations, and personal growth scales (Ryff, 1989; Ryff & Keyes, 1995).

Self-efficacy Assessments. As with coping theory, metacognitive knowledge has also been shown to influence self-efficacy, that is, those with strong self-efficacy are more likely to use metacognitive strategies (Coutinho & Neuman, 2008). Coutinho and Neuman (2008) found a strong relationship between metacognition and self-efficacy; therefore, in the current study, the MAI declarative, procedural and conditional knowledge scales were used as a measure for self-efficacy assessments.

Coping Process. In terms of academic integration, the knowledge of how to link academic adjustment strategies and regulate cognition to adapt is a type of metacognitive awareness. Regulation of cognition includes the subcomponents: planning, information management, comprehension monitoring, debugging strategies, and evaluation (Schraw & Dennison, 1994). Therefore, these subcomponents were collectively used as measures of the coping process in the current study.

Specifically, the metacognitively aware student is more likely to employ problem-focused behavior such as planning to cope with stressful encounters prior to learning. For this reason, the Metacognitive Awareness Inventory (MAI) planning scale validated by Schraw and Dennison (1994) was used as a proxy for coping strategies as an entry characteristic. Subsequently the MAI comprehension monitoring, debugging and evaluation strategies scales were used as pre and posttest measures to model the approach/avoidance coping process and stress reduction strategies throughout the persistence model.

Attributions: Locus of Control. In the current study, items relating to locus of control from the environmental mastery, positive relations, and personal growth (PWB) scales (Ryff, 1989; Ryff & Keyes, 1995) were used as indicators for internal or external attribution. Mirels (1970) and Lange and Tiggemann (1981) found that Rotter's (1966) internal-external control measurement instrument has two dimensions. One dimension is characterized by individual beliefs about environmental mastery, and the other is related to beliefs about control over social systems. Other studies cite locus of control subdimensions related to fate/chance and interpersonal respect (Garza & Widlak, 1977). The PWB scales comprise of items corresponding to the overall facets of environmental mastery as well as locus of control subdimensions such as fate/chance, and interpersonal respect. For example, items indicating control over one's direction in life (environmental mastery), efficacy of personal effort (personal growth), and perceptions of others about one's likability (positive relations) are used as measures for factorial categories mentioned in the literature (e.g., Mirels 1970; Lange & Tiggemann; 1981; Garza & Widlak, 1977).

Intermediate Outcomes

The fourth set of variables in the hypothesized model represent intermediate student outcomes, and are another set mediators toward persistence. Intermediate outcomes will be represented by academic and social integration. The latent variable academic integration will be indicated by two SOB subscales: 1) Perceived Faculty Support (PFS), and 2) Perceived Classroom Comfort (PCC) (Hoffman et al., 2003). Social integration will be indicated by two

SOB subscales: 1) Perceived Peer Support (PPS), and Subscale 2) Perceived Isolation (PI) (Hoffman et al., 2003).

Attitudes and Behavior

Institutional fit, a latent variable with three indicators from the Leadership Scale (TGLQ) (Timm & Gates, 2018) will represent student attitudes in the hypothesized model. The hypothesized model illustrates that attitudes directly affect behavior. Persistence behavior is the final endogenous variable, and will indicated by one measured indicator. Table 4 describes subsequent term persistence for the three samples of students enrolled in the Fall semesters 2018-2020. Table 5 describes Fall 2018 cohort persistence into Fall 2020.

Table 4

Persistence Status for Student Survey Respondents in Fall 2018 (n=1225), Fall 2019 (n=2718), and Fall 2020 (n=2362)

	Survey Respondents Total [a]		Final Sample Total	
Spring Enrollment	Persisted	Did not Persist	Persisted	Did not Persist
Fall 2018-Spring 2019	1177	35	183	-
Fall 2019-Spring 2020	2628	90	747 [b]	16 [b]
Fall 2020-Spring 2021	2266	78	411 [b]	5 [b]

Note. [a] Missing values not included.
[b] Analytic sample for structural models

Table 5

Persistence Status for Students Enrolled in Fall 2018 through Fall 2020

	Survey Respondents Total [a]		Final Sample Total	
Fall Enrollment	Persisted	Did not Persist	Persisted	Did not Persist
Fall 2018-Fall 2019	1082	130	172	11
Fall 2018-Fall 2020	1012	200	164 [b]	19 [b]

Note. [a] Missing values not included.
[b] Analytic sample for structural models

At the time of this study, the Fall 2018 sample had been assessed for persistence three times; once into the subsequent term enrollment, and again into the Fall 2019 semester and Fall 2020 semester (Table 4). Similar year-to-year persistence data were not available for the Fall 2019 and Fall 2020 cohorts; therefore, persistence for those samples was assessed as enrollment into the subsequent term (Table 5).

Control Variables

The following contextual variables are influential in the current study based on their demonstrated relationship to persistence in the research literature: HS GPA, first term college GPA, composite SAT score, and student age.

High School Grades. High school grades represent college readiness and are consistently used in predictive models of persistence and retention due to their reliable effect on college academic achievement. Several studies have found that HS GPA predicts persistence in the first year of college (Stewart et al., 2015; Hoffman & Lowitzki, 2005), and that it is a better predictor of college academic performance than standardized test scores (Munro, 1981).

However, various contradictions exist within the retention body of literature. For example, Stewart et al. (2015) found that both first year college GPA and HS GPA account for 26% of the variance in first-year persistence, and that an inverse relationship between HS GPA and first year college persistence exists. This indicates that while high school academic achievement influences persistence, higher grades may not necessarily lead to greater persistence. Similarly, Kuh et al. (2008) found that student high school grades consisting of mostly Bs (as opposed to mostly As) had a greater a greater probability of predicting persistence into the second year of college. One the reasons for this type of inverse relationship may be due to the differential effects of high school grades on retention for students of color, when compared to those who do not identify as students of color (Hoffman & Lowitzki, 2005). These findings warrant additional research; therefore, HS GPA is included in the current study in order to understand the impact it has on persistence in the Bean and Eaton framework.

Incoming HS GPAs for this study are presented in Table 6. For the Fall 2018 final sample, the mean was 3.82 and standard deviation of .28. For the Fall 2019 final sample, the mean was 3.85 with a standard deviation of .29. For the Fall 2020 final sample, the mean was 3.9 with a standard deviation of .28.

College GPA. College grades are significantly predictive of college persistence and retention and can be a college experience self-selection control variable. (Pascarella & Terenzini, 2005; Mayhew et al., 2016). For example, Grimes (1997) found that first-year college GPA was significantly different for students who persist versus those who do not. Gifford et al. (2006) extended these findings by showing that males and females also had significantly different first-year college GPAs, and that locus of control orientation plays a role in these differences. Other first-year GPA-persistence subgroup connections have been observed for first-generation students as well as students receiving supplemental instruction (Mayhew et al., 2016). Therefore, the end of first-year GPA is an important to take into account because it may explain the relationship between student entry characteristics, locus of control orientation, and persistence.

First semester GPAs for this study are presented in Table 6. For the Fall 2018 final sample, the end of term (EOT) mean was 3.3 and standard deviation of .63. For the Fall 2019 final sample, the mean was 3.23 with a standard deviation of .65. For the Fall 2020 final sample, the mean was 3.5 with a standard deviation of .62.

SAT Composite Score. SAT scores have also been found to be significantly predictive of first year academic achievement (Hoffman & Lowitzki, 2005), and those students who persist into the second year of college typically also have higher SAT scores (McGrath & Braunstein, 1997). While studies have shown significant associations between first year persistence and SAT scores (Cabrera et al., 2013), as with HS GPA, there is still a need to understand whether that relationship will hold while controlling for the environmental interactions, psychological processes, academic and social integration, and student attitudes and intentions. Including SAT scores alongside those educationally purposeful variables in models of first-year persistence can often yield interesting insights indicating compensatory effects (Kuh, 2008).

Student SAT composite scores for this study are presented in Table 6. For the Fall 2018 final sample, the SAT composite mean was 1236.65 and standard deviation of 134.01. For the Fall 2019 final sample, the SAT composite mean was 1216.79 with a standard deviation of 144.86. For the Fall 2020 final sample, the SAT composite mean was 1238.96 with a standard deviation of 138.62.

Student Age. As Mayhew et al. (2016) noted, student age has been a demonstrated correlate of both identity development and self-authorship stages, and functions as a control for maturation. Previous studies have connected self-authorship with coping behaviors (Pizzolato, 2004), locus of control (Mayhew et al., 2016), GPA and persistence (Grimes, 1997). For example, different extracurricular experiences have been shown to affect internal locus of control orientation differently based on age, and depending on whether first-year students were enrolled in a community college or four-year institution. At the individual level, Baxter Magolda's (2008) longitudinal study of self-authorship development in college students showed that individuals in their 20s are focused on navigating crossroads with external influences. Moreover, as these same individuals progress into their 30s, they begin to see obstacles as malleable and can balance conflicts between their identities and external pressures. Baxter Magolda (2008) observed that college students who experience marginalization may develop this same resilient perspective in their 20s.

Student age distributions for this study are presented in Table 6. Across the three samples in this study, the age range was 16 to 23 with a mean of 17.95 and standard deviation of .5. For the Fall 2018 final sample, the age range was 16 to 19 with a mean of 17.89 and standard deviation of .48. For the Fall 2019 final sample, the age range was 17 to 23 with a mean of 17.96 and standard deviation of .5. For the Fall 2020 final sample, the age range was 17 to 21 with a mean of 17.96 and standard deviation of .49.

Table 6

Survey Sample Comparison of Measured Independent Variables

	Final Sample	
	Mean	SD
Fall 2018 (*n* =183)		
Incoming/HS GPA	3.82	0.28
SAT Comp	1236.65	134.01
EOT Campus GPA	3.30	0.63
Student Age	17.89	0.48
Fall 2019 (*n* = 763)		
Incoming/HS GPA	3.85	0.29
SAT Comp	1216.79	144.86
EOT Campus GPA	3.23	0.65
Student Age	17.96	0.50
Fall 2020 (*n* = 416)		
Incoming/HS GPA	3.90	0.28
SAT Comp	1238.96	138.62
EOT Campus GPA	3.50	0.62
Student Age	17.96	0.49

Methodology

Data Analysis

Data Screening. As discussed in the sample and procedures section, screening criteria were employed to include only pre- and post-measure responses of the first-year seminar survey. Survey participants with only pre-test responses and only post-test responses were not included in the analysis. Data were reviewed for missing values and unengaged responses. The data were analyzed as guided by procedures described in Meyers et al. (2006). Univariate and multivariate data screening was conducted, and followed by exploratory factor analysis (EFA) and confirmatory factor analysis (CFA).

For each scale, the responses with the same value across all questions were labeled 'Straightliner'. Frequencies of Straightliner' responses were inspected only for respondents with pre- and post-measures on all scales. An examination of those unengaged responses across all three cohorts (i.e., Fall 2018-2020) revealed 28 unengaged responses for the PWB scale, 37 unengaged responses for the TGLQ scale, 42 unengaged responses for the SOB scale, and 55 unengaged responses for the MAI scale. These unengaged responses were removed prior to the data analysis.

Missing Data. Before proceeding with the data analysis, responses with missing values were screened using the SPSS Frequency function, and subsequently removed. Mertler and Vannatta (2001) recommend that cases with over 15% missing values are deleted, but a more conservative approach was taken for this study. For the Fall 2018 analytic sample missing value cases for the PWB scale were between 19-22%, 13-19% for the MAI scale, 22-24% for the SOB scale, and 22-23% for the TGLQ scale. For the Fall 2019 analytic sample missing value cases for the PWB scale were between 11-28%, 17-35% for the MAI scale, 12-25% for the SOB scale, and 14-31% for the TGLQ scale. For the Fall 2020 analytic sample missing value cases for the PWB scale were between 8-14%, 6-15% for the MAI scale, 9-15% for the SOB scale, and 6-13% for the TGLQ scale.

Univariate Outliers and Normality. All items used to impute latent variable constructs are ordinal or binary; therefore, there were no outliers or cases with extreme values. In large samples, Meyers et al. (2006) and Tabachnick and Fidell (1996) suggest inspection of the shape of the distribution rather than strict reliance on skewness and kurtosis acceptable thresholds due to the influence of N on standard error.

Stem-and-leaf plots were examined for the continuous variables SAT score, HS GPA, end of term college GPA, and student age. These measured variables were screened for only those respondents who had pre and post-test measures. The plots indicated that age was a variable with possible extreme cases, for those respondents under 17 and over 19. Possible extreme value candidates for college GPA less than or equal to 1.87, and incoming HS GPA greater than or equal to 3.09 were also identified. Although there are younger and older students in the respondent samples, those values are common for the freshman demographic, and age alone should not disqualify those cases from being included in analyses. The HS and college GPA outlier candidates should also be monitored rather than excluded, as they are representative of natural variation in the target population. Only age and end of term college GPA exhibited values exceeding a +2.2 acceptable threshold (Sposito et al., 1983); however, other scholars are much more liberal with acceptability of kurtosis thresholds. For example, Kline (2015) considers values greater than 10 to be an issue.

The distribution of the variables for inclusion into the measurement model were reviewed for deviation from normality. Negative skewness (i.e., values above the mean) was found for twenty-five of items with values outside the acceptable range of -2 and +2 (George, & Mallery, 2003). Kurtosis was observed for twenty-six items with acceptable values exceeding +2.2 (Sposito et al., 1983). The deviation for normality was observed for the MAI scale items which are binary; therefore, for SEM purposes, a maximum likelihood (ML) estimation alternative is recommended (Brown, 2015).

Homogeneity of Variance. Because the data were collected in different semesters (i.e., different groups), homogeneity of variance assumptions were observed for the continuous variables in the analysis HS GPA, SAT score, student age, and college GPA. The means of the samples were compared using Levene's test. The variances for the three cohorts 2018-2020 were found to be significantly different ($p < .001$) across end of term college GPA. Therefore, the assumption for equality of variance across cohorts for first semester college GPA is violated. A closer look at the variance values across the three groups indicate that they are very similar, Fall 2018 $s^2 = .49$, Fall 2019 $s^2 = .415$, and Fall 2020 $s^2 = .389$. In cases with large sample sizes, Field (2018) recommends noting the variance ratio. The variance ratio between the largest and smallest variance, .49/.389 = 1.25, which is not drastically different and therefore the significance may be based on use of large sample sizes.

Fall 2018 Cohort Exploratory Factor Analysis (EFA). The EFA was first conducted to evaluate whether the items from the PWB scale loaded together as expected per preestablished subscales, and to check criteria for exploratory validity and reliability. Principal axis factor (PAF) analysis with promax rotation was conducted to assess the underlying structure of the PWB pre-test measures to be included in the structural model. PAF extraction was used because it accounts for covariation, which is the preferred method for SEM (Leech et al., 2011). Oblique rotation was used because it is assumed that the factors are theoretically correlated (Field, 2018).

PWB Scale. Six factors were requested since the PWB items were designed to represent six constructs: autonomy, environmental mastery, personal growth, positive relations, purpose in life, and self-acceptance. Loadings below .3 were suppressed (Tabachnick & Fidell, 1996). After rotation, the first factor accounted for 23.3% of the variance, the second factor accounted for 7.7%, the third 6.7%, the fourth 4.0%, the fifth 3.0%, and the sixth 2.5%. Appendix table C1 displays the items and factor loadings for the pattern matrix. The variables were adequate for exploratory factor analysis based on a KMO of .75. The factor solution explained 47.2% of the variance, and there were no correlations greater than .7 indicating discriminant validity. The Cronbach's alphas for five of the six factors observed were within acceptable-good range between .60 and .80, indicating convergent reliability (Hair, et al., 2014). Only one of the factors, a combination of a lack environmental mastery and positive relations e.g., reversed items, had an alpha below the recommended value of .6. for exploratory analysis. This factor will not be used in the structural model.

In order to achieve discriminant validity and convergent validity, 18 items were removed. Five of the seven positive relations items, five of the seven purpose in life items, and three of the seven personal growth items were removed for low loadings. Additionally two items from the autonomy scale, two items from self-acceptance scale, and one item from the environmental mastery scale were removed.

Six factors were requested for the PWB post-test factor analysis since the overall scale was designed to represent the six aforementioned constructs. This was also done because none of the items had high loadings on their own preestablished subscale, and the PAF solution initially yielded 11 factors. Items representing the autonomy subscale were the only items to have high loadings on their own subscale. Loadings below .3 were suppressed (Tabachnick & Fidell, 1996). After rotation, the first factor accounted for 28.4% of the variance, the second factor accounted for 7.1%, the third 4.5%, the fourth 3.7%, the fifth 3.2%, and the sixth 2.7%. Appendix table C2 displays the items and factor loadings for the pattern matrix. The variables were adequate for exploratory factor analysis based on a KMO of .82. The six-factor solution explained 49.6%, of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the six factors observed were within acceptable-good range between .58 and .82, indicating convergent reliability (Hair, et al., 2014).

In order to achieve discriminant validity and convergent validity, 15 items were removed. Three of the seven positive relations items, two of the seven purpose in life items, and three of the seven personal growth items were removed for low loadings. Additionally two items from the autonomy scale, three items from self-acceptance scale, and two items from the environmental mastery scale were removed. Overall, with the exception of the autonomy scale, PWB items were not reflective of their predetermined constructs.

MAI Scale. Principal components analysis with varimax rotation was conducted to assess how the eight sets of dichotomous variables clustered. Similar to findings from Schraw and Dennison (1994), there was little evidence of an eight-factor solution. Therefore, a restricted two factor solution was requested, based on procedures described in Experiment 1 in Schraw and Dennison's (1994) study. The two-factor solution showed that the items in the subscales planning, comprehension monitoring, debugging strategies, and evaluation subscales had high loadings on the first factor Regulation of cognition. The items from the procedural knowledge, conditional knowledge and declarative knowledge scales loaded had high loadings on the second factor Knowledge about cognition. These results are consistent with Schraw and Dennison's findings from Experiment 1. After rotation, the first component accounted for 13.9% of the variance, and the second component accounted for 5.7% of the variance of the MAI pre-test variables. Appendix table C3 displays the items and component loadings for the rotated components, with loadings less than .3 omitted to improve clarity.

The two-factor solution showed that the MAI post-test items in the subscales planning, comprehension monitoring, and evaluation subscales had high loadings on the first factor Regulation of cognition. The items from the procedural knowledge, conditional knowledge and declarative knowledge scales loaded had high loadings on the second factor Knowledge about cognition. After rotation, the first component accounted for 15.6% of the variance, and the second component accounted for 5.7% of the variance of the MAI post-test variables. Appendix table C4 displays the items and component loadings for the rotated components. In keeping with Schraw and Dennison's findings, results suggest that the scale measures the two metacognitive factors reliably. The Cronbach's alphas for the pre-test MAI components exhibited good reliability ranges, .81 for regulation of cognition, and .76 for knowledge about cognition. The Cronbach's alphas for the post-test MAI components exhibited good reliability ranges, .83 for regulation of cognition, and .74 for knowledge about cognition.

SOB Scale. PAF analysis with promax rotation was conducted to assess the underlying structure for the 26 items in the SOB questionnaire. Six factors emerged from the pre-test items, with perceived peer support dividing into two dimensions. After rotation, the first factor, perceived faculty support/comfort accounted for 36.5% of the variance, the second factor perceived classroom support accounted for 9.9%, the third factor perceived isolation 6.5%, the fourth factor perceived peer support 4.6%, the fifth factor empathetic faculty understanding accounted for 4.2%. The sixth factor perceived peer support/outside of class accounted for 3.0% of the variance, and was the second dimension that emerged from the perceived peer support subscale. Appendix table C5 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity.

The variables were adequate for exploratory factor analysis based on a KMO of .87. The factor solution explained 64.8% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the six factors exhibited good reliability between .80 and .90, indicating convergent reliability (Hair, et al., 2014). In order to achieve discriminant validity and convergent validity, perceived peer support (Pre_PPS5) and perceived faculty support (Pre_PFS2) were removed.

Five factors emerged from the SOB post-test set of measures. After rotation, the first factor, perceived faculty support/comfort accounted for 40.7% of the variance, the second factor perceived isolation accounted for 11.8%, the third factor perceived classroom comfort 5.7%, the fourth factor empathetic faculty understanding 4.0%, the fifth factor perceived peer support accounted for 3.5%. Interestingly, one of the perceived peer support items POST_PPS5 had a high loading on the perceived isolation scale, indicating a dimension of peer support that is oppositional to isolation. Appendix table C6 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity.

The post-test SOB items were adequate for exploratory factor analysis based on a KMO of .87. The factors explained a total variance of 65.8%, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the five factors exhibited good reliability between .85 and .93, indicating convergent reliability (Hair, et al., 2014). In order to achieve discriminant validity and convergent validity, perceived peer support items POST_PPS4, POST_PPS6, POST_PPS7, and POST_PPS8 were removed. Overall, the

SOB scale subdimensions exhibited very high preliminary construct validity for the Fall 2018 sample of students.

TGLQ Scale. PAF analysis with promax rotation was conducted to assess the underlying structure for the 17 items in the TGLQ questionnaire. Items 5,7,13, and 14 were dropped since they were not included in the 2018 version of the questionnaire. Three factors emerged from the pre-test items, indicating three dimensions of confidence, cultural strengths, and institutional fit. After rotation, the first factor, confidence accounted for 36.6% of the variance, the second factor cultural strengths, accounted for 11.1%, and the third factor, academic degree/institutional fit accounted for 7.5%. Appendix table C7 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity. The variables were adequate for exploratory factor analysis based on a KMO of .81. The factors explained a total variance of 55.2%, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the three factors exhibited good reliability between .79 and .84, indicating convergent reliability (Hair, et al., 2014).

Two factors also emerged from the post-test TGLQ variables. After rotation, the first factor, academic degree/institutional fit accounted for 50.4% of the variance, the second factor accounted for 10.0%. Appendix table C8 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity. The post-test TGLQ variables were adequate for exploratory factor analysis based on a KMO of .83. The factor solution explained 60.5% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas for the two factors exhibited good reliability between .84 and .88, indicating convergent reliability (Hair, et al., 2014). In order to achieve discriminant validity and convergent validity, items POST_TGLQ15, POST_TGLQ16, POST_TGLQ8, and POST_TGLQ9 were removed.

Fall 2019 Cohort Exploratory Factor Analysis (EFA). An EFA was also conducted for the Fall 2019 sample to determine whether all the observed variables loaded together as expected for the four scales.

PWB Scale. Six factors were requested because the PWB items were designed to represent six constructs: autonomy, environmental mastery, personal growth, positive relations, purpose in life, and self-acceptance. Loadings below .3 were suppressed (Tabachnick & Fidell, 1996). After rotation, the first factor accounted for 26.1% of the variance, the second factor accounted for 5.7%, the third 3.9%, the fourth 3.0%, the fifth 2.3%, and the sixth 1.6%. Appendix table C9 displays the items and factor loadings for the pattern matrix. The variables were adequate for exploratory factor analysis based on a KMO of .91. The factor solution explained 42.6% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas for five of the six factors observed were within acceptable-good range between .60 and .86, indicating convergent reliability (Hair, et al., 2014). One of the factors combined items from lack of purpose in life and positive relations e.g., reversed items, and had an alpha below the recommended value of .6. for exploratory analysis. This factor will not be used in the structural model.

To achieve discriminant validity and convergent validity, 12 items were removed. One of the seven positive relations items, one of the seven purpose in life items, and two of the seven personal growth items were removed for low loadings. Additionally, six items from the autonomy scale, one item from self-acceptance scale, and one item from the environmental mastery scale were removed.

Six factors were requested for the PWB post-test factor analysis, because the overall PWB scale was designed to represent the six aforementioned constructs. This was also done because none of the items had high loadings on their own preestablished subscale, and the PAF solution initially yielded 8 factors. Loadings below .3 were suppressed (Tabachnick & Fidell, 1996). After rotation, the first factor accounted for 26.4% of the variance, the second factor accounted for 7.0%, the third 3.7%, the fourth 3.5%, the fifth 3.0%, and the sixth 1.7%. Appendix table C10 displays the items and factor loadings for the pattern matrix. The variables were adequate for exploratory factor analysis based on a KMO of .91. The factor solution explained 45.2% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the six factors observed were within acceptable-good range between .59 and .87, indicating convergent reliability (Hair, et al., 2014).

In order to achieve discriminant validity and convergent validity, 14 items were removed. One of the seven positive relations items, and four of the seven personal growth items were removed for low loadings. Additionally three items from the autonomy scale, three items from self-acceptance scale, and three items from the environmental mastery scale were removed.

MAI Scale. Principal components analysis with varimax rotation was conducted to assess how the eight sets of dichotomous variables clustered for the Fall 2019 sample. Similar to the procedure followed for the Fall 2018 sample, a restricted two factor solution was requested, based on procedures described in Experiment 1 in Schraw and Dennison's (1994) study. The PCA for the Fall 2019 sample MAI pre-test measures, showed that the items in the subscales planning, comprehension monitoring, debugging strategies, and evaluation subscales had high loadings on the second factor Regulation of cognition. The items from the procedural knowledge, conditional knowledge and declarative knowledge scales loaded had high loadings on the first factor Knowledge about cognition. After rotation, the first component accounted for 14.8% of the variance, and the second component accounted for 5.7% of the variance of MAI pre-test variables. Appendix table C11 displays the items and component loadings for the rotated components, with loadings less than .3 omitted to improve clarity.

The two-dimensional component order was reversed for the post-test measures. After rotation, the first component accounted for 15.3% of the variance, and the second component accounted for 5.5% of the variance of the MAI post-test variables. Appendix table C12 displays the items and component loadings for the rotated components. The Cronbach's alphas for the MAI pre-test components exhibited good reliability ranges, .78 for regulation of cognition, and .79 for knowledge about cognition. The Cronbach's alphas for the MAI post-test components exhibited good reliability ranges, .8 for regulation of cognition, and .76 for knowledge about cognition.

SOB Scale. PAF analysis with promax rotation was conducted to assess the underlying structure for the 26 items in the SOB questionnaire for the Fall 2019 sample. Four factors emerged from the pre-test variables based on the eigenvalues over 1 criterion. After rotation, the first factor perceived peer support accounted for 29.8% of the variance, the second factor perceived classroom support accounted for 11.3%, the third factor perceived faculty support 7.3%, the fourth factor, perceived isolation accounted for 3.1%. Appendix table C13 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity. The variables were adequate for exploratory factor analysis based on a KMO of .9. The factor solution explained 51.5% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the four factors exhibited good reliability between .81 and .92, indicating convergent reliability (Hair, et al., 2014). In order to achieve discriminant validity and convergent validity, perceived faculty support (Pre_PPF1) and perceived faculty support (Pre_PFS8) were removed.

Four factors emerged from the SOB post-test measures based on the eigenvalues over 1 criterion. After rotation, the first factor, perceived faculty support/comfort accounted for 34.6% of the variance, the second factor perceived peer support accounted for 12.6%, the third factor perceived classroom comfort 7.5%, the fourth factor perceived isolation 3.0%. Appendix table C14 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity.

The post-test SOB measures were adequate for exploratory factor analysis based on a KMO of .92. The factor solution explained 57.7% of the variance, and there were no correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the five factors exhibited good reliability between .83 and .94, indicating convergent reliability (Hair, et al., 2014). The SOB scale subdimensions exhibited very high preliminary construct validity for the Fall 2019 sample of students.

TGLQ Scale. PAF analysis with promax rotation was conducted to assess the underlying structure for the 14 items in the TGLQ questionnaire for the Fall 2019 sample. Four factors emerged from the pre-test measures, indicating four dimensions of the leadership questionnaire. After rotation, the first factor, confidence accounted for 36.7% of the variance, the second factor cultural strengths, accounted for 8.9%, and the third factor, academic degree/institutional fit accounted for 7.4 %. The fourth factor life vision accounted for 5.2% of the variance in the factor solution. Appendix table C15 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity. The variables were adequate for exploratory factor analysis based on a KMO of .87. The factors explained a total variance of 58.2%, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the three factors exhibited good reliability between .80 and .85, indicating convergent reliability (Hair, et al., 2014).

Three factors emerged from the post-test TGLQ measures. After rotation, the first factor, confidence accounted for 40.3% of the variance, the second factor academic degree/institutional fit accounted for 7.7%, and the third factor life vision accounted for 5.0%. Appendix table C16 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity. The post-test TGLQ variables were adequate for exploratory factor analysis based on a KMO of .9. The factor solution explained 52.9% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas for the two factors exhibited good reliability between .79 and .85, indicating convergent reliability (Hair, et al., 2014). Due to an initial factor solution which produced two Heywood cases, items POST_TGLQ6 and POST_TGLQ10 were removed. Heywood cases are communality estimates that are greater than 1.0 (i.e., negative error variance), and are considered improper solutions that should be avoided (Hair et al., 2014).

Fall 2020 Cohort Exploratory Factor Analysis (EFA). An EFA was also conducted for the Fall 2020 sample to determine whether all the observed variables loaded together as expected for the four scales.

PWB Scale. Six factors were requested since the PWB items were designed to represent six constructs: autonomy, environmental mastery, personal growth, positive relations, purpose in life, and self-acceptance. Loadings below .3 were suppressed (Tabachnick & Fidell, 1996). After rotation, the first factor accounted for 26.6% of the variance, the second factor accounted for 4.7%, the third 3.5%, the fourth 3.5%, the fifth 2.4%, and the sixth 1.9%. Appendix table C17 displays the items and factor loadings for the pattern matrix. The variables were adequate for exploratory factor analysis based on a KMO of .90. The factor solution explained 42.7% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas for five of the six factors observed were within acceptable-good range between .65 and .87, indicating convergent reliability (Hair, et al., 2014). One of the factors accounting for the least amount of variance, combined items from lack of personal growth and environmental mastery e.g., reversed items, and had an alpha below the recommended value of .6. for exploratory analysis. This factor will not be used in the structural model. In order to achieve discriminant validity and convergent validity, 10 items were removed. Three of the seven positive relations items and three of the seven personal growth items were removed for low loadings. Additionally two items from the autonomy scale and two items from the environmental mastery scale were removed.

Six factors were requested for the PWB post-test factor analysis since the overall PWB scale was designed to represent six constructs. This was also done because none of the items had high loadings on their own preestablished subscale, and the PAF solution initially yielded 10 factors. Loadings below .3 were suppressed (Tabachnick & Fidell, 1996). After rotation, the first factor accounted for 26.7% of the variance, the second factor accounted for 5.5%, the third 4.8%, the fourth 3.8%, the fifth 3.0%, and the sixth 2.4%. Appendix table C18 displays the items and factor loadings for the pattern matrix. The variables were adequate for exploratory factor analysis based on a KMO of .90. The factor solution explained 46.2% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the six factors observed were within acceptable-good range between .66 and .86, indicating convergent reliability (Hair, et al., 2014). The positive relations item POST_PL1R loaded highly on one factor and thus represented a single-item construct. Hair et al. (2014) recommend that researchers minimize use of single-item constructs in SEM models due to the possibility of identification issues. Therefore, this item will not be used in the structural model.

In order to achieve discriminant validity and convergent validity, 10 items were removed from the PWB post-test factor analysis. Two of the seven positive relations items, and one of the seven personal growth items were removed for low loadings. Additionally one item from the autonomy scale, two items from self-acceptance scale, and three items from the environmental mastery scale were removed.

MAI Scale. Principal components analysis with varimax rotation was conducted to assess how the eight sets of dichotomous variables clustered for the Fall 2020 sample. Similar to the procedure followed for the Fall 2018-19 samples, a restricted two factor solution was requested, based on procedures described in Experiment 1 in Schraw and Dennison's (1994) study. The PCA for the Fall 2020 sample MAI pre-test measures showed that the items in the subscales planning, comprehension monitoring, debugging strategies, and evaluation subscales had high loadings on the first factor Regulation of cognition. The items from the procedural knowledge, conditional knowledge and declarative knowledge scales loaded had high loadings on the second factor Knowledge about cognition. After rotation, the first component accounted for 12.8% of the variance, and the second component accounted for 5.3% of the total variance explained by the pre-test items. Appendix table C19 displays the items and component loadings for the rotated components, with loadings less than .3 omitted to improve clarity.

For the post-test measures, after rotation the first component accounted for 17.6% of the variance, and the second component accounted for 5.8% of the variance of the MAI post-test items. Appendix table C20 displays the items and component loadings for the rotated components. The Cronbach's alphas for the MAI pre-test components exhibited good reliability ranges, .75 for regulation of cognition, and .73 for knowledge about cognition. The Cronbach's alphas for the MAI post-test components exhibited good reliability ranges, .84 for regulation of cognition, and .81 for knowledge about cognition.

SOB Scale. PAF analysis with promax rotation was conducted to assess the underlying structure for the 26 items in the SOB questionnaire for the Fall 2020 sample. Three factors emerged from the pre-test variables based on the eigenvalues over 1 criterion. After rotation, the first factor perceived peer support accounted for 31.6% of the variance, the second factor perceived faculty support accounted for 13.3%, and the third factor perceived classroom support 8.4%. Appendix table C21 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity. The variables were adequate for exploratory factor analysis based on a KMO of .9. The factor solution explained 53.3% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the four factors exhibited good reliability between .84 and .92, indicating convergent reliability (Hair, et al., 2014). In order to achieve discriminant validity and convergent validity, perceived isolation items Pre_PI1R and Pre_PI4R were removed, and perceived faculty support Pre_PFS1 and Pre_PFS10 were removed.

Four factors emerged from the SOB post-test measures based on the eigenvalues over 1 criterion. After rotation, the first factor, perceived isolation accounted for 36.1% of the variance, the second factor perceived faculty support accounted for 14.1%, the third factor perceived classroom comfort 7.4%, the fourth factor perceived peer support 3.3%. Appendix table C22 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity. The post-test SOB measures were adequate for exploratory factor analysis based on a KMO of .91. The factor solution explained 60.9% of the variance, and there were no correlations greater than .7 indicating discriminant validity. The Cronbach's alphas of the five factors exhibited good reliability between .83 and .93, indicating convergent reliability (Hair, et al., 2014).

TGLQ Scale. PAF analysis with promax rotation was conducted to assess the underlying structure for the 14 items in the TGLQ questionnaire for the Fall 2020 sample. Four factors emerged from the pre-test measures, indicating four dimensions of the leadership questionnaire. After rotation, the first factor, confidence accounted for 32.3% of the variance, the second factor cultural strengths, accounted for 8.9%, and the third factor, academic degree/institutional fit accounted for 7.5%. The fourth factor life vision accounted for 4.7% of the variance in the factor solution. Appendix table C23 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity. The variables were adequate for exploratory factor analysis based on a KMO of .82. The factors explained a total variance of 53.4%, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas for the four factors exhibited good reliability between .60 and .86, indicating convergent reliability (Hair, et al., 2014). Due to an initial factor solution that produced a Heywood case, the item POST_TGLQ6 was removed (Hair et al., 2014).

Three factors emerged from the post-test TGLQ measures. After rotation, the first factor, academic degree/institutional fit for 46.2% of the variance, the second factor confidence accounted for 9.7%, and the third factor life vision accounted for 7.3%. Appendix table C24 displays the items and factor loadings for the rotated factors, with loadings less than .3 omitted to improve clarity. The post-test TGLQ variables were adequate for exploratory factor analysis based on a KMO of .85. The factor solution explained 53.3% of the variance, and there were no factor correlations greater than .7 indicating discriminant validity. The Cronbach's alphas for the two factors exhibited good reliability between .77 and .86, indicating convergent reliability (Hair, et al., 2014). Due to an initial factor solution which produced a Heywood case, item POST_TGLQ6 was removed (Hair et al., 2014).

Fall 2018 Cohort Confirmatory Factor Analysis (CFA). The EFA pattern matrices presented in Appendix C were used to validate the measurement models through CFA in AMOS for the PWB, SOB, and TGLQ scales. Due to the nonnormal distribution of the MAI dichotomously scored items (see Univariate Outliers and Normality section), composite subscales were used to create parcels for the MAI theoretical dimensions as confirmed by the PCA analyses presented in Appendix C. Therefore, MAI subdimensions will not be considered latent factors and are not included in the CFAs.

Due to the unbalanced sample sizes for multigroup moderators (i.e., gender, underrepresented group, first-generation status), invariance testing was not performed for the Fall 2018 measurement models as these moderators will not be included in the structural model. This is to mitigate the possibility that multigroup moderation with unbalanced sample sizes may lead to an underestimation of the moderating effect or inflation of statistical power (Memon et al., 2019). For each of the CFAs across three cohorts, measurement validity will be assessed on the pre-test variable factor structures, and latent scores for post-test variables will be developed off of this structure.

The measurement model of the Fall 2018 PWB pre-test variables was assessed. The model fit was acceptable based on thresholds described in Hair, et al. (2014): CMIN/DF = 1.40 with p=0.0; CFI = 0.901; SRMR = 0.077; RMSEA = 0.041. Factorial validity and reliability were observed. As presented in Table 7, the composite ratio (CR) indicated convergent reliability for 4 out of 6 values above 0.70. Based on the average variance extracted (AVE) value alone, convergent validity for the six-factor structure is unsatisfactory. However, Malhotra (2010) argues that convergent validity can also be assessed based on the CR values, even if "more than 50% of the variance is due to error" (Malhotra, 2010, p. 702). Consequently, adequate convergent validity was established through the CRs for this scale. The square root of the AVE comparison (diagonal values in table 7) to inter-factor correlations indicates discriminant validity for all of the factors.

Table 7

PWB Pre-test Fall 2018 CFA Validity Analysis

Construct	CR	AVE	MSV	1	2	3	4	5	6
1	0.804	0.457	0.530	0.676					
2	0.781	0.417	0.241	0.313*	0.646				
3	0.701	0.453	0.076	0.196†	0.151	0.673			
4	0.717	0.476	0.525	0.724***	0.465***	0.263*	0.690		
5	0.620	0.383	0.470	0.685***	0.188	0.275*	0.403*	0.619	
6	0.687	0.428	0.530	0.728***	0.491***	0.174	0.640***	0.498**	0.655

Note. Significance of Correlations: * $p < 0.05$, ** $p < 0.010$, *** $p < 0.001$

The measurement model of the SOB pre-test Fall 2018 variables was assessed. The model fit was acceptable: CMIN/DF = 1.50 with p=0.0; CFI = 0.929; SRMR = 0.073; RMSEA = 0.066. Factorial validity and reliability were observed. As presented in Table 8, the CR indicated convergent reliability for all the factors, as they had CRs above 0.70. Based on the AVE values alone, convergent validity for the five-factor structure is adequate since all values were greater than .5. Discriminant validity was observed for all of the factors based on the inter-factor correlation values which are less than the square root of the AVE values diagonally presented in Table 8.

Table 8

SOB Pre-test Fall 2018 CFA Validity Analysis

	CR	AVE	MSV	1	2	3	4	5	6
1	0.871	0.576	0.308	0.759					
2	0.909	0.716	0.303	0.551***	0.846				
3	0.872	0.631	0.472	0.458***	0.456***	0.794			
4	0.845	0.585	0.481	0.418***	0.532***	0.687***	0.765		
5	0.837	0.566	0.308	0.555***	0.397***	0.418***	0.282*	0.752	
6	0.807	0.584	0.481	0.541***	0.493***	0.539***	0.693***	0.418***	0.764

Note. Significance of Correlations: * $p < 0.05$, ** $p < 0.010$, *** $p < 0.001$

The measurement model of the TGLQ pre-test Fall 2018 variables was assessed. The model fit was acceptable (Hair, et al., 2014): CMIN/DF = 1.72 with p=0.0; CFI = 0.945; SRMR = 0.081; RMSEA = 0.08. Factorial validity and reliability were observed. As presented in Table 9, the CR indicated convergent reliability for all the factors, as they had CRs above 0.70. Based on the AVE values, convergent validity for the three-factor structure is adequate since two out of three AVE values were greater than .5. Discriminant validity was observed for all of the factors based on the square root of the AVE values, which are greater than any inter-factor correlation in Table 9.

Table 9

TGLQ Pre-test Fall 2018 CFA Validity Analysis

Construct	CR	AVE	MSV	1	2	3
1	0.824	0.489	0.157	0.700		
2	0.817	0.547	0.194	0.397***	0.740	
3	0.779	0.542	0.194	0.393**	0.441***	0.736

Note. Significance of Correlations: * $p < 0.05$, ** $p < 0.010$, *** $p < 0.001$

Fall 2019 Cohort Confirmatory Factor Analysis (CFA). The measurement model of the Fall 2019 PWB pre-test variables was assessed. The model fit was acceptable based on thresholds described in Hair, et al. (2014): CMIN/DF = 1.82 with p=0.0; CFI = 0.916; SRMR = 0.067; RMSEA = 0.041. Factorial validity and reliability were observed. As presented in Table 10, the CRs indicated convergent reliability for 3 out of 6 values above 0.70. Based on the AVE values alone, convergent validity for the six-factor structure is unsatisfactory. However, per Malhotra (2010) convergent validity can also be assessed based on the CR values. Consequently, adequate convergent validity was established through the CRs for this scale. The square root of the AVE comparison (diagonal values in Table 10) to inter-factor correlations indicates discriminant validity for all but two of the factors. When discriminant validity was assessed using the heterotrait-monotrait (HTMT) approach, all construct shared variances were below the .85 stringent criterion (Henseler et al., 2015) (see Table 11). Using this comparative method, discriminant validity is confirmed.

Table 10

PWB Pre-test Fall 2019 CFA Validity Analysis

	CR	AVE	MSV	1	2	3	4	5	6
1	0.825	0.543	0.676	0.737					
2	0.874	0.502	0.644	0.802***	0.708				
3	0.597	0.347	0.500	0.472***	0.707***	0.589			
4	0.659	0.393	0.637	0.798***	0.571***	0.598***	0.627		
5	0.518	0.279	0.524	0.623***	0.633***	0.103	0.418**	0.528	
6	0.707	0.453	0.676	0.822***	0.640***	0.292*	0.743***	0.724***	0.673

Note. Significance of Correlations: * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

Table 11

PWB Pre-test Fall 2019 Factor Discriminant Validity HTMT Analysis

	1	2	3	4	5	6
1						
2	0.771					
3	0.412	0.648				
4	0.791	0.602	0.478			
5	0.581	0.608	0.134	0.369		
6	0.831	0.617	0.187	0.805	0.645	

Using the multigroup function in AMOS, configural, metric, and scalar invariance were assessed for the groups: male/female, first-generation/non-first generation, and underrepresented student group/non-underrepresented group. Configural invariance is a representation of similarity across overall multigroup factor solutions and loading patterns when groups are tested simultaneously (Byrne, 2010). Metric invariance is a comparison of the item (level) intercepts between groups when the factor loadings are constrained to be equal, and is intended to establish whether the different groups understood the items similarly (Van de Schoot et al., 2012). In contrast, scalar invariance is a comparison of factor scores when factor loadings and item intercepts are constrained to be equal (Van de Schoot et al., 2012). When these equality constraints are imposed, a significant chi-square value signals invariance, e.g., the groups understood the questions differently. Configural invariance was achieved for the Fall 2019 PWB constructs across groups (i.e., invariance between male/female, first-generation/non-first generation, and underrepresented student group/non-underrepresented group) as evidenced by good model fit thresholds discussed by Hair et al. (2014). Partial metric invariance was achieved for the male/female and underrepresented/non-underrepresented student groups, and full metric and scalar invariance was achieved for first generation/non first generation groups.

The measurement model of the Fall 2019 SOB pre-test variables was assessed. The model fit was acceptable based on thresholds described in Hair, et al. (2014): CMIN/DF = 2.59 with p=0.0; CFI = 0.94; SRMR = 0.043; RMSEA = 0.056. Factorial validity and reliability were observed. As presented in Table 12, the CRs indicated convergent reliability for all values above 0.70. Based on the AVE values alone, convergent validity for the four-factor structure was not established as two of the four values were below .5. However, per Malhotra (2010) convergent validity can also be assessed based on the CR values. Consequently, adequate convergent validity was established through the CRs for this scale. The square root of the AVE comparison (diagonal values in Table 12) to inter-factor correlations indicates discriminant validity for all of the factors. Using the multigroup function in AMOS, configural and metric invariance were assessed for the groups: male/female, first-generation/non-first-generation, and underrepresented student group/non-underrepresented group. Configural invariance was achieved for the Fall 2019 SOB constructs as evidenced by good model fit thresholds discussed by Hair et al. (2014). Full metric and scalar invariance was achieved for male and female groups, and partial metric invariance was achieved for the underrepresented/non-underrepresented student groups. Nonsignificant chi-square values also indicated metric invariance for first generation/non first generation groups.

Table 12

SOB Pre-test Fall 2019 CFA Validity Analysis

	CR	AVE	MSV	1	2	3	4
1	0.885	0.494	0.562	0.703			
2	0.923	0.751	0.160	0.377***	0.866		
3	0.822	0.434	0.156	0.315***	0.395***	0.659	
4	0.816	0.528	0.562	0.750***	0.400***	0.324***	0.726

Note. Significance of Correlations: * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

The measurement model of the Fall TGLQ pre-test variables was assessed. The model fit was acceptable based on thresholds described in Hair, et al. (2014): CMIN/DF = 3.78 with p=0.0; CFI = 0.94; SRMR = 0.068; RMSEA = 0.077. Factorial validity and reliability were observed. As presented in Table 13, the CRs indicated convergent reliability for all values above 0.70. Convergent validity for the four-factor structure was established based on the AVE values alone, as all values were below .5. The square root of the AVE comparison (diagonal values in Table 13) to inter-factor correlations indicates discriminant validity for all of the factors. Using the multigroup function in AMOS, configural and metric invariance were assessed for the groups: male/female, first-generation/non-first generation, and underrepresented student group/non-underrepresented group. Configural invariance was achieved for the Fall 2019 TGLQ constructs as evidenced by good model fit thresholds discussed by Hair et al. (2014). Full metric and scalar invariance was achieved for male and female groups, and partial scalar invariance was achieved for the underrepresented/non-underrepresented student groups. Nonsignificant chi-square values indicated metric invariance for first generation/non first generation and underrepresented/non-underrepresented student groups.

Table 13

TGLQ Pre-test Fall 2019 CFA Validity Analysis

	CR	AVE	MSV	1	2	3	4
1	0.793	0.492	0.351	0.701			
2	0.837	0.639	0.214	0.426***	0.799		
3	0.851	0.656	0.345	0.471***	0.378***	0.810	
4	0.787	0.552	0.351	0.592***	0.462***	0.588***	0.743

Note. Significance of Correlations: * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

Fall 2020 Cohort Confirmatory Factor Analysis (CFA). The measurement model of the Fall 2020 PWB pre-test variables was assessed. The model fit was acceptable based on thresholds described in Hair, et al. (2014): CMIN/DF = 1.92 with p=0.0; CFI = 0.902; SRMR =

0.057; RMSEA = 0.054. Factorial validity and reliability were observed. As presented in Table 14, the CRs indicated convergent reliability for 3 out of 6 values above 0.70. Based on the AVE values alone, convergent validity for the six-factor structure is unsatisfactory. However, per Malhotra (2010) convergent validity can also be assessed based on the CR values. Consequently, adequate convergent validity was established through the CRs for this scale, as 5 out of 6 values were above .6. The square root of the AVE comparison (diagonal values in Table 14) to inter-factor correlations indicates discriminant validity for all but two of the factors. When discriminant validity was assessed using the heterotrait-monotrait (HTMT) approach, all construct shared variances were below the .85 stringent criterion (Henseler et al., 2015) (see table 15). Using this comparative method, discriminant validity is confirmed. Configural invariance was achieved for the Fall 2020 PWB constructs as evidenced by good model fit thresholds discussed by Hair et al. (2014). Full metric and scalar invariance was achieved for two of the groups: first-generation/non-first generation, and underrepresented student /non-underrepresented student group. Full metric and partial scalar invariance was achieved between male/female groups.

Table 14

PWB Pre-test Fall 2020 CFA Validity Analysis

	CR	AVE	MSV	1	2	3	4	5	6
1	0.845	0.411	0.780	0.641					
2	0.832	0.499	0.780	0.883***	0.706				
3	0.682	0.353	0.316	0.562**	0.468**	0.594			
4	0.654	0.344	0.226	0.406*	0.476**	0.399*	0.586		
5	0.722	0.494	0.251	0.501***	0.344**	0.406**	0.018	0.703	
6	0.574	0.403	0.237	0.486**	0.456*	0.082	0.201	0.469**	0.635

Note. Significance of Correlations: * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

Table 15

PWB Pre-test Fall 2020 Factor Discriminant Validity HTMT Analysis

	1	2	3	4	5	6
1						
2	0.886					
3	0.547	0.446				
4	0.414	0.494	0.401			
5	0.522	0.412	0.527	0.026		
6	0.488	0.520	0.043	0.105	0.452	

The measurement model of the Fall 2020 SOB pre-test variables was assessed. The model fit was acceptable based on thresholds described in Hair, et al. (2014): CMIN/DF = 2.38 with p=0.0; CFI = 0.925; SRMR = 0.056; RMSEA = 0.066. Factorial validity and reliability were observed. As presented in Table 16, the CRs indicated convergent reliability for all values above 0.70. Based on the AVE values alone, convergent validity for the four-factor structure was not established as one of the three values were below .5. However, per Malhotra (2010) convergent validity can also be assessed based on the CR values. Consequently, adequate convergent validity was established through the CRs for this scale. The square root of the AVE comparison (diagonal values in Table 16) to inter-factor correlations indicates discriminant validity for all of the factors. Configural invariance was achieved for the Fall 2020 SOB constructs as evidenced by good model fit thresholds discussed by Hair et al. (2014). Full metric and scalar invariance was achieved all student groups (i.e,. invariance between male/female, first-generation/non-first generation, and underrepresented student group/non-underrepresented group).

Table 16

SOB Pre-test Fall 2020 CFA Validity Analysis

	CR	AVE	MSV	1	2	3
1	0.914	0.521	0.151	0.722		
2	0.848	0.418	0.168	0.315***	0.646	
3	0.922	0.748	0.168	0.388***	0.410***	0.865

Note. Significance of Correlations: * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

The measurement model of the Fall TGLQ pre-test variables was assessed. The model fit was acceptable based on thresholds described in Hair, et al. (2014): CMIN/DF = 3.22 with p=0.0; CFI = 0.923; SRMR = 0.056; RMSEA = 0.082. Factorial validity and reliability were observed. As presented in Table 17, the CRs indicated convergent reliability for 3 out of 4 values above 0.70. Based on the AVE values alone, convergent validity for the four-factor structure was not established as two of the four values were below .5. However, per Malhotra (2010) convergent validity can also be assessed based on the CR values. Consequently, adequate convergent validity was established through the CRs for this scale as all values are above .6. The square root of the AVE comparison (diagonal values in Table 17) to inter-factor correlations indicates discriminant validity for all of the factors. Configural invariance was achieved for the Fall 2020 TGLQ constructs as evidenced by good model fit thresholds discussed by Hair et al. (2014). Full metric and scalar invariance was achieved all student groups (i.e., invariance between male/female, first-generation/non-first generation, and underrepresented student group/non-underrepresented group).

Table 17

TGLQ Pre-test Fall 2020 CFA Validity Analysis

	CR	AVE	MSV	1	2	3	4
1	0.866	0.683	0.363	0.826			
2	0.764	0.454	0.532	0.459***	0.674		
3	0.819	0.602	0.399	0.536***	0.486***	0.776	

	CR	AVE	MSV	1	2	3	4
4	0.623	0.359	0.532	0.602***	0.729***	0.632***	0.599

Note. Significance of Correlations: * $p < 0.050$, ** $p < 0.010$, *** $p < 0.001$

Common Method Bias. MacKenzie and Podsakoff (2012) and Maruyama (1998) indicate that method variance may be present in survey scale administrations for several possible reasons that can subsequently bias construct validity and reliability. Further, systematic sources of method variance may create biasing effects by also inflating construct relationships and producing type I error (Podsakoff et al., 2003). Sources of method bias include respondent selection of socially desirable items, or respondent lack of motivation due to cognitive effort, lack of interest, low need for self-expression, or agreeableness (MacKenzie & Podsakoff, 2012). Podsakoff et al. (2003) suggest a post-hoc technique for parceling out extraneous variance by modeling method variance as a common latent factor (CLF). For all CFAs conducted for the 2018-2020 samples, Gaskin and Lim's (2017) AMOS CFA plugin was used to test whether the shared variance across all the construct items is significantly different from zero. When the zero constraints test was applied to the PWB, SOB and TGLQ CFAs, the chi-square difference between the unconstrained models, and the models where all paths are constrained to zero was nonsignificant. When the effect of the CLF was applied to all the corresponding measures within each CFA (Table 18), nonsignificant chi-square difference tests indicate that common method bias was not present across samples.

Table 18

Model Comparisons for Common Method Bias

Specific Bias Test	X^2	DF	Delta X^2	*p*-value
	Fall 2018 PWB CFA			
Unconstrained Model	449.825	342	X^2=0.000	1.000
Zero Constrained Model	449.825	342	DF=0	

Specific Bias Test	X^2	DF	Delta X^2	*p*-value
Fall 2018 SOB CFA				
Unconstrained Model	283.234	211	X^2=0.000	1.000
Zero Constrained Model	283.234	211	DF=0	
Fall 2018 TGLQ CFA				
Unconstrained Model	33.653	37	X^2=0.000	1.000
Zero Constrained Model	33.653	37	DF=0	
Fall 2019 PWB CFA				
Unconstrained Model	594.992	212	X^2=0.000	1.000
Zero Constrained Model	594.992	212	DF=0	
Fall 2019 SOB CFA				
Unconstrained Model	379.261	181	X^2=0.000	1.000
Zero Constrained Model	379.261	181	DF=0	
Fall 2019 TGLQ CFA				
Unconstrained Model	112.881	57	X^2=0.000	1.000
Zero Constrained Model	112.881	57	DF=0	
Fall 2020 PWB CFA				
Unconstrained Model	583.780	303	X^2=0.000	1.000
Zero Constrained Model	583.780	303	DF=0	
Fall 2020 SOB CFA				
Unconstrained Model	488.404	205	X^2=0.000	1.000
Zero Constrained Model	488.404	205	DF=0	
Fall 2020 TGLQ CFA				
Unconstrained Model	109.964	46	X^2=0.000	1.000
Zero Constrained Model	109.964	46	DF=0	

Multivariate Outliers and Normality. Maximum likelihood estimation assumes multivariate normality. Therefore, the assumptions of multivariate normality were checked before the structural models were tested. The AMOS multivariate assessment for normality indicated that kurtosis for the Fall 2018-2020 pre-test measures exceeded the > 5.00 threshold. According to Byrne (2010), values > 5 are indicative of data that are not distributed normally.

The multivariate c.r. which exceeded 1.96 was indicative of multivariate nonnormality. As recommended by Byrne (2010), one strategy to address multivariate non-normality is the application of bootstrapping in AMOS.

The Mahalanobis d-squared values were examined to assess multivariate outliers. The 2018 and 2020 sample pre-test measures had 0-8 cases per scale with significant Mahalanobis d-squared values at the $p < .001$ level. The 2019 pre-test measures had up to 21 cases per scale with significant Mahalanobis d-squared values at the $p < .001$ level. However, because the highest Mahalanobis d-squared values were not typically distant in range from the other distance values (Byrne, 2010), it was determined that it would not be an optimal solution to remove cases.

Sample Size and Statistical Power. There is a consensus among methodologists that SEM is intended as a large sample analytical technique (Kline, 2015). Several studies however have suggested that one-size fits all guidelines for SEM and Factor Analysis (FA) sample size determination are unrealistic (Wolf et al., 2013; MacCallum et al., 1999). Various practical considerations are involved in the determination of a minimum acceptable sample size for EFA and CFA (Hair et al., 2014), and thus SEM more generally. When contemplating optimal sample size determination Tabachnick and Fidell (1996) maintain that rules of thumb from FA apply to SEM as well.

Studies supporting the use of smaller sample sizes (e.g., $N < 100$) have typically used Monte Carlo simulation analyses to show that sample size requirements can vary by the number of indicators per factor (Wolf et al., 2013; Marsh et al., 1998) as well as communalities among variables (MacCallum et al., 1999; Hair et al., 2014). Communality values in FA are the proportions of variance explained in variable(s) from the remaining variables in the data (Field, 2018). Specifically, MacCallum et al. (1999) indicate that communalities must be high (e.g., above .6) and that the factors should be clearly and strongly defined, or overdetermined. Under these conditions, sample size has less of an effect on recovery of population factors, and smaller sample sizes (e.g., $N < 100$) may be adequate. In terms of CFA, Marsh et al. (1998) argue that there are advantages to having more indicators per factor (p/f), and that this ratio has compensatory effects when working with small sample sizes. Irrespective of sample size, Field (2018) suggests that factors with four or more loadings of at least .6 are reliable. And when considering practical significance criteria in working with sample sizes of 50-350, Hair et al. (2014) recommend factor loadings of .30-.75 for power of 80 percent.

Thus, there is a broad range and variability in acceptable sample size selection for FA and SEM, insofar as guidelines are qualified by the estimation technique and model complexity (Hair et al., 2014; Kline, 2015). In the current study, two out of three samples consist of $N > 200$, which offers acceptable power for data analysis and exceeds the median sample size across SEM studies in different disciplines (Kyriazos, 2018; Kline, 2015). Maximum likelihood, the preferred estimation method for valid and stable results for sample sizes $N > 50$ (Hair et al., 2014), has been employed across all CFAs in the current study.

An evaluation of sample size adequacy for factor loadings with statistical significance of .05 and power level of 80 percent for the current study are displayed in Table 19. A rough check of whether the factor loadings are statistically significant indicates that the limited sample size for the Fall 2018 cohort may not produce sufficient statistical power to detect significant results for the MAI measures. Therefore, the statistical significance of factors based on this scale should be interpreted with caution. It should be noted however that for every analysis, MAI measures were split into two parcels of 12-15 items, or 12-15 indicators per factor. Per Marsh et al. (1998), 12 items per factor are sufficient for proper solutions in small sample sizes (e.g., $N < 100$).

On the other hand, sample sizes of more than 300 and average factor loadings exceeding .35 are considered significant for the Fall 2019 and Fall 2020 cohorts (Hair et al., 2014). As indicated in Appendix C, all PWB, SOB and TGLQ factors consist of approximately 3-6 items each and are deemed sufficient for accurate parameter estimates given those Ns (Marsh et al., 1998).

Table 19

Significant Factor Loadings Based on Sample Size

Measure (scale)/ Final Sample	Average Loading per Factor	Threshold [a]	Interpretation of Loading(s) According to Sample Size
		Fall 2018 Cohort	
PWB (n = 97)	.56	≥.55-.60	Significant
SOB (n = 97)	.73	≥.55-.60	Significant
MAI (n = 97)	.43	≥.55-.60	Not Significant
TGLQ (n = 97)	.70	≥.55-.60	Significant
		Fall 2019 Cohort	
PWB (n = 357)	.52	≥.30	Significant
SOB (n = 357)	.70	≥.30	Significant
MAI (n = 357)	.47	≥.30	Significant
TGLQ (n = 357)	.73	≥.30	Significant
		Fall 2020 Cohort	
PWB (n = 305)	.55	≥.30-.35	Significant
SOB (n = 305)	.73	≥.30-.35	Significant
MAI (n = 305)	.44	≥.30-.35	Significant
TGLQ	.68	≥.30-.35	Significant

Measure (scale)/ Final Sample	Average Loading per Factor	Threshold [a]	Interpretation of Loading(s) According to Sample Size
(n = 305)			

Note. [a] Guidelines for significant factor loadings from Hair et al. (2014).

Chapter 4 Results

This chapter is organized in four sections which present the main analyses and study findings. The first three sections present the Fall 2018-2020 cohort statistical analyses in sequence. After the SEM analyses, the main findings are summarized in order of the research questions discussed in Chapter One. Appendices D and E support the findings in these sections. Appendix D provides latent variable descriptive statistics and correlations used in the SEM models, and Appendix E features all the mediating relationships for every model, specifying how and when the indirect effects occur.

Fall 2018 Cohort SEM

Of the 183 respondents from the Fall 2018 cohort, 97 cases were aggregated for analysis of the structural model. The remaining 86 individuals were dropped from the SEM analysis due to missing values, since AMOS requires complete cases to compute model fit statistics. Weighted average factor scores for the 20 latent variables were used for the structural equation model. Appendix D contains the descriptive statistics and correlations of the Fall 2018 latent variables.

Maximum likelihood estimation was employed to estimate the model. Overall the model exhibited excellent fit according to thresholds established by Hu and Bentler (1999) and Hair et al., (2014): CMIN/DF = 1.2 with $p = 0.043$; CFI = .95, RMSEA =.045, SRMR = .09. The fit was achieved after post hoc model modifications in an effort to achieve a parsimonious model.

The model was significantly improved by the addition of a path between locus of control (post) (Locus_t2) and self-efficacy (post) assessments (SEAssess_t2) $X^2_{\text{diff}} = 11.15$ ($p < .01$). A path between classroom academic integration (AcadIntegPCC) and social integration in terms of isolation (SocialIntegPI) $X^2_{\text{diff}} = 3.5$ ($p < .10$) also improved model fit statistics. While not included in the original theoretical framework, these paths are supported by theory. As for the first path that was added, Au (2015) showed that both locus of control and self-efficacy are connected indirectly through the students' outcome control influence. As for the second path, it is strongly in alignment with Tinto's (1975) idea that a lack of congruency with the academic environment can lead to isolation, and ultimately withdrawal. Therefore, the intellectual and social congruence is represented by this path. Moreover, Cabrera et al. (1992) found that there is a significant direct effect of academic integration on social integration.

The squared multiple correlation for the persistence variable is $R^2 = .11$, thus 11% of the variance is accounted for by the model. This R^2 value was significant ($p < .05$), and ten of the R^2 values for the other endogenous variables in the model were significant at the $p < .01$ level. Table 20 illustrates that all the endogenous variables in the model had statistically significant explanatory power. The final parsimonious model, including significant standardized coefficients is illustrated in Figure 2.

Table 20

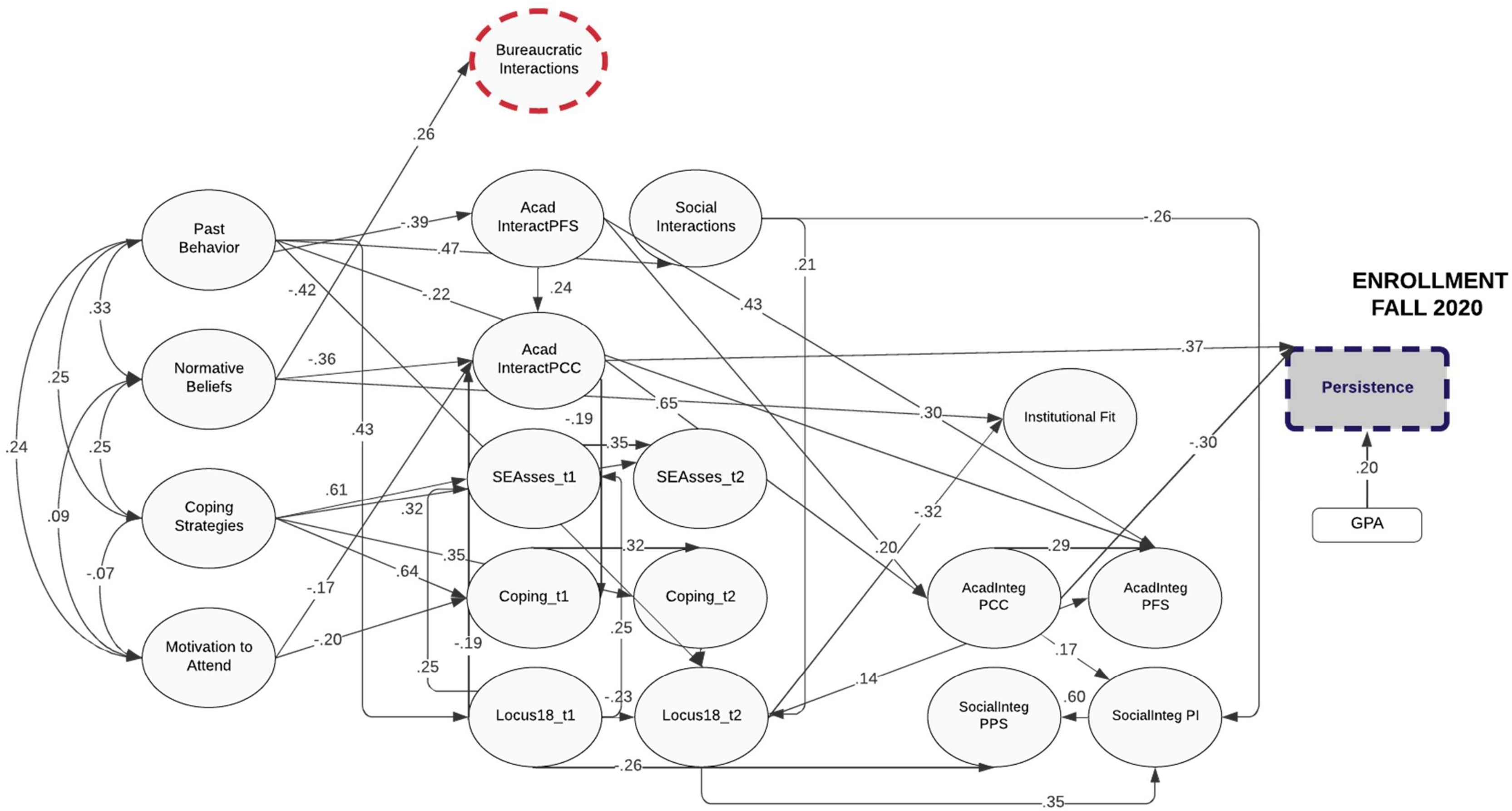
Squared Multiple Correlations Fall 2018 Cohort

Endogenous Variable	Estimate
AcadInteract_PFS_t1	0.15**
Locus_t1	0.19**
AcadInteract_PCC_t1	0.33*
SocInt18_t1	0.22**
AcadInt_PCC_t2	0.55**
Locus_t2	0.25*
SocInteg_PI_t2	0.25*
SEAsses_t1	0.47**
CopingProcess_t1	0.51**
SEAsses_t2	0.48*
CopingProcess_t2	0.37**
Fall3_Enrolled (Persistence)	0.11*
InstFit	0.22**
SocInteg_PPS_t2	0.45**

Endogenous Variable	Estimate
AcadInt_PFS_t2	0.60*
QI_19	0.07**

Figure 2

Final 2018 SEM Model with Standardized Weights



Control Variables

The control variables entered into the model include composite SAT score, student age, HS GPA and first-year cumulative GPA. Only the HS GPA was significantly predictive of persistence in terms of re-enrollment into the third year of college (p <.10). In contrast to expectation, the composite SAT score, end of term college GPA, and student age variables were not significantly predictive of persistence into the third year.

Direct Effects

Bootstrapping produces a more rigorous estimation of the effects in the model (Preacher et al., 2007) and is often used as a remedy for nonnormal sample distributions (Blunch, 2013; Field, 2018). In the current model, parameter estimates were derived from bias-corrected 90% confidence intervals (CIs) and standard errors calculated from 2,000 bootstrapped samples. The results from the parsimonious model support the theory that the perceived classroom comfort academic interactions variable (AcadInteractPCC) has the only statistically significant direct relationship with persistence (β = 0.33), and that the strength of the effect size is weak (.05). Normative beliefs (β = 0.30) and locus of control (post) (β = -0.32) had a statistically significant relationships with institutional fit (InsFit18), and accounted for 22% of its variance.

Two variables had statistically significant relationships with perceived peer support social integration (SocialIntegPPS) and accounted for 45% of its variance. These variables were social integration in terms of perceived isolation (SocialIntegPI) (β = 0.60) and locus of control (pre) (β = -0.20). Two variables also had statistically significant relationships with perceived isolation social integration (SocialIntegPI). These variables were locus of control (post) (β = 0.35) and social interactions (β = -0.26), and accounted for 24% of the variance.

Two variables had statistically significant relationships with perceived classroom comfort academic integration (AcadIntegPCC) and accounted for 55% of its variance. These variables were faculty support academic interactions (β= 0.20) and classroom comfort academic interactions (β = 0.65). Two variables also had statistically significant relationships with perceived faculty support academic integration (AcadIntegPFS). These variables were (AcadIntegPCC) classroom comfort academic integration (β = 0.29) and past behavior (β = -0.22), and they accounted for 60% of the variance.

The proportion of variance representing psychological processes was supported by statistically significant structural paths predicting the locus of control, self-efficacy, and coping constructs. Nineteen percent of the variance was explained by the effects of past behavior (β =.43) on the locus of control pre-test measure. The coping process pre-test measure was predicted by coping strategies (β=.64), classroom academic interactions (β=-.19), and motivation to attend (β=-.20), which explained 51% of the variance. The self-efficacy assessments pre-test measure was predicted by coping strategies (β=.61), and locus of control (β =.25), accounting for 48% of the variance.

Out of the psychological outcome measures, the self-efficacy post-test measure was found to be directly affected by the self-efficacy pre-test measure (β=.35), locus of control (post) (β=-.26), and coping strategies (β =.32), and these variables accounted for 48% of the variance. The largest effect on the coping process post-test measure was from coping strategies (β=.35), and the second largest effect was the coping process pre-test measure (β=.32). Both of these variables accounting for 37% variance. Only the past behavior variable (β=.-42) significantly predicted the locus of control post-test measure and a medium effect size was found (.17) for this predictor.

Five variables contributed significantly to the environmental interactions in the model. The past behavior latent variable had statistically significant relationships with social interactions and faculty support academic interactions (AcadInteractPFS), (β= .47) and (β= -.39) respectively. Two variables had a statistically significant relationship with classroom academic interactions (AcadInteractPCC), normative beliefs (β= -.36) and (AcadInteractPFS) faculty support academic interactions (β= .24), which represented 27% of the variance. Surprisingly, only one variable was significantly predictive of the bureaucratic interactions (Quality Interactions/QI) NSSE variable. Normative beliefs contributed significantly to bureaucratic interactions (QI) (β= .26), and accounted for 7% of the variance.

Indirect Effects

Bootstrapping for specific indirect effects was computed in order to identify unique indirect effects for every mediating path in the model. Every significant standardized regression weight in Appendix Table E1 confirms mediation, and those estimates that are nonsignificant indicate mediation was not present. Three indirect effects were significant at the $p < .001$ level. Based on the product of coefficients, the strongest mediating relationship was that of coping strategies on self-efficacy. Coping strategies exert an indirect effect on the self-efficacy post-test measure, and self-efficacy (pre-test) was a significant mediator (β = .28). Locus of control exerts an indirect effect on peer support social integration, and perceived isolation was a significant mediator in this relationship (β= .20). Past behavior as measured by environmental mastery, self-acceptance, and purpose in life, exerts an indirect effect on the perceived faculty support academic integration. The faculty support academic interactions variable is a significant mediator in this relationship (β= -.17).

Six relationships were significant at the $p < .01$ level. Normative beliefs exert an indirect effect on classroom academic integration ($\beta = -.23$), and faculty support academic integration ($\beta = -.23$). The classroom academic interactions pre-test measure was a significant mediator in both paths. When normative beliefs were not taken into account, classroom academic integration still significantly mediated the path between the initial classroom academic interactions (pre-test) measure and the faculty support academic integration post-test measure ($\beta = .18$). Additionally, the path between past behavior and the classroom academic integration was significantly mediated by perceived faculty support academic integration pre-test measure ($\beta = -.08$). Both sets of relationships indicate that faculty support academic integration is influenced by normative beliefs and past behavior as they function through classroom academic interaction and integration.

Ten indirect effects influenced persistence as measured by fall enrollment into the third semester, and all were significant at the $p < .05$ level. Only two of these indirect effects had positive standardized regression weights. The path between past behavior and persistence was significantly and negatively mediated by both faculty support academic interactions and classroom academic interactions and integration ($\beta = -.09$). When past behavior was not considered, these mediating relationships were still significant and positively related. That is, classroom academic interactions and academic integration ($\beta = .16$) significantly and positively mediated the relationship between faculty support academic interactions and persistence. Classroom academic interactions also mediated the relationship between normative beliefs ($\beta = -.12$) and locus of control ($\beta = -.06$) and persistence. Locus of control was a significant mediator in two paths leading to persistence, and both of those paths functioned through classroom academic interactions. Thus, out of the psychological processes (self-efficacy, coping, locus of control), locus of control is the most predominant mediator affecting persistence outcomes for the Fall 2018 cohort.

Four indirect effects influenced institutional fit as measured by confidence in the value of an academic degree, and all were significant at the $p < .05$ level. The path between past behavior and institutional fit was significantly mediated by both locus of control pre-test/post-test measures ($\beta = -.10$), and the social interactions pre-test measure ($\beta = .10$). When past behavior was not taken into account, the locus of control post-test measure still significantly mediated the path to institutional fit ($\beta = .07$).

The results of the mediation tests at the $p < .10$ level are summarized in Appendix Table E1. Five of these mediating paths influenced persistence. The classroom academic interactions variable was a significant mediator in all paths. The path between motivation to attend and persistence was an association that demonstrated classroom academic interactions also function through personal growth goals.

Fall 2019 Cohort SEM

Of the 763 respondents from the Fall 2019 cohort, 357 cases were aggregated for analysis of the structural model. The remaining 406 individuals were dropped from the SEM analysis due to missing values since AMOS requires complete cases to compute model fit statistics. Weighted average factor scores for the 18 latent variables were used for the structural equation model. Appendix E contains the descriptive statistics and correlations of the Fall 2019 latent variables.

Maximum likelihood estimation was employed to estimate the model. Overall the model exhibited acceptable fit according to thresholds established by Hu and Bentler (1999) and Hair et al., (2014): CMIN/DF = 2.19 with p = 0.000; CFI = .93, RMSEA =.058, SRMR = .06. The fit was achieved after post hoc model modifications in an effort to achieve a parsimonious model. The model was significantly improved by the addition of a path between faculty support academic interactions (AcadInteractPFS) classroom academic interactions (AcadInteractPCC) X^2_{diff} = 18.49 (p < .001). The model was also significantly improved by a path between classroom academic integration (AcadIntegPCC) and (AcadIntegPFS) faculty support academic integration X^2_{diff} = 9.47 (p < .01). A path between (AcadIntegPFS) faculty support academic integration and peer social integration (SocIntegPPS) also improved model fit statistics X^2_{diff} = 8.11 (p < .01). A path that was added between classroom academic integration (AcadIntegPCC) and perceived isolation social integration (SocIntegPI) significantly improved model fit X^2_{diff} = 51.32 (p < .01) along with a path predicting AcadIntegPFS) faculty support academic integration from perceived isolation social integration (SocIntegPI) X^2_{diff} = 11.32 (p < .01). Finally, a path between (SocIntegPI) to (SocIntegPPS) X^2_{diff} = 170.13 (p < .001) was added on the basis of improved model fit. While not included in Bean and Eaton's theoretical framework, these paths are supported by theory. For example, in validating Bandura's Social Cognitive Model, Vogt

(2008) underscored that for students in specific majors such as engineering, encouraging faculty behaviors and interactions such as class discussions and mentoring, play a critical role in student interactions with the classroom environment. In terms of integration, the path between faculty support academic integration and peer social integration is critical for commuting students since the classroom is the intersection where academic and social integration come together, an idea supported by Tinto (1993) and Demaris and Kritsonis (2008). Furthermore, Cabrera et al. (1992) found that there is a reciprocal relationship between academic and social integration.

The squared multiple correlation associated with persistence into the second semester is $R^2 = .04$, thus 4% of the variance in persistence is accounted for by the predictors. This R^2 value was significant ($p < .01$), as were all the R^2 values for the endogenous variables in the model. Table 21 illustrates that all the endogenous variables in the model had statistically significant explanatory power. The final parsimonious model, including significant standardized coefficients is illustrated in Figure 3.

Table 21

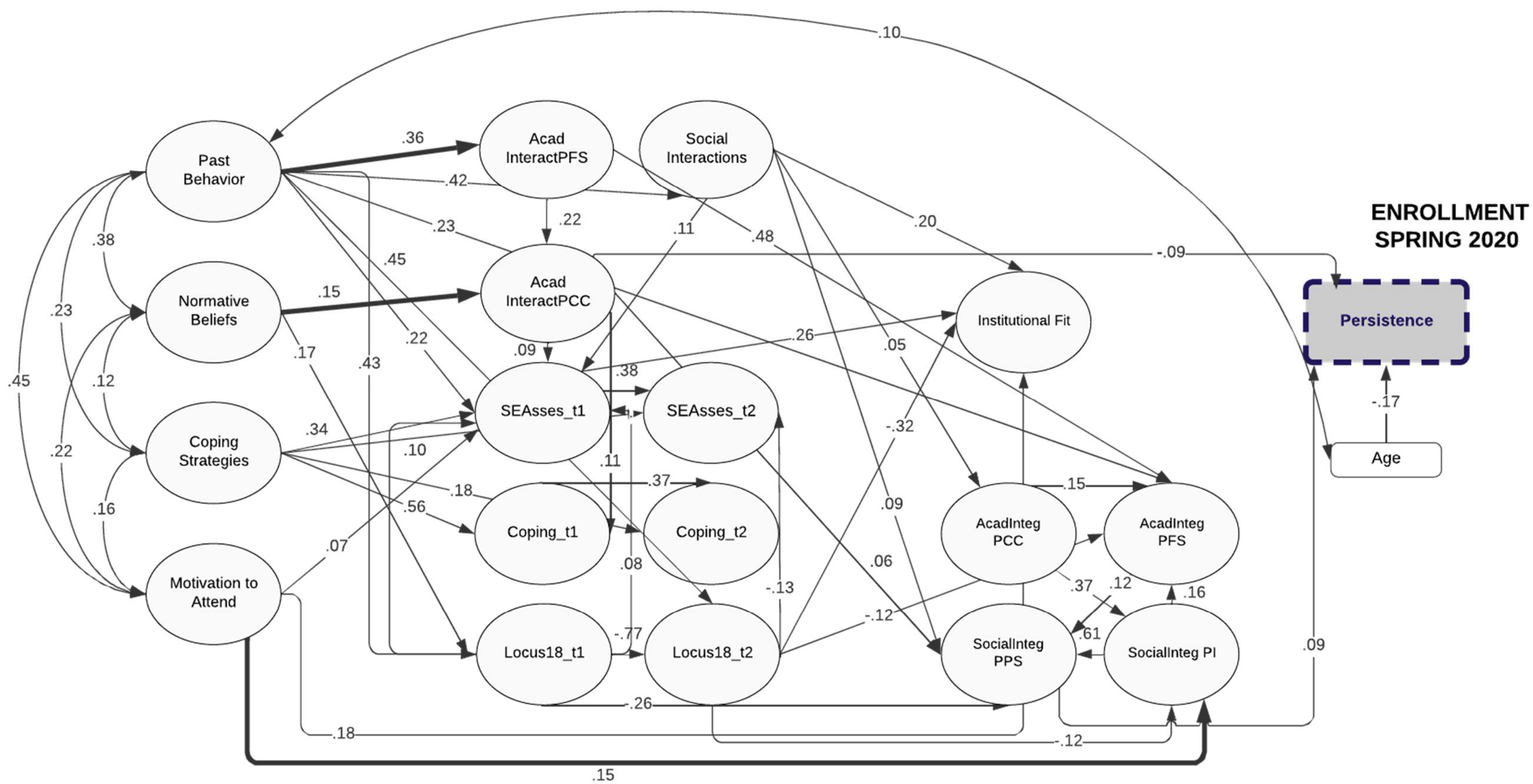
Squared Multiple Correlations Fall 2019 Cohort

Endogenous Variable	Estimate
AcadInteract_PFS_t1	0.13**
AcadInteract_PCC_t1	0.20**
Locus_t1	0.28**
SocInt_t1	0.18**
AcadInteg_PCC_t2	0.52**
Locus_t2	0.59**
SocInteg_PI_t2	0.20**
AcadInteg_PFS_t2	0.39**
SEAsses_t1	0.34**
CopingProcess_t1	0.33**
SocInteg_PPS_t2	0.49**
SEAsses_t2	0.23**
CopingProcess_t2	0.25**
Term2_Enrolled (Persistence)	0.04**

Endogenous Variable	Estimate
InstFit	0.21**

Figure 3

Final 2019 SEM Model with Standardized Weights



Control Variables

The control variables entered into the model include composite SAT score, student age, HS GPA and first-year cumulative GPA. Only student age was significantly predictive of persistence in terms of re-enrollment into subsequent semester of college (p <.01). In contrast to expectation, the composite SAT score, and the end of term GPA were not significantly predictive of persistence into the second year.

Direct Effects

In the current model, parameter estimates were derived from bias-corrected 90% confidence intervals (CIs) and standard errors calculated from 2,000 bootstrapped samples. None of the variables had a statistically significant relationship with persistence. Social interactions (β = 0.20), motivation to attend interactions (β = 0.18), and self-efficacy (pre) (β = 0.26) had statistically significant relationships with institutional fit (InsFit19), and accounted for 21% of its variance.

Four variables had statistically significant relationships with perceived peer support social integration (SocialIntegPPS) and accounted for 49% of its variance. These variables were social integration in terms of perceived isolation (SocialIntegPI) (β = 0.61) social interactions (β = 0.09), faculty support academic integration (β = 0.12), and classroom academic interactions (β = 0.06). Three variables also had statistically significant relationships with perceived isolation social integration (SocialIntegPI). These variables were locus of control (post) (β = -0.12), motivation to attend (β = 0.15), classroom academic integration (β = 0.37), and accounted for 20% of the variance.

Classroom academic interactions (AcadInteract_PCC) (β = 071) had the only statistically significant relationships with classroom academic integration (AcadIntegPCC) and accounted for

52% of its variance. Four variables also had statistically significant relationships with perceived faculty support academic integration (AcadIntegPFS). These variables were (AcadIntegPCC) classroom academic integration (β = 0.15), (AcadIntegPI) social integration in terms of perceived isolation (β = 0.16), locus of control (post) (β = -0.12), and faculty support academic interactions (β = 0.48). These variables accounted for 39% of the variance.

The proportion of variance representing psychological processes was supported by statistically significant structural paths predicting the locus of control, self-efficacy, and coping constructs. Twenty-eight percent of the variance was explained by the effects of past behavior (β =0.45) and normative beliefs (β = 0.17) on the locus of control pre-test measure. The coping process pre-test measure was predicted by coping strategies (β= 0.56) and classroom academic interactions (β= 0.11), which explained 33% of the variance. The self-efficacy assessments pre-test measure was significantly predicted by coping strategies (β= 0.34), social interactions (β= 0.11), and past behavior (β= 0.22), which accounted for 33% of the variance.

Out of the psychological outcome measures, the self-efficacy post-test measure was found to be significantly predicted by the self-efficacy pre-test measure (β= 0.38) and locus of control (post) (β= -0.13), and these variables accounted for 22% of the variance. The largest effect on the coping process post-test measure was from coping process pre-test measure (β= 0.37), and the second largest effect was the coping strategies measure (β= 0.18). Both of these variables accounting for 25% variance. Only the locus of control pre-test measure (β= -0.77) significantly predicted the locus of control post-test measure, thus the pre-test measure explained 59% of the variance in locus of control.

Three variables contributed significantly to the environmental interactions in the model. The past behavior latent variable had statistically significant relationships with classroom academic interactions (AcadInteractPCC) and faculty support academic interactions (AcadInteractPFS), (β = 0.23) and (β = 0.36) respectively. Two other variables also significantly predicted classroom academic interactions (AcadInteractPCC): normative beliefs (β = 0.15) and (AcadInteractPFS) faculty support academic interactions (β = 0.22). The three predictors of classroom academic interactions explained 20% of the variance. Past behavior also significantly predicted social interactions (β = 0.42) and accounted for 18% of the variance.

Indirect Effects

Bootstrapping for specific indirect effects was computed in order to identify unique indirect effects for every mediating path in the model. Every significant standardized regression weight in Appendix Table E2 confirms mediation, and those estimates that are nonsignificant indicate mediation was not present. Twenty-two indirect effects were significant at the $p < .001$ level. Based on the product of coefficients, the strongest mediating relationship was that of classroom academic interactions on social integration/perceived isolation (β = 0.26). Classroom academic integration is a significant mediator on the path between classroom academic interactions and social integration/perceived isolation (CI range 0.19 to 0.31). This same mediating path was significant on 15 other occasions when academic interactions predicted faculty support academic integration and peer support social integration (β = 0.16), and was also significant 9 times when past behavior predicted classroom academic integration (β = 0.17).

Coping strategies exert an indirect effect on self-efficacy, and self-efficacy (pre-test) was significant mediator in this relationship (β = 0.13) and (CI range 0.06 to 0.12). This same path was significant when coping strategies predicted institutional fit (β = 0.09), indicating that self-efficacy is a significant mediator of institutional fit (CI range 0.20 to 0.5). Both self-efficacy (β =

0.06) and social interactions ($\beta = 0.09$) significantly mediated the path between past behavior institutional fit.

Thirty-four relationships were significant at the $p < .01$ level. The strongest mediating relationship was that of past behavior on locus of control ($\beta = -0.34$), with locus of control (post-test) as the significant mediator. Locus of control was a significant mediator in both paths between past behavior and faculty support academic integration (CI range 0.02 to 0.08), and past behavior and self-efficacy (post-test) (CI range 0.00 to 0.01). The same mediating path was significant ($\beta = -0.13$) between normative beliefs and peer support social integration (CI range 0.00 to 0.01), and normative beliefs and faculty support academic integration (CI range 0.01 to 0.038).

Seventeen indirect effects influenced persistence as measured by fall enrollment into the subsequent semester, and all were significant at the $p < .05$ level. The path between past behavior and persistence was significantly and negatively mediated by locus of control, faculty support academic interactions, and peer social interactions ($\beta = -0.34$). When locus of control was not a mediator in this path, the same indirect effects were positive and significant ($\beta = 0.26$). The same indirect effects were present in the path between normative beliefs and persistence. Locus of control mediated the effect of normative beliefs on persistence through faculty support academic integration and peer social integration ($\beta = -0.13$). Classroom academic interactions also mediated the effect of normative beliefs on persistence through classroom academic integration, faculty support academic integration and peer/social integration ($\beta = 0.11$). These mediating relationships imply that locus of control may negatively impact persistence if it were not for faculty support academic integration, and social integration including perceived isolation and perceived peer support.

Nine indirect effects influenced institutional fit as measured by confidence in the value of an academic degree, and the self-efficacy (pre-test) measure was a significant mediator in 8 of those paths. The path between past behavior and institutional fit was significantly mediated by social interactions ($\beta = 0.09$, $p < .001$), and faculty support academic integration, classroom academic integration and, self-efficacy ($\beta = 0.08$, p < .05). When past behavior was not taken into account, self-efficacy mediated the path between coping strategies and institutional fit ($\beta = 0.09$, $p < .001$).

The results of the mediation tests at the $p < .10$ level are summarized in Appendix Table E2. Twenty-six of these mediating paths influenced persistence. The perceived peer support social integration variable was a significant mediator in all paths. The path between motivation to attend and persistence was an association that demonstrated perceived isolation and peer support social integration also function through personal growth goals.

Multi-Group Moderation

The multigroup comparison between male and female students had acceptable model fit: CMIN/DF = 1.68 with $p = 0.000$; CFI = .92, RMSEA =.044, SRMR = .09. The unconstrained and constrained models were not significantly different from each other ($p = .91$). The nonsignificant p-value signifies that the multigroup gender moderator was impotent; therefore, there were no differences between groups. Since model-level differences were not present, path-level differences were not evaluated.

The multigroup comparison between underrepresented students and non-underrepresented students had acceptable model fit: CMIN/DF = 1.71 with $p = 0.000$; CFI = .91, RMSEA =.045, SRMR = .09. There was not a statistically significant difference between students in underrepresented student groups and non-underrepresented students (p = .14) at the model-level; consequently, path-level differences were not evaluated.

Similarly, the multigroup comparison between first-generation and non-first-generation students yielded acceptable model fit: CMIN/DF = 1.75 with p = 0.000; CFI = .91, RMSEA =.046, SRMR = .09. However, the unconstrained and constrained models were significantly different (p = .026). Since this global test indicated model-level differences across the two groups, path-level differences were examined. A path-level difference between first-generation students and non-first-generation student was found on the relationship between past behavior and faculty support academic interactions, and the direct effect was stronger for non-first-generation students. The chi-square difference test was significant when this path was constrained to be equal across groups (p = .001) (see bolded path in Figure 3). Additionally, a statistically significant path-level difference between first-generation students and non-first generation students exists on the relationship between normative beliefs and classroom academic interactions. The chi-square difference test was also significant when this path was constrained to be equal across groups (p =0.024) (see bolded path in Figure 3). The direct effect was stronger for first-generation students. Another statistically significant path-level difference exists from motivation to attend to social integration, indicating that the effect was different for first-generation students and non-first generation students. The chi-square test was also significant (p= 0.034) when that path was constrained to be equal across groups. In Figure 3, this path is also bolded in the overall model for reference.

Fall 2020 Cohort SEM

Of the 416 respondents from the Fall 2020 cohort, 305 cases were aggregated for analysis of the structural model. The remaining 111 individuals were dropped from the SEM analysis due to missing values since AMOS requires complete cases to compute model fit statistics. Weighted average factor scores for the 17 latent variables were used for the structural equation model. Appendix D contains the descriptive statistics and correlations of the Fall 2020 latent variables.

Maximum likelihood estimation was employed to estimate the model. Overall the model exhibited excellent fit according to thresholds established by Hu and Bentler (1999) and Hair et al., (2014): CMIN/DF = 1.55 with p = 0.000; CFI = .97, RMSEA =.042, SRMR = .05. The fit was achieved after post hoc model modifications in an effort to achieve a parsimonious model. The model was significantly improved by the addition of a path between classroom academic interactions (AcadInteractPCC) and faculty support academic interactions (AcadInteractPFS) X^2 diff = 13.62 ($p < .001$). The model was also significantly improved by a path between faculty support academic integration (AcadIntegPFS) and classroom academic integration (AcadIntegPCC) X^2 diff = 73.3 ($p < .001$). A path between (AcadIntegPCC) classroom academic integration and peer social integration (SocIntegPPS) also improved model fit statistics X^2 diff = 24.06 ($p < .001$). Two paths that was added between self-efficacy assessments and coping process at both timepoints significantly improved model fit, X^2 diff = 20.82 ($p < .001$) and X^2 diff = 48.6 ($p < .001$) respectively. While not included in the original theoretical framework, these paths are supported by theory. For example, Milem and Berger (1997) found that peer classroom interactions were predictive of involvement with faculty or faculty interactions. And while incorporating ideas from Bandura’s Social Cognitive Model, Vogt (2008) confirmed that the openness of faculty, and their availability and support increased student self-regulating behaviors in the classroom (i.e., classroom comfort). Regarding the academic and social integration causal ordering, Cabrera et al. (1992) found that there is a significant direct effect of academic integration on social integration that was not in Tinto’s original (1975) theory.

The squared multiple correlation associated with persistence into the second semester is $R^2 = .05$, thus 5% of the variance in persistence is accounted for by the predictors. This R^2 value was significant ($p < .01$), as were all the R^2 values for the endogenous variables in the model. Table 22 illustrates that all the endogenous variables in the model had statistically significant explanatory power. The final parsimonious model, including significant standardized coefficients is illustrated in Figure 4.

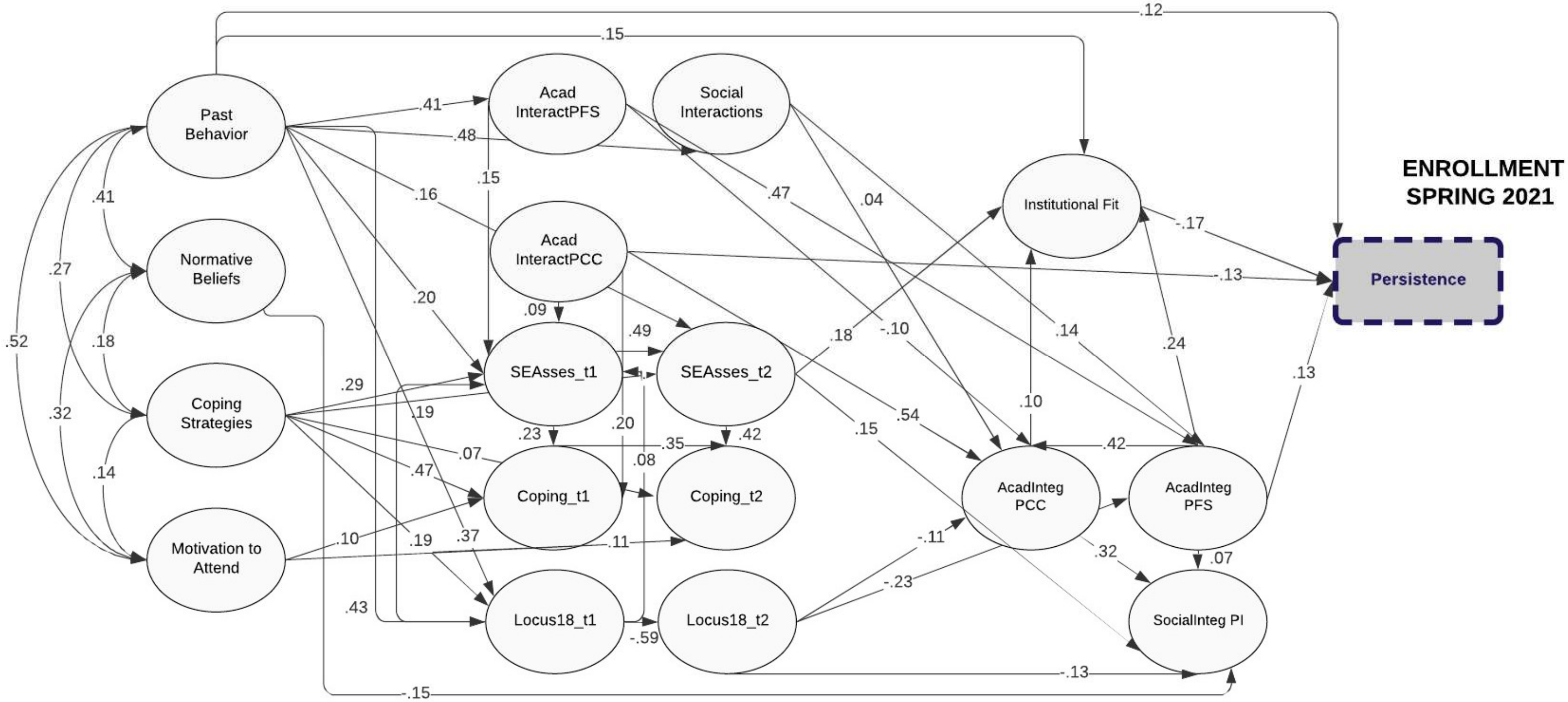
Table 22

Squared Multiple Correlations Fall 2020 Cohort

Endogenous Variable	Estimate
AcadInteractPCC	0.27**
Locus_t1	0.21**
AcadInteract_PFS	0.27**
Locus_t2	0.46**
SEAsses_t1	0.33**
SocInt_t1	0.23**
AcadInteg_PFS_t2	0.34**
AcadInteg_PCC_t2	0.56**
SEAsses_t2	0.46**
InstFit	0.23**
CopingProcess_t1	0.39**
Term2_Enrolled (Persistence)	0.05**
SocInteg_t2	0.20**
CopingProcess_t2	0.43**

Figure 4

Final 2020 SEM Model with Standardized Weights



Control Variables

The control variables entered into the model include composite SAT score, student age, HS GPA and first-year cumulative GPA. In contrast to expectation, none of the control variables were significantly predictive of persistence in terms of re-enrollment into subsequent semester of college.

Direct Effects

In the current model, parameter estimates were derived from bias-corrected 90% confidence intervals (CIs) and standard errors calculated from 2,000 bootstrapped samples. Four of the variables had a statistically significant relationship with persistence. Institutional fit (InsFit20), (β = -0.17), past behavior (β = 0.12), classroom academic interactions (β = -0.13), and faculty support academic integration (β = 0.13), had significantly predicted persistence and accounted for 5% the variance. Four variables also had a statistically significant relationship with institutional fit. Self-efficacy assessments (post), (β = 0.18), past behavior (β = 0.15), classroom academic integration (β = 0.10), and faculty support academic integration (β = 0.24), had significantly predicted institutional fit and accounted for 23% the variance.

Two variables had statistically significant relationships with social integration in terms of peer support and perceived isolation, and accounted for 20% of the variance. These variables were locus of control (post) (β = -0.13) and self-efficacy assessments (post) (β = 0.15).

Four variables had statistically significant relationships with classroom academic integration (AcadIntegPCC). Classroom academic interactions (AcadInteract_PCC) (β = 0.54), faculty support academic integration (AcadIntegPFS) (β = 0.42), locus of control (post) (β = -0.11), and faculty support academic interactions (AcadInteractPFS) (β = -0.10), predicted classroom academic integration and accounted for 56% of its variance. Four variables also had statistically significant relationships with perceived faculty support academic integration (AcadIntegPFS). These variables were (AcadInteractPFC) faculty support academic interactions (β = 0.47), social interactions (β = 0.14), locus of control (pre/post) (β = -0.24/-0.23). These variables accounted for 34% of the variance.

The proportion of variance representing psychological processes was supported by statistically significant structural paths predicting the locus of control, self-efficacy, and coping constructs. Twenty-one percent of the variance was explained by the effects of past behavior (β = 0.37) and coping strategies (β = 0.19) on the locus of control pre-test measure. The coping process pre-test measure was predicted by coping strategies (β = 0.47), motivation to attend (β = 0.10), and self-efficacy assessments (β = 0.23), which explained 39% of the variance. The self-efficacy assessments pre-test measure was significantly predicted by coping strategies (β = 0.30), past behavior (β = 0.21), classroom academic interactions (β = 0.20), faculty academic interactions (β =.15), which accounted for 33% of the variance.

Out of the psychological outcome measures, the self-efficacy post-test measure was found to be significantly predicted by the self-efficacy pre-test measure (β = 0.49), coping strategies (β = 0.19) and past behavior (β = 0.16), and these variables accounted for 46% of the variance. The largest effect on the coping process post-test measure was from self-efficacy assessment pre-test measure (β = 0.42), and the second largest effect was the coping process pre-test measure (β = 0.35). Motivation to attend also significantly predicted coping (β = 0.11), and all three of these variables accounting for 43% variance. Both the locus of control pre-test measure (β = -0.59) and past behavior (β = -0.17) significantly predicted the locus of control post-test measure, and these variables explained 46% of the variance in locus of control (post).

Three variables contributed significantly to the environmental interactions in the model. The past behavior latent variable had statistically significant relationships with classroom academic interactions (AcadInteractPCC) ($\beta = 0.20$), faculty support academic interactions (AcadInteractPFS) ($\beta = 0.41$), and social interactions ($\beta = 0.48$). Normative beliefs ($\beta = 0.41$) predicted classroom academic interactions (AcadInteractPCC). Classroom academic interactions (AcadInteractPCC) predicted faculty support academic interactions (AcadInteractPFS) ($\beta = 0.20$). The two sets of predictors of classroom academic interactions and faculty support academic interactions both explained 27% of the variance respectively. Past behavior also significantly predicted social interactions ($\beta = 0.48$) and accounted for 23% of the variance.

Indirect Effects

Bootstrapping for specific indirect effects was computed in order to identify unique indirect effects for every mediating path in the model. Every significant standardized regression weight in Appendix Table E3 confirms mediation, and those estimates that are nonsignificant indicate mediation was not present.

Eighty-three indirect effects were significant at the $p < .001$ level. Based on the product of coefficients, the strongest mediating relationship was that of normative beliefs on social integration ($\beta = 0.26$). Classroom academic interactions and classroom academic integration are significant mediators on the path between normative beliefs and social integration (CI range 0.049 to 0.122). Classroom academic interactions and classroom academic integration were significant mediators on three other occasions and when past behavior predicted social integration ($\beta = 0.11$).

Fourteen of these indirect effects influenced persistence. The strongest of these mediating relationships was that of past behavior on persistence in terms of subsequent semester enrollment

(β = -0.22). Locus of control was a significant mediator in this relationship, and in seven other paths leading to persistence. Faculty support academic integration (AcadIntegPFS) and institutional fit were significant mediators in all the paths leading to persistence. Twenty-three indirect effects influenced institutional fit. The strongest of these mediating relationships was that of past behavior on institutional fit, with locus of control and faculty support academic integration as significant mediators (β = -0.22). Other indirect effects on institutional fit occurred through coping strategies, and locus of control and faculty support academic integration were once again significant mediators (β = 0.14).

One hundred and nine relationships were significant at the $p < .01$ level. In addition to the aforementioned indirect effects, another mediating path emerged between coping strategies and persistence. The self-efficacy pre/post measures were significant mediators in this path (β = 0.14). Self-efficacy was a significant mediator in 41 paths such that higher scores in coping strategies, classroom academic interactions, and autonomy/normative beliefs bring about greater self-efficacy, which then leads to institutional fit and persistence. Another strong relationship that emerged was that of past behavior on institutional fit (β = 0.10), with self-efficacy (pre/post) as the significant mediators.

Twenty-two indirect effects influenced persistence as measured by fall enrollment into the subsequent semester, and all were significant at the $p < .05$ level. The path between locus of control and persistence was significantly mediated by classroom academic interactions, faculty support academic interactions, and institutional fit (β = 0.13). When locus of control was not a mediator in this path, the same indirect effects were negative and still significant (β = -0.01). The same indirect effects were present in the path between coping strategies and persistence. Locus of control mediated the effect of coping strategies on persistence through faculty support academic integration and institutional fit (β = -0.12). Locus of control also mediated the effect of past behavior on persistence through faculty support academic integration, classroom academic integration, and institutional fit (β = -0.09). When locus of control was not present in the path, academic integration still mediated the path between past behavior and persistence. These mediating relationships imply that locus of control may positively impact persistence alongside faculty support academic integration, and that academic integration has similar positive effects when past behavior is considered.

Eighty indirect effects influenced institutional fit as measured by confidence in the value of an academic degree. Faculty support academic integration was a significant mediator in 42 of those paths, and classroom academic integration was a significant mediator in 20 of the paths. Locus of control was a significant predictor in 25 of the paths leading to institutional fit. The path between past behavior and institutional fit was significantly mediated by classroom and faculty support academic interactions (β = 0.04, $p < .01$); and faculty support academic interactions and faculty support academic integration (β = 0.19, $p < .001$). When past behavior was not taken into account, self-efficacy mediated the path between academic interactions and institutional fit (β = 0.10, $p < .01$). Self-efficacy was also a significant mediator in the path between coping strategies and institutional fit (β = 0.14, $p < .01$).

The results of the mediation tests at the $p < .10$ level are summarized in Appendix Table E3. Thirty-seven of these mediating paths influenced persistence. Normative beliefs were found to influence persistence through classroom academic interactions and classroom academic integration (β= 0.22). The path between faculty support academic interactions and persistence was also mediated by faculty support academic integration and classroom academic integration (β= 0.20). Thus, the effects of normative beliefs on persistence may be explained by a corresponding increase in academic interactions. The effects of academic interactions on persistence may also be explained by faculty support academic integration and classroom academic integration.

Multi-Group Moderation

The multigroup comparison between male and female students had acceptable model fit: CMIN/DF = 1.37 with p = 0.000; CFI = .96, RMSEA =.035, SRMR = .08. The unconstrained and constrained models were not significantly different from each other (p = .28). The nonsignificant p-value signifies that the multigroup gender moderator was impotent; therefore, there were no differences between groups. Since model-level differences were not present, path-level differences were not evaluated.

The multigroup comparison between underrepresented students and non-underrepresented students had excellent model fit: CMIN/DF = 1.46 with p = 0.000; CFI = .95, RMSEA =.039, SRMR = .08. There was not a statistically significant difference between students in underrepresented student groups and non-underrepresented students (p = .17) at the model-level; consequently, path-level differences were not evaluated.

Similarly, the multigroup comparison between first-generation and non-first-generation students yielded acceptable model fit: CMIN/DF = 1.4 with p = 0.000; CFI = .96, RMSEA =.036, SRMR = .07. The unconstrained and constrained models were also not significantly different (p = .23). Since this global test did not indicate model-level differences across the two student groups, path-level differences were not examined. Therefore, the chi-square difference tests for all three multi-group analyses provided evidence that all three multi-group moderation models are the same across the pairs of groups.

Summary of SEM Results

The goals of the present study were to examine how well the theoretical model explains the first-year student persistence process, as well as which factors in the model are most important. Model fit statistics should be considered in order to understand whether the hypothesized model is an accurate representation of reality, (i.e., if the coefficients in the model are meaningful) (Cudeck & Browne, 1983). Cudeck and Browne (1983) argue that the search for any one optimal model should be deemphasized, instead several alternative approximations of reality that perform well in future samples should be considered.

Fit statistics and squared multiple correlations (SMC) for the three models are presented in Table 23. The model fit statistics for the three models are within the acceptable range, with the 2020 SEM model producing the best fit. The model fit statistics and thresholds for the 2020 SEM indicate that it is the superior model with the highest CFI and lowest SRMR and RMSEA fit measures (Hu & Bentler, 1999). Since the models are non-nested, the information theory-based indices Akaike Information Criterion (AIC), Browne-Cudeck Criterion (BCC), and the expected cross-validation index (EVCI) (Browne & Cudeck, 1992) are also presented, and results are consistent with the absolute and relative fit indices. The smaller values of the information theory goodness of fit indices indicate that the 2020 SEM model is expected to cross-validate in similar or new samples from the same population (Byrne, 2010; Loehlin & Beaujean, 2016). For example, the 2020 SEM exhibits the smallest EVCI value and therefore signals that it is the optimal model for replication (Byrne, 2010). The AIC and BCC are also used in a similar manner to compare models against each other, and the result is the same ranking order of the models as implied by the EVCI. It is prudent to compare cross-validation criteria when exploratory modifications are made to the structural models, as is the case with the current study (Loehlin & Beaujean, 2016).

While the variance explained for persistence was not substantial, all R^2 values were statistically significant (Tables 20, 21, and 22). The R^2 decreased by .07 from the 2018 SEM to the 2019 SEM, and increased by .01 between the 2019 and 2020 SEMs. Therefore, the model including NSSE independent variables with persistence into the third year as the final endogenous variable had the most explanatory power. The R^2 between the 2019 and 2020 SEM models improved slightly with the removal of the control variables, while all the same latent variables were included.

Table 23

Overall Fit Statistics and Model Comparisons

Measure	Threshold[a]	2018 SEM	2019 SEM	2020 SEM
CMIN	--	199.70	313.34	154.84
DF	--	167.00	143.00	100.00
CMIN/DF	Between 1 and 3	1.20	2.19	1.55
CFI	>0.95	0.95	0.93	0.97
SRMR	<0.08	0.09	0.06	0.05
RMSEA	<0.06	0.05	0.06	0.04
PClose	>0.05	0.62	0.07	0.83
AIC	--	369.70	487.34	296.84
BCC	--	420.24	498.25	306.30
ECVI	--	3.85	1.37	0.98
R^2 - Persistence	--	0.11	0.04	0.05

Note. CMIN = chi-square value; DF = degrees of freedom; CFI = comparative fit index; SRMR = standardized root mean residual; RMSEA = root mean square error of approximation; PClose = probability of getting a sample of RMSEA value; [a]Hu and Bentler (1999) "Cutoff Criteria for Fit Indexes in Covariance Structure Analysis: Conventional Criteria Versus New Alternatives"

The SMCs of the other variables in each of the three SEMs (Tables 20, 21, 22) were also significant and accounted for a large amount of the variance in the predictive models. The SMCs of the other endogenous variables in the 2018 SEM included: faculty support academic integration (60%), classroom academic integration (55%), coping process (pre-test) (51%), self-efficacy (post-test) (48%), self-efficacy (pre-test) (47%), peer social integration (45%), coping process (post-test) (37%), coping process (post-test) (37%), classroom academic interaction (33%).

In the 2019 SEM, the following endogenous variables demonstrated the most amount of explained variance: locus of control (post-test) (59%), classroom academic integration (52%), peer social integration (49%), faculty support academic integration (39%), self-efficacy (pre-test) (34%), coping process (pre-test) (33%), and locus of control (pre-test) (28%).

In the 2020 SEM, the endogenous variables classroom academic integration (56%), locus of control (post-test) (46%), self-efficacy (post-test) (46%), coping process (post-test) (43%), coping process (pre-test) (39%), faculty support academic integration (34%), and self-efficacy (pre-test) (33%) demonstrated the most amount of variance. The final models specifically addressed the following research questions related to the conceptual model depicted in Figure 1.

Research Question 1

The first research question asked: Which psychological processes (self-efficacy, coping, attributions: locus of control) account for the most variance in the persistence outcome?

In the 2018 SEM, none of the psychological processes directly influenced persistence into the third year of college; however, locus of control influenced classroom academic interactions and classroom academic integration, which were predictors of persistence. Therefore, classroom academic interactions ($\beta = -0.06$, $p < .05$) and classroom academic integration ($\beta = -0.12$, $p < .10$) were mediators in the persistence outcomes.

While none of the psychological processes directly predicted persistence into the second term in the 2019 SEM, locus of control influenced faculty academic integration and peer social integration, which were predictors of persistence ($\beta = 0.09$, $p < 0.10$). Other indirect effect paths implied that locus of control mediates the relationship between past behavior and persistence, and normative beliefs and persistence. Both of those relationships also functioned through social integration and faculty support academic integration. The locus of control (pre-test) measure did have a negative relationship with its post-test measure; therefore, locus of control negatively mediated the effect past behavior on persistence (β = -.34, p < .05) and normative beliefs on persistence ($\beta = -0.13$, $p < .05$).

Similarly, none of the psychological processes directly influenced persistence into the subsequent semester of college in the 2020 SEM. However, locus of control influenced faculty support academic integration, classroom academic integration, and institutional fit ($\beta = 0.14$, $p < .001$), which were predictors of persistence. Locus of control also mediated the path between past behavior, academic integration, institutional fit, and persistence ($\beta = -0.22$, $p < .05$). Self-efficacy mediated the path between coping strategies and persistence ($\beta = 0.14$, $p < .01$), past behavior and persistence ($\beta = 0.10$, $p < .01$), and normative beliefs and persistence ($\beta = 0.08$, $p < .01$). The results of this study support the theory that locus of control and self-efficacy influence persistence indirectly. Thus, locus of control and self-efficacy account for the most variance in the persistence outcome, and those effects are indirect.

Research Question 2

The second research question asked: How do student engagement indicators affect the persistence of students within the semester of their initial college enrollment?

In the 2018 SEM, the NSSE construct Quality of Interactions was used a proxy for bureaucratic interactions, and the Supportive Environment NSSE construct was used as a proxy for interactions external to the institution. Neither of the variables were significantly predictive of persistence. In the context of the Bean and Eaton theoretical framework, the Supportive Environment variable was not found to be influential, and was dropped from the model. This is not surprising given the that the items representing the NSSE construct were not in exact alignment with the external influences intended by the theoretical framework.

As a representation of bureaucratic interactions, the NSSE Quality of Interactions construct was directly predicted by students' normative beliefs, and it accounted for 7% of the variance in the model overall ($\beta = 0.26$, $p < .01$). Notwithstanding the 2018 SEM fit acceptability, the overall model did demonstrate a better R^2 than the other two SEMs, and therefore NSSE variables should continue to be used for further analyses of direct effects when they are available.

Research Question 3

The third research question asked: does the model differ based on group differences including gender, first-generation status, and ethnicity? And, is the psychological process of persistence moderated by gender, first-generation status, or underrepresented group identification?

Student ethnicity was dichotomized as underrepresented student group and non-underrepresented student group. The students classified within an underrepresented group were African American/Black, Hispanic/Latino, and Native American/American Indian. All other ethnicities were categorized into the non-underrepresented group per IPEDS categorizations.

The extent to which the models differed based on the parameters tested across the three groups was marginal. The multi-group analysis was not performed on the 2018 SEM due to the small sample size. Tables 24 and 25 reveal that the fit statistics for the 2019 and 2020 SEM models produce adequate fit in all three moderating groups.

To assess whether the hypothesized model operates equivalently across the groups, gender (male/female), first-generation (FG/non-FG), and underrepresented student group (URG/non-URG), the path coefficients within the SEMs for each cohort were constrained to be equal to each other. In the 2019 SEM, the chi-square test for differences revealed that the hypothesized model was variant between first-generation and non-first-generation students $X^2 = (286, N = 460) = 500.70, p < .001$. However, there were no other statistically significant differences between the pairs of groups for each of the 2019 and 2020 SEMs. Therefore, the psychological process of persistence was not moderated by student subgroups other than those who self-identified as first-generation.

The comparison of pathways across the two moderated student groups indicates that the effect of normative beliefs is more influential on first-generation students' class-related academic interactions (β =0.29, $p < .001$) than it is for non-first-generation students (β = 0.04, $p = .55$). This finding is supported by social norms research in that the influence of normative beliefs is salient in novel or unfamiliar contexts when there are no individual preestablished standards (Schultz et al., 2008). This process is consistent with ideas set forth by Mayhew et al. (2016) about the shifting relationship of students' self-authoring journeys in ambiguous or novel situations. Mayhew and colleagues alluded that perhaps marginalizing experiences reinforce self-authorship in this group, and consequently strengthen self-directedness in classroom academic interactions during the first semester. To elaborate the findings to classroom related interactions, additional research is still needed to explain the effect of the college environment on first-generation students' autonomy (i.e., lower normative influence) (Mayhew et al., 2016).

Also, in line with findings from Mayhew et al. (2016), non-first-generation students are predisposed to benefit more from faculty interactions. In the current study, the comparison of pathways across the two student groups indicate that non-first-generation students' past behaviors are more influential on their faculty support academic interactions (β = 0.47, p < .001) than those of first-generation students (β =0.19, p < .05). That is, past behaviors such as environmental mastery and self-acceptance had only a moderate impact on interactions with faculty among first-generation students, but had stronger effects for all other students.

Interestingly, the positive effect of motivation to attend on classroom social integration was stronger for students whose parents attended college (β =0.25, p < .01) than it was for their first-generation peers (β =0.03, p =.71). It seems that non-first generation students are better able to actualize their purpose for learning through interacting with others, and generally feel less isolated as a result. This pathway was not significant for first-generation students signaling those motivations to learn or self-actualize did not have a statistically significant impact on classroom social integration.

Table 24

Fall 2019 SEM: Model Fit for Multi-Group Moderators (Gender, First-Generation, Underrepresented Group)

	Gender	Underrepresented/Non-underrepresented	First-Generation
Measure	Estimate	Estimate	Estimate
CMIN	480.64	488.93	500.70
DF	286.00	286.00	286.00
CMIN/DF	1.68	1.71	1.75
CFI	0.92	0.91	0.91
SRMR	0.09	0.10	0.09
RMSEA	0.04	0.05	0.05
PClose	0.94	0.90	0.84

Note. CMIN = chi-square value; DF = degrees of freedom; CFI = comparative fit index; SRMR = standardized root mean residual; RMSEA = root mean square error of approximation; PClose = probability of getting a sample of RMSEA value.

Table 25

Fall 2020 SEM: Model Fit for Multi-Group Moderators (Gender, First-Generation, Underrepresented Group)

	Gender	Underrepresented/Non-underrepresented	First-Generation
Measure	Estimate	Estimate	Estimate
CMIN	273.40	291.96	278.16
DF	200.00	200.00	200.00
CMIN/DF	1.37	1.46	1.39
CFI	0.96	0.95	0.96
SRMR	0.08	0.08	0.07
RMSEA	0.06	0.04	0.04
PClose	1.0	0.98	0.99

Note. CMIN = chi-square value; DF = degrees of freedom; CFI = comparative fit index; SRMR = standardized root mean residual; RMSEA = root mean square error of approximation; PClose = probability of getting a sample of RMSEA value.

Chapter 5 Discussion

Current Findings and Prior Research

Taken together, these findings shed light on the psychological process of college student persistence from the first to second semester of college, and from the first to third year of college. An advantage of the current design is that the psychological model of college student retention was replicated within three independent samples and the proposed theoretical framework was validated. The cross-validation is evidenced by absolute, relative, and comparitive goodness of fit measures of the three SEMs in support of the hypothesized model. While there are variations of indirect effects within the cohorts, the overall findings are relatively consistent, and the 2020 model exhibits the most potential for future replication. The overall variances explained by the SEMs were 11%, 4%, and 5%. While these effect sizes are small, they are typical of social-psychological constructs which function within the broader context of complex educational systems (Yeager & Walton, 2011).

The Effects of Locus of Control, Self-Efficacy and Coping

In line with this conclusion, one of the consistent findings across the three cohorts in this study is that the latent constructs locus of control, self-efficacy, and coping processes function indirectly through academic interactions and academic integration to influence persistence. According to Yeager and Walton (2011), non-cognitive influences are powerful processes that are often hard to see but have significant effects when altered. Notably, in the 2018 SEM, locus of control played a particularly relevant mediational role. This construct score was skewed toward internal attribution and mediated the path between past behavior and persistence through academic interactions and academic integration. In the 2019 SEM, locus of control mediated the path between past behavior and self-efficacy. Moreover, similar findings from the 2020 SEM elaborate conclusions from Wood et al. (2015) that self-efficacy was predictive of students' interactions with academic advisors. In the current study, faculty academic interactions predicted overall self-efficacy, and consequently self-efficacy was predictive of perceived faculty support academic integration. Thus, a self-reinforcing recursive process is activated.

Another finding from this study supports the results form Vrugt et al. (1997) and Phillips and Gully (1997) who proposed that self-efficacy, academic performance, and learning goal orientations are malleable beliefs, with the latter study illustrating that this relationship may function through internal locus of control. In particular, the SEM 2019 findings relating to the mediating role of locus of control and self-efficacy on institutional fit illuminate this previous research. For example, Phillips and Gully (1997) stated that students with higher learning goal orientations tend to have higher self-efficacy than those with lower learning goal orientations. In the current study, motivation to attend in terms of personal growth and purpose in life orientation was found to function through self-efficacy beliefs and leads to feelings of institutional fit. Taken together, these findings suggest that there is the potential that self-efficacy beliefs that can be molded through growth mindsets so that feelings of institutional fit and loyalty can be strengthened.

Results from the 2020 SEM demonstrated that coping strategies can indirectly influence persistence through locus of control and self-efficacy. Coping strategies (i.e., the way in which students regulate demands from the college environment through planning), influenced persistence indirectly through locus of control and self-efficacy. Both relationships functioned through academic integration in terms of faculty support, as well as institutional fit. This corroborates findings from Parker et al. (2005) who observed that a linkage exists between student stress management strategies and interpersonal interactions, and that this path leads to academic success (persistence). In the current study, the path between student use of self-regulatory coping strategies and persistence was positively mediated by self-efficacy but was negatively mediated by external locus of control.

The evidence indicates that a broad range of experiences can enhance the benefits of self-regulatory coping strategies on student development (Pascarella et al., 2004). For example, these conditional effects can be enabled by enhancing student self-efficacy or internal locus of control either through academic or nonacademic experiences. Prior research has shown that colleges have programmatic control over how they influence extracurricular student experiences through facilitating a better understanding of study strategies (i.e., coping strategies) or course selection (Pascarella et al., 2004). Moreover, reinforcing self-regulatory coping behaviors through instruction or into the curriculum may help students develop greater capacities to adapt to the new environment through strengthening self-efficacy (Mayhew et al., 2016; Eisenbarth, 2012; Pizzolato, 2004). It would be important to uncover which of these constructs (self-efficacy or locus of control) is more amenable to change so that interventions in first-year experience programs can be deployed accordingly (Wang et al., 2012).

The Effects of Environmental Interactions, Academic and Social Integration

Environmental Interactions. Comfort within the classroom, or academic interactions, was the most important mediator toward persistence for the Fall 2018 and Fall 2019 cohorts. This finding is in alignment with Mayhew et al. (2016) and Pike et al. (1997) who have suggested that classroom interactions introduce students to diverse perspectives, and that these perspectives activate self-directness and self-authorship within students, a lasting long-term effect of college. Academic interactions within the classroom also had significant direct effects on persistence for the Fall 2018, 2019, and 2020 cohorts.

The pattern of findings for the Fall 2018-2020 SEMs agree with but also qualify Milem and Berger's (1997) results. For example, Milem and Berger found that academic integration for the first-year freshman sample was significantly and positively predicted by involvement with faculty. The current study also found that to be true; however, this relationship was not stable across contexts. For the Fall 2020 cohort, there is a slight negative relationship between faculty support interactions at the beginning of the semester (time 1) and classroom academic integration at the end of the semester (time 2). This means that students who reported greater comfort with faculty interactions such as seeking help or discussing problems outside of class at the beginning of the semester were less likely to be academically integrated in the classroom setting at the end of the semester. This relationship was negative in Fall 2020, but positive in Fall 2018, indicating cohort particularities based on the environmental context. This inverse relationship may be largely related to the move to online instruction due to the COVID-19 pandemic in 2020 which explains the decrease in classroom academic interactions overall.

Another pattern of intriguing findings across cohorts was also apparent in the relationship between classroom academic interactions and persistence as measured by re-enrollment into the second term (first-year) and re-enrollment into the third year of college. Students who reported comfort with classroom interactions such as asking questions in class or speaking up and sharing opinions were more likely to persist into the third year. This same relationship was also significant for persistence into the second term; however, the regression coefficient was indicative of a negative relationship for both the 2019 and 2020 cohorts. Because the underlying academic interactions dimension was based on a sense of belonging subscale, this could mean that the effect of academic interactions on persistence are not uniform over time (i.e., 1st year/3rd year reenrollment) given a greater sense of belonging can develop over time. This pattern contradicts previous findings from Hausmann et al. (2007) who suggested that sense of belonging declines over time. While students' morale can contextually shift based on social group membership, the advantage of this study is that it considers the effects of antecedent variables for three samples across time allowing comparability. Thus, the differences across cohorts could be due to the fact that comfort in classroom academic interactions is subjectively influenced by students' past behaviors (environmental mastery and self-acceptance), normative beliefs, as well as faculty academic interactions. This aligns with longitudinal findings from Spady (1971) who observed that student intellectual development across time is based on faculty contacts or having opportunities to develop those contacts.

Therefore, constraints imposed by the environment or context alter the student experience as conceptualized by the theoretical model. Despite different student experiences in the same local context, the explanatory mechanism in the path analytic framework serves as a conceptual tool to identify subtle changes in student perceptions. Subtle changes in student experiences and perceptions can trigger the need for modifications to different programs or interventions in the first-year experience setting.

Academic Integration and Social Integration. Academic integration had both a significant direct effect on persistence and played a significant mediating role in many of the direct effects leading toward persistence.

Academic integration in terms of perceived faculty support was a significant mediator in the 2018 SEM in 15 of the indirect effects in Appendix Table E1, while classroom academic integration was a significant mediator in 44 of the indirect effects. On the other hand, social integration was a significant mediator in 34 of the indirect effects in Appendix Table E1. None of the social integration indirect effects in this cohort predicted persistence. In the 2019 SEM, academic integration in terms of perceived faculty support was a significant mediator in 81 of the indirect effects in Appendix Table E2, while classroom academic integration was a significant mediator in 75 of the indirect effects. In contrast, social integration was a significant mediator in 119 of the indirect effects in Appendix Table E2. And in the 2020 SEM, academic integration in terms of perceived faculty support was a significant mediator in 151 of the indirect effects in Appendix Table E3, while classroom academic integration was a significant mediator in 120 of the indirect effects. Social integration was only a significant mediator in 47 of the indirect effects in Appendix Table E3. None of the significant social integration indirect effects in this cohort lead to persistence.

The significant indirect effects of academic integration were more prominent than the social integration indirect effects in the 2018 and 2019 cohorts. Similarly, the significant indirect effects of academic integration were five times more prevalent than the indirect effects of social integration in the 2020 cohort. This indicates that the effects of academic and social integration on persistence in this first-year context are not equivalent. These findings are empirically supported in four-year universities (Munro, 1981; Cabrera et al., 1992, Pike et al., 1997; Brower, 1992) and demonstrate that there is not a parity between academic and social integration in their effects on student persistence. Munro (1981) found that academic integration had a significant effect on departure, while social integration did not. Within similar frameworks, Cabrera et al. (1992) and Pike et al. (1997) found a direct effect of academic integration on persistence, and that the same relationship did not exist between social integration and persistence. Munro's study was multi-institutional, whereas data from Cabrera et al. (1992) and Pike et al. (1997) were derived from single institutions. In Brower's (1992) terms, students integrate when they are able to choose the priority, frequency, and timing of tasks within each of the integration domains.

The Effects of Multi-group Moderators

One of the objectives of this study was to understand group-level differences in (ethnicity, gender, and first-generation status) relationships between variables. Studies examining the effects of group-level differences on locus of control, self-efficacy and coping are abundant and largely context-dependent (Nora et al., 1996; Phinney & Haas, 2003; Pizzolato, 2004; Wood et al., 2015; Salinas & Llanes, 2003; Aguayo et al., 2011; Gifford et al., 2006; Grimes, 1997; Kang et al., 2015; Llamas et al., 2018; Llamas & Consoli, 2012; Stewart & Schwarzer, 1996; Vrugt et al., 1997; Phillips & Gully, 1997; Anderson et al., 2016). Within the current study's particular context and population, there were no statistically significant differences between males and females on the SEM path coefficients within the examined cohorts. There were also no statistically significant differences between the dichotomized underrepresented/non-underrepresented student subgroups. This could potentially be due to the aggregated nature of the moderator variable. And while an analysis of specific effects for all-inclusive racial/ethnic identities is out of this study's scope, the multigroup analyses support reflections and interpretations for first-generation students supported in prior research.

Group-level differences between first-generation and non-first-generation students were examined. For the Fall 2019 student cohort, there were differences in the relationship between first-generation students' environmental mastery and self-acceptance and how those past behaviors influenced their perception of supportive faculty interactions. The effect of this past behavior construct on faculty academic interactions was stronger for non-first-generation students. This implies that non-first-generation students are more likely to be self-directed and confident with how they perceive supportive faculty interactions. The pathway between normative beliefs and perceived comfort in classroom interactions was also significantly different between first-generation and non-first-generation students. The influence of other people's thoughts and actions on students' comfort in classroom academic interactions was six times stronger for first generation students when compared to non-first-generation students. This effect is much stronger than proposed by Mayhew et al. (2016) who cited evidence that the influence of peer interactions on well-being is twice as strong for first-generation students. The conceptualization of normative beliefs in the current context is much more broad than the peer interactions construct, and denotes the influence of variety of individuals. It seems to follow those first-generation students involved in the current study are at a crossroads phase between transitioning from reliance of external influences to developing their own inner voice (Carpenter & Peña, 2017), which may be a unique challenge when compared to experiences of students with one or more parents who attended college. The current study corroborates evidence from Mayhew et al. (2016) and Pizzolato (2005), which suggests that support from peers, family, faculty, or institutional staff can allow first-generation students to feel more comfortable in the classroom setting. That is, first generation students' comfort in classroom academic interactions can be improved to the extent to which the influences of others enable students' self-authorship. In the long term, this further suggests that different models of college success may apply for first-generation students as certain extracurricular influences may weaken students' internal locus of control over the years (Pascarella et al., 2004).

More needs to be understood about first-generation students' pursuit of personal growth objectives and motivations, and how these factors relate to classroom social engagement in the first-year of college. The current study corroborates findings from Katrevich and Aruguete (2017) suggesting that social integration might be challenging for first-generation students. There is indication that personal motivational factors do not predict feelings of social integration for first-generation students in the same way that they do for their continuing-generation counterparts.

It is important to note that marginalizing experiences and academic interactions challenges can manifest for those students who self-identified as first-generation due to their to underrepresented group membership or SES in relationship to broader systemic barriers. Carpenter and Peña (2017) cite that 30% of first-generation students who experience dissonance in self-authoring experiences can be categorized as students of color. In the current study, 52% of students who self-identified as first-generation in the 2019 cohort sample were also Hispanic or Latino/a, and 64% of the first-generation students were female. The higher representation of Hispanic or Latino/a ethnicity in the first-generation group, compared to the overall 2019 USEM survey respondent breakdown, signals that the Hispanic or Latino/a multicultural community may face similar challenges in faculty interactions, comfort in the classroom, and social integration. It may be that first-generation multigroup differences are influenced by the intersectionality of cultural or gender experiences with institutional agents inside and outside the classroom. Further research on these intersecting relationships with historically marginalized groups is needed with the current study measures.

The Effects of Entry Characteristics

When student age, composite SAT score, high school GPA, and end of term college GPA were accounted for in Bean and Eaton's model of college student retention, the relationships between persistence and some or all of those background characteristics disappear. This is suggestive of the fact that there is shared variance among those entry characteristics and the psychological processes. For example, high-school GPA remained a significant predictor of persistence only in the 2018 SEM model. While in the 2020 SEM, there was so much shared variance that the student background characteristics were no longer significantly related to subsequent term persistence. This may indicate that students' precollege characteristics including high school grades and standardized test scores are not as instrumental in predicting first-year persistence over and above psychological and environmental interactions measures in the current model. Instead, what students do in their first-year of college is equally or more important in predicting persistence than their prior academic achievement and first-year GPAs (Grimes, 1997). For example, practices commonly associated with educationally purposeful activities have been found to have an offsetting effect on lower academic achievement at entry as well as first year GPA (Kuh, 2008).

Limitations

There are some limitations to the using existing data collection instruments, and SEM in general. Because SEM is mainly a confirmatory statistical technique, researchers test specific hypotheses to find a best-fitting model. However, if a researcher implements changes in order to find the best model, then the analysis becomes exploratory. In this case, "appropriate steps should be taken to protect against Type I error" (Tabachnick & Fidell, 1996, p. 714). In terms of external validity, SEM results can only be generalized to the types of samples used in the analysis.

Another limitation is that explaining behavior is enormously complex endeavor, and the measures that are being used are not an exact match to the psychological theories in the model as it was originally conceptualized. Instead, the measures are the best theoretical substitutions available from the data and in some cases do not completely align with definitions from the seminal literature. Since the latent measures are multidimensional in nature, future studies should employ measures that more broadly apply all dimensions of a theorized construct.

Based on the availability of data, there were no theoretical substitutions for some measures in the theoretical framework. Consequently, the Intent to Persist and Institutional Commitment measures were omitted from the adapted Bean and Eaton (2000) model. Despite these limitations, the overall theory remained as close as possible to how it was conceptualized, even though the content of the measures may vary.

A third limitation is the incompleteness of responses, and consequently missing data. Missing data is problematic in that it has both practical and substantive repercussions on the analyses and results (Hair et al., 2014). Missing data substantially decreases sample size and may systematically vary across variables and cases, thus producing different values if particular variables or cases are deleted. In the current study, missing data were caused by 1) missing values at time points (e.g., pre/but no post participation, or post/but no pre participation), and 2) differences between participant nonresponse on certain scale items. This resulted in significant loss of cohort respondents and analytic sample cases, and is threat to validity in quantitative research. In the current study, cases were deleted if missing data were present for one of these reasons, so that parameter estimates could be successfully computed with the available data in AMOS.

A fourth limitation is that the analyses rely heavily on self-reported data. All responses on the PWB, MAI, TGLQ, and SOB scales are self-reported, while the persistence measures, grades and SAT scores are institutional data. Specifically, since participants were not randomly sampled, instances of selection bias based on student availability and student interest may be present.

Another limitation of the current study is that construct measurement equivalence is not present across the three cohorts, and therefore cross-group comparability should be interpreted with caution. The overall variability of factor structures limits the conceptual applicability of the construct meaning across samples. Appendices B and C detail the observed items used to compose latent factors and indicate that measurement scales have inconsistent factor structures across different samples. The CFAs demonstrated that the optimal fit for the PWB, SOB, MAI, and TGLQ factor solutions varied from year to year. Had the same number of factors and structures been observed for each scale, CFA would've been appropriately used to test levels of invariance across the three successive cohorts. However, dimensional invariance (same number of factors) for all scales was not even supported at the EFA stage. The most pronounced example of this was the PWB scale. PWB factor structures varied across the cohorts and had neither dimensional nor metric invariance across the three samples, suggesting that students may respond differently to items depending on context. Further research is needed to determine why some of the scales and subscales lack invariance over time.

In an investigation comparing more than 20 studies, Cunningham et al. (2015) have found that even well-established clinical scales can have varied constructs longitudinally. When Cunningham et al. (2015) found that results from EFAs and CFAs were non-invariant across time points, they specified and evaluated the models separately at time 1 and time 2. The current study followed a similar approach, except separate models were evaluated separately across cohorts (not repeated measures). Consequently, the limited construct validity across time should be taken into consideration.

Implications for Practice

More broadly, this study corroborated evidence that the quality of student interactions with other students, academic advisors, faculty, student services and administrative staff is influenced by normative beliefs (Pike et al., 1997) as a function of self-directedness and autonomy (Mayhew et al., 2016). Those findings from the current study are underscored in the relationship between the normative beliefs latent variable and the NSSE construct quality of interactions for the Fall 2018 cohort. A better understanding of these interactions can help institutional administrators develop services and programs to better meet the needs of students, particularly in an era of teaching and learning in an online environment.

As engagement indicators and HIPs in postsecondary education become more widespread, it is important that practitioners continue to document how and for whom they are most impactful as a pathway toward persistence (Pike et al., 2017). One of the findings of this study was that first-generation students' comfort in interactions with faculty differ when compared to those of non-first-generation students, and that those interactions are more affected by normative influences particularly in a classroom setting. A better understanding is needed of how this specific HIP feature fosters compensatory effects for first-generation students (Kuh, & Schneider, 2017). Finley and McNair (2013) cite that as the number of HIPs first-generations students participate in increases, their engagement in deep learning approaches tends to improve when compared to their counterparts who have not participated in HIPs. Therefore, practitioners should continue to examine the extent to which HIPs incorporating faculty interactions are salient in students' self-authoring journey, and whether those HIP features exhibit positive relationships with first-year persistence and overall college retention. While all undergraduate students likely benefit from engagement in HIPs (Finley & McNair, 2013), it is likely that in the current context, specific support is needed for first-generation students specifically to boost confidence in faculty interactions and classroom comfort interactions.

Implications for Future Research

As college student success and retention models continue to evolve and build on one another, the theoretical framework applied in the current study may not fully capture students' experiences given the quantitative nature of the survey measures. For example, while the academic interaction measures examine the quality of overall belongingness students report in the classroom or with faculty, one is not able to draw conclusions about the lasting effects after the first semester or into later years of college.

Moving forward, it will be important to carry out comparative studies of the context surrounding the COVID-19 pandemic period. Specifically, this period may have altered prior research findings related to first-year student persistence and retention. The disruptions to faculty interactions, classroom interactions, and other interpersonal relationships due to the COVID-19 pandemic may have played a unique role in the relationship between of institutional fit and persistence and warrant further research. In the current study, a negative relationship between institutional fit and persistence only appeared for those students who entered college in 2020. Those students who perceived the value of an academic degree, how an academic degree supports their family, community, or personal life vision were less likely to persist into the subsequent term. This counterintuitive finding may be due to restrictions on social distancing or experiences with online learning modalities that led to feelings of disappointment in the college experience. It would be important to explore the extent to which the significant effects in the current study are reproduced in later years and right before graduation. Additionally, comparisons from different timepoints should be accompanied by qualitative analyses of student self-reflection for a greater understanding of student perceptions.

This study’s findings emphasize that HIPs such as first-year seminars and learning communities may enhance faculty and classroom academic interactions, and ultimately academic and social integration lead toward persistence. Faculty academic interactions and classroom academic interactions also facilitate social integration leading toward persistence. However, there is still a need to assess the differences in HIP direct effects on both achievement and persistence for students who participated in HIP first-year seminar sections or programs, and those who did not.

In the current investigation, measures of interpersonal competencies exhibited the most direct effects on persistence revealing that additional research is still needed on the constructs intended as measurements of intra-individual learning competencies (Stecher & Hamilton, 2014; Wang et al., 2012; Parker et al., 2005). Latent measures of intra-individual SEL competencies such as locus of control, self-efficacy, and coping were employed in the current research; however, additional analyses are needed to compare the growth in these competencies to measures of achievement, as well as which variables are more susceptible to change than others.

There is also still more to learn about the longitudinal changes in students’ malleable learning competencies (e.g., locus of control, self-efficacy, coping) as related to the HIP enrollment (e.g., first year seminars, learning communities). Assessments for intraindividual change over time would require complete data over multiple repeated measures. If three or more measurement timepoints are available per individual, such analyses can be handled through covariance structures in SEM or Latent Growth Curve (LGC) models (Byrne, 2010). The psychological model of college student retention offers a promising framework for an exploration of HIP compensatory benefits and student subgroups differences in terms of starting rates and growth trajectories.

Conclusions and Recommendations

The Bean and Eaton model serves as a valuable conceptual framework in a student persistence context due to the structure that tracks psychological processes, integration, and subsequent behavior. The model supported overall evidence that high impact educational practices or programs that influence students' self-authoring can encourage faculty and classroom academic interactions that reinforce self-efficacy and indirectly influence academic and social integration. Instructors who understand how students' coping style affects their performance will be well equipped to understand students' motivation in an effort to teach and relate more effectively (Struthers et al., 2000). Freshman seminars should integrate time management instruction and self-regulatory activities into their curriculum to reduce stress and increase student confidence during their first semester (Struthers et al., 2000; Vrugt et al., 1997).

There are a few important issues that need further study. First, researchers have found that self-attributions resulting in motivation, growth mindset, and grit are often mediators of academic performance and play an instrumental role in academic behaviors (NAS, 2018; Yeager & Walton, 2011; Eccles & Wigfield, 2002; Anderson et al., 2016; Farrington et al., 2012). There is a need for theoretical integration of these malleable learning dispositions with engagement indicators within student success models. In the context of the current study, this may help explain different integration effects for first-generation students. Second, previous research has yet to clarify differential student outcomes within diverse post-secondary education contexts over time. Addressing this research gap would prove valuable in informing effective programs and interventions that target academic behaviors through the constructs explored in this study. Finally, future research should focus on disaggregating influences confirmed herein by ethnicity, full-time and part-time student status as well by targeted programmatic initiatives (e.g., HIPs and features). To extend and elaborate the current study, retention scholars and practitioners should incorporate determinants of intention and commitment, as well as persistence data for subsequent years of college alongside qualitative data of lived experiences. Latent growth curve modeling for longitudinal data with three or more timepoints should be incorporated to understand student growth and development past the first-year of college.

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Appendix A

USEM Survey Questionnaire

PWB

Please indicate your degree of agreement (using a score ranging from 1, "Strongly Disagree" - 6, "Strongly Agree") to the following sentences:

I am not afraid to voice my opinions, even when they are in opposition to the opinions of most people.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

In general, I feel I am in charge of the situation in which I live.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

I am not interested in activities that will expand by horizons.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

Most people see me as loving and affectionate.

2 3 4 5

1 Strongly Disagree					6 Strongly Agree
○	○	○	○	○	○

I live life one day at a time and don't really think about the future.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

When I look at the story of my life, I am pleased with how things have turned out.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

Please indicate your degree of agreement (using a score ranging from 1, "Strongly Disagree" - 6, "Strongly Agree") to the following sentences:

My decisions are not usually influenced by what everyone else is doing.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

The demands of everyday life often get me down.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

I think it is important to have new experiences that challenge how you think about yourself and the world.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
◯	◯	◯	◯	◯	◯

Maintaining close relationships has been difficult and frustrating for me.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
◯	◯	◯	◯	◯	◯

I have a sense of direction and purpose in life.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
◯	◯	◯	◯	◯	◯

In general, I feel confident and positive about myself.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
◯	◯	◯	◯	◯	◯

Please indicate your degree of agreement (using a score ranging from 1, "Strongly Disagree" - 6, "Strongly Agree") to the following sentences:

I tend to worry about what other people think of me.

1	2	3	4	5	6
Strongly Disagree ◯	◯	◯	◯	◯	Strongly Agree ◯

I do not fit very well with the people and the community around me.

1	2	3	4	5	6
Strongly Disagree ◯	◯	◯	◯	◯	Strongly Agree ◯

When I think about it, I haven't really improved much as a person over the years.

1	2	3	4	5	6
Strongly Disagree ◯	◯	◯	◯	◯	Strongly Agree ◯

I often feel lonely because I have few close friends with whom to share my concerns.

1	2	3	4	5	6
Strongly Disagree ◯	◯	◯	◯	◯	Strongly Agree ◯

My daily activities often seem trivial and unimportant to me.

1	2	3	4	5	6
Strongly Disagree ◯	◯	◯	◯	◯	Strongly Agree ◯

I feel like many of the people I know have gotten more out of life than I have.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

Please indicate your degree of agreement (using a score ranging from 1, "Strongly Disagree" - 6, "Strongly Agree") to the following sentences:

I tend to be influenced by people with strong opinions.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

I am quite good at managing the many responsibilities of my daily life.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

I have a sense that I have developed a lot as a person over time.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

I enjoy personal and mutual conversations with family members or friends.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

I don't have a good sense of what it is I'm trying to accomplish in life.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

I like most aspects of my personality.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

Please indicate your degree of agreement (using a score ranging from 1, "Strongly Disagree" - 6, "Strongly Agree") to the following sentences:

I have confidence in my opinions, even if they are contrary to the general consensus.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

I often feel overwhelmed by my responsibilities.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

I do not enjoy being in new situations that require me to change my old familiar ways of doing things.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
◯	◯	◯	◯	◯	◯

People would describe me as a giving person, willing to share my time with others.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
◯	◯	◯	◯	◯	◯

I enjoy making plans for the future and working to make them a reality.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
◯	◯	◯	◯	◯	◯

In many ways, I feel disappointed about my achievements in life.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
◯	◯	◯	◯	◯	◯

Please indicate your degree of agreement (using a score ranging from 1, "Strongly Disagree" - 6, "Strongly Agree") to the following sentences:

It's difficult for me to voice my own opinions on controversial matters.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

I have difficulty arranging my life in a way that is satisfying to me.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

For me, life has been a continuous process of learning, changing and growth.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

I have not experienced many warm and trusting relationships with others.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

Some people wander aimlessly through life, but I am not one of them.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

My attitude about myself is probably not as positive as most people feel about themselves.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

Please indicate your degree of agreement (using a score ranging from 1, "Strongly Disagree" - 6, "Strongly Agree") to the following sentences:

I judge myself by what I think is important, not by the values of what others think is important.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

I have been able to build a home and a lifestyle for myself that is much to my liking.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

I gave up trying to make big improvements or changes in my life a long time ago.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

I know that I can trust my friends, and they know they can trust me.

1 Strongly Disagree	2	3	4	5	6 Strongly Agree
○	○	○	○	○	○

I sometimes feel as if I've done all there is to do in life.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

When I compare myself to friends and acquaintances, it makes me feel good about who I am.

1	2	3	4	5	6
Strongly Disagree					Strongly Agree

SCS-SF

HOW I TYPICALLY ACT TOWARDS MYSELF IN DIFFICULT TIMES

Please read each statement carefully before answering. For each item, indicate how often you behave in the stated manner, using the following scale: 1 = "Almost never" to 5 = "Almost always".

When I fail at something important to me I become consumed by feelings of inadequacy.

1	2	3	4	5
Almost never				Almost always

I try to be understanding and patient towards those aspects of my personality I don't like.

1 Almost never	2	3	4	5 Almost always
○	○	○	○	○

When something painful happens I try to take a balanced view of the situation.

1 Almost never	2	3	4	5 Almost always
○	○	○	○	○

When I'm feeling down, I tend to feel like most other people are probably happier than I am.

1 Almost never	2	3	4	5 Almost always
○	○	○	○	○

HOW I TYPICALLY ACT TOWARDS MYSELF IN DIFFICULT TIMES

Please read each statement carefully before answering. For each item, indicate how often you behave in the stated manner, using the following scale: 1 = "Almost never" to 5 = "Almost always".

I try to see my failings as part of the human condition.

1 Almost never	2	3	4	5 Almost always
○	○	○	○	○

When I'm going through a very hard time, I give myself the caring and tenderness I need.

1	2	3	4	5
Almost never	○	○	○	Almost always

When something upsets me I try to keep my emotions in balance.

1	2	3	4	5
Almost never	○	○	○	Almost always

When I fail at something that's important to me, I tend to feel alone in my failure.

1	2	3	4	5
Almost never	○	○	○	Almost always

HOW I TYPICALLY ACT TOWARDS MYSELF IN DIFFICULT TIMES

Please read each statement carefully before answering. For each item, indicate how often you behave in the stated manner, using the following scale: 1 = "Almost never" to 5 = "Almost always".

When I'm feeling down I tend to obsess and fixate on everything that's wrong.

1	2	3	4	5
Almost never	○	○	○	Almost always

When I feel inadequate in some way, I try to remind myself that feelings of inadequacy are shared by most people.

1	2	3	4	5
Almost never				Almost always

I'm disapproving and judgmental about my own flaws and inadequacies.

1	2	3	4	5
Almost never				Almost always

I'm intolerant and impatient towards those aspects of my personality I don't like.

1	2	3	4	5
Almost never				Almost always

TGLQ

Please rate the following statements on the following scale: 1 = "Strongly Disagree", 2 = "Disagree", 3 = "Somewhat Disagree", 4 = "Somewhat Agree", 5 = "Agree", 6 = Strongly Agree".

I feel confident in my ability to support the personal development of my peers.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I can explain the value of an academic degree.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I can explain how an academic degree supports my family or community.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I can explain how an academic degree supports my personal life vision.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

Please rate the following statements on the following scale: 1 = "Strongly Disagree", 2 = "Disagree", 3 = "Somewhat Disagree", 4 = "Somewhat Agree", 5 = "Agree", 6 = Strongly Agree".

I can name five personal values.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I can name five personal cultural strengths.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I can explain how my cultural strengths support my student success.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I am confident in my personal life vision.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I am confident that I can find on-campus solutions to any of the challenges I face.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

Please rate the following statements on the following scale: 1 = "Strongly Disagree", 2 = "Disagree", 3 = "Somewhat Disagree", 4 = "Somewhat Agree", 5 = "Agree", 6 = Strongly Agree".

I am confident in my ability to address conflicts that may emerge with my peers.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I am confident in my ability to address conflicts that may emerge with my family members.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I am confident in my ability to address conflicts that may emerge with faculty/staff.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I have a clearer vision of what I want to do after college.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

I am enrolled in an academic area that will support my career goals.

1	2	3	4	5	6
Strongly Disagree	Disagree	Somewhat Disagree	Somewhat Agree	Agree	Strongly Agree

MAI-R

Think of yourself as a **learner**. Read each statement carefully. Consider if the statement is true or false as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.). Check True or False as appropriate.

	True	False
I ask myself periodically if I am meeting my goals.	○	○
I consider several alternatives to a problem before I answer.	○	○
I try to use strategies that have worked in the past.	○	○
I pace myself while learning in order to have enough time.	○	○
I understand my intellectual strengths and weaknesses.	○	○

Think of yourself as a **learner**. Read each statement carefully. Consider if the statement is true or false as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.). Check True or False as appropriate.

	True	False
I think about what I really need to learn before I begin a task.	○	○
I know how well I did once I finish a test.	○	○
I set specific goals before I begin a task.	○	○
I know what kind of information is most important to learn.	○	○
I ask myself if I have considered all options when solving a problem.	○	○

Think of yourself as a **learner**. Read each statement carefully. Consider if the statement is true or false as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.). Check True or False as appropriate.

	True	False
I am good at organizing information.	○	○
I have a specific purpose for each strategy I use.	○	○
I learn best when I know something about the topic.	○	○
I know what the teacher expects me to learn.	○	○
I am good at remembering information.	○	○

Think of yourself as a **learner**. Read each statement carefully. Consider if the statement is true or false as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.). Check True or False as appropriate.

	True	False
I use different learning strategies depending on the situation.	○	○
I ask myself if there was an easier way to do things after I finish a task.	○	○
I have control over how well I learn.	○	○
I periodically review to help me understand important relationships.	○	○

Think of yourself as a **learner**. Read each statement carefully. Consider if the statement is true or false as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.). Check True or False as appropriate.

	True	False
I ask myself questions about the material before I begin.	◯	◯
I think of several ways to solve a problem and choose the best one.	◯	◯
I summarize what I've learned after I finish.	◯	◯
I ask others for help when I don't understand something.	◯	◯
I can motivate myself to learn when I need to.	◯	◯

Think of yourself as a **learner**. Read each statement carefully. Consider if the statement is true or false as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.). Check True or False as appropriate.

	True	False
I am aware of what strategies I use when I study.	◯	◯
I find myself analyzing the usefulness of strategies while I study.	◯	◯
I use my intellectual strengths to compensate for my weaknesses.	◯	◯
I am a good judge of how well I understand something.	◯	◯
I find myself using helpful learning strategies automatically.	◯	◯

Think of yourself as a **learner**. Read each statement carefully. Consider if the statement is true or false as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.). Check True or False as appropriate.

	True	False
I find myself using helpful learning strategies automatically.	◯	◯
I find myself pausing regularly to check my comprehension.	◯	◯
I know when each strategy I use will be most effective.	◯	◯
I ask myself how well I accomplish my goals once I'm finished.	◯	◯
I ask myself if I have considered all options after I solve a problem.	◯	◯

Think of yourself as a **learner**. Read each statement carefully. Consider if the statement is true or false as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.). Check True or False as appropriate.

	True	False
I change strategies when I fail to understand.	◯	◯
I read instructions carefully before I begin a task.	◯	◯
I ask myself if what I'm reading is related to what I already know.	◯	◯
I reevaluate my assumptions when I get confused.	◯	◯
I organize my time to best accomplish my goals.	◯	◯

Think of yourself as a **learner**. Read each statement carefully. Consider if the statement is true or false as it generally applies to you when you are in the role of a learner (student, attending classes, university etc.). Check True or False as appropriate.

	True	False
I learn more when I am interested in the topic.	◯	◯
I ask myself questions about how well I am doing while I am learning something new.	◯	◯
I ask myself if I learned as much as I could have once I finish a task.	◯	◯
I stop and go back over new information that is not clear.	◯	◯
I stop and reread when I get confused.	◯	◯

PSS

The questions in this scale ask you about your feelings and thoughts **during the last month**. In each case, you will be asked to indicate *how often* you felt or thought a certain way on the following scale: 0 = "Never", 1 = "Almost Never", 2 = "Sometimes", 3 = "Fairly Often", 4 = "Very Often".

In the last month, how often have you been upset because of something that happened unexpectedly?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often
◯	◯	◯	◯	◯

In the last month, how often have you felt that you were unable to control the important things in your life?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often

In the last month, how often have you felt nervous and "stressed"?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often

In the last month, how often have you felt confident about your ability to handle your personal problems?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often

In the last month, how often have you felt that things were going your way?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often

The questions in this scale ask you about your feelings and thoughts **during the last month**. In each case, you will be asked to indicate *how often* you felt or thought a certain way on the following scale: 0 = "Never", 1 = "Almost Never", 2 = "Sometimes", 3 = "Fairly Often", 4 = "Very Often".

In the last month, how often have you found that you could not cope with all the things that you had to do?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often

In the last month, how often have you been able to control irritations in your life?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often

In the last month, how often have you felt that you were on top of things?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often

In the last month, how often have you been angered because of things that were outside of your control?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often

In the last month, how often have you felt difficulties were piling up so high that you could not overcome them?

0	1	2	3	4
Never	Almost Never	Sometimes	Fairly Often	Very Often

SOB-R

Please rate each item on the following scale: 1 = "Completely Untrue", 2 = "Mostly Untrue", 3 = "Equally True and Untrue", 4 = "Mostly True", 5 = "Completely True".

I have met with classmates outside of class to study for an exam.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

If I miss class, I know students who I could get notes from.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I discuss events which happened outside of class with my classmates.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I have discussed personal matters with students who I met in class.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I could contact another student from class if I had a question.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

Please rate each item on the following scale: 1 = "Completely Untrue", 2 = "Mostly Untrue", 3 = "Equally True and Untrue", 4 = "Mostly True", 5 = "Completely True".

Other students are helpful in reminding me when assignments are due or when tests are approaching.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I have developed personal relationships with other students in class.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I invite people I know from class to do things socially.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel comfortable contributing to class discussions.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel comfortable asking a question in class.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

Please rate each item on the following scale: 1 = "Completely Untrue", 2 = "Mostly Untrue", 3 = "Equally True and Untrue", 4 = "Mostly True", 5 = "Completely True".

I feel comfortable volunteering ideas or opinions in class.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

Speaking in class is easy because I feel comfortable.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

It is difficult to meet other students in class.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

No one in my classes knows anything personal about me.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I rarely talk to other students in my class.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

Please rate each item on the following scale: 1 = "Completely Untrue", 2 = "Mostly Untrue", 3 = "Equally True and Untrue", 4 = "Mostly True", 5 = "Completely True".

I know very few people in my class.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel comfortable talking about a problem with faculty.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel comfortable asking a teacher for help if I do not understand course-related material.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel that a faculty member would be sensitive to my difficulties if I shared them.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel comfortable socializing with a faculty member outside of class.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

Please rate each item on the following scale: 1 = "Completely Untrue", 2 = "Mostly Untrue", 3 = "Equally True and Untrue", 4 = "Mostly True", 5 = "Completely True".

I feel that a faculty member would be sympathetic if I was upset.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel that a faculty member would take the time to talk to me if I needed help.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

If I had a reason, I would feel comfortable seeking help from a faculty member outside of class time (office hours etc.).

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel comfortable seeking help from a teacher before or after class.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel that a faculty member really tried to understand my problem when I talked about it.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

I feel comfortable asking a teacher for help with a personal problem.

1	2	3	4	5
Completely Untrue	Mostly Untrue	Equally True and Untrue	Mostly True	Completely True

Appendix B

Latent Variables and Item Indicators

Table B1

Fall 2018 SEM: Latent Variables and Item Indicators

Latent Variable	Operational Definition	Variable Indicators	Question Code
Past Behavior	Past behaviors, academic and social experiences related to student preparation for college success (Bean & Eaton, 2001)	1. In many ways, I feel disappointed about my achievements in life. 2. My daily activities often seem trivial and unimportant to me. 3. I have difficulty arranging my life in a way that is satisfying to me. 4. When I look at the story of my life, I am pleased with how things have turned out. 5. I have been able to build a home and a lifestyle for myself that is much to my liking.	SA5R PL3R EM6R SA1 EM7
Normative Beliefs	Self-determination and independence (or lack thereof) when confronted with perspectives of others (Ryff 1989; Bean & Eaton, 2001)	1. I am not afraid to voice my opinions, even when they are in opposition to the opinions of most people. 2. My decisions are not usually influenced by what everyone else is doing. 3. I tend to be influenced by people with strong opinions. 4. I have confidence in my opinions, even if they are contrary to the general consensus. 5. It's difficult for me to voice my own opinions on controversial matters.	A1 A2 A4R A5 A6R
Coping Strategies	Regulation of cognition (planning) as a form of coping strategy in the	1. I pace myself while learning in order to have enough time.	P_1_1 P_2_1

Latent Variable	Operational Definition	Variable Indicators	Question Code
	face of stressors (Schraw & Dennison, 1994; Bean & Eaton, 2001)	2. I think about what I really need to learn before I begin a task. 3. I set specific goals before I begin a task. 4. I ask myself questions about the material before I begin. 5. I think of several ways to solve a problem and choose the best one. 6. I read instructions carefully before I begin a task. 7. I organize my time to best accomplish my goals.	P_3_1 P_4_1 P_5_1 P_6_1 P_7_1
Motivation to Attend	Motivational factors influence intention, and ultimately behavior (Ajzen, 1991)	1. I am not interested in activities that will expand by horizons. 2. I gave up trying to make big improvements or changes in my life a long time ago. 3. I sometimes feel as if I've done all there is to do in life.	PG1R PG7R PL7R
Bureaucratic Interactions	Interactions that occur during campus interaction within the areas of student services and administrative services (registrar, financial aid, etc.) (Bean & Eaton, 2001)	Quality of Interactions with: 1. Students 2. Academic advisors 3. Faculty 4. Student services staff (career services, student activities, housing, etc.) 5. Other administrative staff and offices (registrar, financial aid, etc.)	QI_19
Academic Interactions (PFS pre-test)	Interactions with faculty members (Bean & Eaton, 2001; Hoffman et al., 2002)	1. I feel that a faculty member would be sensitive to my difficulties if I shared them. 2. I feel that a faculty member would be sympathetic if I was upset. 3. I feel that a faculty member would take the time to talk to me if I needed help. 4. I feel that a faculty member really tried to understand my problem when I talked about	PFS3 PFS5 PFS6 PFS9

Latent Variable	Operational Definition	Variable Indicators	Question Code
Academic Interactions (PCC pre-test)	Interactions within the classroom (Bean & Eaton, 2001 Hoffman et al., 2002)	1. I feel comfortable contributing to class discussions. 2. I feel comfortable asking a question in class. 3. I feel comfortable volunteering ideas or opinions in class. 4. Speaking in class is easy because I feel comfortable.	PCC1 PCC2 PCC3 PCC4
Social Interactions	Reactions to social interactions based on prior experiences and strategies chosen to navigate new environment (Bean & Eaton, 2001)	1. I do not fit very well with the people and the community around me. 2. I often feel lonely because I have few close friends with whom to share my concerns. 3. I often feel overwhelmed by my responsibilities.	EM3R PR3R EM5R
Interactions External to the Institution	Interactions outside the institution (Bean & Eaton, 2001)	1. Providing support to help students succeed academically 2. Using learning support services (tutoring services, writing center, etc.) 3. Encouraging contact among students from different backgrounds (social, racial/ethnic, religious, etc.) 4. Providing opportunities to be involved socially 5. Providing support for your overall well-being (recreation, health care, counseling, etc.) 6. Helping you manage your non-academic responsibilities (work, family, etc.) 7. Attending campus activities and events (performing arts, athletic events, etc.) 8. Attending events that address important social, economic, or political issues	SE_19
Self-efficacy Assessments (pre-test/post-test)	Student perception of abilities to carry out academic tasks (Bean & Eaton, 2001)	1. I understand my intellectual strengths and weaknesses.	DK_1_1 DK_2_1 CM_3_1

Latent Variable	Operational Definition	Variable Indicators	Question Code
		2. I know what kind of information is most important to learn. 3. I ask myself if I have considered all options when solving a problem. 4. I am good at organizing information. 5. I have a specific purpose for each strategy I use. 6. I am good at remembering information. 7. I have control over how well I learn. 8. I periodically review to help me understand important relationships. 9. I use my intellectual strengths to compensate for my weaknesses. 10. I am a good judge of how well I understand something. 11. I find myself using helpful learning strategies automatically. 12. I find myself using helpful learning strategies automatically. 13. I know when each strategy I use will be most effective. 14. I reevaluate my assumptions when I get confused. 15. I learn more when I am interested in the topic. 16. I stop and go back over new information that is not clear.	DK_3_1 PK_2_1 DK_5_1 DK_6_1 CM_4_1 CK_4_1 DK_7_1 PK_4_1 PK_4_1 CK_5_1 DS_3_1 DK_8_1 DS_4_1
Coping Process (Approach/Avoidance) (pre-test/post-test)	The knowledge of how to link academic adjustment strategies and regulate cognition to adapt is a type of metacognitive awareness. Bean and Eaton (2001) view academic integration as a type of adaptation	1. I ask myself periodically if I am meeting my goals. 2. I consider several alternatives to a problem before I answer. 3. I use different learning strategies depending on the situation.	CM_1_1 CM_2_1 CK_2_1 E_2_1 E_3_1 PK_3_1 CM_5_1

Latent Variable	Operational Definition	Variable Indicators	Question Code
		4. I ask myself if there was an easier way to do things after I finish a task. 5. I summarize what I've learned after I finish. 6. I am aware of what strategies I use when I study. 7. I find myself analyzing the usefulness of strategies while I study. 8. I find myself pausing regularly to check my comprehension. 9. I ask myself how well I accomplish my goals once I'm finished. 10. I ask myself if I have considered all options after I solve a problem. 11. I ask myself questions about how well I am doing while I am learning something new. 12. I ask myself if I learned as much as I could have once I finish a task.	CM_6_1 E_4_1 E_5_1 CM_7_1 E_6_1
Attributions: Locus of Control (pre-test/post-test)	Individuals ascribe causality based on internal factors (e.g., ability, effort) and external factors (e.g., luck, task difficulty), and whether those factors are controllable and stable (Weiner, 1985)	1. In general, I feel I am in charge of the situation in which I live. 2. Most people see me as loving and affectionate. 3. I am quite good at managing the many responsibilities of my daily life.	EM1 PR1 EM4
Academic Integration (PCC post-test)	Outcomes from classroom successes/failures as well as outcomes from psychological processes: coping, locus of control, and self-efficacy (Bean & Eaton, 2001)	1. I feel comfortable contributing to class discussions. 2. I feel comfortable asking a question in class. 3. I feel comfortable volunteering ideas or opinions in class. 4. Speaking in class is easy because I feel comfortable.	PCC1 PCC2 PCC3 PCC4
Academic Integration (PFS post-test)	Outcomes from classroom successes/failures as well as	1. I feel that a faculty member would be sensitive to my difficulties if I shared them.	PFS3 PFS5

Latent Variable	Operational Definition	Variable Indicators	Question Code
	outcomes from psychological processes: coping, locus of control, and self-efficacy (Bean & Eaton, 2001)	2. I feel that a faculty member would be sympathetic if I was upset. 3. I feel that a faculty member would take the time to talk to me if I needed help. 4. I feel that a faculty member really tried to understand my problem when I talked about	PFS6 PFS9
Social Integration (PI post-test)	Social integration in terms of perceived isolation (lack of social support) (Bean & Eaton, 2001; Tinto, 1975)	1. It is difficult to meet other students in class. 2. No one in my classes knows anything personal about me. 3. I rarely talk to other students in my class. 4. I know very few people in my class.	PI1R PI2R PI3R PI4R
Social Integration (PPS post-test)	Social integration in terms of perceived peer support (social support) (Bean & Eaton, 2001; Tinto, 1975)	1. I have discussed personal matters with students who I met in class. 2. Other students are helpful in reminding me when assignments are due or when tests are approaching. 3. I have developed personal relationships with other students in class. 4. I invite people I know from class to do things socially.	PPS4 PPS6 PPS7 PPS8
Institutional Fit	A sense of student fitting into the institution as a result of psychological responses and academic and social integration (Bean & Eaton)	1. I can explain the value of an academic degree. 2. I can explain how an academic degree supports my family or community. 3. I can explain how an academic degree supports my personal life vision.	TGLQ2 TGLQ3 TGLQ4

Table B2

Fall 2019 SEM: Latent Variables and Item Indicators

Latent Variable	Operational Definition	Variable Indicators	Question Code
Past Behavior	Past behaviors, academic and social experiences that are responsible for preparing a student to succeed in college (Bean & Eaton, 2001)	1. In general, I feel I am in charge of the situation in which I live. 2. I am quite good at managing the many responsibilities of my daily life. 3. I have a sense of direction and purpose in life. 4. In general, I feel confident and positive about myself. 5. I like most aspects of my personality. 6. I have been able to build a home and a lifestyle for myself that is much to my liking.	EM1 EM4 PL2 SA2 SA4 EM7
Normative Beliefs	Self-determination, independence when faced with perspectives of others (Ryff 1989; Bean & Eaton, 2001)	1. My decisions are not usually influenced by what everyone else is doing. 2. I tend to worry about what other people think of me. 3. I tend to be influenced by people with strong opinions.	A2 A3R A4R
Coping Strategies	Regulation of cognition (planning) as a form of coping strategy in the face of stressors (Schraw & Dennison, 1994; Bean & Eaton, 2001)	1. I pace myself while learning in order to have enough time. 2. I think about what I really need to learn before I begin a task. 3. I set specific goals before I begin a task. 4. I ask myself questions about the material before I begin. 5. I think of several ways to solve a problem and choose the best one. 6. I read instructions carefully before I begin a task. 7. I organize my time to best accomplish my goals.	P_1_1 P_2_1 P_3_1 P_4_1 P_5_1 P_6_1 P_7_1

Latent Variable	Operational Definition	Variable Indicators	Question Code
Motivation to Attend	Motivational factors influence intention, and ultimately behavior (Ajzen, 1991)	1. I don't have a good sense of what it is I'm trying to accomplish in life. 2. I gave up trying to make big improvements or changes in my life a long time ago. 3. I sometimes feel as if I've done all there is to do in life.	PL4R PG7R PL7R
Academic Interactions (PFS pre-test)	Interactions with faculty members (Bean & Eaton, 2001; Hoffman et al., 2002)	1. I feel comfortable socializing with a faculty member outside of class. 2. I feel that a faculty member would be sympathetic if I was upset. 3. I feel that a faculty member would take the time to talk to me if I needed help. 4. If I had a reason, I would feel comfortable seeking help from a faculty member outside of class time (office hours etc.). 5. I feel that a faculty member really tried to understand my problem when I talked about it. 6. I feel comfortable asking a teacher for help with a personal problem.	PFS4 PFS5 PFS6 PFS7 PFS9 PFS10
Academic Interactions (PCC pre-test)	Interactions within the classroom (Bean & Eaton, 2001 Hoffman et al., 2002)	1. I feel comfortable contributing to class discussions. 2. I feel comfortable asking a question in class. 3. I feel comfortable volunteering ideas or opinions in class. 4. Speaking in class is easy because I feel comfortable.	PCC1 PCC2 PCC3 PCC4
Social Interactions	Reactions to social interactions based on prior experiences and strategies chosen to navigate new environment (Bean & Eaton, 2001)	1. Most people see me as loving and affectionate. 2. I enjoy personal and mutual conversations with family members or friends. 3. People would describe me as a giving person, willing to share my time with others.	PR1 PR4 PR5

Latent Variable	Operational Definition	Variable Indicators	Question Code
Self-efficacy Assessments (pre-test/post-test)	Student perception of abilities to carry out academic tasks (Bean & Eaton, 2001)	1. I understand my intellectual strengths and weaknesses. 2. I know what kind of information is most important to learn. 3. I am good at organizing information. 4. I have a specific purpose for each strategy I use. 5. I know what the teacher expects me to learn. 6. I am good at remembering information. 7. I have control over how well I learn. 8. I can motivate myself to learn when I need to. 9. I am aware of what strategies I use when I study. 10. I use my intellectual strengths to compensate for my weaknesses. 11. I am a good judge of how well I understand something. 12. I find myself using helpful learning strategies automatically. 13. I know when each strategy I use will be most effective.	DK_1_1 DK_2_1 DK_3_1 PK_2_1 DK_4_1 DK_5_1 DK_6_1 CK_3_1 PK_3_1 CK_4_1 DK_7_1 PK_4_1 CK_5_1
Coping Process (Approach/Avoidance) (pre-test/post-test)	The knowledge of how to link academic adjustment strategies and regulate cognition to adapt is a type of metacognitive awareness. Bean and Eaton (2001) view academic integration as a type of adaptation	1. I know what kind of information is most important to learn. 2. I am good at organizing information. 3. I ask myself if there was an easier way to do things after I finish a task. 4. I periodically review to help me understand important relationships. 5. I summarize what I've learned after I finish. 6. I find myself analyzing the usefulness of strategies while I study. 7. I find myself pausing regularly to check my comprehension.	DK_2_1 DK_3_1 E_2_1 CM_4_1 E_3_1 CM_5_1 CM_6_1 E_4_1 E_5_1 DS_2_1 DS_3_1 CM_7_1

Latent Variable	Operational Definition	Variable Indicators	Question Code
		8. I ask myself how well I accomplish my goals once I'm finished. 9. I ask myself if I have considered all options after I solve a problem. 10. I change strategies when I fail to understand. 11. I reevaluate my assumptions when I get confused. 12. I ask myself questions about how well I am doing while I am learning something new. 13. I ask myself if I learned as much as I could have once I finish a task.	E_6_1
Attributions: Locus of Control (pre-test/post-test)	Individuals ascribe causality based on internal factors (e.g., ability, effort) and external factors (e.g., luck, task difficulty), and whether those factors are controllable and stable (Weiner, 1985)	1. I often feel overwhelmed by my responsibilities. 2. The demands of everyday life often get me down. 3. I do not enjoy being in new situations that require me to change my old familiar ways of doing things.	EM5R EM2R PG5R
Academic Integration (PCC post-test)	Outcomes from classroom successes/failures as well as outcomes from psychological processes: coping, locus of control, and self-efficacy (Bean & Eaton, 2001)	1. I feel comfortable contributing to class discussions. 2. I feel comfortable asking a question in class. 3. I feel comfortable volunteering ideas or opinions in class. 4. Speaking in class is easy because I feel comfortable.	PCC1 PCC2 PCC3 PCC4
Academic Integration (PFS post-test)	Outcomes from classroom successes/failures as well as outcomes from psychological processes: coping, locus of control, and self-efficacy (Bean & Eaton, 2001)	1. I feel comfortable socializing with a faculty member outside of class. 2. I feel that a faculty member would be sympathetic if I was upset. 3. I feel that a faculty member would take the time to talk to me if I needed help.	PFS4 PFS5 PFS6 PFS7 PFS9 PFS10

Latent Variable	Operational Definition	Variable Indicators	Question Code
		4. If I had a reason, I would feel comfortable seeking help from a faculty member outside of class time (office hours etc.). 5. I feel that a faculty member really tried to understand my problem when I talked about it. 6. I feel comfortable asking a teacher for help with a personal problem.	
Social Integration (PI post-test)	Social integration in terms of perceived isolation (lack of social support) (Bean & Eaton, 2001; Tinto, 1975)	1. It is difficult to meet other students in class. 2. No one in my classes knows anything personal about me. 3. I rarely talk to other students in my class. 4. I know very few people in my class.	PI1R PI2R PI3R PI4R
Social Integration (PPS post-test)	Social integration in terms of perceived peer support (social support) (Bean & Eaton, 2001; Tinto, 1975)	1. I have met with classmates outside of class to study for an exam. 2. If I miss class, I know students who I could get notes from. 3. I discuss events which happened outside of class with my classmates. 4. I have discussed personal matters with students who I met in class. 5. I could contact another student from class if I had a question. 6. Other students are helpful in reminding me when assignments are due or when tests are approaching. 7. I have developed personal relationships with other students in class. 8. I invite people I know from class to do things socially.	PPS1 PPS2 PPS3 PPS4 PPS5 PPS6 PPS7 PPS8
Institutional Fit	A sense of student fitting into the institution as a result of	1. I can explain the value of an academic degree.	TGLQ2 TGLQ3

Latent Variable	Operational Definition	Variable Indicators	Question Code
	psychological responses and academic and social integration (Bean & Eaton)	2. I can explain how an academic degree supports my family or community. 3. I can explain how an academic degree supports my personal life vision.	TGLQ4

Table B3

Fall 2020 SEM: Latent Variables and Item Indicators

Latent Variable	Operational Definition	Variable Indicators	Question Code
Past Behavior	Past behaviors, academic and social experiences that are responsible for preparing a student to succeed in college (Bean & Eaton, 2001)	1. In general, I feel I am in charge of the situation in which I live. 2. When I look at the story of my life, I am pleased with how things have turned out. 3. In general, I feel confident and positive about myself. 4. My daily activities often seem trivial and unimportant to me. 5. I feel like many of the people I know have gotten more out of life than I have. 6. I like most aspects of my personality. 7. In many ways, I feel disappointed about my achievements in life. 8. I have been able to build a home and a lifestyle for myself that is much to my liking.	EM1 SA1 SA2 PL3R SA3R SA4 SA5R EM7
Normative Beliefs	Self-determination, independence when faced with perspectives of others (Ryff 1989; Bean & Eaton, 2001)	1. I am not afraid to voice my opinions, even when they are in opposition to the opinions of most people. 2. My decisions are not usually influenced by what everyone else is doing. 3. I have confidence in my opinions, even if they are contrary to the general consensus. 4. I judge myself by what I think is important, not by the values of what others think is important.	A1 A2 A5 A7
Coping Strategies	Regulation of cognition (planning) as a form of coping strategy in the face of stressors (Schraw &	1. I pace myself while learning in order to have enough time.	P_1_1 P_2_1 P_3_1

Latent Variable	Operational Definition	Variable Indicators	Question Code
	Dennison, 1994; Bean & Eaton, 2001)	2. I think about what I really need to learn before I begin a task. 3. I set specific goals before I begin a task. 4. I ask myself questions about the material before I begin. 5. I think of several ways to solve a problem and choose the best one. 6. I read instructions carefully before I begin a task. 7. I organize my time to best accomplish my goals.	P_4_1 P_5_1 P_6_1 P_7_1
Motivation to Attend	Motivational factors influence intention, and ultimately behavior (Ajzen, 1991)	1. I think it is important to have new experiences that challenge how you think about yourself and the world. 2. I enjoy personal and mutual conversations with family members or friends. 3. People would describe me as a giving person, willing to share my time with others. 4. For me, life has been a continuous process of learning, changing and growth.	PG2 PR4 PR5 PG6
Academic Interactions (PFS pre-test)	Interactions with faculty members (Bean & Eaton, 2001; Hoffman et al., 2002)	1. I feel comfortable talking about a problem with faculty. 2. I feel that a faculty member would be sensitive to my difficulties if I shared them. 3. I feel comfortable socializing with a faculty member outside of class. 4. I feel that a faculty member would be sympathetic if I was upset. 5. I feel that a faculty member would take the time to talk to me if I needed help. 6. If I had a reason, I would feel comfortable seeking help from a faculty member outside of class time (office hours etc.).	PFS1 PFS3 PFS4 PFS5 PFS6 PFS7 PFS8 PFS9

Latent Variable	Operational Definition	Variable Indicators	Question Code
		7. I feel comfortable seeking help from a teacher before or after class. 8. I feel that a faculty member really tried to understand my problem when I talked about it.	
Academic Interactions (PCC pre-test)	Interactions within the classroom (Bean & Eaton, 2001 Hoffman et al., 2002)	1. I feel comfortable contributing to class discussions. 2. I feel comfortable asking a question in class. 3. I feel comfortable volunteering ideas or opinions in class. 4. Speaking in class is easy because I feel comfortable.	PCC1 PCC2 PCC3 PCC4
Social Interactions	Reactions to social interactions based on prior experiences and strategies chosen to navigate new environment (Bean & Eaton, 2001)	1. I do not fit very well with the people and the community around me. 2. Maintaining close relationships has been difficult and frustrating for me. 3. I have not experienced many warm and trusting relationships with others.	EM3R PR2R PR6R
Self-efficacy Assessments (pre-test/post-test)	Student perception of abilities to carry out academic tasks (Bean & Eaton, 2001)	1. I know how well I did once I finish a test. 2. I know what kind of information is most important to learn. 3. I am good at organizing information. 4. I have a specific purpose for each strategy I use. 5. I know what the teacher expects me to learn. 6. I am good at remembering information. 7. I have control over how well I learn. 8. I can motivate myself to learn when I need to. 9. I am aware of what strategies I use when I study. 10. I use my intellectual strengths to compensate for my weaknesses. 11. I find myself using helpful learning strategies automatically.	E_1_1 DK_2_1 DK_3_1 PK_2_1 DK_4_1 DK_5_1 DK_6_1 CK_3_1 PK_3_1 CK_4_1 PK_4_1 CK_5_1 DS_4_1 DK_1_1

Latent Variable	Operational Definition	Variable Indicators	Question Code
		12. I know when each strategy I use will be most effective. 13. I stop and go back over new information that is not clear. 14. I understand my intellectual strengths and weaknesses.	
Coping Process (Approach/Avoidance) (pre-test/post-test)	The knowledge of how to link academic adjustment strategies and regulate cognition to adapt is a type of metacognitive awareness. Bean and Eaton (2001) view academic integration as a type of adaptation	1. I ask myself periodically if I am meeting my goals. 2. I consider several alternatives to a problem before I answer. 3. I ask myself if I have considered all options when solving a problem. 4. I ask myself if there was an easier way to do things after I finish a task. 5. I periodically review to help me understand important relationships. 6. I summarize what I've learned after I finish. 7. I find myself analyzing the usefulness of strategies while I study. 8. I find myself pausing regularly to check my comprehension. 9. I ask myself how well I accomplish my goals once I'm finished. 10. I ask myself if I have considered all options after I solve a problem. 11. I ask myself questions about how well I am doing while I am learning something new. 12. I ask myself if I learned as much as I could have once I finish a task.	CM_1_1 CM_2_1 CM_3_1 E_2_1 CM_4_1 E_3_1 CM_5_1 CM_6_1 E_4_1 E_5_1 CM_7_1 E_6_1

Latent Variable	Operational Definition	Variable Indicators	Question Code
Attributions: Locus of Control (pre-test/post-test)	Individuals ascribe causality based on internal factors (e.g., ability, effort) and external factors (e.g., luck, task difficulty), and whether those factors are controllable and stable (Weiner, 1985)	1. I often feel overwhelmed by my responsibilities. 2. I do not enjoy being in new situations that require me to change my old familiar ways of doing things.	EM5R PG5R
Academic Integration (PCC post-test)	Outcomes from classroom successes/failures as well as outcomes from psychological processes: coping, locus of control, and self-efficacy (Bean & Eaton, 2001)	1. I feel comfortable contributing to class discussions. 2. I feel comfortable asking a question in class. 3. I feel comfortable volunteering ideas or opinions in class. 4. Speaking in class is easy because I feel comfortable.	PCC1 PCC2 PCC3 PCC4
Academic Integration (PFS post-test)	Outcomes from classroom successes/failures as well as outcomes from psychological processes: coping, locus of control, and self-efficacy (Bean & Eaton, 2001)	1. I feel comfortable talking about a problem with faculty. 2. I feel that a faculty member would be sensitive to my difficulties if I shared them. 3. I feel comfortable socializing with a faculty member outside of class. 4. I feel that a faculty member would be sympathetic if I was upset. 5. I feel that a faculty member would take the time to talk to me if I needed help. 6. If I had a reason, I would feel comfortable seeking help from a faculty member outside of class time (office hours etc.). 7. I feel comfortable seeking help from a teacher before or after class. 8. I feel that a faculty member really tried to understand my problem when I talked about it.	PFS1 PFS3 PFS4 PFS5 PFS6 PFS7 PFS8 PFS9

Latent Variable	Operational Definition	Variable Indicators	Question Code
Social Integration (PPS post-test) and (PI post-test)	Social integration in terms of perceived peer support (social support) (Bean & Eaton, 2001; Tinto, 1975) and social integration in terms of perceived isolation (lack of social support) (Bean & Eaton, 2001; Tinto, 1975)	1. I have met with classmates outside of class to study for an exam. 2. If I miss class, I know students who I could get notes from. 3. I discuss events which happened outside of class with my classmates. 4. I have discussed personal matters with students who I met in class. 5. I could contact another student from class if I had a question. 6. Other students are helpful in reminding me when assignments are due or when tests are approaching. 7. I have developed personal relationships with other students in class. 8. I invite people I know from class to do things socially. 9. No one in my classes knows anything personal about me. 10. I rarely talk to other students in my class.	PPS1 PPS2 PPS3 PPS4 PPS5 PPS6 PPS7 PPS8 PI2R PI3R
Institutional Fit	A sense of student fitting into the institution as a result of psychological responses and academic and social integration (Bean & Eaton)	1. I can explain the value of an academic degree. 2. I can explain how an academic degree supports my family or community. 3. I can explain how an academic degree supports my personal life vision.	TGLQ2 TGLQ3 TGLQ4

Appendix C

EFA Pattern Matrices

Table C1

EFA Pattern Matrix PWB Pre-test Fall 2018

	Factors					
	α =.80	α =.76	α =.69	α =.60	α =.70	α =.58
Pre_SA5R	0.86					
Pre_PL3R	0.78					
Pre_EM6R	0.76					
Pre_SA1	0.52					
Pre_EM7	0.37					
Pre_A6R		0.76				
Pre_A1		0.73				
Pre_A5		0.65				
Pre_A4R		0.60				
Pre_A2		0.56				
Pre_PL7R			0.88			
Pre_PG1R			0.68			
Pre_PG7R			0.48			
Pre_PG6						
Pre_PR1				0.67		
Pre_EM4	0.42			0.57		
Pre_EM1				0.50		
Pre_PG4						
Pre_SA2					0.71	
Pre_SA6R	0.41				0.57	
Pre_SA7					0.51	
Pre_PR3R					0.32	0.57
Pre_EM5R						0.34
Pre_A7		0.32				-0.34
Pre_EM3R						0.31

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.[a]

Table C2

EFA Pattern Matrix PWB Post-test Fall 2018

	Factor					
	α =.82	α =.79	α =.78	α =.68	α =.70	α = .58
POST_SA1	0.717					
POST_PL2	0.675					
POST_EM1	0.629					
POST_PL6	0.610					
POST_PG4	0.399					
POST_EM7	0.398					
POST_PL5	0.380					
POST_EM6R		0.894				
POST_SA5R		0.665				
POST_PR6R		0.584				
POST_PR7		0.560				
POST_PG3R		0.528				
POST_A3R			0.734			0.561
POST_EM5R			0.686			
POST_EM2R			0.464			
POST_SA6R			0.434			
POST_PL3R			0.328			
POST_PR1				0.820		
POST_PR5				0.741		
POST_SA4				0.368		
POST_PL7R					0.911	
POST_PG1R					0.636	
POST_PG6					0.499	
POST_A2						0.661
POST_A7						0.559
POST_A5						0.404
POST_A1						

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

Table C3

MAI Rotated Component Matrix Pre-test Fall 2018

	Component	
	α =.81	α =.76
Pre_CM_7_1	0.740	
Pre_E_6_1	0.598	
Pre_E_4_1	0.577	
Pre_P_4_1	0.513	
Pre_P_3_1	0.509	
Pre_E_5_1	0.456	
Pre_CM_5_1	0.449	
Pre_PK_3_1	0.432	
Pre_CM_6_1	0.419	
Pre_P_2_1	0.397	
Pre_CM_2_1	0.394	
Pre_CK_2_1	0.392	
Pre_E_3_1	0.378	
Pre_CM_1_1	0.368	
Pre_P_5_1	0.340	
Pre_E_2_1	0.311	
Pre_P_6_1	0.301	
Pre_DS_5_1		
Pre_E_1_1		
Pre_CK_1_1		
Pre_CK_4_1		0.561
Pre_DK_6_1		0.519
Pre_P_1_1	0.384	0.502
Pre_DK_3_1		0.482
Pre_PK_4_1		0.481
Pre_P_7_1		0.458
Pre_DS_3_1		0.425
Pre_DK_5_1		0.423
Pre_DK_2_1		0.409
Pre_DS_4_1		0.405

Pre_CM_4_1		0.396
Pre_CM_3_1	0.315	0.384
Pre_CK_5_1	0.303	0.383
Pre_PK_2_1		0.328
Pre_DK_8_1		0.321
Pre_DK_7_1		0.307
Pre_DK_1_1		0.307
Pre_DS_2_1		
Pre_CK_3_1		
Pre_DK_4_1		
Pre_DS_1_1		
Pre_PK_1_1		

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

Table C4

MAI Rotated Component Matrix Post-test Fall 2018

	Component	
	α =.83	α =.74
POST_E_5_1	0.614	
POST_P_2_1	0.584	
POST_P_4_1	0.574	
POST_E_6_1	0.544	
POST_CM_3_1	0.520	0.373
POST_CM_5_1	0.513	
POST_P_7_1	0.512	
POST_PK_2_1	0.484	
POST_P_3_1	0.479	
POST_CK_5_1	0.478	
POST_PK_3_1	0.462	
POST_CM_6_1	0.444	
POST_E_3_1	0.428	
POST_P_5_1	0.423	
POST_E_4_1	0.414	
POST_CM_4_1	0.409	
POST_CM_7_1	0.394	0.335
POST_P_1_1	0.377	
POST_CM_2_1	0.358	
POST_E_2_1	0.305	
POST_DS_5_1		
POST_CK_2_1		
POST_DK_8_1		
POST_DK_7_1		0.666
POST_DK_2_1		0.534
POST_CK_4_1		0.503
POST_E_1_1		0.492
POST_CK_3_1		0.465
POST_DK_3_1		0.461

POST_DK_6_1	0.459
POST_CM_1_1	0.458
POST_DK_1_1	0.402
POST_PK_1_1	0.389
POST_DS_3_1	0.343
POST_DK_4_1	0.304
POST_P_6_1	
POST_PK_4_1	
POST_DS_2_1	
POST_DK_5_1	
POST_DS_4_1	
POST_DS_1_1	
POST_CK_1_1	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.[a]

Table C5

EFA Pattern Matrix SOB Pre-test Fall 2018

	Factor					
	α =.87	α =.90	α =.87	α =.84	α =.83	α =.80
Pre_PFS1	0.925					
Pre_PFS7	0.741					
Pre_PFS8	0.738					
Pre_PFS4	0.670					
Pre_PFS10	0.580					
Pre_PCC3		0.991				
Pre_PCC1		0.907				
Pre_PCC4		0.739				
Pre_PCC2		0.567				
Pre_PI1R			0.864			
Pre_PI3R			0.821			
Pre_PI4R			0.679			
Pre_PI2R			0.678			
Pre_PPS8				0.794		
Pre_PPS7				0.641		
Pre_PPS4				0.624		
Pre_PPS6				0.620		
Pre_PFS5					0.851	
Pre_PFS3					0.838	
Pre_PFS9					0.674	
Pre_PFS6					0.497	
Pre_PPS1						0.889
Pre_PPS2						0.659
Pre_PPS3						0.592

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

Table C6

EFA Pattern Matrix SOB Post-test Fall 2018

	Factor				
	α =.89	α =.85	α =.93	α =.90	α =.85
POST_PFS1	0.958				
POST_PFS4	0.743				
POST_PFS8	0.718				
POST_PFS2	0.654				
POST_PFS10	0.623				
POST_PFS7	0.614				
POST_PI4R		0.933			
POST_PI3R		0.848			
POST_PI2R		0.702			
POST_PI1R		0.645			
POST_PPS5		0.406			
POST_PCC1			0.959		
POST_PCC3			0.871		
POST_PCC2			0.812		
POST_PCC4			0.741		
POST_PFS5				0.943	
POST_PFS3				0.809	
POST_PFS6				0.702	
POST_PFS9				0.622	
POST_PPS3					0.818
POST_PPS1					0.807
POST_PPS2					0.703

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.

Table C7

EFA Pattern Matrix TGLQ Pre-test Fall 2018

	Factor		
	α =.83	α =.84	α =.79
Pre_TGLQ10	0.883		
Pre_TGLQ11	0.875		
Pre_TGLQ9	0.594		
Pre_TGLQ12	0.574		
Pre_TGLQ1	0.524		
Pre_TGLQ8	0.449		
PRE_TGLQ17		0.940	
Pre_TGLQ6		0.918	
PRE_TGLQ16		0.520	
PRE_TGLQ15		0.443	
Pre_TGLQ4			0.881
Pre_TGLQ3			0.700
Pre_TGLQ2			0.676

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.[a]
a. Rotation converged in 4 iterations.

Table C8

EFA Pattern Matrix TGLQ Post-test Fall 2018

	Factor	
	α =.88	α =.84
POST_TGLQ3	0.956	
POST_TGLQ2	0.829	
POST_TGLQ4	0.780	
POST_TGLQ17	0.612	
POST_TGLQ6	0.594	
POST_TGLQ1	0.450	
POST_TGLQ11		0.892
POST_TGLQ10		0.818
POST_TGLQ12		0.641

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.[a]
a. Rotation converged in 3 iterations.

Table C9

EFA Pattern Matrix PWB Pre-test Fall 2019

	Factor					
	α =.86	α =.85	α =.72	α =.48	α =.60	α =.66
Pre_PR3R	0.762					
Pre_PR2R	0.727					
Pre_PR6R	0.692					
Pre_EM3R	0.654					
Pre_SA3R	0.484					
Pre_PL3R	0.409					
Pre_SA5R	0.340					
Pre_PL2		0.721		0.317		
Pre_SA2		0.692				
Pre_SA7		0.612				
Pre_SA1		0.558				
Pre_EM7		0.556				
Pre_PL6		0.545		0.383		
Pre_SA4		0.511				
Pre_EM4		0.470				
Pre_EM1		0.446				
Pre_PG2			0.675			
Pre_PR5			0.621			
Pre_PR1			0.587			
Pre_PR4			0.577			
Pre_PG6			0.438			
Pre_PG1R			0.382			
Pre_PL4R				0.533		
Pre_PL1R				0.490		
Pre_PG7R				0.382		
Pre_PL7R						
Pre_A4R					0.545	
Pre_A2					0.533	
Pre_A3R					0.531	
Pre_A7					0.301	
Pre_EM2R						0.601
Pre_EM5R						0.562

Pre_PG5R	0.346

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 11 iterations.

Table C10

EFA Pattern Matrix PWB Post-test Fall 2019

	Factor					
	α =.87	α =.85	α =.61	α =.67	α =.59	
POST_PR3R	0.812					
POST_EM3R	0.784					
POST_PR2R	0.770					
POST_SA3R	0.629					
POST_PR6R	0.625					
POST_PL3R	0.603					
POST_EM2R	0.531					
POST_SA5R	0.478					
POST_PG5R	0.325					
POST_PL2		0.899				
POST_PL6		0.700				
POST_SA2		0.632				
POST_EM4		0.589				
POST_PL5		0.551				
POST_PL4R		0.533				
POST_SA1		0.457				
POST_EM1		0.379				
POST_PL7R			0.540			
POST_PG7R			0.513			
POST_PL1R			0.457			
POST_PG1R			0.427			
POST_PR5				0.706		
POST_PR1				0.705		
POST_A5					0.601	
POST_A2					0.572	
POST_A4R					0.550	
POST_A7					0.430	
POST_PR7						0.614

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Table C11

MAI Rotated Component Matrix Pre-test Fall 2019

	Component	
	α =.79	α =.78
Pre_DK_2_1	0.577	
Pre_CK_3_1	0.568	
Pre_PK_3_1	0.558	
Pre_DK_3_1	0.553	
Pre_CK_5_1	0.544	
Pre_PK_4_1	0.540	
Pre_DK_7_1	0.510	
Pre_P_7_1	0.455	
Pre_CK_4_1	0.441	
Pre_DK_1_1	0.433	
Pre_DK_6_1	0.431	
Pre_PK_2_1	0.427	
Pre_DK_5_1	0.400	
Pre_P_1_1	0.394	
Pre_DK_4_1	0.392	
Pre_E_1_1		
Pre_DS_4_1		
Pre_P_6_1		
Pre_DS_5_1		
Pre_DS_1_1		
Pre_CK_1_1		
Pre_DK_8_1		
Pre_E_5_1		0.627
Pre_E_6_1		0.590
Pre_P_5_1		0.559
Pre_E_4_1		0.551
Pre_CM_7_1		0.539
Pre_CM_3_1		0.511
Pre_CM_2_1		0.484
Pre_P_2_1		0.459
Pre_P_4_1		0.454
Pre_E_3_1		0.411

Pre_CM_5_1	0.402
Pre_CM_4_1	0.390
Pre_DS_3_1	0.376
Pre_P_3_1	0.352
Pre_DS_2_1	0.346
Pre_E_2_1	0.330
Pre_CM_6_1	0.316
Pre_CM_1_1	
Pre_CK_2_1	
Pre_PK_1_1	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Table C12

MAI Rotated Component Matrix Post-test Fall 2019

	Component	
	α =.80	α =.76
POST_CM_7_1	0.653	
POST_E_6_1	0.605	
POST_E_4_1	0.567	
POST_P_4_1	0.549	
POST_CM_4_1	0.518	
POST_P_2_1	0.504	
POST_CM_5_1	0.483	
POST_E_5_1	0.478	
POST_E_3_1	0.436	
POST_P_7_1	0.404	
POST_P_3_1	0.400	
POST_CK_5_1	0.398	0.305
POST_CM_6_1	0.385	
POST_P_5_1	0.371	
POST_CM_1_1	0.358	
POST_E_2_1	0.344	
POST_CM_3_1	0.337	
POST_P_1_1		
POST_DS_2_1		
POST_E_1_1		
POST_DK_7_1		0.531
POST_CK_3_1		0.530
POST_DK_6_1		0.491
POST_DK_3_1		0.484
POST_PK_4_1		0.472
POST_DK_8_1		0.459
POST_DS_5_1		0.447
POST_DK_1_1		0.444
POST_CK_4_1		0.426
POST_PK_3_1		0.408
POST_CK_1_1		0.406
POST_PK_1_1		0.406
POST_PK_2_1	0.302	0.392
POST_DK_5_1		0.371

POST_DS_4_1			0.370
POST_DK_2_1			0.338
POST_CM_2_1		0.315	0.316
POST_CK_2_1			
POST_DS_1_1			
POST_DS_3_1			
POST_DK_4_1			
POST_P_6_1			

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Table C13

EFA Pattern Matrix SOB Pre-test Fall 2019

	Factor			
	α =.90	α =.94	α =.90	α =.83
Pre_PPS5	0.799			
Pre_PPS7	0.782			
Pre_PPS3	0.722			
Pre_PPS6	0.680			
Pre_PPS8	0.680			
Pre_PPS4	0.665			
Pre_PPS2	0.660			
Pre_PPS1	0.501			
Pre_PCC3		0.917		
Pre_PCC2		0.864		
Pre_PCC1		0.851		
Pre_PCC4		0.820		
Pre_PFS6			0.745	
Pre_PFS5			0.733	
Pre_PFS7			0.640	
Pre_PFS9			0.622	
Pre_PFS10			0.611	
Pre_PFS4			0.609	
Pre_PFS3			0.428	
Pre_PFS2			0.319	
Pre_PI3R				0.736
Pre_PI1R				0.671
Pre_PI4R				0.662
Pre_PI2R				0.566

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Table C14

EFA Pattern Matrix SOB Post-test Fall 2019

	Factor			
	α =.90	α =.90	α =.94	α =.83
POST_PFS6	0.860			
POST_PFS5	0.805			
POST_PFS7	0.766			
POST_PFS9	0.735			
POST_PFS8	0.718			
POST_PFS10	0.660			
POST_PFS4	0.608			
POST_PFS3	0.606			
POST_PFS1	0.572			
POST_PFS2	0.513			
POST_PPS7		0.821		
POST_PPS3		0.776		
POST_PPS2		0.747		
POST_PPS5		0.745		
POST_PPS6		0.727		
POST_PPS8		0.680		
POST_PPS4		0.677		
POST_PPS1		0.672		
POST_PCC3			0.912	
POST_PCC1			0.889	
POST_PCC2			0.878	
POST_PCC4			0.852	
POST_PI3R				0.872
POST_PI1R				0.645
POST_PI2R				0.617
POST_PI4R				0.524

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Table C15

EFA Pattern Matrix TGLQ Pre-test Fall 2019

	Factor			
	α =.80	α =.82	α =.85	α =.80
Pre_TGLQ10	0.903			
Pre_TGLQ12	0.738			
Pre_TGLQ11	0.707			
Pre_TGLQ1	0.451			
Pre_TGLQ9	0.396			
Pre_TGLQ6		0.995		
Pre_TGLQ7		0.857		
Pre_TGLQ5		0.457		
Pre_TGLQ3			0.927	
Pre_TGLQ2			0.842	
Pre_TGLQ4			0.591	0.341
Pre_TGLQ14				0.805
Pre_TGLQ13				0.804
Pre_TGLQ8				0.625

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table C16

EFA Pattern Matrix TGLQ Scales Post-test Fall 2019

	Factor		
	α =.81	α =.85	α =.78
POST_TGLQ12	0.766		
POST_TGLQ11	0.708		
POST_TGLQ7	0.613		
POST_TGLQ5	0.577		
POST_TGLQ9	0.531		
POST_TGLQ1	0.445		
POST_TGLQ3		0.894	
POST_TGLQ2		0.777	
POST_TGLQ4		0.748	
POST_TGLQ13			0.903
POST_TGLQ14			0.541
POST_TGLQ8	0.345		0.520

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table C17

EFA Pattern Matrix PWB Pre-test Fall 2020

	Factor					
	α =.87	α =.79	α =.71	α =.65	α =.71	α =.50
Pre_SA2	0.917					
Pre_SA6R	0.764					
Pre_EM7	0.689					
Pre_SA1	0.570					
Pre_SA7	0.547					
Pre_SA4	0.481					
Pre_PL3R	0.433					
Pre_SA5R	0.403					
Pre_EM1	0.384					
Pre_SA3R	0.367					
Pre_PG3R						
Pre_PL6		0.714				
Pre_PL1R		0.639				
Pre_PL4R		0.615				
Pre_PL2		0.596				
Pre_PL5		0.578				
Pre_EM4		0.382				
Pre_PG2			0.847			
Pre_PG6			0.692			
Pre_PR4			0.581			
Pre_PR5			0.453			
Pre_PL7R			0.411			
Pre_A1				0.651		
Pre_A5				0.581		
Pre_A2				0.419		
Pre_A7				0.390		
Pre_A4R				0.333		
Pre_PR2R					0.724	
Pre_PR6R					0.684	
Pre_EM3R					0.423	
Pre_PG5R						0.616
Pre_EM5R						0.365

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 8 iterations.

Table C18

EFA Pattern Matrix PWB Post-test Fall 2020

	Factor					
	α =.87	α =.86	α =.78	α =.72	α =.66	
POST_EM7	0.757					
POST_PL2	0.719					
POST_SA1	0.650					
POST_PL5	0.631					
POST_SA2	0.626					
POST_SA7	0.617					
POST_EM1	0.590					
POST_EM4	0.570					
POST_PL6	0.554					
POST_PR3R		0.918				
POST_PR2R		0.752				
POST_PR6R		0.651				
POST_EM3R		0.580				
POST_SA3R		0.502				
POST_SA5R		0.497				
POST_PL3R		0.470				
POST_PG6			0.806			
POST_PG2			0.792			
POST_PG1R	-0.309		0.620			
POST_PL7R			0.436			
POST_PG7R			0.419			
POST_PG3R			0.390			
POST_PG5R						
POST_A6R				0.747		
POST_A5				0.617		
POST_A1				0.602		
POST_A2				0.337		
POST_A4R				0.336		
POST_A7				0.303		
POST_PR1					0.722	
POST_PR5					0.561	
POST_PL1R						0.672

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 8 iterations.

Table C19

MAI Rotated Component Matrix Pre-test Fall 2020

	Component	
	α =.75	α =.73
Pre_E_6_1	0.578	
Pre_E_4_1	0.566	
Pre_P_2_1	0.544	
Pre_CM_5_1	0.495	
Pre_CM_7_1	0.492	
Pre_E_5_1	0.481	
Pre_P_4_1	0.453	
Pre_P_1_1	0.398	
Pre_CM_3_1	0.370	
Pre_CM_1_1	0.366	
Pre_E_3_1	0.364	
Pre_CM_4_1	0.362	
Pre_CM_6_1	0.359	
Pre_P_7_1	0.349	
Pre_P_5_1	0.346	
Pre_E_2_1	0.333	
Pre_CM_2_1	0.321	
Pre_P_3_1		
Pre_DS_3_1		
Pre_CK_2_1		
Pre_DS_2_1		
Pre_P_6_1		
Pre_CK_1_1		
Pre_DK_8_1		
Pre_CK_4_1		0.526
Pre_DK_5_1		0.520
Pre_DK_6_1		0.502
Pre_CK_3_1		0.494
Pre_PK_2_1		0.479
Pre_PK_4_1		0.473
Pre_CK_5_1		0.465
Pre_DK_3_1		0.463
Pre_DK_1_1		0.460
Pre_DS_4_1		0.417

Pre_PK_3_1	0.406
Pre_DK_2_1	0.379
Pre_DK_4_1	0.354
Pre_E_1_1	0.324
Pre_DS_1_1	
Pre_DK_7_1	
Pre_PK_1_1	
Pre_DS_5_1	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Table C20

MAI Rotated Component Matrix Post-test Fall 2020

	Component	
	α =.84	α =.81
POST_CM_7_1	0.673	
POST_E_4_1	0.628	
POST_E_2_1	0.591	
POST_E_6_1	0.574	
POST_P_4_1	0.572	
POST_E_5_1	0.557	
POST_CM_5_1	0.531	
POST_E_3_1	0.525	
POST_CM_3_1	0.522	
POST_P_2_1	0.488	0.314
POST_P_5_1	0.483	
POST_CM_6_1	0.466	
POST_CM_4_1	0.418	0.308
POST_CM_1_1	0.363	0.333
POST_CM_2_1	0.363	
POST_DS_3_1	0.309	
POST_DS_2_1	0.304	
POST_DS_4_1	0.300	
POST_PK_1_1		
POST_CK_1_1		
POST_DS_5_1		
POST_DS_1_1		
POST_DK_3_1		0.576
POST_P_1_1		0.561
POST_DK_6_1		0.544
POST_DK_5_1		0.533
POST_CK_3_1		0.532
POST_PK_4_1		0.517
POST_P_7_1		0.516
POST_PK_2_1		0.483
POST_CK_4_1		0.473
POST_CK_5_1		0.458
POST_DK_2_1		0.444
POST_PK_3_1		0.438

POST_DK_4_1	0.405
POST_DK_1_1	0.356
POST_DK_7_1	0.344
POST_P_3_1	0.332
POST_CK_2_1	0.329
POST_E_1_1	
POST_DK_8_1	
POST_P_6_1	

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.

Table C21

EFA Pattern Matrix SOB Pre-test Fall 2020

	Factor		
	α =.91	α =.84	α =.92
Pre_PPS7	0.849		
Pre_PPS3	0.806		
Pre_PPS4	0.803		
Pre_PPS8	0.746		
Pre_PPS5	0.745		
Pre_PPS2	0.726		
Pre_PI2R	0.724		
Pre_PI3R	0.644		
Pre_PPS6	0.569		
Pre_PPS1	0.529		
Pre_PFS6		0.817	
Pre_PFS9		0.734	
Pre_PFS7		0.727	
Pre_PFS5		0.670	
Pre_PFS8		0.656	
Pre_PFS1		0.558	
Pre_PFS4		0.466	
Pre_PFS3		0.373	
Pre_PCC3			0.896
Pre_PCC1			0.892
Pre_PCC4			0.866
Pre_PCC2			0.744

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table C22

EFA Pattern Matrix SOB Post-test Fall 2020

	Factor			
	α =.90	α =.88	α =.93	α =.83
POST_PI2R	0.829			
POST_PI4R	0.828			
POST_PI3R	0.816			
POST_PI1R	0.717			
POST_PPS7	0.635			
POST_PPS8	0.576			
POST_PPS4	0.547			
POST_PFS6		0.912		
POST_PFS5		0.881		
POST_PFS9		0.759		
POST_PFS7		0.707		
POST_PFS3		0.696		
POST_PFS8		0.573		
POST_PFS1		0.455		
POST_PFS4		0.447		
POST_PCC3			0.956	
POST_PCC1			0.906	
POST_PCC4			0.854	
POST_PCC2			0.822	
POST_PPS5				0.775
POST_PPS6				0.711
POST_PPS2				0.648

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 6 iterations.

Table C23

TGLQ Pattern Matrix PWB Scales Pre-test Fall 2020

	Factor			
	1	2	3	4
Pre_TGLQ2	0.848			
Pre_TGLQ3	0.846			
Pre_TGLQ4	0.733			
Pre_TGLQ10		0.949		
Pre_TGLQ12		0.668		
Pre_TGLQ11		0.545		
Pre_TGLQ1		0.405		
Pre_TGLQ13			0.935	
Pre_TGLQ14			0.726	
Pre_TGLQ8			0.618	
Pre_TGLQ7				0.825
Pre_TGLQ9				0.338
Pre_TGLQ5				0.320

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Table C24

TGLQ Pattern Matrix PWB Scales Post-test Fall 2020

	Factor		
	1	2	3
POST_TGLQ3	0.949		
POST_TGLQ2	0.890		
POST_TGLQ4	0.764		
POST_TGLQ5	0.362		
POST_TGLQ10		0.832	
POST_TGLQ12		0.690	
POST_TGLQ11		0.639	
POST_TGLQ9		0.492	
POST_TGLQ1		0.489	
POST_TGLQ7		0.366	
POST_TGLQ13			0.959
POST_TGLQ14			0.698
POST_TGLQ8			0.654

Extraction Method: Principal Axis Factoring.
Rotation Method: Promax with Kaiser Normalization.
a. Rotation converged in 5 iterations.

Appendix D

Latent Variable Descriptive Statistics and Correlations Between Constructs

Table D1

Fall 2018 SEM: Latent Variable Descriptive Statistics

	Mean	SD	N
PastBehavior	-0.03	0.94	97
CopingStrat	0.71	0.25	97
MotivAttend	-0.02	0.90	97
NormBeliefs	0.01	0.96	97
SocInt	-0.12	1.05	97
AcadInteract18_PFS_t1	-0.03	0.95	97
AcadInteract18_PCC_t1	-0.01	0.98	97
SocInteg18_PPS_t2	-0.26	0.93	97
SocInteg18_PI_t2	-0.24	0.91	97
AcadInt18_PFS_t2	-0.14	0.93	97
AcadInt18_PCC_t2	-0.24	0.98	97
Locus18_t1	0.04	0.78	97
Locus18_t2	0.22	0.76	97
CopingProcess18_t1	0.71	0.23	97
CopingProcess18_t2	0.78	0.21	97
SEAsses18_t1	0.79	0.17	97
SEAsses18_t2	0.82	0.18	97
InstFit18	0.10	1.01	97
QI_19	43.90	10.94	97
SE_19	37.01	12.45	97

Table D2

Fall 2018 SEM: Correlations Between Constructs

	Past Behavior	CopingStrat	MotivAttend	NormBeliefs	SocInt	AcadInteract _PFS_t1	AcadInteract _PCC_t1
PastBehavior	--						
CopingStrat	.249*	--					
MotivAttend	.240*	-0.071	--				
NormBeliefs	.329**	.254*	0.090	--			
SocInt	.469**	0.148	0.004	.261**	--		
AcadInteract_PFS_t1	-.389**	-0.125	-0.007	-.239*	-.358**	--	
AcadInteract_PCC_t1	-.323**	-.246*	-.240*	-.466**	-.281**	.370**	--
SocInteg_PPS_t2	-0.170	-0.084	-0.029	-0.063	-.356**	0.113	.208*
SocInteg_PI_t2	-.332**	-0.050	-0.064	-0.081	-.339**	.217*	0.131
AcadInt_PFS_t2	-.547**	-0.189	-0.178	-.307**	-.281**	.656**	.444**
AcadInt_PCC_t2	-.371**	-.271**	-0.133	-.435**	-.371**	.437**	.726**
Locus_t1	.434**	.215*	.240*	.240*	.302**	-.264**	-.372**
Locus_t2	-.421**	-0.092	-0.072	-.280**	-0.058	0.153	.225*
CopingProcess_t1	0.137	.687**	-0.194	.226*	.203*	-0.110	-.295**
CopingProcess_t2	.207*	.567**	-0.014	0.048	0.034	-0.087	-0.126
SEAsses_t1	.276**	.657**	0.030	.281**	0.148	-0.168	-.297**
SEAsses_t2	.323**	.568**	0.042	0.128	0.134	-0.172	-0.180
InstFit18	0.190	0.161	0.103	.382**	0.023	-0.029	-0.162
QI_19	0.156	.260*	0.114	.263**	0.069	-0.044	-.379**
SE_19	0.169	.265**	-0.008	0.179	0.103	-0.019	-.298**

Table D2 (continued).

	SocInteg_PPS_t2	SocInteg_PI_t2	AcadInt_PFS_t2	AcadInt_PCC_t2	Locus_t1	Locus_t2
PastBehavior						
CopingStrat						
MotivAttend						
NormBeliefs						
SocInt						
AcadInteract_PFS_t1	pp					
AcadInteract_PCC_t1						
SocInteg_PPS_t2	--					
SocInteg_PI_t2	.656**	--				
AcadInt_PFS_t2	.225*	.282**	--			
AcadInt_PCC_t2	.282**	.322**	.577**	--		
Locus_t1	-.383**	-.316**	-.360**	-.400**	--	
Locus_t2	0.176	.381**	.342**	0.159	-.346**	--
CopingProcess_t1	-0.122	-0.086	-0.115	-.331**	.244*	-0.049
CopingProcess_t2	0.028	-0.002	-.229*	-.246*	0.193	-0.134
SEAsses_t1	-0.037	-0.011	-.232*	-.214*	.375**	-.245*
SEAsses_t2	-0.027	-0.093	-.329**	-.208*	.319**	-.376**
InstFit18	-0.082	-0.124	-.254*	-0.185	0.173	-.397**
QI_19	-0.041	-0.050	-0.130	-.290**	.211*	-0.193
SE_19	-0.114	0.021	-0.144	-0.132	0.153	-0.129

Table D2 (continued).

	CopingProcess_t1	CopingProcess_t2	SEAsses_t1	SEAsses_t2	InstFit18	QI_19
PastBehavior						
CopingStrat						
MotivAttend						
NormBeliefs						
SocInt						
AcadInteract_PFS_t1						
AcadInteract_PCC_t1						
SocInteg_PPS_t2						
SocInteg_PI_t2						
AcadInt_PFS_t2						
AcadInt_PCC_t2						
Locus_t1						
Locus_t2						
CopingProcess_t1	--					
CopingProcess_t2	.560**	--				
SEAsses_t1	.526**	.365**	--			
SEAsses_t2	.371**	.623**	.623**	--		
InstFit18	0.124	0.109	0.108	0.152	--	
QI_19	.297**	0.091	.367**	.260*	.256*	--
SE_19	.220*	0.176	.378**	.260**	-0.030	.373**

Table D3

Fall 2019 SEM: Latent Variable Descriptive Statistics

	Mean	SD	N
PastBehavior	-0.07	0.92	357
NormBeliefs	-0.03	0.82	357
MotivAttend	-0.04	0.87	357
CopingStrat	0.67	0.24	357
SocInt	-0.06	0.89	357
Locus19_t1	-0.10	0.82	357
Locus19_t2	0.24	0.84	357
CopingProcess19_t1	0.67	0.22	357
CopingProcess19_t2	0.66	0.24	357
SEAsses19_t1	0.73	0.22	357
SEAsses19_t2	0.85	0.16	357
AcadInteract_PFS19_t1	-0.04	0.91	357
AcadInteract_PCC19_t1	-0.08	0.96	357
SocInteg_PI19_t2	-0.15	0.92	357
SocInteg_PPS19_t2	0.10	0.94	357
AcadInteg_PFS19_t2	0.03	0.94	357
AcadInteg_PCC19_t2	0.12	0.99	357
InstFit19	-0.01	0.91	357

Table D4

Fall 2019 SEM: Correlations Between Constructs

	Past Behavior	NormBeliefs	MotivAttend	CopingStrat	SocInt	Locus_t1	Locus_t2	Coping Process_t1
NormBeliefs	.379**							
MotivAttend	.453**	.218**						
CopingStrat	.231**	.122*	.165**					
SocInt	.419**	0.067	.257**	0.059				
Locus19_t1	.511**	.337**	.321**	.177**	0.075			
Locus19_t2	-.407**	-.297**	-.240**	-0.102	-0.028	-.770**		
CopingProcess_t1	.173**	0.086	0.094	.571**	0.057	0.079	-0.044	
CopingProcess_t2	.159**	0.067	.122*	.394**	.105*	0.021	-0.046	.474**
SEAsses_t1	.452**	.221**	.299**	.431**	.266**	.308**	-.219**	.389**
SEAsses_t2	.298**	.152**	.247**	.280**	.121*	.165**	-.220**	.216**
AcadInteract_PFS_t1	.360**	.178**	.176**	.251**	.213**	.260**	-.235**	.230**
AcadInteract_PCC_t1	.369**	.274**	.198**	.145**	.191**	.241**	-.245**	.186**
SocInteg_PI_t2	.243**	.208**	.248**	0.059	.157**	.216**	-.237**	0.045
SocInteg_PPS_t2	.229**	0.078	.180**	.123*	.221**	.118*	-.156**	0.057
AcadInteg_PFS_t2	.336**	.177**	.200**	.113*	.205**	.267**	-.299**	.109*
AcadInteg_PCC_t2	.349**	.259**	.195**	.150**	.185**	.182**	-.235**	.152**
InstFit19	.320**	0.081	.308**	.109*	.318**	0.097	-0.059	.104*

Table D4 (continued).

	Coping Process _t2	SEAsses _t1	SEAsses _t2	AcadInteract _PFS_t1	AcadInteract _PCC_t1	SocInteg _PI_t2	SocInteg _PPS_t2	AcadInteg _PFS_t2	AcadInteg _PCC_t2
NormBeliefs									
MotivAttend									
CopingStrat									
SocInt									
Locus19_t1									
Locus19_t2									
CopingProcess_t1									
CopingProcess_t2									
SEAsses_t1	.222**								
SEAsses_t2	.461**	.452**							
AcadInteract_PFS_t1	.217**	.274**	.125*						
AcadInteract_PCC_t1	.161**	.275**	.142**	.332**					
SocInteg_PI_t2	.137**	.167**	.181**	.231**	.309**				
SocInteg_PPS_t2	.168**	.172**	.203**	.227**	.291**	.684**			
AcadInteg_PFS_t2	.177**	.188**	.259**	.570**	.256**	.351**	.365**		
AcadInteg_PCC_t2	.185**	.298**	.257**	.280**	.723**	.419**	.400**	.367**	
InstFit19	.183**	.366**	.332**	.116*	0.104	.161**	.185**	.194**	.200**

Table D5

Fall 2020 SEM: Latent Variable Descriptive Statistics

	Mean	SD	N
PastBehavior	0.02	0.89	305
NormBeliefs	-0.03	0.86	305
MotivAttend	-0.01	0.85	305
SocInt	0.03	0.88	305
CopingStrat	0.70	0.24	305
Locus_t1	0.01	0.71	305
Locus_t2	0.11	0.65	305
CopingProcess_t1	0.71	0.22	305
CopingProcess_t2	0.76	0.22	305
SEAsses_t1	0.77	0.20	305
SEAsses_t2	0.81	0.20	305
AcadInteract_PFS_t1	0.03	0.93	305
AcadInteract_PCC_t1	-0.01	0.97	305
AcadInteg_PCC_t2	0.02	0.96	305
AcadInteg_PFS_t2	0.00	0.95	305
SocInteg_t2	-1.07	0.96	305
InstFit20	-0.02	0.94	305

Table D6

Fall 2020 SEM: Correlations Between Constructs

	Past Behavior	Norm Beliefs	Motiv Attend	SocInt	Coping Strat	Locus20_t1	Locus20_t2	Coping Process_t1
NormBeliefs	.407**							
MotivAttend	.522**	.319**						
SocInt	.479**	.217**	.301**					
CopingStrat	.268**	.178**	.143*	.181**				
Locus20_t1	.422**	.190**	.170**	.408**	.293**			
Locus20_t2	-.415**	-.202**	-.186**	-.285**	-.282**	-.661**		
CopingProcess_t1	.240**	.169**	.218**	.159**	.579**	.257**	-.227**	
CopingProcess_t2	.300**	.191**	.255**	.174**	.433**	.228**	-.277**	.518**
SEAsses_t1	.429**	.293**	.219**	.245**	.412**	.295**	-.267**	.446**
SEAsses_t2	.419**	.243**	.200**	.286**	.434**	.273**	-.309**	.346**
AcadInteract_PFS_t1	.482**	.292**	.342**	.237**	.154**	.218**	-.150**	.200**
AcadInteract_PCC_t1	.369**	.490**	.267**	.180**	.204**	.269**	-.162**	.246**
AcadInteg_PCC_t2	.331**	.362**	.253**	.247**	.167**	.224**	-.279**	.125*
AcadInteg_PFS_t2	.377**	.213**	.249**	.235**	.206**	0.093	-.203**	.131*
SocInteg_PI_t2	.153**	0.038	0.103	.212**	.222**	.202**	-.250**	.223**
InstFit20	.346**	.191**	.275**	.283**	.169**	.177**	-.208**	0.105

Table D6 (continued).

Fall 2020 SEM: Correlations Between Constructs

	Coping Process_t2	SEAsses _t1	SEAsses _t2	AcadInteract _PFS_t1	AcadInteract _PCC_t1	AcadInteg _PCC_t2	AcadInteg _PFS_t2	Soc Integ_t2
NormBeliefs								
MotivAttend								
SocInt								
CopingStrat								
Locus20_t1								
Locus20_t2								
CopingProcess_t1								
CopingProcess_t2								
SEAsses_t1	.370**							
SEAsses_t2	.526**	.636**						
AcadInteract_PFS_t1	.185**	.365**	.255**					
AcadInteract_PCC_t1	.251**	.387**	.293**	.348**				
AcadInteg_PCC_t2	.269**	.279**	.397**	.337**	.599**			
AcadInteg_PFS_t2	.187**	.265**	.329**	.516**	.135*	.477**		
SocInteg_PI_t2	.259**	.191**	.300**	.135*	.228**	.390**	.265**	
InstFit20	.285**	.312**	.355**	.284**	.184**	.329**	.398**	0.101

Appendix E

Cohort Bootstrap Analysis of Indirect Effects

Table E1

Fall 2018 Cohort Bootstrap Analysis of Indirect Effects

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → Locus of Control_t1 → AcadInteract_PCC	-0.082†	0.05	-0.173, -0.013
Past Behavior → Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC	-0.082*	0.05	-0.121, -0.009
Past Behavior → Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	-0.082†	0.08	-0.033, 0
Past Behavior → Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	-0.082†	0.07	-0.022, 0
Past Behavior → Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC → Fall3_Enrolled	-0.082†	0.06	0, 0.016
Past Behavior → Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	-0.082*	0.04	-0.039, -0.002
Past Behavior → Locus of Control_t1 → AcadInteract_PCC → Fall3_Enrolled	-0.082*	0.04	-0.026, -0.001
Past Behavior → Locus of Control_t1 → Locus of Control_t2	-0.099	0.10	-0.191, 0
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI	-0.099†	0.07	-0.098, -0.004
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	-0.099†	0.06	-0.064, -0.002

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS	-0.099	0.14	-0.047, 0
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → InstFit18	-0.099*	0.04	0.007, 0.103
Past Behavior → Locus of Control_t1 → SocInteg_PPS	-0.088*	0.02	-0.175, -0.025
Past Behavior → AcadInteract_PFS → AcadInteract_PCC	-0.094*	0.02	-0.201, -0.028
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC	-0.094*	0.02	-0.131, -0.019
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	-0.094†	0.06	-0.038, -0.001
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	-0.094†	0.05	-0.025, -0.001
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → Fall3_Enrolled	-0.094*	0.04	0.001, 0.018
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	-0.094*	0.02	-0.043, -0.004
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → Fall3_Enrolled	-0.094*	0.02	-0.03, -0.002
Past Behavior → AcadInteract_PFS → AcadInteg_PCC	-0.078**	0.01	-0.162, -0.026
Past Behavior → AcadInteract_PFS → AcadInteg_PCC → SocInteg_PI	-0.078†	0.06	-0.047, -0.001
Past Behavior → AcadInteract_PFS → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	-0.078†	0.06	-0.031, -0.001

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → AcadInteract_PFS → AcadInteg_PCC → Fall3_Enrolled	-0.078*	0.04	0.001, 0.02
Past Behavior → AcadInteract_PFS → AcadInteg_PCC → AcadInteg_PFS	-0.078**	0.01	-0.051, -0.006
Past Behavior → AcadInteract_PFS → AcadInteg_PFS	-0.169***	0.00	-0.287, -0.093
Past Behavior → SocInt18_t1 → Locus of Control_t2	0.098†	0.06	0.014, 0.208
Past Behavior → SocInt18_t1 → Locus of Control_t2 → SocInteg_PI	0.098†	0.05	0.005, 0.11
Past Behavior → SocInt18_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	0.098*	0.04	0.005, 0.059
Past Behavior → SocInt18_t1 → Locus of Control_t2 → AcadInteg_PFS	0.098†	0.08	0.001, 0.055
Past Behavior → SocInt18_t1 → Locus of Control_t2 → InstFit18	0.098*	0.05	-0.14, -0.005
Past Behavior → SocInt18_t1 → SocInteg_PI	-0.118*	0.02	-0.222, -0.032
Past Behavior → SocInt18_t1 → SocInteg_PI → SocInteg_PPS	-0.118*	0.02	-0.152, -0.019
Past Behavior → Locus of Control_t2 → SocInteg_PI	-0.144*	0.02	-0.293, -0.04
Past Behavior → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	-0.144*	0.01	-0.165, -0.03
Past Behavior → Locus of Control_t2 → AcadInteg_PFS	-0.060†	0.07	-0.191, -0.004

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → Locus of Control_t2 → InstFit18	0.134*	0.02	0.03, 0.378
MotivAttend18_t1 → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	-0.106†	0.09	-0.045, 0
MotivAttend18_t1 → AcadInteract_PCC → AcadInteg_PCC → Fall3_Enrolled	-0.106†	0.07	0.001, 0.037
MotivAttend18_t1 → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	-0.106†	0.09	-0.081, -0.001
MotivAttend18_t1 → AcadInteract_PCC → Fall3_Enrolled	-0.054†	0.06	-0.059, -0.002
MotivAttend18_t1 → CopingProcess_t1 → CopingProcess_t2	-0.049*	0.03	-0.029, -0.003
Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC	-0.122†	0.07	-0.288, -0.014
Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	-0.122†	0.09	-0.089, -0.001
Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	-0.122†	0.08	-0.057, 0
Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC → Fall3_Enrolled	-0.122†	0.07	0.001, 0.041
Locus of Control_t1 → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	-0.122†	0.05	-0.095, -0.005
Locus of Control_t1 → AcadInteract_PCC → Fall3_Enrolled	-0.062*	0.05	-0.068, -0.003
Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI	-0.078†	0.09	-0.219, -0.003

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	-0.078†	0.08	-0.136, -0.004
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS	-0.033	0.14	-0.138, 0.002
Locus of Control_t1 → Locus of Control_t2 → InstFit18	0.073*	0.04	0.018, 0.228
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC	0.156*	0.03	0.044, 0.277
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	0.156†	0.07	0.001, 0.077
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.156†	0.06	0.001, 0.05
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → Fall3_Enrolled	0.156*	0.04	-0.041, -0.002
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	0.156*	0.02	0.01, 0.089
AcadInteract_PFS → AcadInteract_PCC → Fall3_Enrolled	0.079*	0.02	0.004, 0.069
AcadInteract_PFS → AcadInteg_PCC → SocInteg_PI	0.036†	0.08	0.002, 0.092
AcadInteract_PFS → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.036†	0.06	0.002, 0.062
AcadInteract_PFS → AcadInteg_PCC → Fall3_Enrolled	-0.051*	0.05	-0.042, -0.002
AcadInteract_PFS → AcadInteg_PCC → AcadInteg_PFS	0.055**	0.01	0.019, 0.106

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC	-0.231**	0.00	-0.355, -0.117
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	-0.231†	0.08	-0.084, -0.002
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	-0.231†	0.07	-0.057, -0.002
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → Fall3_Enrolled	-0.231†	0.06	0.002, 0.052
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	-0.231**	0.00	-0.115, -0.025
NormBeliefs → AcadInteract_PCC → Fall3_Enrolled	-0.116*	0.02	-0.081, -0.009
SocInt18_t1 → Locus of Control_t2 → SocInteg_PI	0.072†	0.07	0.007, 0.169
SocInt18_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	0.072†	0.06	0.006, 0.09
SocInt18_t1 → Locus of Control_t2 → InstFit18	-0.067†	0.06	-0.208, -0.007
SocInt18_t1 → SocInteg_PI → SocInteg_PPS	-0.149*	0.02	-0.249, -0.034
AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.117†	0.09	0.003, 0.149
AcadInteract_PCC → AcadInteg_PCC → Fall3_Enrolled	-0.165†	0.07	-0.115, -0.005
AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	0.176**	0.00	0.083, 0.263

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
CopingStrat18 → SEAsses_t1 → SEAsses_t2	0.280***	0.00	0.108, 0.298
CopingStrat18 → CopingProcess_t1 → CopingProcess_t2	0.221*	0.02	0.051, 0.335
Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	0.204***	0.00	0.139, 0.365
AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.108†	0.09	0.004, 0.23

Note. Significance estimates: *** $p < .001$, ** $p < .01$, * $p < .05$, † $p < .10$.

Table E2

Fall 2019 Cohort Bootstrap Analysis of Indirect Effects

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → AcadInteract_PFS → AcadInteract_PCC	0.080***	0.00	0.046, 0.129
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC	0.080***	0.00	0.034, 0.097
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	0.080***	0.00	0.01, 0.035
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS	0.080***	0.00	0.001, 0.008
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.080**	0.00	0, 0.001
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.080*	0.04	0, 0
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.080***	0.00	0.006, 0.023
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS → Term2_Enrolled	0.080†	0.08	0, 0.001
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	0.080**	0.01	0.003, 0.018
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS	0.080**	0.01	0, 0.003
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.080†	0.06	0, 0
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → CopingProcess_t1	0.080*	0.01	0.001, 0.004

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → CopingProcess_t1 → CopingProcess_t2	0.080*	0.01	0, 0.002
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → SEAsses_t1	0.080*	0.05	0, 0.004
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2	0.080*	0.04	0, 0.001
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → SEAsses_t1 → InstFit19	0.080*	0.03	0, 0.005
Past Behavior → AcadInteract_PFS → AcadInteract_PCC → Term2_Enrolled	0.080*	0.03	-0.003, 0
Past Behavior → AcadInteract_PFS → AcadInteg_PFS	0.171**	0.00	0.118, 0.228
Past Behavior → AcadInteract_PFS → AcadInteg_PFS → SocInteg_PPS	0.171*	0.01	0.007, 0.041
Past Behavior → AcadInteract_PFS → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.171†	0.07	0, 0.001
Past Behavior → SocInteract → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS	0.020†	0.10	0, 0.004
Past Behavior → SocInteract → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.020†	0.05	0, 0.001
Past Behavior → SocInteract → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.020†	0.06	0, 0
Past Behavior → SocInteract → AcadInteg_PCC → AcadInteg_PFS	0.020†	0.09	0, 0.01
Past Behavior → SocInteract → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS	0.020†	0.06	0, 0.002

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → SocInteract → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.020†	0.08	0, 0
Past Behavior → SocInteract → SEAsses_t1	0.047*	0.01	0.004, 0.02
Past Behavior → SocInteract → SEAsses_t1 → SEAsses_t2	0.047**	0.01	0.001, 0.006
Past Behavior → SocInteract → SEAsses_t1 → InstFit19	0.047**	0.01	0.004, 0.024
Past Behavior → SocInteract → SocInteg_PPS	0.038*	0.02	0.011, 0.073
Past Behavior → SocInteract → SocInteg_PPS → Term2_Enrolled	0.038†	0.08	0, 0.002
Past Behavior → SocInteract → InstFit19	0.085***	0.00	0.05, 0.128
Past Behavior → AcadInteract_PCC → AcadInteg_PCC	0.167***	0.00	0.099, 0.261
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	0.167***	0.00	0.032, 0.095
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS	0.167***	0.00	0.004, 0.02
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.167**	0.00	0, 0.003
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.167*	0.04	0, 0
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.167***	0.00	0.02, 0.062

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS → Term2_Enrolled	0.167†	0.10	0, 0.002
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	0.167**	0.00	0.01, 0.049
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS	0.167**	0.01	0.001, 0.009
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.167†	0.06	0, 0
Past Behavior → AcadInteract_PCC → CopingProcess_t1	0.025*	0.01	0.002, 0.011
Past Behavior → AcadInteract_PCC → CopingProcess_t1 → CopingProcess_t2	0.025**	0.01	0.001, 0.005
Past Behavior → AcadInteract_PCC → SEAsses_t1	0.021*	0.04	0.001, 0.012
Past Behavior → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2	0.021*	0.04	0, 0.003
Past Behavior → AcadInteract_PCC → SEAsses_t1 → InstFit19	0.021*	0.03	0.001, 0.015
Past Behavior → AcadInteract_PCC → Term2_Enrolled	-0.021*	0.04	-0.008, -0.001
Past Behavior → Locus of Control_t1 → Locus of Control_t2	-0.344**	0.00	-0.374, -0.253
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI	-0.344*	0.03	0.009, 0.072
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS	-0.344*	0.01	0.002, 0.015

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	-0.344*	0.01	0, 0.002
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	-0.344*	0.04	0, 0
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	-0.344*	0.02	0.006, 0.045
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS → Term2_Enrolled	-0.344†	0.09	0, 0.001
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS	-0.344**	0.01	0.017, 0.075
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → SocInteg_PPS	-0.344*	0.01	0.001, 0.011
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	-0.344†	0.06	0, 0
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SEAsses_t2	-0.344**	0.01	0.003, 0.013
Past Behavior → Locus of Control_t1 → SEAsses_t1 → SEAsses_t2	0.038†	0.08	0, 0.005
Past Behavior → Locus of Control_t1 → SEAsses_t1 → InstFit19	0.038†	0.07	0.001, 0.022
Past Behavior → SEAsses_t1 → SEAsses_t2	0.083***	0.00	0.007, 0.024
Past Behavior → SEAsses_t1 → InstFit19	0.056***	0.00	0.027, 0.101
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC	0.158***	0.00	0.098, 0.251

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	0.158***	0.00	0.031, 0.095
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS	0.158***	0.00	0.004, 0.021
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.158**	0.00	0, 0.003
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.158*	0.04	0, 0
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.158***	0.00	0.019, 0.061
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS → Term2_Enrolled	0.158†	0.09	0, 0.002
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	0.158**	0.01	0.008, 0.047
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS	0.158*	0.01	0.001, 0.008
AcadInteract_PFS → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.158†	0.06	0, 0
AcadInteract_PFS → AcadInteract_PCC → CopingProcess_t1	0.023*	0.02	0.001, 0.011
AcadInteract_PFS → AcadInteract_PCC → CopingProcess_t1 → CopingProcess_t2	0.023*	0.01	0.001, 0.005
AcadInteract_PFS → AcadInteract_PCC → SEAsses_t1	0.020*	0.05	0.001, 0.011
AcadInteract_PFS → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2	0.020*	0.04	0, 0.003

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
AcadInteract_PFS → AcadInteract_PCC → SEAsses_t1 → InstFit19	0.020*	0.03	0.001, 0.014
AcadInteract_PFS → AcadInteract_PCC → Term2_Enrolled	-0.020*	0.03	-0.008, -0.001
AcadInteract_PFS → AcadInteg_PFS → SocInteg_PPS	0.056*	0.01	0.019, 0.105
AcadInteract_PFS → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.056†	0.08	0, 0.003
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC	0.105*	0.01	0.039, 0.206
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	0.105**	0.01	0.014, 0.076
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS	0.105**	0.00	0.002, 0.016
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.105**	0.01	0, 0.002
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.105*	0.04	0, 0
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.105**	0.01	0.009, 0.049
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS → Term2_Enrolled	0.105†	0.08	0, 0.001
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	0.105**	0.01	0.005, 0.039
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS	0.105*	0.01	0, 0.007

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
NormBeliefs → AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.105*	0.05	0, 0
NormBeliefs → AcadInteract_PCC → CopingProcess_t1	0.015*	0.02	0.001, 0.009
NormBeliefs → AcadInteract_PCC → CopingProcess_t1 → CopingProcess_t2	0.015*	0.02	0, 0.004
NormBeliefs → AcadInteract_PCC → SEAsses_t1	0.013†	0.06	0, 0.009
NormBeliefs → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2	0.013*	0.05	0, 0.003
NormBeliefs → AcadInteract_PCC → SEAsses_t1 → InstFit19	0.013*	0.04	0, 0.011
NormBeliefs → AcadInteract_PCC → Term2_Enrolled	-0.013*	0.03	-0.007, 0
NormBeliefs → Locus of Control_t1 → Locus of Control_t2	-0.129**	0.01	-0.2, -0.058
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI	-0.129*	0.02	0.004, 0.041
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS	-0.129*	0.01	0.001, 0.008
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	-0.129**	0.01	0, 0.001
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	-0.129*	0.03	0, 0
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	-0.129*	0.02	0.002, 0.025

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS → Term2_Enrolled	-0.129†	0.07	0, 0.001
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS	-0.129**	0.01	0.006, 0.038
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → SocInteg_PPS	-0.129**	0.01	0.001, 0.006
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	-0.129*	0.05	0, 0
NormBeliefs → Locus of Control_t1 → Locus of Control_t2 → SEAsses_t2	-0.129**	0.01	0.001, 0.006
NormBeliefs → Locus of Control_t1 → SEAsses_t1	0.014†	0.06	0, 0.01
NormBeliefs → Locus of Control_t1 → SEAsses_t1 → SEAsses_t2	0.014†	0.05	0, 0.003
NormBeliefs → Locus of Control_t1 → SEAsses_t1 → InstFit19	0.014†	0.05	0.001, 0.011
Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI	0.091*	0.03	0.024, 0.176
Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS	0.091*	0.01	0.004, 0.036
Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.091*	0.01	0, 0.006
Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.091*	0.04	0, 0
Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	0.091*	0.02	0.016, 0.111

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Locus of Control_t1 → Locus of Control_t2 → SocInteg_PI → SocInteg_PPS → Term2_Enrolled	0.091†	0.09	0, 0.003
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS	0.094*	0.01	0.035, 0.172
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → SocInteg_PPS	0.094*	0.01	0.004, 0.027
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.094†	0.06	0, 0.001
Locus of Control_t1 → Locus of Control_t2 → SEAsses_t2	0.097**	0.01	0.008, 0.031
Locus of Control_t1 → SEAsses_t1 → SEAsses_t2	0.032†	0.09	0, 0.013
Locus of Control_t1 → SEAsses_t1 → InstFit19	0.022†	0.07	0.002, 0.053
AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI	0.261***	0.00	0.185, 0.314
AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS	0.261***	0.00	0.015, 0.071
AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.261**	0.00	0.002, 0.011
AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.261*	0.05	0, 0
AcadInteract_PCC → AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.261***	0.00	0.108, 0.207
AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS	0.104**	0.01	0.038, 0.161

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS	0.104*	0.01	0.003, 0.03
AcadInteract_PCC → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.104†	0.06	0, 0.001
AcadInteract_PCC → CopingProcess_t1 → CopingProcess_t2	0.039*	0.02	0.003, 0.017
AcadInteract_PCC → SEAsses_t1 → SEAsses_t2	0.034†	0.06	0.001, 0.012
AcadInteract_PCC → SEAsses_t1 → InstFit19	0.023†	0.05	0.004, 0.05
SocInteract → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.018†	0.06	0, 0.001
SocInteract → AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.018†	0.07	0, 0
SocInteract → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS	0.007†	0.07	0, 0.004
SocInteract → AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.007†	0.08	0, 0
SocInteract → SEAsses_t1 → SEAsses_t2	0.043*	0.01	0.003, 0.014
SocInteract → SEAsses_t1 → InstFit19	0.029*	0.01	0.01, 0.057
SocInteract → SocInteg_PPS → Term2_Enrolled	0.008†	0.08	0, 0.005
Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS	-0.018*	0.01	-0.047, -0.005

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	-0.018*	0.01	-0.008, -0.001
Locus of Control_t2 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	-0.018*	0.04	0, 0
Locus of Control_t2 → SocInteg_PI → SocInteg_PPS	-0.072*	0.02	-0.142, -0.021
Locus of Control_t2 → SocInteg_PI → SocInteg_PPS → Term2_Enrolled	-0.072†	0.09	-0.004, 0
Locus of Control_t2 → AcadInteg_PFS → SocInteg_PPS	-0.014*	0.01	-0.034, -0.005
Locus of Control_t2 → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	-0.014†	0.06	-0.001, 0
AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS	0.057***	0.00	0.021, 0.095
AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.057**	0.01	0.003, 0.015
AcadInteg_PCC → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.057*	0.05	0, 0
AcadInteg_PCC → SocInteg_PI → SocInteg_PPS	0.224**	0.00	0.144, 0.276
AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS	0.017*	0.01	0.004, 0.041
AcadInteg_PCC → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.017†	0.07	0, 0.001
MotivAttend19_t1 → SocInteg_PI → AcadInteg_PFS	0.024**	0.00	0.009, 0.052

Indirect Effect Path	ß	p-value	90% CI (lower, upper)
MotivAttend19_t1 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.024**	0.01	0.001, 0.008
MotivAttend19_t1 → SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.024*	0.04	0, 0
MotivAttend19_t1 → SocInteg_PI → SocInteg_PPS	0.092**	0.01	0.041, 0.158
MotivAttend19_t1 → SocInteg_PI → SocInteg_PPS → Term2_Enrolled	0.092†	0.09	0, 0.004
MotivAttend19_t1 → SEAsses_t1 → InstFit19	0.018†	0.09	0, 0.044
SocInteg_PI → AcadInteg_PFS → SocInteg_PPS	0.018**	0.01	0.007, 0.04
SocInteg_PI → AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.018†	0.05	0, 0.001
CopingStrat19 → SEAsses_t1 → SEAsses_t2	0.127***	0.00	0.057, 0.119
CopingStrat19 → SEAsses_t1 → InstFit19	0.087***	0.00	0.202, 0.499
CopingStrat19 → CopingProcess_t1 → CopingProcess_t2	0.205**	0.00	0.145, 0.268
AcadInteg_PFS → SocInteg_PPS → Term2_Enrolled	0.010†	0.09	0, 0.006

Note. Significance of Estimates: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$

Table E3

Fall 2020 Cohort Bootstrap Analysis of Indirect Effects

Indirect Path	ß	p-value	90% CI (lower, upper)
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.221†	0.06	-0.002, 0
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteg_PCC	0.221***	0.00	0.187, 0.329
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteg_PCC → SocInteg	0.221***	0.00	0.049, 0.122
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	-0.219†	0.08	0, 0.007
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC → InstFit20	-0.219†	0.08	0, 0.008
Past Behavior → Locus of Control_t1 → Locus of Control_t2	-0.219***	0.00	-0.203, -0.118
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS	-0.219***	0.00	0.029, 0.089
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC	-0.219***	0.00	0.013, 0.04
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	-0.219***	0.00	0.004, 0.014
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → InstFit20	-0.219***	0.00	0.006, 0.025
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	-0.219***	0.00	-0.001, 0
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → Term2_Enrolled	-0.219**	0.00	0, 0.002

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC	-0.219**	0.01	0.01, 0.046
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC → SocInteg	-0.219**	0.00	0.003, 0.017
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.219*	0.05	0, 0
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.219*	0.04	0, 0
Past Behavior → Locus of Control_t1 → Locus of Control_t2 → SocInteg	-0.219*	0.02	0.01, 0.058
SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.203***	0.00	0.164, 0.298
AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.198†	0.06	-0.002, 0
AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC	0.198***	0.00	0.152, 0.28
AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.198***	0.00	0.04, 0.105
Past Behavior → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.194†	0.05	-0.001, 0
Past Behavior → AcadInteract_PFS → AcadInteg_PFS	0.194***	0.00	0.151, 0.281
Past Behavior → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC	0.194***	0.00	0.059, 0.131
Past Behavior → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.194***	0.00	0.016, 0.049

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → AcadInteract_PFS → AcadInteg_PFS → InstFit20	0.194***	0.00	0.024, 0.083
Past Behavior → AcadInteract_PFS → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.194***	0.00	-0.003, 0
Past Behavior → AcadInteract_PFS → AcadInteg_PFS → Term2_Enrolled	0.194**	0.01	0.001, 0.008
AcadInteract_PCC → AcadInteg_PCC → SocInteg	0.176***	0.00	0.112, 0.24
Coping Strategies → CopingProcess_t1 → CopingProcess_t2	0.166***	0.00	0.108, 0.208
Coping Strategies → SEAsses_t1 → SEAsses_t2	0.144***	0.00	0.079, 0.173
Coping Strategies → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.144***	0.00	0.035, 0.086
Coping Strategies → SEAsses_t1 → SEAsses_t2 → InstFit20	0.144**	0.01	0.039, 0.185
Coping Strategies → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.144**	0.00	-0.006, 0
Coping Strategies → SEAsses_t1 → SEAsses_t2 → SocInteg	0.144**	0.00	0.031, 0.162
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	0.137†	0.08	0, 0.023
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS	0.137***	0.00	0.099, 0.282
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC	0.137***	0.00	0.043, 0.124

Indirect Path	ß	p-value	90% CI (lower, upper)
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.137***	0.00	0.013, 0.044
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → InstFit20	0.137***	0.00	0.02, 0.079
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.137***	0.00	-0.003, 0
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → Term2_Enrolled	0.137**	0.01	0.001, 0.007
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.137*	0.04	-0.001, 0
AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.136***	0.00	0.081, 0.202
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	-0.115†	0.07	0, 0.015
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC → InstFit20	-0.115†	0.07	0, 0.019
Coping Strategies → Locus of Control_t1 → Locus of Control_t2	-0.115***	0.00	-0.483, -0.176
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS	-0.115***	0.00	0.052, 0.205
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC	-0.115***	0.00	0.023, 0.091
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	-0.115***	0.00	0.006, 0.03
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → InstFit20	-0.115***	0.00	0.011, 0.056

Indirect Path	ß	p-value	90% CI (lower, upper)
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	-0.115***	0.00	-0.002, 0
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → Term2_Enrolled	-0.115**	0.00	0, 0.005
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC	-0.115**	0.00	0.02, 0.102
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC → SocInteg	-0.115**	0.00	0.006, 0.036
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.115*	0.04	0, 0
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.115*	0.04	0, 0
Coping Strategies → Locus of Control_t1 → Locus of Control_t2 → SocInteg	-0.115*	0.01	0.019, 0.131
AcadInteract_PFS → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.114***	0.00	-0.006, -0.001
AcadInteract_PFS → AcadInteg_PFS → InstFit20	0.114**	0.00	0.056, 0.18
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → InstFit20	0.110†	0.09	0, 0.031
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → SocInteg	0.110***	0.00	0.019, 0.067
Past Behavior → AcadInteract_PCC → AcadInteg_PCC	0.110**	0.00	0.066, 0.178
Past Behavior → AcadInteract_PCC → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.110*	0.05	-0.001, 0

Indirect Path	ß	p-value	90% CI (lower, upper)
Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	-0.100†	0.09	-0.038, 0
Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC	-0.100***	0.00	-0.215, -0.079
Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	-0.100***	0.00	-0.078, -0.022
Past Behavior → SEAsses_t1 → SEAsses_t2	0.100***	0.00	0.012, 0.034
Past Behavior → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.100***	0.00	0.006, 0.017
Past Behavior → SEAsses_t1 → SEAsses_t2 → InstFit20	0.100**	0.00	0.007, 0.036
Past Behavior → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.100**	0.00	-0.001, 0
Past Behavior → SEAsses_t1 → SEAsses_t2 → SocInteg	0.100**	0.00	0.006, 0.032
Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.100*	0.05	0, 0.001
Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	-0.097†	0.09	-0.041, 0
Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC	-0.097***	0.00	-0.227, -0.077
Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	-0.097***	0.00	-0.081, -0.024
AcadInteract_PCC → SEAsses_t1 → SEAsses_t2	0.097***	0.00	0.011, 0.03

Indirect Path	ß	p-value	90% CI (lower, upper)
AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.097***	0.00	0.005, 0.015
AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → InstFit20	0.097**	0.01	0.006, 0.033
AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.097**	0.00	-0.001, 0
AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → SocInteg	0.097**	0.00	0.005, 0.029
Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.097*	0.04	0, 0.001
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → InstFit20	0.093†	0.09	0, 0.012
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.093†	0.05	0, 0
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.093***	0.00	-0.001, 0
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS	0.093**	0.00	0.044, 0.144
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC	0.093**	0.00	0.019, 0.066
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.093**	0.00	0.005, 0.024
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → InstFit20	0.093**	0.00	0.009, 0.043
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → Term2_Enrolled	0.093**	0.01	0, 0.004

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	-0.089†	0.09	-0.011, 0
Past Behavior → Locus of Control_t1 → AcadInteg_PFS	-0.089***	0.00	-0.152, -0.055
Past Behavior → Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC	-0.089***	0.00	-0.068, -0.022
Past Behavior → Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	-0.089***	0.00	-0.025, -0.007
Past Behavior → Locus of Control_t1 → AcadInteg_PFS → InstFit20	-0.089***	0.00	-0.044, -0.01
Past Behavior → Locus of Control_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	-0.089***	0.00	0, 0.001
Past Behavior → Locus of Control_t1 → AcadInteg_PFS → Term2_Enrolled	-0.089**	0.01	-0.004, 0
Past Behavior → Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.089*	0.04	0, 0
SEAsses_t1 → SEAsses_t2 → InstFit20	0.086**	0.01	0.145, 0.664
SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.086**	0.00	-0.021, -0.002
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.081†	0.08	0, 0
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.081†	0.07	0, 0
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → AcadInteg_PFS → Term2_Enrolled	0.081†	0.08	0, 0

Indirect Path	ß	p-value	90% CI (lower, upper)
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1	0.081***	0.00	0.011, 0.029
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2	0.081***	0.00	0.005, 0.015
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.081***	0.00	0.002, 0.007
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → CopingProcess_t1	0.081***	0.00	0.002, 0.009
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.081***	0.00	0.001, 0.003
SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.081***	0.00	0.055, 0.141
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → InstFit20	0.081**	0.00	0.003, 0.016
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.081**	0.00	0, 0
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → SocInteg	0.081**	0.00	0.003, 0.013
NormBeliefs20_t1 → AcadInteract_PCC → SEAsses_t1 → CopingProcess_t2	0.081*	0.04	-0.005, 0
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.080†	0.07	0, 0
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → InstFit20	0.080†	0.09	0, 0.001
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.080†	0.05	0, 0

Indirect Path	ß	p-value	90% CI (lower, upper)
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → Term2_Enrolled	0.080†	0.06	0, 0
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → InstFit20	0.080†	0.09	0, 0.006
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.080†	0.05	0, 0
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC → InstFit20	0.080†	0.07	-0.004, 0
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.080***	0.00	-0.001, 0
Coping Strategies → SEAsses_t2 → CopingProcess_t2	0.080***	0.00	0.042, 0.114
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS	0.080**	0.00	0.043, 0.138
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1	0.080**	0.01	0.001, 0.006
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2	0.080**	0.01	0.001, 0.003
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20	0.080**	0.01	0, 0.003
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.080**	0.00	0, 0
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → SocInteg	0.080**	0.01	0, 0.003
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.080**	0.00	0, 0.001

Indirect Path	ß	p-value	90% CI (lower, upper)
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1	0.080**	0.00	0, 0.002
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.080**	0.00	0, 0.001
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS	0.080**	0.00	0.021, 0.072
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC	0.080**	0.00	0.009, 0.032
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.080**	0.00	0.003, 0.011
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → InstFit20	0.080**	0.00	0.004, 0.021
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → Term2_Enrolled	0.080**	0.01	0, 0.002
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t2	0.080*	0.03	-0.001, 0
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC	0.080*	0.02	-0.021, -0.002
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.080*	0.04	0, 0
NormBeliefs20_t1 → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC → SocInteg	0.080*	0.02	-0.007, -0.001
Locus of Control_t1 → Locus of Control_t2 → SocInteg	0.079*	0.02	0.028, 0.181
AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.075**	0.01	-0.001, 0

Indirect Path	ß	p-value	90% CI (lower, upper)
AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → SocInteg	0.075**	0.01	0.003, 0.025
AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.075**	0.01	0.003, 0.013
AcadInteract_PFS → SEAsses_t1 → SEAsses_t2	0.075*	0.01	0.005, 0.027
AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20	0.075*	0.01	0.003, 0.029
SEAsses_t1 → SEAsses_t2 → SocInteg	0.072**	0.01	0.137, 0.594
Coping Strategies → SEAsses_t1 → CopingProcess_t1	0.068***	0.00	0.037, 0.098
Coping Strategies → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.068***	0.00	0.013, 0.039
Past Behavior → SEAsses_t2 → CopingProcess_t2	0.066**	0.00	0.009, 0.026
Past Behavior → SocInt20_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	0.065†	0.08	0, 0.009
Past Behavior → SocInt20_t1 → AcadInteg_PFS	0.065**	0.01	0.028, 0.121
Past Behavior → SocInt20_t1 → AcadInteg_PFS → AcadInteg_PCC	0.065**	0.01	0.012, 0.054
Past Behavior → SocInt20_t1 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.065**	0.01	0.004, 0.02
Past Behavior → SocInt20_t1 → AcadInteg_PFS → InstFit20	0.065**	0.01	0.006, 0.034

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → SocInt20_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.065**	0.00	-0.001, 0
Past Behavior → SocInt20_t1 → AcadInteg_PFS → Term2_Enrolled	0.065**	0.01	0, 0.003
Past Behavior → SocInt20_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.065*	0.04	0, 0
Past Behavior → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.063†	0.07	0, 0
Past Behavior → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.063†	0.06	0, 0
Past Behavior → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → Term2_Enrolled	0.063†	0.07	0, 0
Past Behavior → AcadInteract_PFS → SEAsses_t1	0.063**	0.01	0.005, 0.023
Past Behavior → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2	0.063**	0.01	0.003, 0.012
Past Behavior → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20	0.063**	0.01	0.002, 0.013
Past Behavior → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.063**	0.01	0, 0
Past Behavior → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → SocInteg	0.063**	0.01	0.002, 0.01
Past Behavior → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.063**	0.01	0.001, 0.006
Past Behavior → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1	0.063**	0.00	0.001, 0.007

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.063**	0.00	0, 0.003
Past Behavior → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t2	0.063*	0.05	-0.004, 0
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC → InstFit20	0.062†	0.08	0, 0.027
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC	0.062**	0.01	0.031, 0.143
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC → SocInteg	0.062**	0.01	0.01, 0.054
Locus of Control_t1 → Locus of Control_t2 → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.062*	0.04	-0.001, 0
AcadInteract_PFS → AcadInteg_PFS → Term2_Enrolled	0.059**	0.01	0.002, 0.017
Locus of Control_t1 → AcadInteg_PFS → InstFit20	-0.058***	0.00	-0.137, -0.033
Locus of Control_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	-0.058***	0.00	0, 0.004
SocInt20_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	0.057†	0.09	0, 0.019
SocInt20_t1 → AcadInteg_PFS → AcadInteg_PCC	0.057**	0.01	0.024, 0.111
SocInt20_t1 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.057**	0.01	0.008, 0.041
SocInt20_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.057*	0.05	-0.001, 0

Indirect Path	ß	p-value	90% CI (lower, upper)
Locus of Control_t2 → AcadInteg_PFS → InstFit20	-0.056***	0.00	-0.146, -0.037
Locus of Control_t2 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	-0.056***	0.00	0.001, 0.005
AcadInteract_PCC → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.054†	0.06	-0.004, 0
NormBeliefs20_t1 → AcadInteract_PCC → Term2_Enrolled	-0.052**	0.01	-0.016, -0.002
Past Behavior → SEAsses_t1 → CopingProcess_t1	0.047***	0.00	0.006, 0.02
Past Behavior → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.047***	0.00	0.002, 0.007
Coping Strategies → Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	-0.046†	0.08	-0.026, 0
Coping Strategies → Locus of Control_t1 → AcadInteg_PFS	-0.046***	0.00	-0.343, -0.092
Coping Strategies → Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC	-0.046***	0.00	-0.156, -0.039
Coping Strategies → Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	-0.046***	0.00	-0.053, -0.011
Coping Strategies → Locus of Control_t1 → AcadInteg_PFS → InstFit20	-0.046***	0.00	-0.094, -0.018
Coping Strategies → Locus of Control_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	-0.046***	0.00	0, 0.003
AcadInteract_PCC → SEAsses_t1 → CopingProcess_t1	0.046***	0.00	0.005, 0.018

Indirect Path	ß	p-value	90% CI (lower, upper)
AcadInteract_PCC → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.046***	0.00	0.002, 0.007
Coping Strategies → Locus of Control_t1 → AcadInteg_PFS → Term2_Enrolled	-0.046**	0.00	-0.009, -0.001
Coping Strategies → Locus of Control_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.046*	0.04	0, 0.001
AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.042†	0.06	-0.003, 0
Past Behavior → AcadInteract_PCC → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.041†	0.08	0, 0
Past Behavior → AcadInteract_PCC → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.041†	0.07	0, 0
Past Behavior → AcadInteract_PCC → SEAsses_t1 → AcadInteg_PFS → Term2_Enrolled	0.041†	0.08	0, 0
Past Behavior → AcadInteract_PCC → SEAsses_t1	0.041***	0.00	0.004, 0.017
Past Behavior → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2	0.041***	0.00	0.002, 0.009
Past Behavior → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.041***	0.00	0.001, 0.004
Past Behavior → AcadInteract_PCC → SEAsses_t1 → CopingProcess_t1	0.041***	0.00	0.001, 0.005
Past Behavior → AcadInteract_PCC → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.041***	0.00	0, 0.002
Past Behavior → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → InstFit20	0.041**	0.00	0.001, 0.009

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.041**	0.00	0, 0
Past Behavior → AcadInteract_PCC → SEAsses_t1 → SEAsses_t2 → SocInteg	0.041**	0.00	0.001, 0.008
Past Behavior → AcadInteract_PCC → SEAsses_t1 → CopingProcess_t2	0.041*	0.04	-0.003, 0
Past Behavior → AcadInteract_PFS → AcadInteg_PCC → InstFit20	-0.040†	0.08	-0.015, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	0.040†	0.10	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.040†	0.05	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.040†	0.10	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → InstFit20	0.040†	0.09	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → Term2_Enrolled	0.040†	0.05	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → InstFit20	0.040†	0.07	0, 0.003
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC → InstFit20	0.040†	0.05	-0.002, 0
AcadInteg_PFS → InstFit20 → Term2_Enrolled	-0.040***	0.00	-0.011, -0.001
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.040***	0.00	0, 0

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → AcadInteract_PCC → AcadInteract_PFS	0.040**	0.00	0.015, 0.078
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1	0.040**	0.01	0, 0.003
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2	0.040**	0.01	0, 0.002
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20	0.040**	0.01	0, 0.002
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.040**	0.00	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → SocInteg	0.040**	0.01	0, 0.002
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.040**	0.01	0, 0.001
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1	0.040**	0.00	0, 0.001
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.040**	0.00	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS	0.040**	0.00	0.007, 0.041
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC	0.040**	0.00	0.003, 0.019
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.040**	0.00	0.001, 0.006
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → InstFit20	0.040**	0.00	0.001, 0.012

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → Term2_Enrolled	0.040**	0.00	0, 0.001
Past Behavior → AcadInteract_PFS → AcadInteg_PCC	-0.040*	0.03	-0.089, -0.01
Past Behavior → AcadInteract_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.040*	0.05	0, 0
Past Behavior → AcadInteract_PFS → AcadInteg_PCC → SocInteg	-0.040*	0.03	-0.032, -0.003
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.040*	0.05	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t2	0.040*	0.03	-0.001, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.040*	0.04	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC	0.040*	0.02	-0.012, -0.001
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.040*	0.03	0, 0
Past Behavior → AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC → SocInteg	0.040*	0.02	-0.004, 0
Past Behavior → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20	0.038†	0.07	0, 0.005
Past Behavior → Locus of Control_t2 → AcadInteg_PFS	0.038***	0.00	0.02, 0.072
Past Behavior → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC	0.038***	0.00	0.008, 0.032

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → SocInteg	0.038***	0.00	0.003, 0.011
Past Behavior → Locus of Control_t2 → AcadInteg_PFS → InstFit20	0.038***	0.00	0.004, 0.02
Past Behavior → Locus of Control_t2 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.038***	0.00	-0.001, 0
Past Behavior → Locus of Control_t2 → AcadInteg_PFS → Term2_Enrolled	0.038**	0.00	0, 0.002
Past Behavior → Locus of Control_t2 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.038*	0.04	0, 0
MotivAttend20_t1 → CopingProcess_t1 → CopingProcess_t2	0.036*	0.03	0.002, 0.019
AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1	0.035**	0.01	0.003, 0.016
AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.035**	0.01	0.001, 0.006
Locus of Control_t2 → AcadInteg_PCC → SocInteg	-0.034**	0.01	-0.097, -0.019
Coping Strategies → SEAsses_t2 → InstFit20	0.034**	0.00	0.054, 0.261
Coping Strategies → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.034**	0.00	-0.008, -0.001
SocInt20_t1 → AcadInteg_PFS → InstFit20	0.033**	0.01	0.012, 0.07
SocInt20_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.033**	0.00	-0.002, 0

Indirect Path	ß	p-value	90% CI (lower, upper)
Coping Strategies → SEAsses_t1 → CopingProcess_t2	-0.032*	0.05	-0.065, -0.005
AcadInteract_PFS → AcadInteg_PCC → SocInteg	-0.031*	0.04	-0.068, -0.007
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.030†	0.07	0, 0
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.030†	0.06	0, 0
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → Term2_Enrolled	0.030†	0.07	0, 0
Locus of Control_t1 → AcadInteg_PFS → Term2_Enrolled	-0.030**	0.01	-0.012, -0.001
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1	0.030**	0.01	0.002, 0.012
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2	0.030**	0.01	0.001, 0.006
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20	0.030**	0.01	0.001, 0.006
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.030**	0.01	0, 0
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → SocInteg	0.030**	0.01	0.001, 0.006
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → SEAsses_t2 → CopingProcess_t2	0.030**	0.01	0, 0.003
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1	0.030**	0.01	0.001, 0.004

Indirect Path	ß	p-value	90% CI (lower, upper)
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t1 → CopingProcess_t2	0.030**	0.01	0, 0.001
AcadInteract_PCC → AcadInteract_PFS → SEAsses_t1 → CopingProcess_t2	0.030*	0.04	-0.002, 0
Locus of Control_t2 → AcadInteg_PFS → Term2_Enrolled	-0.029**	0.01	-0.014, -0.001
SEAsses_t2 → InstFit20 → Term2_Enrolled	-0.029**	0.01	-0.042, -0.004
Past Behavior → SEAsses_t2 → InstFit20	0.028**	0.01	0.01, 0.056
Past Behavior → SEAsses_t2 → InstFit20 → Term2_Enrolled	0.028**	0.00	-0.002, 0
Coping Strategies → SEAsses_t2 → SocInteg	0.028**	0.00	0.042, 0.219
SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.027†	0.09	-0.002, 0
Past Behavior → AcadInteract_PCC → Term2_Enrolled	-0.026**	0.01	-0.009, -0.001
Past Behavior → InstFit20 → Term2_Enrolled	-0.025*	0.01	-0.009, -0.001
Past Behavior → SEAsses_t2 → SocInteg	0.023**	0.00	0.009, 0.049
Past Behavior → SEAsses_t1 → CopingProcess_t2	-0.022†	0.05	-0.012, -0.001
AcadInteract_PCC → SEAsses_t1 → CopingProcess_t2	-0.022†	0.05	-0.011, -0.001

Indirect Path	ß	p-value	90% CI (lower, upper)
Past Behavior → Locus of Control_t2 → SocInteg	0.022*	0.02	0.007, 0.046
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC → InstFit20	-0.019†	0.07	-0.007, 0
Coping Strategies → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.019†	0.09	-0.002, 0
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC	-0.019*	0.03	-0.044, -0.005
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.019*	0.05	0, 0
AcadInteract_PCC → AcadInteract_PFS → AcadInteg_PCC → SocInteg	-0.019*	0.02	-0.016, -0.002
Past Behavior → Locus of Control_t2 → AcadInteg_PCC → InstFit20	0.017†	0.07	0, 0.006
Past Behavior → Locus of Control_t2 → AcadInteg_PCC	0.017**	0.00	0.008, 0.036
Past Behavior → Locus of Control_t2 → AcadInteg_PCC → SocInteg	0.017**	0.00	0.002, 0.013
SocInt20_t1 → AcadInteg_PFS → Term2_Enrolled	0.017**	0.01	0, 0.007
AcadInteract_PFS → SEAsses_t1 → CopingProcess_t2	-0.017*	0.05	-0.01, -0.001
Past Behavior → Locus of Control_t2 → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.017*	0.04	0, 0
AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.016†	0.06	-0.007, 0

Indirect Path	ß	p-value	90% CI (lower, upper)
SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.016†	0.10	-0.006, 0
Past Behavior → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.013†	0.08	0, 0
Past Behavior → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.013†	0.08	0, 0
Past Behavior → SEAsses_t1 → AcadInteg_PFS → Term2_Enrolled	0.013†	0.09	0, 0.001
AcadInteract_PCC → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.013†	0.09	0, 0
AcadInteract_PCC → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.013†	0.08	0, 0
AcadInteract_PCC → SEAsses_t1 → AcadInteg_PFS → Term2_Enrolled	0.013†	0.09	0, 0.001
AcadInteract_PFS → AcadInteg_PCC → InstFit20	-0.010†	0.09	-0.032, 0
Locus of Control_t2 → AcadInteg_PCC → InstFit20	-0.010†	0.08	-0.05, -0.001
AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	0.010†	0.07	0, 0
AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → InstFit20 → Term2_Enrolled	0.010†	0.06	0, 0
AcadInteract_PFS → SEAsses_t1 → AcadInteg_PFS → Term2_Enrolled	0.010†	0.08	0, 0.001
AcadInteract_PFS → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.010*	0.05	0, 0.001

Indirect Path	ß	p-value	90% CI (lower, upper)
Locus of Control_t2 → AcadInteg_PCC → InstFit20 → Term2_Enrolled	-0.010*	0.04	0, 0.001

Note. Significance of Estimates: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, † $p < 0.10$