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Noncognitive Attributes as a Measure for College Admission: Exploring the Relationship Between Cognitive and Noncognitive Factors in First-Year College Student Success

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by

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Dedication

I dedicate this dissertation to my parents, John and Linda. Thank you for encouraging me, inspiring me, and, most of all, loving me. You have been my biggest allies and champions my entire life. Thank you for believing in me and teaching me to believe in myself. Never have the Little Engine That Could's words motivated more than these past four years… "I think I can, I think I can, I think I can."

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Abstract

Cognitive factors, such as standardized test scores and high school grade point average, have historically been used to predict college success. Many colleges and universities place great importance on these cognitive factors when making admissions decisions. However, enrollment leaders question the predictive validity of these factors due to recent studies advocating for the use of noncognitive assessments. The purpose of this study was to examine the role that noncognitive attributes have in predicting college student success and whether their predictive power is greater than that of standardized test scores and high school grade point average. This study employed a quantitative methodology using a correlational predictive research design. The study investigated the Student Strengths Inventory (SSI) assessment results on 1,104 first-year students at a mid-sized public regional comprehensive university in the southeast United States. The SSI results were analyzed to determine if the SSI noncognitive subscales (educational commitment, academic engagement, academic self-efficacy, resiliency, social comfort, and campus engagement) predict first-year grade point average and retention better than standardized test scores and high school grade point average. The study's findings showed that academic self-efficacy, academic engagement, resiliency, campus engagement, high school GPA, and SAT score were statistically significant in predicting first-year GPA. The study's second finding showed that the only significant predictor of retention was high school GPA. Implications of this study are to quantify the role that noncognitive attributes have in predicting student success and how higher education institutions might assess these variables as part of the admissions process.

Keywords: college student success, admission criteria, cognitive factors, noncognitive variables

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Chapter 1: Introduction

The goal of a college admission office is to admit qualified students who can achieve success manifested by graduation from the institution. In 2017, the average first-year student acceptance rate into a four-year college was 66.9%, up from 63% in 2013 (Clinedinst, 2019). In contrast, the average freshman to sophomore retention rate at a four-year institution was 62%. Finally, only 41% of students graduate from the institution where they began in less than four years (National Center for Education Statistics, 2019). Higher education institutions pay attention to these statistics when developing admissions criteria and student success programs. These numbers indicate that while students meet the admission qualifications, they often have difficulty persisting past the first year and to graduation. The question on many enrollment leaders' minds is whether their institutions use the "best" admissions criteria and whether the students who are enrolling possess the skills and qualifications needed to succeed at the college level. In a period of limited fiscal and human resources, colleges and universities must analyze these factors if they wish to understand why some students successfully transition to college while others do not.

In 2019, the Higher Education Analytics Center at the University of Chicago conducted a study on the American public's perception of college admissions practices. This study's findings showed that 38% of survey respondents believe the admissions process is fair, while 36% considered it unfair (NCES, 2019). The opinions expressed in this study were reflected in headlines in the popular press calling for an examination of the college admissions process. These headlines alleged that affluent parents paid tutors to take the SAT or ACT for their children (Gluckman, 2019), thus creating a "side door" at many colleges and universities to admit nonqualified applicants (Thomason, 2019). Furthermore, many elite institutions are dropping standardized test requirements for admission (Jaschik, 2019). In response to critics, enrollment leaders are challenged with determining which measures to incorporate into the admissions decision process, finding what best predicts student success while ensuring that the process is both equitable and focused on longer-term outcomes like student attrition.

As enrollment leaders consider alternative options to optimize admissions leading to student success, recent publications have focused on how the admissions process might change in the future if standardized tests were replaced with a noncognitive assessment (Buckley et al., 2018; Duckworth, 2016; Zwick, 2019). Research on noncognitive predictors of student success has been conducted for over the last half-century (Oliveri & Ezzo, 2014); however, it is only within the past 10 to 15 years that enrollment managers began to recognize the limitations of cognitive factors, such as standardized tests and high school grade point average. Many advocate for better predictors of success (Gore, 2012). The adoption of noncognitive assessments, either used within the admissions process or after admission but before enrollment, will help institutions identify students who are “engaged, resilient, confident, driven to succeed, and who have the psychological constitution to thrive under stress” (Gore, 2012, p. 2). Institutions can then use this information to develop programming to support student success, retention, and persistence (Gore, 2012). These are provocative ideas to consider as enrollment leaders work to position their institutions for success in enrolling students, but also for success in retaining and graduating students.

Standardized tests have been considered the gold standard in determining college entrance and predicting student success (Atkinson & Geiser, 2009; Soares, 2012). The intended goal of these tests, both the SAT and ACT, was to open the doors of higher education to not only the social elite but to make access to higher education more easily attainable by the masses

(Soares, 2012). Enrollment leaders question the validity of these tests (NACAC, 2008, 2016), and some research has shown that standardized test scores are not the best predictor of student success and retention in college (Hiss & Franks, 2014). Syverson et al. (2018) studied 28 test-optional institutions to determine if the schools met their intended outcomes of increasing applications and enrollment, particularly from underrepresented students and students from low socioeconomic statuses. Each school saw an increase in the number of applications, and all but one school saw an increase in diversity both in applications and enrollment. Syverson et al. (2018) described the following:

> We also found that non-submitters were often admitted at lower rates than Submitters, but, on average, enrolled (yielded) at substantially higher rates. Their [high school] GPAs were modestly lower than the submitters, and, upon entering college, their First-Year GPAs and Cumulative GPAs were comparably lower. However, they ultimately graduated at rates equivalent to, or marginally higher than, submitters, the ultimate proof of success. (p. 4)

Despite this research, most colleges and universities still require submission of these tests for admission (Applerouth & Zabrucky, 2017; Holmes, 2015), and millions of students take these tests each year (ACT, n.d.; College Board, n.d.).

Test-Optional Admissions

Some colleges and universities have responded to critics by implementing test-optional admissions policies. Today, more than 1,000 colleges and universities deemphasize the importance of standardized tests when making admissions decisions, with many institutions not requiring the submission of standardized tests at all (fairtest.org, 2018; Syverson et al., 2018). For most institutions, the rationale to become test-optional is varied. Preliminary research indicates that schools implementing test-optional admission policies desire to increase application numbers (Syverson, 2007), want to increase diversity (Oliveri & Ezzo, 2014; Syverson et al., 2018), or want to acknowledge that standardized tests are not an accurate predictor of success (Gore, 2012; Hiss & Franks, 2014).

Many college-bound students and their families question why more schools have not implemented test-optional policies (Hiss & Franks, 2014). This is possibly because standardized tests are ingrained in the cultural ethos of admission offices, and change is a difficult task (Syverson, 2007). Additionally, the current research on test-optional admission policies has yielded conflicting results (Belasco et al., 2015; Saboe & Terrizzi, 2019; Syverson et al., 2018). A recent lawsuit against the University of California system calls for the immediate elimination of both the SAT and ACT as a requirement for admission, alleging this requirement violates state civil rights laws against specific populations (Hoover, 2019). The outcome of this case may impose more rapid changes than colleges and universities are currently prepared to handle. Historically, admissions officers have measured an applicant's potential for college success by evaluating high school grade point average and SAT/ACT scores, which are both measures of cognitive ability (Gore, 2012; Syverson et al., 2018). Gore (2012) posited that these two measures have limited ability to predict college success writing, "Scores and high school GPA only account for about 20% of the variability we see in student outcomes" (p. 1). In a proposal to eliminate the use of the SAT for admission at the University of California, Berkley, Geiser (2016) wrote that the "SAT exhibits differential prediction, differential item functioning, and related psychometric functions when used with black and Latino" students (p. 1). It is evident from the research cited above that for the last decade, the paradigm has shifted away from standardized test scores for making sound admissions decisions.

Admissions Practices

There is a substantial body of research that argues traditional admissions measures, such as variability in high school grade calculations and course rigor (Atkinson & Geiser, 2009; Buckley et al., 2018; Syverson, 2007; Zwick, 2002), along with secondary school disparities (Zwick, 2002), limit colleges and universities in selecting candidates for admission. Proponents for a holistic admissions review believe that a combination of cognitive and noncognitive factors provides a more equitable analysis than a primary focus on test scores and grade point average (Allensworth & Clark, 2020; Bastedo et al., 2018). At this juncture, holistic evaluation methods need to be incorporated, assessing both the cognitive and noncognitive factors that best predict academic performance; however, the difficulty is in narrowing down which noncognitive factors colleges and universities should assess for admissions decisions.

Noncognitive Factors

Extant research on noncognitive predictors of student success is vast, with numerous assessments measuring these attributes (Bowman et al., 2019; Crède & Kuncel, 2008; Gore et al., 2019; Metz et al., 2015; Oliveri & Ezzo, 2014; Robbins et al., 2006). The implementation of a noncognitive assessment can assist institutions in measuring a wide array of factors, such as students' academic skills, their attitude toward engaging academically and socially, and their commitment to staying in school (Metz et al., 2015). For reference, Sommerfeld (2011) referred to cognitive factors as academic measures, such as test scores and grades. In contrast, noncognitive factors are nonacademic and include traits and behaviors that help students adjust and cope with the college transition. Noncognitive refers to the "motivational, psychological, and social variables" that impact student success (Metz et al., 2015, p. 8). Many different noncognitive assessment instruments assess various combinations of noncognitive factors; yet, regardless of the instrument used, institutions use this data in similar ways to improve student outcomes (Gore, 2012; Metz et al., 2015).

Student Strengths Inventory

While at the University of Utah, Paul Gore conducted a meta-analytic study on measures of student success. This study found that students who were predicted to underperform based on HSGPA and standardized test scores performed better academically and persisted at higher rates than students who were predicted to over perform based on HSGPA and standardized test scores (Gore, 2012; Mendrinos, 2014). Using these results, Gore developed six noncognitive constructs that he grouped within three categories that he believed contributed to student success (Mendrinos, 2014).

The groups are academic performance, academic persistence, and emotional intelligence (Gore, 2012). Gore (2012) posited that academic engagement and academic self-efficacy predict academic achievement. Educational commitment and campus engagement predict academic persistence, while social comfort and resiliency predict emotional intelligence (Gore, 2012). Gore (2012) additionally posited that campuses should consider these variables when developing programs to improve student success. Gore (2012) opined that college administrators should study these noncognitive factors of success over and beyond more traditional cognitive factors. Through this study, Gore and his colleagues developed the Student Strengths Inventory (SSI) to assess noncognitive factors related to college student outcomes (Gore et al., 2019; Metz et al., 2015). Gore (2012) argued that while many noncognitive variables impact student success, the six SSI variables, when assessed together, provide greater predictive accuracy in determining student success outcomes. Gore et al. (2019) wrote, “All of these constructs play a prominent role in dominant theories of college student persistence and some of the motivational theories that have been used to explain academic achievement" (p. 56).

Statement of the Problem

For almost a century, standardized tests, combined with high school grade point average, have been utilized as essential measures in determining a student's admission into college (Allensworth & Clark, 2020; Atkinson & Geiser, 2009; Berger, 2012), with most colleges and universities requiring submission of these cognitive indicators for admission (Appelrouth & Zabrucky, 2017; Clinedinst, 2019). Standardized tests have been found to provide good predictive value in determining first-year college GPA (Cortes, 2013; Dahlke et al., 2019; Shaw & Mattern, 2013). However, Dahlke et al.'s (2019) research shows these tests either over or underpredict GPA for underrepresented and low socioeconomic populations. This is problematic for institutions that focus specifically on cognitive measures in the admissions process and limits a fair consideration for students from marginalized populations. Enrollment leaders tasked with broadening access to higher education for all student populations have responded by adapting current admission practices.

Contradictory research findings identified the problem of colleges placing considerable emphasis on cognitive factors, specifically standardized test scores, in the admission decision process, potentially excluding candidates from consideration (Syverson et al., 2018). In response, proponents of expanding college access advocate for assessing noncognitive factors in the admission process. Sternberg et al. (2012) argued the predictive value of cognitive indicators is more reliable when combined with noncognitive attributes. Noncognitive indicators, such as academic self-efficacy, academic, and campus engagement, commitment to goals, and grit, are not measured by traditional admissions tests, yet research shows they are potential predictors of student success (Akos & Kretchmar, 2017; Gore, 2012; Gore et al., 2019; Le et al., 2005; Metz et al., 2015). In response to this, Gore et al. (2019) developed the Student Strengths Inventory (SSI), a valid and reliable instrument. The SSI measures six noncognitive constructs: academic self-efficacy, academic engagement, campus engagement, resiliency, educational commitment, and social comfort. However, it is not clear how well each of these constructs, which are subscales of the SSI, predict academic success and persistence (FYGPA and retention), and if they are better predictors than traditional cognitive predictors such as HSGPA and SAT/ACT scores (Gore, 2012; Gore et al., 2019; Metz et al., 2015).

Purpose of the Study

The purpose of this quantitative, correlational predictive study was to examine the effects of the SSI noncognitive subscale scores, the SAT score, and high school grade point average on first-year college grade point average and first-year to second-year retention, and to determine whether the SSI subscale scores are better predictors of FYGPA and retention. The population for this study included a subset of the first-year student cohort at a public, regional university in the Southeast United States. The primary objective of this study was to investigate whether cognitive criteria (standardized test score and HSGPA) or noncognitive attributes (SSI noncognitive subscale scores) better predict FYGPA and first-year to second-year retention through the lens of student retention theory (Tinto, 1975, 1993) and motivational theory (Bean & Eaton, 2001; Wigfield & Eccles, 2000).

Research Questions and Hypotheses

RQ1. To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and high school GPA (HSGPA) predict first-year college grade point average (FYGPA)?

H_0: SAT score, HSGPA, and the six noncognitive subscale scores do not predict FYGPA.

H_1: SSI noncognitive subscale scores will be more predictive of FYGPA than HSGPA and SAT score.

RQ2: To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and HSGPA predict first-year to second-year college retention?

H_0: SAT score, HSGPA, and the six noncognitive subscale scores do not predict first-year to second-year college retention.

H_2: SSI noncognitive subscale scores will be more predictive of first-year to second-year retention than high school GPA and SAT score.

Definitions of Terms

The following definition of terms will assist the reader in understanding the key terms used throughout the study.

Academic engagement. Refers to the value a student places on their schoolwork and academics (Campus Labs, 2018; Gore, 2012).

Academic self-efficacy. Refers to students' belief and confidence in their ability to perform academically (Gore, 2012).

American College Test (ACT). Refers to the ACT's national college entrance examination (www.act.org).

Campus engagement. Refers to students' desire to be involved in extra-curricular activities and their attachment to the campus (Gore, 2012).

Educational commitment. Refers to a student's belief in the value of a college degree and their understanding of why they are in college (Gore, 2012).

Expected family contribution (EFC). Refers to the amount of funds that a family can contribute toward paying for a student's education. This amount is calculated through a Department of Education (DOE) formula upon submission of the Free Application for Federal Student Aid (FAFSA; www.fafsa.ed.gov).

First year grade point average (FYGPA). Refers to the student's grade point average after the first year of college (Gore et al., 2019).

First-year retention (FYR). Refers to the retention of a student from the first year of college to the second year of college, indicates that a student returned for their second year (Demetriou & Schmitz-Sciborski, 2011).

Free application for federal student aid (FAFSA). Refers to the Department of Education application for federal financial aid. Students are potentially eligible for Pell grants and federal direct student loans, and federal PLUS (parent loans) upon submission (www.fafsa.ed.gov).

Grit. Refers to the noncognitive construct defined as the power and perseverance for long term goals (Duckworth, 2016).

High school grade point average (HSGPA). Explains the recorded high school grades from final high school transcript collected before the student enrolls. This GPA is typically reported on a 0.0 to 4.0 scale (Clinedinst, 2019).

Motivation. Refers to the desire or willingness to achieve goals (Bean & Eaton, 2001).

Noncognitive factors. Refers to psychosocial, behavior, and character traits that students display, such as leadership, motivation, persistence, creativity, resiliency, and grit (Gore et al., 2019; Metz et al., 2015).

Resiliency. Refers to how an individual handles challenges and responds to stress (Gore, 2012).

SAT. Refers to the national college entrance exam administered by the College Board (www.collegeboard.org).

Self-efficacy. Refers to the belief in one's ability to succeed in a task or accomplish a goal (Bandura, 1986).

Social comfort. Refers to an individual's ability to interact and communicate with others and adapt to new social situations (Gore, 2012).

Standardized tests. Interchangeable term that refers to either the ACT or the SAT (Zwick, 2019).

Test-optional admissions. Refers to admissions policies that do not require submission of standardized tests for admission (Hiss & Franks, 2014).

Summary

This chapter provided an overview of the current state of college admissions and the challenges facing enrollment leaders. The problem outlined focused on how chief enrollment officers should analyze the significance of cognitive factors, such as standardized tests and high school GPA, to predict student success while also exploring noncognitive assessments and their value in the admission process. Early research on noncognitive attributes of college student success is promising; however, there are no definitive guidelines for incorporating these attributes into the admission process. The institution from which the data is drawn recently implemented the Student Strengths Inventory assessment, and before this dissertation study, had not analyzed the results for assessment purposes. The purpose of this study is to examine the SSI results for possible changes to the admissions criteria to affect a more holistic evaluation process.

The next chapter will provide an overview of traditional admissions criteria, their use in college admission, and a history of standardized tests. The chapter will then discuss the practice of validity studies to examine the efficacy of the admissions process. Next, the chapter will discuss noncognitive attributes and early research on the use of noncognitive assessments in college admissions. The chapter will conclude with an extensive examination of the constructs of grit, self-efficacy, and motivation and how these constructs are assessed and evaluated, specifically as these constructs relate to the SSI noncognitive subscales: academic self-efficacy, academic engagement, campus engagement, educational commitment, social comfort, and resiliency.

Chapter 2: Review of the Literature

Cognitive factors, such as standardized test scores and high school grade point average, are primarily used to determine entrance into college and to predict first-year college grade point average (FYGPA); however, there is limited evidence that shows these factors predict college success after the first year (Cortes, 2013; Sternberg, 2012). Colleges and universities have started to explore variables that are better predictors of student transition and long-term success. This chapter begins with an overview of current admissions practices. Then, the chapter examines the study's variables by examining the history of college admissions tests and their prevalence within the current admissions landscape and the predictive value of high school grade point average. Validity studies are discussed next. This section also explores the vast array of variables that colleges and universities use to investigate the efficacy of their admissions process.

The chapter then explores the noncognitive attributes under investigation in this study through the lens of Vincent Tinto's landmark theory on student transition and strengths-based models of student success utilizing motivational theory. The chapter concludes with an in-depth analysis of the history of noncognitive research and assessment for potential use in the college admissions process with a discussion of grit, self-efficacy, and motivation and their relationship to the six Student Strengths Inventory noncognitive subscales: educational commitment, resiliency, academic self-efficacy, academic engagement, campus engagement, and social comfort.

A vast array of research was examined in this literature review. The research primarily included empirical studies within scholarly journals and some research and annual admissions reports. To begin my research, I used terms such as "college admissions," "standardized tests," "grit," and "noncognitive variables," primarily in databases such as EBSCO, ERIC, and JSTOR.

This yielded many results spanning decades of research, specifically from pioneers in the field such as William Sedlacek, Robert Sternberg, and William Syverson. I then filtered for studies within the past 10 to 15 years from peer-reviewed journals such as *The Journal of Student Retention, The Journal of Career Assessment, and the Journal of College Orientation and Transition*. This search uncovered the work of Paul Gore and colleagues, where I searched the terms “academic self-efficacy,” “academic engagement,” “educational commitment,” “campus engagement,” “social comfort,” and “resiliency.” Though not peer-reviewed, the *Journal of College Admission* served as a resource. Other key terms searched included “self-efficacy,” “student success,” “achievement,” “college success, “validity studies,” “motivation,” “retention,” “academic performance,” and “college admissions criteria.” These keywords uncovered a large volume of research related to college student success and outcomes. The research studies and results relevant to this study are synthesized and presented within this chapter.

Selecting Students: Admissions Criteria

Some may anticipate that the selection of students involves highly trained admissions officers rigorously reviewing each applicant, at times selecting students by chance or through gimmicks. While similar factors are considered in the decision process, the admissions review and selection process is unique at every institution (Bastedo et al., 2018; Clinedinst, 2019). At most institutions, no definitive set of criteria guarantees a student admission because institutions consider institutional characteristics such as diversity, enrollment size, and acceptance rates, in addition to students’ demographic information, cognitive information, and other required application materials (Clinedinst, 2019). There is also the notion of selectivity. While highly selective institutions like Ivy League universities use a very structured review process, less selective institutions use a much less rigorous selection process (Karen, 2017; Tremblay, 2013).

Gatekeepers

Admissions officers serve a variety of roles on their campuses—marketers, counselors, and gatekeepers. While the term gatekeeper is most often referenced regarding elite or selective admissions, all admission committee members influence who is admitted and who is not (Karen, 2017). Jacques Steinberg, a *New York Times* columnist, popularized the concept of gatekeeping in college admissions in his 2002 book titled *The Gatekeepers: Inside the Admissions Process of a Premier College*. This book chronicled the admissions process and those charged with making admissions decisions at Wesleyan University. Tremblay (2013) described gatekeeping as “the act determining who is offered admission and who is not” (p. 16). Interestingly, the practice of gatekeeping in American higher education dates to early admissions practices at Harvard College in the 1600s (Thelin, 2011; Tremblay, 2013).

The process of selecting students for admission has evolved over the past 300 years. Bastedo et al. (2018) argued that despite the public’s interest in this process, very few studies have examined “actual admissions policies” and which factors include or exclude students from consideration (p. 783). While it is clear the admissions practices that utilize multiple measures do not focus solely on academic achievement, “the gatekeeping processes that drive admissions decisions at colleges and universities remains unclear” (Bastedo et al., 2018, p. 783).

The selection process has also evolved as enrollment managers increasingly utilize data to determine who to admit based on predictions of the applicants’ likelihood to enroll (Ruffalo Noel Levitz, 2018). Notions of intent and access are considered in this process. Many students intend to go to college; whereas, not as many have access to the opportunity to go to college (Tremblay, 2013). This notion of college access has become increasingly important as nationwide demographic changes will alter the population of college-bound students by 2025 to include more underrepresented populations (Fagioli, 2013; Grawe, 2018). Proponents of holistic admission have believed this approach will reduce inequalities in the decision process; yet, there is no universal approach to a holistic review process (Bastedo et al., 2018). Enrollment managers and college administrators must determine which criteria are more important in admitting applicants and how they reflect the institution's mission and goals (Fagioli, 2013).

State of College Admission

Each year the National Association for College Admissions publishes the *State of College Admission*. A chapter in this report focuses on factors that institutions consider in admissions decisions. For the freshmen cohort admitted in fall 2017, academic performance in high school is regarded as the most critical factor for the admission decision, followed by 45.7% of schools giving considerable importance to scores on the SAT or ACT test (Clinedinst, 2019). Factors considered moderately important are personal qualities and student interests, as demonstrated by essays, resumes, extra-curricular involvement, and letters of recommendation (Clinedinst, 2019). A relatively small number of institutions placed considerable importance on interviews, work experience, or portfolios (Clinedinst, 2019). Table 1 reflects a visual representation of the responses.

Table 1

Percentage of Colleges Attributing Different Levels of Importance to Factors in Admissions Decisions: First-Time Freshmen, Fall 2017

Factor	Considerable Importance		Moderate Importance		Limited Importance		No Importance	
	n	%	*n*	%	*n*	%	*n*	%
Grades in All Courses	220	74.5	220	15.0	220	5.5	220	5.0
Grades in Coll. Prep Courses	220	73.2	220	16.8	220	5.9	220	4.1
Strength of Curriculum	219	62.1	219	21.9	219	8.7	219	7.3
Admissions Test Scores (SAT, ACT)	221	45.7	221	37.1	221	12.2	221	5.0
Essay or Writing Sample	220	23.2	220	33.2	220	24.1	220	19.5
Student's Demonstrated Interest	218	16.1	218	23.9	218	28.0	218	32.1
Counselor Recommendation	218	15.1	218	40.4	218	26.6	218	17.9
Teacher Recommendation	219	14.2	219	40.2	219	26.5	219	19.2
Class Rank	220	9.1	220	29.1	220	34.1	220	27.7
Extracurricular Activities	219	6.4	219	42.9	219	32.0	219	18.7
Portfolio	219	6.4	219	11.9	219	26.9	219	54.8
Subject Test Scores (AP, IB)	219	5.5	219	18.3	219	35.2	219	41.1
Interview	219	5.5	219	16.4	219	28.3	219	49.8
Work	217	4.1	217	28.6	217	36.9	217	30.4
State Graduation Exam Scores	218	2.3	218	8.7	218	18.8	218	70.2
SAT II Scores	216	1.9	216	5.6	216	14.8	216	77.8

Note: Adapted from NACAC Admissions Trends Survey, 2018–19.

Traditional Admission Approaches

The admissions evaluation process traditionally has followed two models—a quantitative or qualitative approach. Regardless of which method an institution uses, the application process generally requires submitting an application, a high school transcript, and a standardized assessment test score (SAT or ACT; Bastedo et al., 2018). However, as discussed in the previous chapter, many institutions no longer require the submission of test scores.

The quantitative admissions approach, also called the meritocratic approach, assesses high school GPA, high school rank (if applicable), and scores on standardized tests against a rubric or formula to make the admission decision (Bastedo et al., 2018). The rubric includes the minimum criteria a student must have for admission, often working on a sliding scale for test scores and grade point average (Atkinson, 2002; Bastedo et al., 2018). Advocates of formula admission applaud its efficiency and that the utilization of multiple measures helps the institution predict student success in validity studies (Zwick, 2019). Proponents of this approach also recognize the merits of providing an objective measure to balance the more subjective qualitative approach (Horn, 2005).

Institutions that utilize a qualitative approach consider high school GPA, class rank, and standardized test scores, but also require the submission of essays, resumes, and letters of recommendation for the decision-making process (Bastedo et al., 2018). Often referred to as *holistic admissions*, proponents believe that this approach assesses character and personal qualities, in addition to academic potential (Atkinson, 2002). Holistic admissions reviews are more time consuming for admissions officers yet provides more students with opportunities for access to college (Bastedo et al., 2018). Over 35% of high school seniors submitted applications to seven or more schools for the fall of 2017, up from 17% in fall 2005 (Clinedinst, 2019;

Soodik, 2017). These increased application numbers create a burden for admissions officers who must review the applications. At a public four-year institution with an enrollment of 10,000 students, each admissions officer reviews an average of 1,035 applications annually (Clinedinst, 2019). Holistic admission practices have been more successful at small liberal arts colleges because they can conduct an intensive review of fewer applications (Bastedo et al., 2018; Fagioli, 2013).

Bastedo et al. (2018) conducted focus groups with admissions officers at fifteen selective admissions institutions to gather feedback about holistic admissions and how it is practiced across their campuses. The results showed that holistic admission means many things. For some institutions, it means looking beyond high school GPA and test scores to evaluating essays and student involvement (Bastedo et al., 2018). Other institutions incorporated these factors, plus considered the context of the applicant's high school, family situation, and adversity or hardship the applicant faced, calling this a full context review (Bastedo et al., 2018). Not surprisingly, Bastedo et al.'s (2018) findings showed that institutions that utilize a whole context approach admitted applicants from low socioeconomic and from underrepresented populations at higher rates.

Summary of Selecting Students

The process of selecting students for admission has been described as ambiguous, creating a lack of transparency for students seeking to understand their chances of gaining access to their institution of choice (Bastedo et al., 2018). Students have been concerned about their odds of being admitted, while colleges and universities have competed to admit and enroll the most qualified students. This pressure has increased as high school seniors elect to apply to more colleges. Fagioli (2013) wrote that "clearly defined admission criteria that are in line with an institution's goals and mission are vital" (p. 10). To increase efficiency for the institution and efficacy for the student in the admissions process, institutions must define the criteria most relevant to their institution and assess those measures in the admissions process.

History of Standardized Testing

In the early years of American higher education, standardized tests were not a criterion for gaining admission into an institution (Thelin, 2011; Zwick, 2019). During the Colonial period, entrance to higher education was reserved for elite white males primarily to enter the clergy or to study law or medicine (Thelin, 2011). Access to higher education in the 18th and 19th centuries opened to women and African Americans; however, institutions were generally segregated and founded to serve specific populations (Thelin, 2011). Access to higher education continued to broaden throughout the 20th century and generally followed two paths: selective institutions required applicants to sit for lengthy essay-based exams, and less selective institutions automatically admitted students from an approved list of high schools (Atkinson & Geiser, 2009; Thelin, 2011; Zwick, 2019).

College Entrance Examination Board

The College Entrance Examination Board (CEEB) tests were the first college entrance tests (Zwick, 2019). Twelve elite institutions, including Harvard and Yale, developed the CEEB tests in 1900 (Zwick, 2019). These College Board tests were rigorous and intended to measure an applicant's intelligence (Berger, 2012; Zwick, 2019). The College Boards, or CEEB tests, were the first "gatekeepers in the educational hierarchy" (Berger, 2012, p. 167). These tests served their purpose in the early part of the 20th century at the elite institutions; however, a growing high school population (Berger, 2012), as well as advances in intelligence testing precipitated by

World War I, led admissions offices to look for an admission assessment that was available for the masses (Atkinson & Geiser, 2009; Zwick, 2019).

World War I and the Army Alpha Test

America's entrance into World War I necessitated a much larger military. This led to the development of the U.S. War Department's multiple-choice intelligence assessments (Berger, 2012; Zwick, 2019). The United States military was interested in determining which recruits were intelligent or "smart enough to be a leader" (Berger, 2012, p. 167). The U.S. Army participated in the first large-scale intelligence test, the Army Alpha Test (Mendrinos, 2014), in history, with over two million recruits tested (Berger, 2012). The Army Alpha test was modeled after IQ tests (Syverson, 2007) and attempted to measure talent and potential (Atkinson & Geiser, 2009) to select the best- to be commissioned officers (Berger, 2012).

The benefit of the Army Alpha Test was that it could quickly and easily identify potential officers by assessing mental ability while also having an effective automated scoring method (Mendrinos, 2014; Zwick, 2019). Colleges and universities subsequently looked closely at the Army's model in assessing the use of wide-scale entrance examinations (Berger, 2012; Soares, 2012; Zwick, 2019). Intelligence scholars lauded the Army Alpha test's objectivity, concluding that the test was "reliable and valid" (Berger, 2012, p. 168). Because the Army Alpha Test possessed these two crucial qualities, higher education was interested in adapting it for use in the admissions process (Berger, 2012; Soares, 2012); thus, the SAT was born.

SAT

First introduced in 1926, the Scholastic Aptitude Test (SAT) was developed to measure intelligence and aptitude, not subject matter mastery (Soares, 2012). Unlike the College Boards, many more institutions adopted the SAT allowing students to apply to more than one institution resulting in greater access to higher education across the country (Atkinson & Geiser, 2009). The SAT could be administered on a broad scale to thousands of students and scored quickly (Atkinson & Geiser, 2009; Zwick, 2019). The similarities between early IQ tests and the SATs were deliberate. They grew from the assumption that "intelligence was a unitary, inherited attribute, was not subject to change over a lifetime, and could be measured in a single number" (Atkinson & Geiser, 2009, p. 666). Early adopters of the SAT were primarily private, selective institutions (Soares, 2012). Until the mid to 1950s, public institutions did not readily use the SAT for admission, instead preferring to admit applicants with an earned high school diploma (Soares, 2012; Syverson, 2007).

The end of World War II and the creation of the GI Bill opened the doors of higher education to a broad population of potential students who might not have initially considered the attainment of a college degree (Altschuler & Blumin, 2009; Bastedo et al., 2018; Thelin, 2011). More colleges began utilizing SAT scores to determine an applicant's likelihood to perform well in college (Atkinson & Geiser, 2009). The SAT held considerable appeal with the American public as it symbolized the meritocratic culture of American college admissions (Atkinson & Geiser, 2009; Bastedo et al., 2018). Mainly, the SAT leveled the playing field for college admissions officers in a way GPA could not. Sternberg (2012) opined that the SAT's intended purpose was to open the doors of higher education and substitute the class-based system with one of meritocracy. This concept of selecting the most academically talented students without regard to their social class or economic status developed with the best of intentions (Bastedo et al., 2018; Nahai, 2013).

Evaluation of the SAT. The SAT has evolved in content, structure, and even name, in its almost hundred-year history. In 1990, the name changed to the Scholastic Assessment Test. In

1996, the SAT became known only by the initials, which now do not stand for anything (Atkinson & Geiser, 2009). The test items and format have changed repeatedly, as well as descriptions of what the SAT should measure (Atkinson & Geiser, 2009). The nonprofit organization, the College Board, which administers the SAT, describes the test as measuring “critical thinking” (Atkinson & Geiser, 2009, p. 666). Recent changes in 2005 and 2016 have reinforced the concept of the test as a measure of critical thinking ability, which is one area colleges and universities equate with student success (Zwick, 2019).

In 2001, the President of the University of California (UC), Richard Atkinson, questioned the use of the SAT and asked the UC academic senate to consider eliminating it as an admission requirement (Atkinson, 2002; Bastedo et al., 2018). Atkinson’s (2002) remarks received widespread press and garnered the attention of hundreds of college and university presidents. The College Board responded to Atkinson’s criticisms and concern over the current test format and made significant changes in 2005 (Atkinson & Geiser, 2009). The updated SAT deleted the verbal section, replaced it with a critical reading section, and added a writing section (Atkinson & Geiser, 2009). The writing component is a timed essay meant to simulate the testing environment students would face in college (Atkinson & Geiser, 2009). The math section was also revised to incorporate higher-level algebra-based questions (Atkinson & Geiser, 2009). The maximum score changed from 1600 to 2400 to recognize the addition of the writing component. Atkinson and Geiser (2009) posited that the 2005 SAT revisions were “not statistically superior to the old test in predicting success in college” (p. 667).

In 2016, the SAT underwent another revision (Zwick, 2019). The most notable change was the elimination of the writing component. This change was met with criticism because some researchers found the writing section the most predictive of college success of the three sections

(Atkinson & Geiser, 2009; Zwick, 2019). The two mandatory sections now include math and evidence-based reading and writing, which measures reading, writing, and language (Zwick, 2019). All answers are multiple-choice, excluding a portion of the math exam requiring supplied answers (Zwick, 2019). There is an optional essay where test takers are scored in reading, analysis, and writing (Zwick, 2019). There has been limited research on the predictive validity of the most recent revisions; however, early studies conclude that these changes were linked to instructional goals that make the test more closely aligned with the ACT (Zwick, 2019).

ACT

In 1959, E.F. Lindquist developed the American College Testing Program (ACT) as a competitor to the SAT (Atkinson & Geiser, 2009; Soares, 2012). East coast institutions primarily utilized the SAT, and midwestern institutions wanted an alternative test (Syverson, 2007). Lindquist believed the ACT should measure achievement, not ability (Atkinson & Geiser, 2009). The ACT test was developed to match standards taught in specific core subject areas within secondary schools' curricula (Atkinson & Geiser, 2009). Speaking about the ACT, Lindquist stated the following:

> The examination must make him feel that he [the student] has *earned* the right to go to college by his own efforts, not that he is entitled to go to college because of his innate abilities or aptitudes, regardless of what he has done in high school. In other words, the examination must be regarded by him as an *achievement* test. (as cited by Atkinson & Geiser, 2009, p. 668)

The ACT currently includes four multiple-choice sections: English, math, reading, and science (Zwick, 2019). Scores are provided for each section, along with a total composite score (Zwick, 2019). The 2016 changes to the ACT included an optional writing component that provides both writing and English language arts scores (Zwick, 2019). A science, technology, engineering, and math, or STEM, score is also calculated based on the student's scores on the math and science sections (Zwick, 2019).

Summary of Standardized Testing

Interestingly, the SAT and ACT have become more similar over time, with the SAT testing more subject matter mastery and the ACT extending testing time (Atkinson & Geiser, 2009; Zwick, 2019). Most colleges and universities use these tests interchangeably. Zwick (2019) opined there is a "deep national ambivalence about admissions testing" because of concerns that colleges and universities require admissions tests as a measure of institutional quality due to high test scores and low admission rates (p. 131). Standardized test proponents claim that scores are highly predictive of college outcomes. At the same time, opponents argue that these tests have no predictive value beyond the FYGPA, especially in predicting retention and persistence to graduation (Zwick, 2019). Due to this polarized perspective, colleges and universities may benefit from conducting validity studies and examining the current research on standardized test value. These studies should help institutions to predict student outcomes and, potentially, altering current admissions criteria.

High School Grade Point Average

It is common practice for admissions professionals to consider both high school grades and standardized test scores when reviewing applications. Galla et al. (2019) call these criteria the "gatekeepers of university admissions" (p. 2). Interestingly, some college ranking groups, such as *U.S. News and World Report,* give three times more weight to standardized test scores than GPA in their annual Best Colleges rankings (Morse & Brooks, 2020). Admissions officers have shifted their view of how much weight to give HSGPA versus standardized test scores when making decisions. The 2019 *State of College Admission* report concluded that 75% of colleges placed "considerable importance" on high school grades, whereas 46% of colleges placed "considerable importance" on test scores (Clinedinst, 2019). Notably, this statistic differs from responses on the National Association of College Admissions Counseling's (NACAC) 2016 test score validity report, where 51% of institutions placed considerable importance on standardized test scores. Research shows that HSGPA is the single best predictor of FYGPA because it accounts for approximately 30% of the variance in FYGPA; this is despite differences in high school grading scales and curricula (Atkinson, 2002; Zahner et al., 2014; Zwick, 2002).

A recent study, which utilized data from 17,000 Chicago public school students who attended a four-year college, tested the assumption that the high school a student attended impacted their college readiness (Allensworth & Clark, 2020). The authors analyzed student demographic characteristics, high school information, college outcomes, and college characteristics using hierarchical linear and nonlinear regression models to determine the relationships between variables (Allensworth & Clark, 2020). The findings concluded that students with the same high school grade point average (HSGPA) and ACT scores but attended different high schools graduated from college at very different rates. However, the relationship of HSGPA to college graduation was more substantial, more consistent, and larger than school effects (Allensworth & Clark, 2020). In contrast, ACT scores had a weak relationship with college graduation, and the high school effect was weaker and smaller (Allensworth & Clark, 2020). This study has important implications for admissions offices as they consider the importance of HSGPA as it relates to college completion.

Role of HSGPA and Self-regulation

Galla et al. (2019) found that self-regulation predicted college completion better than cognitive ability measured by standardized test scores. The authors define self-regulation as “a set of goal-directed motivational and volitional competencies” that include “self-control, and the ability to think, act and feel in ways that are more valuable in the long-run than momentarily alluring alternatives” (Galla et al., 2019, p. 4). Grit, the passion and perseverance for long-term goals, overlaps with self-regulation, as does self-regulated learning, which helps students become independent thinkers and learners (Galla et al., 2019). Galla et al. (2019) used HSGPA to measure self-regulation, noting that “prior research has identified self-regulatory competence as central to academic success at all levels of schooling” (p. 4).

Galla et al. (2019) conducted two separate studies of almost 50,000 students. Their findings concluded that HSGPA predicted college graduation over and above standardized test scores due to self-regulation competencies (Galla et al., 2019). Study one consisted of 47,303 students who applied for admission using the Common Application for the 2009-2010 academic year. This study replicated two prior longitudinal studies (Bowen et al., 2009; Geiser & Santelices, 2007) on the predictive power of high school grades and test scores for college graduation (Galla et al., 2019). Galla et al. (2019) chose a replication study because of increases in grade inflation, and the 2005 revisions to the SAT could warrant different findings of the previous studies. Using a regression analysis with demographic characteristics, as well as HSGPA and SAT/ACT scores as predictors of college outcomes, this study concluded that high GPA and standardized test scores were positively correlated. Furthermore, the predictive validity of HSGPA in predicting college graduation was stronger than was the predictive validity of standardized test scores (Galla et al., 2019). These findings replicated the results of the previous studies.

The researchers' second study focused on 1,622 high school seniors to determine how HSGPA predicts college graduation using self-regulation as the mediating factor to explain differences (Galla et al., 2019). Self-regulation was assessed through student ratings on grit and self-control, as well as teacher ratings of these factors (Galla et al., 2019). Cognitive ability was evaluated through measures of verbal ability, fluid reasoning, working memory, and processing speed (Galla et al., 2019). Using confirmatory factor analysis and structural models to test the strength of relationships among variables, the findings of study two concluded that self-regulation explains the predictive validity of high school grades for college graduation. In contrast, cognitive ability explained the predictive validity of test scores for college graduation (Galla et al., 2019).

This research has profound implications for admissions offices (Galla et al., 2019). First, their findings supported a holistic approach to college admissions. The authors asserted that there is not one single assessment of student competence and that the best admissions practices incorporate various criteria (Galla et al., 2019). They also cautioned against using self-reported assessments for admissions because students can "fake" answers for better results (Galla et al., 2019, p. 29). Lastly, Galla et al. (2019) encouraged institutions to examine the 2016 revision to the SAT for potential stronger correlations between test scores and self-regulation because the changes made were to reflect content mastery similar to classroom learning.

Predicting Student Success and Retention

When a student chooses not to return to an institution for their second year and beyond, there are negative repercussions for both the student and the institution (Shaw & Mattern, 2013).

For the students, there is a loss of self-confidence to do collegiate-level work (Shaw & Mattern), earlier payback of student loans, and loss of future job earnings (McCullum, 2019; Shaw & Mattern, 2013). For the institution, there is a loss of tuition revenue (Shaw & Mattern, 2013), lowered institutional rankings due to retention rates (Morse & Brooks, 2020), and increased recruitment expenditures to fill the enrollment losses due to attrition (Ruffalo Noel Levitz, 2018). Colleges and universities have examined many data points and variables that impact retention to develop programs or interventions that ensure a successful transition (Shaw & Mattern, 2013). The National Association for College Admissions Counseling has encouraged institutions to conduct validity studies on entering freshmen cohorts to examine which admissions criteria best predict FYGPA and retention, which are standard measures of student success for most colleges and universities (NACAC, 2016).

Test Score Validity

In 2008, NACAC formed a commission to address the use of standardized test scores in the admissions process. One recommendation put forth in the *Report of the Commission on the Use of Standardized Tests in Undergraduate Admission* was that colleges and universities should regularly conduct validity studies on the predictive power of the SAT and ACT and that different student populations based on gender and ethnicity should be studied for variation across groups (NACAC, 2008). The Commission also recommended that admissions officers acquire general knowledge about the tests' components, about score disparity across student populations, and an understanding of what predictive validity means and why it is essential for understanding student success (NACAC, 2008).

NACAC (2016) followed this report with a report on the *Use of Predictive Validity to Inform Admissions Practices*. NACAC (2016) maintains that “college admissions professionals should research the degree to which standardized tests predict achievement in college alone and in conjunction with other credentials for all students…" (p. 4). NACAC (2016) surveyed members and found that 78% of the responding institutions required standardized tests for admissions, and of those, 51% placed considerable importance on these scores. The survey respondents had similar institutional characteristics of four-year colleges nationwide related to admissions selectivity; however, survey respondents were from institutions with larger than average student enrollments (NACAC, 2016). Fifty-one percent of the respondents reported conducting validity studies annually (NACAC, 2016). The survey results showed that the institutions most likely to conduct validity studies required test scores for admission and had more selective admissions requirements (NACAC, 2016). FYGPA was the most common outcome measure and indicator of success, while predictors used in the regression models were standardized test scores and HSGPA (NACAC, 2016).

Validity studies provide institutions with data that is used to inform decision-making in areas across campus, from admissions to student success to academic affairs. Of the original NACAC survey group, eleven institutions provided a more in-depth analysis of their validity studies, and the variables included (NACAC, 2016). These institutions are not representative of the broader higher education landscape, but their observations provided admissions professionals with points to consider on their campuses (NACAC, 2016). The primary variables used were FYGPA, retention, HSGPA, high school class rank, standardized test score, the rigor of high school curriculum, quality of the high school, writing ability, and applicant sub-groups (e.g., athletes, special admits, and underrepresented populations; NACAC, 2016). The study results indicated that HSGPA had the strongest correlation with achievement at the postsecondary level, with most colleges having correlation coefficients between 0.63 and 0.71 (NACAC, 2016).

Correlation coefficients above 0.6 indicate a strong relationship (Salkind, 2017). The standardized test correlations varied by institution because there was no standard practice of how each school used the scores in their study (NACAC, 2016). The highest correlations between FYGPA and standardized test scores focused on one component of the test, the writing/critical reading sections, which had a correlation coefficient of 0.29 (NACAC, 2016). The high school curriculum, quality of the high school, and class rank had minimal impact on correlation results (NACAC, 2016). There were some slight differences in predicting FYGPA among applicant sub-groups (NACAC, 2016). The student-athlete performance had divergent results among institutions (NACAC, 2016). Some schools found that their student-athletes significantly underperformed. Another found their athletes underperformed but not significantly. Finally, one school found that their athletes significantly overperformed what the admissions criteria predicted (NACAC, 2016).

Predictive Bias/Differential Prediction. Critics of college admissions tests argue that the tests are biased against specific student subgroups, specifically underrepresented minorities and females. Multiple studies (Aguinis et al., 2010, 2016; Mattern & Patterson, 2012) have examined the predictive bias of the SAT with different conclusions. According to Aguinis et al. (2016), the *Standards for Educational and Psychological Testing* state, “the term predictive bias may be used when evidence is found that differences exist in patterns associated with test scores and other variables for different groups” (p. 1045). Aguinis et al. (2016) used the term differential prediction, which “refers to a difference in the prediction scores across subgroups and does not stipulate which group’s scores are over- or under-predicted” (p. 1045).

In 2010, Aguinis and colleagues received national attention for their study on differential prediction among preemployment testing for African Americans. Aguinis et al. (2010) concluded that cognitive ability tests overestimate African American job performance. Despite the national attention garnered for this study, Aguinis et al. (2010) were criticized because their conclusions were made based on simulated data (race was added as a dummy variable) and because of a biased statistical model (Berry & Zhao, 2015). This study led to additional research on predictive bias and a study of college admission testing, rather than cognitive ability testing for employment.

In response to Aguinis et al.'s (2010) conclusions, Matterson and Patterson (2012) conducted a large-scale study of 475,000 SAT takers between 2006-2008. Mattern and Patterson (2012) opined that Aguinis et al.'s (2010) conclusions were faulty because their statistical model did not adequately detect slope differences, and the effect of the intercept was overestimated. Using a much larger sample size and regression lines to account for traditional analyses of predictive bias, Mattern and Patterson (2012) concluded that standardized test scores, in conjunction with HSGPA, best-predicted FYGPA with minimal predictive bias, which supports previous research. Mattern and Patterson (2012) found slope and intercept differences where college GPA was overpredicted for Black and Hispanic students and underpredicted for female students. Mattern and Patterson (2012) posited that the slope difference for females was not large enough to detect significant differences in FYGPA, and when predictive bias is present, it favors minority groups. This validated previous research on minority performance on the SAT regarding overprediction, which concluded African Americans, Hispanics, and Native Americans score between .1 to .3 lower on actual FYGPA versus predicted FYGPA based on SAT scores (Fagioli, 2013). The reasons for overprediction of GPA are not well understood, and additional research is needed (Fagioli, 2013). Additionally, more research is required to determine why standardized test scores underpredict FYGPA for females (Fagioli, 2013).

Using Mattern and Patterson's (2012) raw data set, Aguinis et al. (2016) replicated the study with similar results; however, they noted that Mattern and Patterson (2012) might have copied incorrect results due to a typographical error. Despite this error, Aguinis et al. (2016) posited that it did not impact their conclusions. Counter to Mattern and Patterson's (2012) claims that predictive bias/differential prediction does not exist in college admission testing, Aguinis et al. (2016) concluded there is "substantial variability in differential prediction across samples" (p. 1053). Aguinis et al. (2016) speculated that intuitional-level characteristics like size, selectivity, student demographics, and student characteristics influence differential prediction. However, further research is required to determine each attribute's impact on the role of predictive bias in college admissions tests.

Differential Validity. Different from predictive bias or differential prediction, differential validity examines whether test score and performance differences are significant across groups when "computed separately within two or more groups" (Dahlke et al., 2019, p. 814). While each method addresses fairness in the selection of applicants, Dahlke et al. (2019) argued that differential validity offers a different perspective of test score efficacy because it examines predictions within groups and then examines those differences across groups; whereas, the other methods only consider subgroup mean differences using regression lines. Using earlier research from Berry and Sackett (2009) that addressed criteria contamination of validity studies because of differences in student course-taking patterns, Dahlke et al. (2019) examined how the SAT's predictive power was strengthened based on student course grades by gender and ethnicity. Their findings illustrate that the SAT does predict FYGPA across all racial groups when accounting for course-taking patterns; however, there were significant differences in predicting four-year college performance between Black and White students (Dahlke et al., 2019). This study found significant differences in the SAT's ability to predict performance by gender. The SAT's ability to predict college GPA for males was significantly lower and even increased when controlling for course-taking patterns (Dahlke et al., 2019). The implications of this study in practice provide enrollment leaders valuable information regarding a student's potential major area of study selection related to performance on the SAT. This study also informed enrollment leaders of the value of first-year course selection as one method contributing to student success.

Looking Beyond Traditional Criteria

Stemler (2012) posited that admissions tests should predict how well an applicant will succeed in college, noting that disagreement exists regarding what constitutes success. The primary measure of student success is first-year grade point average (FYGPA) because it is a standard variable among nearly all first-year cohorts (NACAC, 2016; Stemler, 2012). FYGPA does have some drawbacks as this variable may be impacted by a student's major selection (Dahlke et al., 2019; Stemler, 2012) or professor bias (good or bad; Stemler, 2012). Stemler (2012) posited that colleges and universities are better served by placing less emphasis on FYGPA as a measure of success and look to their mission statements to determine if students are meeting the broader skills desired. Stemler (2012) then encouraged institutions to investigate the role of standardized tests in meeting these broader objectives. The investigation should examine student aptitude, ability, and achievement while recognizing the limitations of the SAT and ACT as a test of cognitive skills to develop institutional assessments (Stemler, 2012).

Higher education should prepare students with domain-specific knowledge and domain-general abilities (Stemler, 2012). This preparation goes beyond standard validity tests where SAT/ACT scores predict FYGPA. Preferably, institutions should develop psychometric measures that assess a broad range of skills, such as cultural competence and ethical reasoning (Stemler, 2012). These assessments would measure the "value-added" (Stemler, 2012, p. 14) to students in both the cognitive and domain-specific areas. Current admissions criteria measure past achievement. Stemler (2012) believed this practice measures achievement over ability. Stemler (2012) wrote, "The emphasis on product over process has fueled a culture that all too often values grades rather than learning and financial gain at the expense of social responsibility." (p. 15).

Institutional-Level Characteristics

As noted previously in the discussion on traditional admissions criteria, institutional characteristics frequently factor into the decision-making process, along with cognitive factors. Shen et al. (2012) examined institutional characteristics that have not previously been examined to determine how they generalize across situations. In their study, Shen et al. (2012) created seven factors of institutional-level characteristics: selectivity, size and financial need, cost, homogenous campus life, classic predictors (e.g., high school grades and standardized test scores), alternative predictors (e.g., letters of recommendation and extra-curricular activities), and math science preparation. Two additional institutional factors, the percentage of females and the percentage of underrepresented minorities, were also considered (Shen et al., 2012). Data from 110 institutions were collected via College Board information. They were examined using correlations among the institutional factors and admissions selectivity, along with multiple regression analysis to determine whether institutional characteristics "predict variations in test validity" (Shen et al., 2012, p. 211). The results showed that the SAT was a stronger predictor of FYGPA than institution-specific data across the entire data set, but that "institutional differences account for an additional 32 percent of the variance in differences in test validity between schools" (Shen et al., 2012, p. 211). The authors concluded the SAT has stronger power to predict first-year grades at selective institutions who used classic predictors (e.g., high school grades and standardized test scores); whereas, at larger, less selective, more diverse institutions who used alternative admissions predictors, the SAT has less power in predicting first-year grades (Shen et al., 2012).

Summary of Predicting Success and Retention

As noted previously, validity studies have been important tools for institutions to assess the performance of their students and the efficacy of their admissions processes (Aguinis et al., 2016; Dahlke et al. 2019; NACAC, 2016; Mattern & Patterson, 2012; Shen et al., 2012; Stemler, 2012). While national validity studies provided beneficial information, institutions should take caution when generalizing the results to their campuses. Shen et al. (2012) urged institutions to examine their admissions criteria considering the findings that schools utilizing classic admissions predictors showed higher SAT validities. Proponents of college access would caution institutions not to rely too heavily on traditional admissions predictors because of the variability of institutional characteristics that impact student performance. Institutions need to study their data to determine whether test scores and HSGPA predict student outcomes (NACAC, 2016), whether admissions requirements are consistent with the institutional mission (Stemler, 2012), and whether student- and institutional-level data align to support successful student transitions (Shen et al., 2012). It is at this inflection point that institutions can begin to modify current admissions practices to impose alternative assessments for greater student success.

Theoretical Framework: College Student Transition and Success

Higher education institutions have worked toward successfully graduating their students and have devoted financial and human resources in support of this (Shaw & Mattern, 2013).

Student persistence, or retention, has been studied at colleges and universities since the 1930s (Demetriou & Schmitz-Sciborski, 2011). Retention is an institution's ability to enroll a student from matriculation to graduation (Demetriou & Schmitz-Sciborski, 2011). The National Center for Education Statistics (NCES) showed that the average freshman to sophomore retention rate for the fall 2016 cohort at four-year public institutions was 81% (NCES, 2019). This rate varied by admissions selectivity, where more selective institutions retained 96%, whereas open admission institutions retained only 62% of their students (NCES, 2019). Retention beyond the first year has been a concern for institutions because only 60% of students complete a degree at the institution where they started within six years (NCES, 2019), a figure mostly unchanged in the last century (Demetriou & Schmitz-Sciborski, 2011). Considering these statistics, enrollment leaders concerned with student attrition have studied which institutional and student characteristics foster successful student matriculation.

Tinto's (1993) student integration model and the strengths-based motivational theory are the lens through which the six noncognitive constructs under investigation in this study are viewed. Academic engagement, campus engagement, social comfort, and educational commitment relate to Tinto's model; whereas, academic self-efficacy and resiliency are motivational-based and explain student achievement.

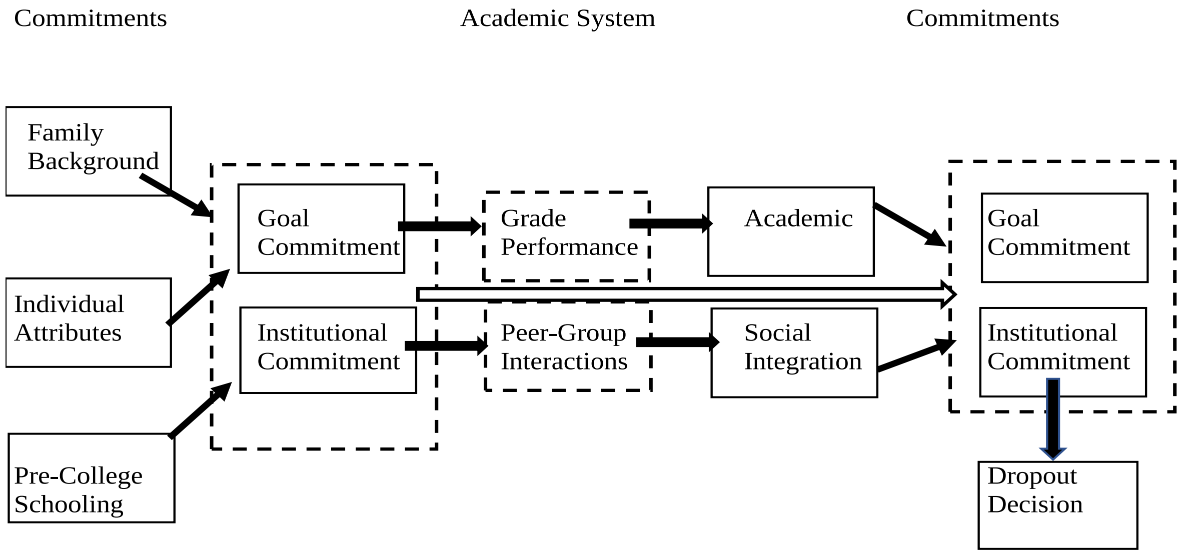
Tinto's Student Integration Model

Vincent Tinto introduced his student transition model in 1975. It has served as the seminal theory from which multiple studies have evolved to make college student retention a widely studied phenomenon (Demetriou & Schmitz-Sciborski, 2011; Hirschy, 2017). Tinto (1975) theorized the most successful students socially integrate into the campus, which increases their commitment to the school and chances of graduation (Demetriou & Schmitz-Sciborski, 2011; Hirschy, 2017). Tinto built his theory off Emile Durkheim's theory on suicide by analogizing suicide with college student departure (Hirschy, 2017; Tucker, 1999). Central to both theories are feelings of isolation and lacking a sense of belonging to a community.

Tinto postulated that students enter college with characteristics that influence their commitment to the institution and their decision to stay or leave (Hirschy, 2017). The institution must create opportunities for integration into the academic and social realms, which establishes a fit between the institution and student (Demetriou & Schmitz-Sciborski, 2011; Hirschy, 2017; Tinto, 1975; Tucker, 1999). The better the fit, the more likely the student is to persist and graduate (Hirschy, 2017). Primary to Tinto's theory is the concept of student commitment. Students experience transitions into the academic realm differently. These experiences impact their academic and social integration. The more opportunities students have to strengthen their commitment to both the institution and their education, the more likely the students are to persist through college (Tinto, 1975).

Figure 1

Vincent Tinto's Explanatory Model of the Dropout Process



Note. Adapted from "Toward a New Predictive Model of Student Retention in Higher Education: An Application of Classical Sociological Theory," by M. Kerby, 2015, *Journal of College Student Retention: Research, Theory & Practice, 17*(2), p. 12. (https://doi.org/10.1177/1521025115578229). Copyright 2015 by Sage.

Since its inception, Tinto (1993, 2007) offered multiple revisions to his theory, primarily rethinking the role that the student plays in deciding to stay or leave an institution (Hirschy, 2017; Tucker, 1999). Reasons why a student may choose to leave an institution, include lack of academic preparation, failure to connect to the academic and social communities, and incongruence between the student's education and occupational goals (Kuh et al., 2006). Tinto encouraged institutions to explore the reasons why a sense of belonging does not occur (Hirschy, 2017; Tucker, 1999). The concept of a sense of belonging will be explored with motivational theories later in the chapter.

Student Strengths Inventory and Student Transition

Gore et al. (2019) researched the development and construct validity of the Student Strengths Inventory (SSI) as a noncognitive assessment of student outcomes. This assessment measured six noncognitive constructs (Gore et al., 2019). Four of these constructs directly relate to Tinto's Student Integration Model: academic engagement, campus engagement, social comfort, and educational commitment.

Academic Engagement. Within the construct of Tinto's (1975) model, academic integration occurs when students interact with faculty both inside and outside of the classroom (Hirschy, 2017); thus, creating a sense of connection or engagement with the academic environment (Gore et al., 2019). These interactions strengthen the students' ties to the institution and their feelings of academic preparedness to succeed at the collegiate level (Hirschy, 2017). Tinto's revised his original model to include the student's commitment to educational goals and the institution's need to match student expectations with the institutional mission related to opportunities for academic engagement (Demetriou & Schmitz-Sciborski, 2011). Institutions succeed in retaining students when they provide high-impact classroom activities and feedback that is timely and relevant (Loveland, 2017), as well as when students understand how the academic environment aligns with the institutional mission (Stemler, 2012). Gore et al.'s (2019) research found that students with high levels of academic engagement were hardworking, conscientious, and placed a high priority on academic tasks. The concept of conscientious directly relates to goal commitment in Tinto's model because this personality factor influences the way someone controls, regulates, and directs their impulses (O'Conner & Pauonen, 2007).

Campus Engagement. Social integration into campus life is critical to a successful transition to college (Tinto, 1975, 1993). Drawing upon earlier college student transition research, Gore et al. (2019) concluded that a student's level of campus involvement was significantly predictive of retention. Gore et al.'s (2019) research supported the assertion of retention scholars that social integration is vital to collegiate success (Demetriou & Schmitz-Sciborski, 2011). The decision to stay or leave campus is made early in a student's career (Tinto & Pusser, 2006). Understanding a student's level of commitment to extra-curricular and peer group involvement early in their first year of college will foster a successful transition.

Social Comfort. Social comfort is related to campus engagement and refers to how comfortable a student is meeting and interacting with new people (Gore et al., 2019). Social comfort assists students in creating a sense of belonging. A student has a greater chance of successfully transitioning to college when the behaviors of the campus community align with the student's values (Hirschy, 2017). Reacting to criticisms of his theory, Tinto (1993) offered revisions that reflected student demographic differences (Demetriou & Schmitz-Sciborski, 2011; Hirschy, 2017). Students from underrepresented backgrounds have a greater feeling of social comfort on a campus that is more inclusive of ethnic, racial, gender, and economic differences (Hirschy, 2017). Students who do not feel they are supported on campus may either separate from their identity or separate from the institution (Hirschy, 2017). Schools may avoid this by identifying and removing cultural barriers that impede successful opportunities for student connection (Tinto, 2004).

Educational Commitment. A student must be committed to their education to have a successful college transition. Goals and commitments comprised a large portion of Tinto's model (Tinto, 1975, 1993). Pretransition characteristics, such as personal, family, and academic factors, can influence a student's commitment to their education (Hirschy, 2017). Students with high levels of educational commitment are more likely to persist in completing their degrees (Gore et al., 2019). In his 1993 revisions, Tinto noted that external factors, such as family commitments and financial resources, could negatively influence educational commitment through no fault of the student or institution (Hirschy, 2017; Tinto & Pusser, 2006). Educational commitment includes both the student's commitment to the institution and to degree attainment.

Motivational Theories of Student Success

More recent research into student transition has explored a strengths-based approach to retention. Rather than focusing on why students leave, this approach explores why students are successful (Demetriou & Schmitz-Scoborski, 2011). The concept of sense of belonging is vital in the college transition process, and students who have a sense of belonging on their campus are more successful in transitioning to college (Museus et al., 2017). A sense of belonging is created when the student's expectations are manifested in the academic and social experience of the campus environment (Museus et al., 2017). A sense of belonging links to motivational theories, including self-efficacy and resiliency (Bandura, 2001; Bean & Eaton, 2001; Wigfield & Eccles, 2000). Motivational theory explains the SSI factors of academic self-efficacy and resiliency.

Academic Self-Efficacy. Self-efficacy is how one perceives their ability to accomplish a goal (Bandura, 2001). Bandura (2001) believed we are "agents of action" (p. 10) and individuals act in ways that reveal their motivation after self-reflection. This posited that individuals perform intentionally, which Bandura called agency. In deliberately setting a plan of action, one cannot know the exact outcome of their plan, but self-regulatory behaviors can help lead to a successful implementation of the plan (Bandura, 2001).

Self-efficacy behaviors have an impact in the academic realm as students transition into collegiate life. When students believe they are competent, they are more likely to complete tasks and develop higher goals (Bean & Eaton, 2001). Bean and Eaton's (2001) psychological model of student retention asserted that as academic self-efficacy increases, so will the integration into the social and educational realms of the institution. This belief that academic self-efficacy is malleable supports Dweck's (2010) research on growth mindset. Students who operate with a growth mindset put forth sufficient mental effort to achieve their goals while also not letting early failure impede those goals (Dweck, 2010). High levels of academic self-efficacy correlate with purpose in life goals (Demetriou & Schmitz-Sciborski, 2011), which can help students have a meaningful college experience. In Gore et al.'s (2019) research, academic self-efficacy strongly correlated with academic engagement and educational commitment. Drawing upon research regarding the relationship between students' academic self-efficacy beliefs and their performance and persistence in school, Gore (2006, 2012) posited there is a strong relationship between academic achievement and persistence and students' confidence to perform well (i.e., academic self-efficacy). Further, Gore (2006, 2012) concluded that this relationship between these noncognitive constructs and student success was stronger than the relationship between student success and cognitive factors, such as the SAT or ACT and high school grade point average.

Resiliency. Resilience has been a characteristic often studied in college students because it has explained the ability to bounce back from failure (Yeager & Dweck, 2012). The college transition process is stressful and learning to cope and manage this stress is critical (Demetriou & Schmitz-Sciborski, 2011; Tinto, 2004). In the *Harvard Business Review* article on "Building Resilience," Seligman (2011) discussed failure and how individuals react to extreme circumstances to overcome failure. Seligman (2011) believed that on the one extreme, there are individuals who fall apart and never recover from failure. In the middle are the individuals who react to the failure but then return to where they were before. Lastly, are those who experience symptoms of the failure but eventually are better off than they were before. Seligman (2011) believed that resilience is teachable and developed a program that the U.S. Army is testing with over one million soldiers. This program was designed on what Seligman (2011) believed are the cornerstones of resilience: positive emotion, engagement, relationships, meaning, and accomplishment.

Like Seligman, Yeager and Dweck (2012) believed that resilience is a malleable trait that can be developed and strengthened, Yeager and Dweck (2012) studied theories of intelligence as being either fixed (entity) or malleable (incremental). Their research showed that when students believe intelligence is fixed, they lack confidence in their intelligence, which compromises their resilience. Positive thinking may develop resilience (Yeager & Dweck, 2012). The concept of optimism is related to positive thinking. Research has shown that students with a predisposition to thinking optimistically had higher levels of motivation and resiliency and were more likely to persist in college (Aspinwall & Taylor, 1992; Solberg Nes et al., 2009). This research has supported Yeager and Dweck's (2012) conclusions that resiliency is strengthened through a mindset that responds to challenges as obstacles that can be overcome with effort, patience, persistence, and strategy.

Resiliency strongly correlates with educational commitment (Gore et al., 2019). Gore (2012) acknowledged that resiliency tends to invoke controversy as a noncognitive variable because it assesses both emotional intelligence and emotional development. Both are essential concepts in understanding how students respond to setbacks, manage stress, and utilize a support network to support their academic goals. These characteristics of resiliency reinforce students' level of commitment to their education and how likely they are to persist after the first year. This correlation supports Tinto's (1975) theory on student transition and the role that commitment has in students' transition to college.

Noncognitive Attributes

James Heckman often has been associated with coining the term *noncognitive* as it relates to student skills and abilities (Harms, 2004). Egalite et al. (2016) wrote, "The terms 'non-cognitive skills' refers to a set of behaviors, attitudes, and strategies that are associated with individual success" (p. 28). Noncognitive skills are varied and include traits such as persistence, grit, dependability, motivation, and resiliency, among others (Harms, 2004). As increasing numbers of students sit for the SAT and ACT each year, colleges and universities must strive to deepen their focus on noncognitive factors and their role in the admission process, especially since research shows these attributes are enhanced through educational programs (Egalite et al., 2016). Many colleges and universities have explored alternative assessments to measure noncognitive factors and how they contribute to academic excellence and student success (Akos & Kretchmar, 2017; Gore et al., 2019; Luthans et al., 2019; Metz et al., 2015; Muenks et al., 2018; Niessen & Maijer, 2017). Fauria and Zellner's (2015) study on which noncognitive variables predict college student success posited that early research on the noncognitive variables raised skepticism about the "exclusivity of cognitive variables for college admission" (p. 90). The study's results showed that most students thought of themselves as successful. Determination and achievement of goals were described as indicators of students' perseverance toward attaining their degree. The study's results indicated that standardized tests might be an additional deterrent to college attainment, which is an essential consideration as institutions look to diversify their campuses considering future demographic shifts (Grawe, 2018).

The challenge facing researchers and practitioners has been developing a noncognitive assessment that the empirical research validates, and that colleges and universities are willing to embrace (Holmes, 2015; Oliveri & Ezzo, 2014; Stemler, 2012). Gore et al. (2019) believed that the SSI was a first step because it identified “a smaller number of factors that demonstrated both strong evidence of impact upon college outcomes as well as being approachable by both students and college personnel” (p. 50). The next section includes a discussion of noncognitive research and assessments as they relate to the Student Strengths Inventory’s indicators of student success, as well as a review of the noncognitive constructs discussed in this dissertation, which are educational commitment, resiliency, academic self-efficacy, academic engagement, social comfort, and campus engagement (Gore et al., 2019).

Early Research

William Sedlacek, one of the pioneers in the study of college readiness, identified eight noncognitive variables contributing to college readiness: positive self-concept regarding academics, realistic self-appraisal, understanding racism, long-term goal setting, having an available support system, demonstrated experience and success with leadership, community service, and knowledge about a field (Sedlacek, 2011; Sommerfeld, 2011). In 1984, Sedlacek and his colleague Tracey developed the Non-Cognitive Questionnaire (NCQ) using these eight variables to close the racial gap in college admissions; however, they noted that the tool could be used as an alternative to standardized tests in making admissions decisions.

While early research on the NCQ was promising, skeptics advocated for research to determine its effectiveness in the admissions process (Mendrinos, 2014). Thomas et al. (2007) conducted a meta-analytic methods study on the NCQ to determine if the questionnaire had predictive validity, look at scoring differences between different racial and ethnic groups, and lastly, determine whether the predictive validity between the groups had any theoretical implications as it relates to the use of the NCQ in admission decisions. This study found that the NCQ did not provide the needed results to make it a popular tool for use in admission decisions (Thomas et al., 2007). The scores on the noncognitive variables did not correlate to GPA, retention, or progress toward a degree. Even so, Thomas et al. (2007) suggested that increased focus on noncognitive factors is critical to increase minority admissions, better predict student performance, and increase retention rates, while also providing greater clarity for current admissions measures.

Realizing the limitations of the NCQ, Sedlacek (2003) advocated for the study of new attributes that could predict academic performance. Drawing upon Sternberg's (2000) successful intelligence model, Sedlacek (2003) believed creativity contributed to academic success but was a complicated construct to measure. Accordingly, the Rainbow Project, a model of successful intelligence, was developed to see if analytical, creative, and practical achievement could be both taught and assessed (Sternberg, 2006). Sternberg's Rainbow Project was designed to evaluate creative and practical thinking. Sternberg and his collaborators created tests that asked over 1,000 high school students to answer creative and practical questions (Sternberg, 2006). Their findings show that broader tests can enhance academic performance and that their tests doubled the accuracy of predicting first-year college GPA over SAT score alone (Sternberg, 2006). Next, Sternberg developed Project Kaleidoscope, a modified assessment tool for admissions offices that succeeded in selecting candidates for admission based on creativity and wisdom (Mendrinos, 2014).

Expanding on Sternberg's theory of successful intelligence Sternberg et al. (2012) developed a new intelligence framework titled WICS. The WICS framework was formed out of two quantitative-based assessments utilized in the Rainbow and Kaleidoscope Projects. WICS is an acronym for wisdom, intelligence, creativity, synthesized. Sternberg et al. (2012) conjectured that individuals need these abilities to succeed in life and that they are dynamic. This framework suggests that conventional tests, like the SAT and ACT, are antiquated and have limitations because they emphasize memory-based abilities (Sternberg et al., 2012). Sternberg et al. (2012) found that after controlling for HSGPA and standardized test scores, students who demonstrated wisdom and creativity performed significantly better in the first year of college than did students who did not have noncognitive assessments as part of the admission process (Farruggia et al., 2018).

Drawing upon Sternberg's framework, Pretz and Kaufman (2015) tested the hypothesis that traditional admissions measures, such as standardized tests, are inadequate measures of creativity. Their study compared outcomes of creativity related tasks to data from the college applications of 610 applicants using confirmatory factor analyses for creativity measures and regression analyses to test the relationship between traditional admissions measures, creativity, and SAT scores (Pretz & Kaufman, 2015). The findings concluded that traditional admissions criteria were not strongly correlated to creativity, noting that creative self-efficacy weakly correlated with conventional cognitive admission measures (Pretz & Kaufman, 2015). Recognizing that nontraditional factors, such as wisdom and creativity, correlate to student success, scholars shifted their focus to how personality factors predict college success.

Emotional Intelligence and Personality

Emotional Intelligence (EI) has garnered attention as it relates to student performance and retention (Sparkman et al., 2012). For this review, emotional intelligence is defined as "a set of skills that a person needs to function effectively in the world" (Sparkman et al., 2012, p. 645).

Emotional intelligence is a critical component of the study of college student success as it has been shown to improve over time and can be increased through deliberate training programs (Gore, 2006; Sparkman et al., 2012). Jaeger and Eagan (2007) concluded that the relationship between EI and academic performance is undetermined since empirical research does not show a strong correlation between EI and academic achievement. Scholars have conducted numerous studies on this relationship with inconsistent findings. They thus have advocated for more focus on these nontraditional predictors of college success (Sparkman et al., 2012), specifically, personality factors.

Personality traits have been studied as predictors of academic performance. In their predictive study, O'Conner and Paunonen (2007) found that behavior, which reflects in personality, can impact academic success. Personality reflects on what an individual will do rather than can do, and personality traits predict college success above traditional cognitive assessments (O'Conner & Paunonen, 2007). The literature on the Big Five factors showed that conscientiousness most accurately and consistently predicted academic performance (Jaeger & Eagan, 2007; O'Connor & Paunonen, 2007; Wilson et al., 2019). However, the Big Five framework has been criticized for its lack of focus on noncognitive skills that predict success (Egalite et al., 2016).

So far, this discussion has examined cognitive and noncognitive predictors of student achievement as separate entities. Zeidner (1998) opined that a successful student achievement model needs to incorporate both cognitive and noncognitive factors. Crède and Kuncel (2008) defined these research areas as social/personality (noncognitive) and learning/cognition (cognitive). Drawing upon Zeidner's (1998) and Crède and Kuncel's (2008) research, Hannon (2014) investigated five social/personality factors, five cognitive learning factors, and SAT scores to predict college GPA of freshmen and nonfreshman students. Using both correlational and regression analyses on a population of 348 undergraduate college students, Hannon (2014) concluded that academic self-efficacy (noncognitive), an epistemic belief of learning (noncognitive), and high-knowledge integration (cognitive) best-explained GPA variance in students.

In contrast, SAT scores could not predict GPA beyond the freshmen year (Hannon, 2014). This study has implications because while each of the noncognitive and cognitive constructs examined correlated to GPA, only academic self-efficacy, an epistemic belief of learning, and high knowledge integration explained the “unique variance in GPA” (Hannon, 2014, p. 55). As students persist through college, the SAT becomes less of a predictor of academic achievement (Hannon, 2014). Colleges can use these results to develop first-year programs that increase students’ self-efficacy and belief in their learning, as well as integrate them into the learning process through experiential learning opportunities. This can increase academic engagement and commitment to the institution and the process of learning.

Grit

The notion of grit is an interesting concept as it relates to assessing student readiness for college. Duckworth et al. (2007) conducted studies to research “why do some individuals accomplish more than others of equal intelligence” (p. 1087). Duckworth et al. (2007) defined grit as “perseverance and passion for long-term goals” (p.1087) and conducted a study using their self-designed grit-scale. They studied the GPAs of Ivy League undergraduates, retention of two cohorts of West Point cadets, and rankings in the National Spelling Bee to determine whether there was a correlation between grit and professional achievement in each population (Duckworth et al., 2007). Utilizing correlational analyses, the authors concluded that grit did not correlate to IQ but positively correlated with the Big Five personality trait conscientiousness. Like emotional intelligence, grit can be improved over time (Duckworth et al., 2007). Duckworth et al. (2007) concluded that achievement is the result of talent and effort—one must put forth energy, time, and stamina to reach the goal. Duckworth et al.'s (2007) research has been criticized because the populations examined were not typical of the general student population (Fosnacht et al., 2019). Egalite et al.'s (2016) replication study of Duckworth et al.'s 2007 study concluded that self-reported grit scores were not correlated with persistence or conscientiousness in a population of high school students and cautioned educators about using grit scores for program development.

Grit in the Postsecondary Context. Grit has relevance in the postsecondary context as admissions leaders look to identify skills and behaviors beyond standardized test scores that contribute to student success and retention (Fosnacht et al., 2019). Some studies on grit show that grittier students succeed better academically and retain at higher rates than less gritty students (Duckworth et al., 2007; Strayhorn, 2014). Whereas, other studies show that grit only moderately correlates to student success (Akos & Kretchmar, 2017; Fosnacht et al., 2019; Muenks et al., 2017).

Within empirical studies in higher education, grit has been studied as a predictor of student success. Akos and Kretchmar (2017) conducted a study to determine if self-reported grit scores adequately predicted FYGPA and persistence toward graduation. Multiple hierarchical regression analyses of 209 first-year undergraduate students concluded that self-reported grit scores were an accurate predictor of GPA, with the perseverance of effort having the highest correlation. The authors suggested that additional research is needed to determine how grit could be used as an assessment for college admission. Muenks et al.'s (2018) study on high school juniors had similar findings, concluding that that consistency of effort was not a strong predictor of motivation or achievement. However, the perseverance of effort is strongly associated with motivation and achievement, and self-efficacy strongly predicted HSGPA. Fosnacht et al.'s (2019) study yielded similar results, in that the only predictive power of grit is in the perseverance of effort domain.

Advancements in the field of positive psychology could help provide noncognitive assessments developed to scale using "contemporary constructs" (Akos & Kretchmar, 2017, p. 165). Luthans et al. (2019) studied how positive psychological capital influences grit and academic performance of undergraduate business students. Correlational and regression analyses of 176 business students concluded that the characteristics of hope, efficacy, resilience, and optimism attributed to grit and increased academic performance (p. 35). This study recognized Akos and Kretchmar's (2017) assertion that positive psychology is a mediator of grit and academic achievement and advocates for additional research on the factors that build and sustain this relationship (Luthans et al., 2019).

Critics of using grit to predict academic performance have argued that noncognitive assessments, like the grit scale, have modest incremental validity in predicting college GPA, as well as academic and job performance (Fosnacht et al., 2019; Niessen & Maijer, 2017). Niessen and Maijer's (2017) research concluded that broadening admissions criteria does not produce the goal of increasing academic performance because noncognitive assessments have lower predictive validity than large-scale cognitive assessments. Similarly, Credé et al.'s (2017) meta-analytic study of grit concluded that grit is not a higher-order personality construct and only moderately correlates with academic performance and college persistence. Recognizing the self-control elements of grit (commitment to goals and resiliency), Duckworth and Seligman (2017) encouraged additional study on these constructs. Scholars have conducted numerous studies on grit with inconsistent findings; thus, advocating for increased focus on this construct as an indicator of college success.

Educational Commitment and Resiliency. Grit has held intrigue with admissions leaders, so it has been important to investigate the relationships between grit and college outcomes (Fosnacht et al., 2019). Throughout the empirical research on grit, perseverance of effort consistently correlated with motivation and achievement, with consistency of effort having modest but not significant correlation (Akos & Kretchmar, 2017; Farruggia et al., 2018; Fosnacht et al., 2019; Muenks et al., 2017). The SSI constructs resiliency and educational commitment most strongly related to the two subconstructs of grit: perseverance of effort and consistency of effort. Luthans et al. (2019) posited that grit and positive psychological capital resources of hope, efficacy, resilience, and optimism are related, but the positive psychological capital HERO resources are higher-order constructs that better predict academic success and engagement.

Despite the arguments that scholars have about grit being distinctive from the personality trait conscientiousness (Crède et al., 2017), or whether current grit assessments are valid (Egalite et al., 2016; Fosnacht et al., 2019), there has been extant research that shows grit positively correlates to successful college outcomes (Luthans et al., 2017). Educational commitment is demonstrated through a student's perseverance to not give up on a goal and their resolve to reach for their goals even through long periods (Luthans et al., 2019). Gore et al.'s (2019) research showed that educational commitment, which includes a student's commitment to earning their degree, shows moderate effects on retention. As a construct of positive psychological capital, resiliency is broader than grit (Luthans et al., 2019). It includes variables such as emotional intelligence, optimism, locus of control, and social support (Gore et al., 2019; Luthans et al., 2019). Gore et al.'s (2019) work with the SSI showed that resiliency "demonstrated positive significant correlations with GPA" (p. 50).

Self-Efficacy

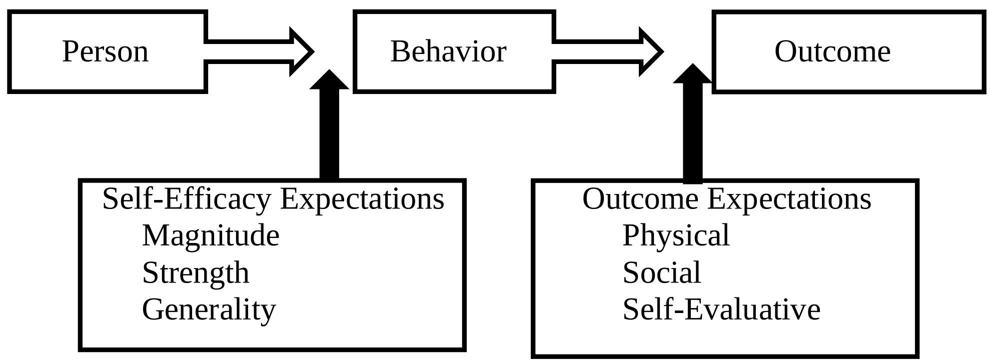
First used in 1977, the concept of self-efficacy examines the beliefs and behaviors of individuals regarding skills and abilities they possess (Bong & Skaalvik, 2003). Bandura (1977) offered this formal definition of self-efficacy:

> Perceived self-efficacy refers to beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments… Such beliefs influence the course of action people choose to pursue, how much effort they put forth in given endeavors, how long they will persevere in the face of obstacles and failures, their resilience to adversity, whether their thought patterns are self-hindering or self-aiding, how much stress and depression they experience in coping with taxing environmental demands, and the level of accomplishments they realize. (Bandura, 1977, as cited by Bong & Skaalvik, 2003, p. 5).

Self-efficacy provides a framework to explain the expectations an individual must have to accomplish tasks within a situation (Bong & Skaalvik, 2003). Bandura (1977) provided this graphic representation to explain his theory.

Figure 2

Diagrammatic Representation of the Difference Between Efficacy Expectations and Outcome Expectations



Note. Adapted from "Self-Efficacy: Toward a Unifying Theory of Behavioral Change," by A. Bandura, 1977, *Psychological Review, 84*(2), p. 193. (https://doi.org/10.1037/h0034845). Copyright 1977 by American Psychological Association.

Using an efficacy outcome, an individual uses a specific behavior to produce the desired result (Bandura, 1977). Bandura's theory examined how one perceives their ability to accomplish a goal. Bandura (2001) believed that individuals are "agents of action" (p. 10) who act in ways that reflect their motivation; and further, posited that individuals have agency (or the ability to act intentionally).

Academic Self-Efficacy. Since the introduction of Bandura's self-efficacy theory, psychologists have used it to "understand and predict human behavior" (Gore, 2006, p. 92). Education scholars have studied self-efficacy as a method to predict student success and persistence in the higher education landscape (Gore, 2006). Academic self-efficacy has been defined as "individuals' confidence in their ability to successfully perform academic tasks at a designated level" (Gore, 2006, p. 93). Scholars have developed many instruments that measure college students' levels of academic self-efficacy, with most early instruments resembling achievement tests (Gore, 2006).

Robbins and colleagues' research was pivotal in validating academic self-efficacy instruments used on college campuses (Gore et al., 2019). In a meta-analytic study, Robbins et al. (2006) studied the relationship between psychosocial and study skills factors and college outcomes to develop an instrument with multidimensional use in predicting college outcomes. Robbins et al. (2006) research found three significant findings: academic self-efficacy accounted for 14% of the variance in college GPA, there was a significant correlation between academic self-efficacy and college persistence, and academic self-efficacy beliefs accounted for a more significant variance in college GPA and persistence than do traditional measures, such as HSGPA and standardized test scores (Gore, 2006).

Students with high levels of academic self-efficacy have higher levels of self-regulatory behaviors and set higher educational goals for themselves (Wilcox & Nordstokke, 2019). Analyzing previous research studies on academic self-efficacy, Wilcox and Nordstokke (2019) posited that academic self-efficacy moderately correlated with academic performance and college GPA. Wilcox and Nordstokke (2019) were interested in how conscientiousness predicted academic self-efficacy. In their study of 66 college students, a linear regression analysis with academic self-efficacy as the outcome variable found that conscientiousness accounted for 42% of the variability of a student's academic self-efficacy (Wilcox & Nordstokke, 2019). This finding validated previous research (Duckworth et al., 2007; Jaeger & Eagan, 2007; O'Connor & Paunonen, 2007) of the importance of conscientiousness on developing self-efficacy beliefs, which in the academic realm contribute to the belief in one's ability to succeed academically.

Academic Engagement. A student is thought to be engaged academically on a campus when they attend class regularly, turn in assignments on time, and take their studies seriously (Mendrinos, 2014). These behaviors are required for a student to perform well. These behaviors also contribute to a greater sense of academic self-efficacy because a student is demonstrating behavior that shows they have the confidence to perform well in the academic environment (Bong & Skaalvik, 2003; Gore, 2006). Robbins et al. (2006) found that students who engaged in pro-academic behaviors, like those mentioned above, had higher levels of academic achievement and persistence. Gore et al. (2019) stated that higher education institutions should recognize that academic self-efficacy and academic engagement are malleable, and they can be enhanced through practice and training potentially within a first-year experience program. Students who have high levels of self-concept and self-appraisal can identify their strengths, accomplishments, and goals for improvement, both academically and socially (Bandura, 1977). How students view themselves will impact how they accomplish their goals. It is at this juncture that the concept of motivation and hope, specifically in the academic realm, have significance in this study.

Motivation

The transition from college to high school is a stressful time for students. To successfully navigate this transition, students need coping skills, and institutions need to provide avenues for students to connect to the new campus environment (Hansen et al., 2014). More recent attention on student success has utilized a strengths-based approach as practitioners have sought to understand what students believe contributes to their success or failure (Demetriou & Schmitz-Sciborski, 2011). Within expectancy theory, motivation plays a critical role in understanding how student emotions can predict future behavior (Demetriou & Schmitz-Sciborski, 2011).

Within expectancy theory, past success or failure will influence future outcomes (Vroom as cited in Demetriou & Schmitz-Sciborski, 2011).

Positive psychology has built upon the framework that individuals possess assets that can be developed and used to improve well-being and happiness. However, individuals are usually not aware of their strengths (Macaskill & Denovan, 2013). Hypothesizing that students who were made aware of their strengths have a higher level of self-confidence and learning, Macaskill and Denovan (2013) designed an intervention study where 214 first-year students were made aware of their strengths, while 40 students in the control group were not. The authors concluded the intervention made students more confident, and they had higher levels of autonomous learning (Macaskill & Denovan, 2013). This study has implications for institutions that want to understand better which campus environments foster successful outcomes.

Academic Hope. Snyder (1995) defined hope as "the process of thinking about one's goals, along with the motivation to move toward those goals (agency), and the ways to achieve those goals (pathways)" (as cited in Hansen et al., 2014, p. 51). Snyder and colleagues (2002) introduced hope theory as a motivational model for use in education. Snyder et al. (2002) postulated that the goal itself does not produce student behavior. Instead, students are successful when they view themselves as agents who follow a route that will allow them to achieve their goals. Within hope, pathways are described as the path one sees as the route to their goals (Dixson et al., 2017). Individuals who are high in pathways are creative, set realistic goals, and have multiple routes to goal attainment when setbacks occur (Dixon et al., 2017). Similar to agency in self-efficacy, having agency within hope means that individuals have confidence and motivation to accomplish goals (Dixson et al., 2017). Individuals high in agency are persistent, motivated, and more likely to persist in stressful situations (Dixson et al., 2017). Snyder et al.'s

(2002) longitudinal study of first-year college students concluded that students scoring higher on the hope scale had higher GPAs, higher graduation rates, and lower academic dismissal rates. High-hope students had higher levels of motivation and practiced positive self-talk when experiencing obstacles (Snyder et al., 2002).

In a study of 297 teenagers, Dixson et al. (2017) studied how hope related to psychological and educational constructs, such as academic self-concept, academic achievement, and self-esteem, finding that hope helps predict students who are psychologically and academically at risk. The authors concluded that academic hope was empirically different from academic self-efficacy because academic self-efficacy focuses on the *can phase*; whereas, academic hope focuses on the *will phase* (Dixson et al., 2017, p. 56). Academic hope was also strongly correlated with college persistence, graduation, and grade point average, predicting these outcomes better than academic self-efficacy (Dixson et al., 2017). Academic hope has relevance in the postsecondary context as it related to a sense of belonging and feeling a part of the community (campus engagement and social comfort). Understanding that hope, particularly academic hope, can be influenced will help higher education institutions create programs to increase feelings of belonging on campus.

In a qualitative study examining how academic hope assisted students in overcoming obstacles, Hansen et al. (2014) interviewed two groups of students: students who achieved a 3.2 or higher FYGPA whose cognitive admissions criteria indicated they would not succeed, and students who were placed on academic probation after their first-year whose cognitive admissions criteria indicated they would succeed. A core theme that emerged was the institutional context and academic support programs. Hansen et al. (2014) posited that students who sought out academic support were better able to navigate the college transition, created an alternative pathway to success, and had higher levels of academic hope. Institutions who wish to increase levels of academic hope in their students should quickly orient students to the availability of social supports and provide a favorable institutional environment for seeking out support (Hansen et al., 2014). The students in this study who were the most successful noted that the institution "provided the students with the academic resources, support, and welcoming environment that they needed" (Hansen et al., 2014, p. 60).

Social Comfort and Campus Engagement. Hope has been strongly linked to academic success, is a malleable trait that can be changed, and positive changes in a student's level of hope can sustain over the years (Dixson et al., 2017). Snyder et al.'s (2002) research concluded similarly and asked whether institutions can teach hopeful thinking to students. This discussion of noncognitive factors has focused on student attributes that contribute to successful college outcomes. However, institutional factors are as important in creating an environment that fosters success (Hansen et al., 2014). The SSI subscales campus engagement, and social comfort, show positive correlations in predicting successful college outcomes (Gore et al., 2019).

Institutional factors, such as program, policies, and services, contributed to students' levels of engagement and comfort on campus and noted that early interventions are the most successful (Hansen et al., 2014). Students most successfully integrate into an institution when they develop peer relationships, connect with mentors, and engage in campus activities (Demetriou & Schmitz-Sciborski, 2011). Higher education practitioners who understand what expectations first-year students have of their campus in terms of getting involved and feeling a sense of belonging are better able to design and develop opportunities to engage students in the social environment (Museus et al., 2017). More importantly, these opportunities can increase students' levels of motivation and hope, both of which can lead to higher levels of achievement, positive thinking, and emotional stability beyond college graduation (Snyder et al., 2002).

Summary

Positive steps have been taken to reduce the reliance on cognitive factors in the admissions process. Noncognitive assessments, like the Student Strengths Inventory, provide an alternative assessment. Reflecting on what the college admissions process might look like in 2030, Paterson (2018) wrote "The material provided in the application process, experts say, will likely continue to become more flexible and offer a wider view of the student" (p. 32). Admission officers need to determine what characteristics are essential for admission and reframe their criteria. Admission policies that recognize the importance of noncognitive variables and use a holistic review of both the cognitive and noncognitive factors are vital as admission officers seek to admit students who can achieve success and ultimately graduate from the institution.

One goal of this literature review was to provide a cursory overview of the vast array of noncognitive attributes that can predict student success. This study will also contribute to the research on noncognitive variables as predictors of student transition and persistence at the institutional level where limited research exists (Hiss & Franks, 2014).

Chapter 3 addresses the study's methodology and research design. In addition, Chapter 3 details the study site, the population sample, the Student Strengths Inventory assessment, the data collection, method, and variables are investigated. Chapter 3 concludes with a discussion of my role as the researcher, ethical considerations, and the assumptions, limitations, and delimitations considered in this study.

Chapter 3: Research Methods

This chapter discusses the research methods and design chosen for this study, as well as the site and population sample, the instrument used, data collection, and analyses. Lastly, the chapter discusses my role as the researcher, ethical considerations, assumptions, limitations, and delimitations of the study.

I examined how the six noncognitive SSI subscale scores, SAT scores, and high school grade point average (HSGPA) predict first-year college outcomes, specifically first-year grade point average (FYGPA) and retention, and if the noncognitive subscale scores are stronger predictors than SAT score and HSGPA. The research questions guiding this study are:

RQ1. To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and HSGPA predict FYGPA?

RQ2: To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and HSGPA predict first-year to second-year college retention?

The correlating hypotheses are:

H_1: SSI noncognitive subscale scores will be more predictive of FYGPA than HSGPA and SAT score.

H_2: SSI noncognitive subscale scores will be more predictive of first-year to second-year retention than HSGPA and SAT score.

Research Design and Methodology

Methodology

This study utilized a post-positivist paradigm. Post-positivists analyze data to determine whether a variable can predict an outcome (Muijs, 2011; Ponterotto, 2005). Post-positivism grew out of the positivist paradigm, which practices an absolutist approach; whereas, post-positivists have believed that phenomena can change, and that societal and cultural advances can alter realities (Butin, 2010; Muijs, 2011; Ponterotto, 2005). I chose this approach because I believe that noncognitive research has influenced what we know about college student success and altered the previous reality that cognitive measures were the best way to predict student success. I used a post-positivist paradigm because this approach supports the assumption that noncognitive attributes are measurable and influence college outcomes.

Quantitative research uses numerical data to describe variables, observe relationships between variables, or explore cause and effect relationships between variables (Butin, 2010; Gall et al., 2007; Vogt, 2007). This study utilized a quantitative, nonexperimental research design because the research questions explore how different variables predict one another, as well as the relationship and strength between the variables (Bickman & Rog, 2009; Black, 2005). The research questions were designed to determine if cognitive factors (e.g., standardized test scores and HSGPA) and noncognitive factors (SSI subscale scores) are predictive variables in understanding college student performance and retention. Further, this study was designed to determine whether the noncognitive factors are a better predictor of FYGPA and first-year to second-year retention. One focus of quantitative research is to answer “what,” “where,” and “when” questions by gathering and analyzing numerical data (Butin, 2010, p. 74). The literature review examined previous empirical research regarding the predictive validity of standardized test scores and HSGPA and college outcomes, as well as introduced the phenomenon of noncognitive factors within the realm of college student success literature.

Muijs (2011) explained that all research explains phenomena and that quantitative research collects numerical data that is analyzed mathematically to answer questions. In contrast, Bickman and Rog (2009) posited that descriptive research does not attempt to explain a phenomenon. Rather, it observes a phenomenon as it occurs to provide a picture of what is happening. While the role of noncognitive attributes in predicting college success is not new, the use of these factors within the admissions process is intriguing as higher education institutions analyze admissions criteria that have a greater likelihood of predicting student success.

Research Design. Vogt (2007) posited that the research questions will determine a study's design, measurement, and analysis. The design focuses on how data is collected and provides a roadmap for how the data, or evidence, answers the research questions (Vogt, 2007). There are many types of research designs, and because this study utilized archival data, a secondary analysis of data occurred (Vogt, 2007). This analysis of the data used correlational predictive design to examine the effect of SAT score, HSGPA, and the SSI subscale scores on FYGPA and first-year to second-year retention on a population of first-year students at a regional university in the Southeastern United States. This study also examined whether the SSI noncognitive subscale scores predict FYGPA and retention better than the SAT score and HSGPA. A correlational predictive design is appropriate for this study because correlation research seeks to understand how two or more variables are related to one another and allows a researcher to predict an outcome (Cohen et al., 2003; Gall et al., 2007). Critical features of correlational research include the following:

> Correlation between 2 or more variables, only collecting data at one point in time, using all scores on a continuum (e.g., 10 to 90), obtaining at least one score for each variable, using the appropriate correlational statistic, and making an interpretation to obtain a conclusion from the results of the statistical test. (Creswell & Guetterman as cited by Seerman, p, 176)

One key difference in this study, unlike most correlational research, is that the data points were collected at various points, primarily through the admissions application and the SSI administration. Correlational predictive research is an appropriate design for this study because the research questions explore how well one variable or variables can predict another variable (Cohen et al., 2003). Regression will explore the prediction piece of the study. Regression is a valuable tool to explain prediction in nonexperimental research because the analysis describes how an independent variable influences an outcome or dependent variable (Vogt, 2007). The regression tests included hierarchical multiple regression and logistic regression.

Correlation research design also seeks to understand predictive relationships between variables (Cohen et al., 2003; Gall et al., 2007). In this study, the predictor or independent variables are SAT score, HSGPA, and SSI subscale scores. The outcome or dependent variable is FYGPA or retention. Essentially, correlational research examines to what extent two (or more) characteristics tend to occur together, and the strength of the relationship (Holton & Burnett, 2005). A correlational predictive design is appropriate because the predictor variables (SSI subscale scores, SAT score, and HSGPA) were measured before the outcome variable (FYGPA or retention), which is a necessary component of predictive correlational design (Black, 2005; Gall et al., 2007). The data collection, sample size, and procedures are discussed later in this chapter.

Study Site

Participants in this study attend a public, regional, comprehensive university located in the southeastern United States. For this study, the university will be referred to by the pseudonym Southeastern University (SU). Southeastern University enrolls approximately 10,500 students. The undergraduate population at SU is approximately 9,800 students, and the fall 2019 first-year class comprised 2,301 full-time students. SU offers over 90 undergraduate majors and programs. The student body at Southeastern University is geographically diverse, with 51% enrolling from within the state, 47% enrolling from 48 other states, and 2% enrolling from over 60 countries. Within the freshmen class, 55% of students are from out-of-state, and 45% are from in-state. The gender ratio of the freshmen class mirrors the student body, with females comprising 55% of the enrollment. Approximately 30% of the student body identifies with an underrepresented or minority population, with the majority (25%) identifying as African American or Black. Southeastern University is unique among its peers in the state in that 38% of the student body receives federal Pell grants, which is an indicator of low socioeconomic status, and 27% of the students identify as first-generation.

Southeastern University is considered moderately selective in its admissions standards. For fall 2019, SU received 15,061 freshman applications for admission and admitted 73% of the applicants who completed their application. Of the 2,301 full-time students who enrolled in fall 2019, the average SAT was a 1098, the average ACT was a 21.7, and the average high school GPA was a 3.21. The standardized test score averages are above both the national and state average. SU recalculates the HSGPA for all admitted applicants. The recalculated GPA includes grades from the 20 core academic classes (English, math, lab science, foreign language, social sciences, fine arts, and academic electives). The quality points from the grade earned (A = 4 points, B = 3 points, etc.) are divided by 20 (the number of credits) to get a standard GPA for each student. This is called the core GPA, and the state’s Council for Higher Education requires all public institutions to report this GPA. This study utilized the core GPA, which is referred to as the high school GPA or HSGPA.

First-year retention has been a focus at Southeastern University for the past decade, as SU retains students at a much lower rate than most of its peer institutions both within and outside the state. The average retention rates at SU's peer institutions is over 70%. SU had a retention low in 2011, where only 59% of the fall 2010 freshmen cohort returned for a second year. This concerns Southeastern University as retention is widely reported in college rankings, and many students use retention as a potential enrollment factor (Morse & Brooks, 2020; Raisman, 2013; Ruffalo Noel Levitz, 2018). Through deliberate campus-wide efforts, retention improved to nearly 70% for the fall 2017 cohort; however, the most recent retention rate for the fall 2018 cohort was 68%. As discussed in the previous chapter, retention has been of critical importance on all college campuses but especially at Southeastern University, where less than 6% of the budget has come from state appropriations. SU is dependent on student tuition revenue for a balanced budget.

Population and Sample

The population used by this study was the fall 2019 freshmen cohort at Southeastern University. I chose this population because this was the first freshmen cohort to take the Student Strengths Inventory (SSI) assessment either before matriculation or within the first two weeks of the semester. SU partnered with Campus Labs for assessment and advising services. Campus Labs, which owns the Student Strengths Inventory, offered a program called Beacon that is an early alert and first year-advising program. The New Student and Family Programs office emailed students over the summer about the SSI and encouraged students to take this assessment before their July orientation. However, students could complete the SSI after they attended orientation. Students received multiple electronic communications about taking the SSI throughout the summer. Students took the SSI independently, and it was not mandatory to complete. Of the 2,301 full-time students in the freshmen cohort, 1,272 (55%) students completed the SSI. To date, SU has not analyzed the results of the SSI.

Sample

The sample for this study included the 1,104 students who completed the SSI assessment and completed the entire academic year at Southeastern University. Hierarchical multiple regression analysis was used to answer the first research question because there are multiple predictors or independent variables (Miles & Shevlin, 2007; Salkind, 2017). Multiple regression is widely used in educational research and is used to “determine the correlation between a criterion variable and a combination of two or more predictor variables” (Gall et al., 2007, p. 353). As sample size impacts the results of regression analyses, it is critical to determine whether the sample size is large enough to make predictions. Green (1991) developed a rule of thumb to determine how many subjects were required to do a regression analysis. Miles and Shevlin (2007) opined there should be “at least 20 participants per independent variable” (p. 119). Green (1991) offered a more robust formula, which suggested the sample size be no less than $50 + 8k$, where k equals the number of independent variables. Vogt (2007) also endorses this formula for using regression analysis. This study has eight independent variables. Green’s (1991) method suggested the sample size be at least 114. The current sample size of 1,104 well exceeds the rule of thumb for regression analysis (Green, 1991; Vogt, 2007).

Logistic regression was used to answer the second research question. Logistic regression is the appropriate test because the dependent variable, retention, is dichotomous (Miles & Shevlin, 2007). Dichotomous variables have only two values (Field, 2018; Miles & Shevlin, 2007), and in this study, students were either retained or not retained. Logistic regression seeks to determine if “predicted values are equal to the real values of the dependent variables” (Miles & Shevlin, 2007, p. 160).

Instrument

Student Strengths Inventory

The Student Strengths Inventory (SSI) is the instrument used for this study. Campus Labs, which owns the SSI, writes that “the Student Strengths Inventory was created based on a meta-analysis of thirty years of research on first-year success” (Campus Labs, 2018). The instrument was developed by researchers and faculty from the University of Utah who were interested in the noncognitive development of college students and researched these noncognitive attributes as predictors of student success (Campus Labs, 2018; Gore et al., 2019). The SSI’s developers based the instrument within the framework of the impact of psychosocial factors on retention and student outcomes and Tinto’s student transition theory (Campus Labs, 2018; Gore et al., 2019). In quantitative research, a good instrument with clear questions and response options, reduces measurement error (Black, 2005; Vogt, 2007).

Initially, the SSI developers began with 243 items that measured noncognitive factors (Campus Labs, 2018). They then reduced this to 81 questions, and finally, upon 11 iterations of testing, decided on 48 questions to include in the final version (Campus Labs, 2018). The 48 statement items use a 6-point Likert-scale with options ranging from *strongly agree* to *strongly disagree* (Campus Labs, 2018). Each of the six SSI subscales is measured with eight statement responses. The six subscales include educational commitment, academic engagement, academic self-efficacy, resiliency, social comfort, and campus engagement (Campus Labs, 2018) and are discussed in more detail later in the chapter. Each section of the assessment begins with the prompt: “Below are statements that describe various attitudes, opinions, and behaviors. Read each statement carefully and indicate how well it describes you by selecting the appropriate response" (Campus Labs, 2018). The SSI results provide individual scores for each of the noncognitive subscales, as well as two indices based on student responses—one for academic success and one for retention. For this study, only the individual noncognitive subscales score was analyzed.

SSI Validity

Gore et al. (2019) researched 760 first-year college students who took both the SSI item development questions and the ACT Engage noncognitive assessment. The SSI development was conducted in three phases. The third phase selected the final questions using exploratory factor analysis and internal consistency and reliability analysis, which established the final version of the instrument (Gore et al., 2019). Campus Labs confirmed this testing and conducted their own empirical investigations with pilot institutions to ensure the instrument's validity and reliability (Campus Labs, 2018).

Three tests were used to establish reliability and validity: Cronbach's alpha reliability scores were calculated across subscales, campus characteristics, and the whole population to ensure internal consistency; both exploratory and confirmatory factor analysis was conducted to determine statistical alignment; and exploratory statistics were used to check for unusual response patterns (Campus Labs, 2018). Factor analysis determines how well items relate to one another, and whether these factors are more efficient than individual variables in determining outcomes (Salkind, 2017). Cronbach's α measures internal consistency, which determines whether the instrument measures the one thing you want to measure and nothing else (Salkind, 2017). The higher the Cronbach's α, the more confidence the researcher has that the instrument is internally consistent (Salkind, 2017). The Cronbach's α average for the six SSI subscales is

0.85, which shows good internal consistency (Campus Labs, 2018; Salkind, 2017). Table 2 provides the Cronbach's α for each of the SSI subscales.

Table 2

Cronbach's α Scores for SSI Factors

SSI Factor	Cronbach's α
Academic Self-Efficacy	.86
Academic Engagement	.80
Educational Commitment	.89
Resiliency	.81
Campus Engagement	.88
Social Comfort	.83

Note. Adapted from Theoretical and Statistical Foundations of the Student Strengths Inventory, by Campus Labs, 2018. (www.campuslabs.com). Copyright 2018 by Campus Labs (Anthology).

Factor Analysis. To measure the initial construct validation of the SSI, Gore et al. (2019) conducted a confirmatory factor analysis to select the 48 items to include in the SSI. The results showed that all the selected items, except one, loaded into the scale for which it has been written; writing that this offered "confirmation of the intended factor structure and providing preliminary construct validity for scores on the SSI" (Gore et al., 2019, p. 52). The confirmatory factor analysis supported the following six correlated scales: academic engagement, academic self-efficacy, campus engagement, social comfort, resiliency, and educational commitment (Gore et al., 2019). Lastly, the relationships between scales had Pearson's *r* correlations ranging from .09 to .60 (Gore et al., 2019).

Other Validity Measures. Campus Labs (2018) provides other measures of construct validity for the SSI outside of the Cronbach's α scores and factor analysis. The SSI is considered to have face validity because it *looks like* it measures what it says it will. The instrument developers consulted published research to confirm whether they measured the noncognitive attributes that impact college outcomes and that the questions were worded correctly (Campus Labs, 2018).

Predictive validity assesses whether an instrument predicts a relationship that is believed to exist based on previous research or evidence (Campus Labs, 2018). The SSI has predictive validity because there is a high correlation between the six noncognitive subscales that predict retention and academic success, which validates that the instrument predicts the relationship that it is believed to predict (Campus Labs, 2018). In discussing predictive validity, Campus Labs (2018) wrote: “In aggregate, the top predictors of both retention and academic success are a combination of the six scales when reviewed in conjunction with standardized test scoring” (p. 4). Lastly, discriminant validity was tested using correlational analysis to confirm predicted relationships using other validity instruments, and descriptive statistics checked for abnormal patterns in responses (Campus Labs, 2018). Discriminant validity examines “the degree to which a construct is dissimilar to other constructs it should be dissimilar to theoretically” (Campus Labs, 2018, p. 4).

Social Desirability. The concept of social desirability is a validity threat in self-report assessments and, most notably in noncognitive assessments, where students may answer questions in a way that presents themselves in the best light (Metz et al., 2015). Metz et al. (2015) cited numerous studies that conclude that social desirability presents a challenge in accurately measuring an instrument’s validity, even noting that individuals with both high self-esteem and emotional intelligence practice higher levels of socially desirable behavior in self-reported assessments. Metz et al. (2015) tested the impact of social desirability on the Student

Strengths Inventory with a sample of 645 undergraduate students. Their results concluded that the college student population did not engage in socially desirable responses on the SSI and this study supports the use of self-reported noncognitive assessments in higher education (Metz et al., 2015). Metz et al. (2015) cautioned these results might not be generalized to other student populations because the study was conducted on one campus, and the sample had few underrepresented students.

Data Collection and Analysis Procedures

Data Collection

After securing IRB approval, the collection of the archival data involved three steps. First, demographic, admissions application, and socioeconomic data were collected from the student information system. This information was obtained when the student completed their admission and financial aid application before enrolling at the institution. This data included age, gender, race/ethnicity, high school GPA, standardized test score, and FAFSA data, such as Pell grant eligibility and first-generation status. The Student Strengths Inventory (SSI) data were collected from the Beacon system. The SSI results are survey-based data. Survey research has been widely used in quantitative research because the researcher can collect data from large samples to generalize to a larger population (Pinsonneault & Kramer, 1993). Survey research typically has sought subjective data, which attempts to understand an individual's beliefs, attitudes, opinions, and experiences (Campus Labs, 2018; Leavy, 2017). Subjective data allows the researcher to examine relationships between variables or differences between groups (Bickman & Rog, 2009; Black, 2005; Pinsonneault & Kramer, 1993). The SSI was facilitated online either before matriculation or within the first two weeks of the semester. The instrument had a flexible timeline for administration, and many institutions chose to administer it before orientation or within the first two weeks of the semester (Campus Labs, 2018). Lastly, the Registrar's office provided first-year GPA and a retention indicator. Retention was indicated by registration for the upcoming fall semester. The Institutional Research office compiled the full data set for me and removed all personally identifiable information.

I worked with the institutional research office to collect the data set. The data included student demographic variables (e.g., age, gender, race, socioeconomic status, and first-generation status), cognitive indicators (e.g., HSGPA and standardized test scores), college success metrics (e.g., FYGPA and retention), and the scores from the six noncognitive SSI subscales. The institutional research office collected the data from across campus, de-identified the data, and shared it with me, the researcher. The data were collected in early fall 2020, once the FYGPA and retention data were available. All personally identifiable information was removed from the data set, and a unique student identification number was assigned to each student record. This identifier was different from the assigned student ID. Thus, it ensured the protection of student data while also allowing me to have one data set that connected the data from multiple sources.

Variables

Variables are contained within research questions and can be independent, dependent, or controlled (Black, 2005; Gall et al., 2007). Once the variables are identified, they must be operationally defined, which explains how the variable will be measured, whether nominal, ordinal, interval, or ratio (Miles & Shevlin, 2007; Salkind, 2017; Vogt, 2007). When using regression, it is recommended that variables are interval; however, nominal variables can be dummy coded in regression analysis if required (Vogt, 2007). Interval scales "have equal distances between any two adjoining numbers, but they have no meaningful zero point" (Vogt, 2007, p. 10). The predictor variables were SAT score, HSGPA, and the six noncognitive SSI subscales (e.g., educational commitment, academic engagement, academic self-efficacy, resiliency, social comfort, and campus engagement). The outcome/criterion variables were FYGPA and the retention indicator.

The SSI instrument assesses 48 items that were presented as statements and used a six-point Likert-scale response ranging from *strongly agree* to *strongly disagree* (Campus Labs, 2018). Each question is scored from 1 to 6 based on the student's response (Campus Labs, 2018). Questions were both negatively and positively worded. The anchors on positively worded questions were 1 = *strongly disagree*, 2 = *disagree*, 3 = *somewhat disagree*, 4 = *somewhat agree*, 5 = *agree,* and *6* = *strongly agree* (E.Siegel, personal communication, August 5, 2020)). An example of a positively worded question is "*I will be able to complete college English requirements with a B or better"* (E. Siegel, personal communication, September 9, 2020). The anchors on the negatively worded questions were 6 = *strongly disagree,* 5 = *disagree,* 4 = *somewhat disagree*, 3 = *somewhat agree*, 2 = *agree*, and 1 = *strongly agree* (E. Siegel, personal communication, August 5, 2020).). An example of a negatively worded question is "*I never know what to say when meeting new* people" (E. Siegel, personal communication, September 9, 2020).

Within the 48 total questions, there were eight questions in each section that correspond to the six noncognitive subscales, allowing for a total possible score of 48 for each subscale (Campus Labs, 2018). Due to the copyright on the SSI, Campus Labs would not approve the instrument to be shared in its entirety. However, Appendix A provides an example of random SSI questions and how each question loads into the specific noncognitive subscale. Each subscale score was given a percentage of 1 – 99 (Campus Labs, 2018). Students with a 24 or lower percentile were considered low in that subscale. Students in the 25 – 75 percentiles were *moderate*, and students in the 76 and higher percentile were considered *high* in that subscale. For this study, the percentiles were not analyzed; only the raw scores for each subscale were included in the analysis. Each variable is described in detail below:

Academic Self-Efficacy. Academic self-efficacy measured a student's confidence in their ability to do well academically and succeed in college. This subscale is related to academic success. Questions that measure academic self-efficacy included, "*I will excel in my chosen major,"* "*I am confident I can maintain a B average in college,"* and "*I am confident that I will succeed in college*" (Campus Labs, 2018; Gore et al., 2019). This was an independent (predictor) variable measured on a scale of 8 to 48.

Academic Engagement. Academic engagement measured the value that a student places on their academics and the amount of attention given to schoolwork. Academic engagement is related to academic success. Sample questions that measure this subscale were, "*I turn my homework in on time," I get to school on time,"* and "*School is a priority for me*" (Campus Labs, 2018; Gore et al., 2019). This was an independent (predictor) variable measured on a scale of 8 to 48.

Educational Commitment. Educational commitment measured the value that a student places on a college degree and their dedication to completing a degree. Educational commitment is related to retention. Sample questions that measure educational commitment included, "*I see value in completing a college education," "If I was offered a good job, I might not finish college,"* and "*I am willing to do whatever it takes to stay in college"* (Campus Labs, 2018; Gore et al., 2019). This was an independent (predictor) variable measured on a scale of 8 to 48.

Resiliency. The resiliency subscale measured how a student approaches challenging situations and stressful events. This subscale is related to both academic success and retention. Some of the questions that measure resiliency included "*I manage stress well," "I am a* *worrier,"* and "*I am quick to react emotionally"* (Campus Labs, 2018; Gore et al., 2019). This was an independent (predictor) variable measured on a scale of 8 to 48.

Campus Engagement. Factors considered on the campus engagement subscale were a student's desire to be involved on campus and how attached, they are to the institution. Campus engagement is related to retention and is considered to develop a sense of belonging. Questions that measure campus engagement included, "*Being active in extra-curricular activities in college is important to me," "I plan to take part in many campus social activities,"* and "*I intend to seek volunteer or service-learning experiences in college"* (Campus Labs, 2018; Gore et al., 2019). This was an independent (predictor) variable measured on a scale of 8 to 48.

Social Comfort. The social comfort subscale measured a student's comfort in social settings and how well they communicate with others. Social comfort is related to retention. Questions that assess social comfort were *"I am comfortable in groups," "I find it easy to talk to strangers,"* and "*I have many friends*" (Campus Labs, 2018; Gore et al., 2019). This was an independent (predictor) variable measured on a scale of 8 to 48.

SAT Score. This cognitive variable was collected through the application process. I utilized a concordance chart to convert all ACT scores to the equivalent SAT score (see Appendix B). I chose to do this so that standardized test scores were reported as a single variable. For students who only submitted the ACT, I concorded the score to the equivalent SAT score. I chose this method since 76% of the sample submitted SAT scores. The institution utilized super-scoring, which calculated a composite score from the highest subtest scores. For example, if a student presented two SAT scores with a higher math score from one test date and a higher evidence-based reading and writing score from another test date, the two highest scores were used to calculate the best composite score. The same was done with ACT scores across multiple test dates. SAT score was an independent (predictor) variable measured on a scale of 400 to 1600.

High School Grade Point Average (HSGPA). This was a cognitive variable collected from grades on the final high school transcript that the student submitted prior to enrollment. This measure was calculated by dividing the number of quality points for each course by the number of academic credits earned. The HSGPA range is 0.0 to 4.0.

First-Year Grade Point Average (FYGPA). This outcome variable measured a student's performance within their first year. This measure was calculated by dividing the number of quality points earned by the total number of academic credits earned in the first year of college. The FYGPA range is 0.0 to 4.0.

Retention. This outcome variable indicated whether a student returned to the institution for their second year. For this study, retention was reported by the student's preregistration for the fall 2020 semester. This was a dependent (criterion) variable measured with either a positive or negative retention score (1 = retained or 0 = not retained). Actual retention was calculated when the student matriculated and began classes for their second year.

Analysis Procedures

The first step in data analysis was to prepare the data (assigning numeric scores, assessing types of scores) and then input the data into a program. SPSS (Statistical Package for the Social Sciences) was the software used to conduct the data analysis. SPSS is one of the most commonly used statistical software packages in educational research, is Windows-based, and very user-friendly (Muijs, 2011). Once the data were in the SPSS software, I developed a codebook that included each variable, a short description of the variable, and how it was defined for measurement. A correlation matrix was calculated for each of the study's variables.

Regression analyses were conducted to present the relationships between the dependent (criterion) variable and the independent (predictor variables).

Descriptive Statistics. The first stage in the data analysis included descriptive statistics. This analysis consisted of demographic characteristics such as age, gender, race/ethnicity collected through application data, and first-generation and socio-economic data collected through FAFSA data.

Correlations between the variables were displayed through a correlation matrix. Scatterplots show the relationship between two variables (Vogt, 2007). A correlation matrix is a useful tool to display the correlation coefficient between multiple variables. This study utilized both tools to demonstrate the relationship between variables visually. These tests examined the statistical significance of the correlation coefficients between the variables (Salkind, 2017). This correlation was especially significant in regression to determine the strength of the association between the variables (Miles & Shevlin, 2007; Salkind, 2017).

A *t*-test test allows a researcher to examine mean differences between groups (Miles & Shevlin, 2007; Salkind, 2017). A *t*-test helps determine if the differences between groups is due to chance or whether the differences are statistically significant (Hoy & Adams, 2016). This study utilized an independent samples *t*-test to observe mean differences between students who were retained and not retained. This analysis was important to better understand whether there were significant differences between students who were retained and not retained related to the variables under investigation in the logistic regression.

Assumptions Testing. Salkind (2017) wrote: “Almost every statistical test has certain assumptions that underlie the use of the test” (p. 212). Assumptions testing in statistical analysis is critical to ensure unambiguous results and valid conclusions. Testing for assumptions shows whether the data is normally distributed, whether the variance is homogeneous, or that data from multiple groups have the same variance, whether the data have a linear relationship, and whether the data are independent (Salkind, 2017).

Hierarchical Multiple Regression. Hierarchical multiple regression will be used to answer the first research question. Hierarchical multiple regression is the appropriate test because the dependent variable (HSGPA) is continuous and because the significance of the independent variables was analyzed in blocks (Vogt, 2007). Assumptions testing in hierarchical multiple regression confirms whether the data meets the criteria listed above before running each statistical analysis. Hierarchical multiple regression requires eight assumptions tests (Laerd Statistics, 2015). The first two assumptions were that the dependent variable was continuous and that there were more than two independent variables (Laerd Statistics, 2015; Miles & Shevlin, 2007; Vogt, 2007). The other assumptions included an independence of observations, linearity between variables, homoscedasticity of residuals, no multicollinearity, no significant outliers, and normally distributed residuals (Laerd Statistics, 2015). In hierarchical multiple regression, the variables must be linear (Laerd, 2015; Vogt, 2007). A scatter plot is used to check for the linearity of each independent variable (Laerd, 2015; Vogt, 2007). Assumptions testing in regression analysis also checked for outliers, skewness, and residuals in the data (Laerd, 2015; Vogt, 2007). The SPSS program conducted the appropriate assumptions testing on the data before results were analyzed and displayed. Assumptions testing was critical because it determined whether hierarchical multiple regression was the appropriate test to answer the first research question (Laerd Statistics, 2015; Salkind, 2017). Chapter 4 discusses the results of the assumptions testing for multiple hierarchical regression.

Logistic Regression. Logistic regression was used to answer the second research question because the dependent variable (retention) was dichotomous. Seven assumptions should be considered on logistic regression. The first two assumptions were that the dependent variable was dichotomous and the independent variables were continuous (Laerd Statistics, 2017; Miles & Shevlin, 2007). The other assumptions included an independence of observations, a presence of at least 15 cases per independent variable, a linear relationship between independent variables and the dependent variable, no multicollinearity, and no significant outliers (Laerd Statistics, 2017). The SPSS program conducted the appropriate assumptions testing before the data were analyzed and results were displayed. Assumptions testing determined whether logistic regression was the appropriate test to answer the second research question (Laerd Statistics, 2017). Chapter 4 discusses the results of the logistic regression assumptions.

Hypothesis Testing. Regression analysis examines how multiple factors influence an outcome. By including multiple factors into the equation, a researcher can make more accurate predictions about the data (Miles & Shevlin, 2007; Vogt, 2007). Salkind (2017) posited that the predictor, or independent variables must be related to the dependent variable, but the independent variables should be unrelated to each other. This allows for the researcher to determine how each predictor variable makes a distinct contribution to the outcome (Salkind, 2017). Hierarchical multiple regression calculates the correlations between the independent variables and then analyzes each variable's effect when the others have been removed (Miles & Shevlin, 2007).

In contrast, logistic regression provides an odds likelihood or odds ratio of how the independent variables influence the dependent variable (Miles & Shevlin, 2007). The goals of the research should shape research questions, and regression analysis helps researchers determine whether all independent variables (e.g., SSI noncognitive subscale score, SAT score, and HSGPA) are predictors of an outcome (e.g., FYGPA and retention), or if each variable has a different effect on the outcome (Vogt, 2007). The research questions are provided below, along with a summary of each regression test:

RQ1. To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and high school grade point average (HSGPA) predict first-year college grade point average (FYGPA)?

H_0: SAT score, HSGPA, and the six noncognitive subscale scores do not predict FYGPA.

H_1: SSI noncognitive subscale scores will be more predictive of FYGPA than HSGPA and SAT score.

The first research question addressed the extent to which SAT score, HSGPA, and the six SSI subscale scores predict first-year college GPA. A hierarchical multiple regression test was run to determine how each independent variable (e.g., SAT score, HSGPA, academic self-efficacy, academic engagement, campus engagement, educational commitment, social comfort, and resiliency) predicted FYGPA. Once the data were downloaded and coded in SPSS, the first step in the hierarchical multiple regression analysis was to conduct assumption testing in each of the six areas addressed above. Once it was determined the data met the six assumptions, the hierarchical multiple regression results were interpreted. The interpretation of the results included an explanation of how much the independent variable within each of the blocks explained the variation in the dependent variable, predicted a dependent variable based on a change to an independent variable, and determined how much the dependent variable changed by one unit change in the independent variable (Laerd Statistics, 2015).

RQ2: To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and HSGPA predict first-year to second-year college retention?

H$_0$: SAT score, HSGPA, and the six noncognitive subscale scores do not predict first-year to second-year college retention.

H$_2$: SSI noncognitive subscale scores will be more predictive of first-year to second-year retention than HSGPA and SAT score.

The second research question examined how well SAT score, HSGPA, and the six noncognitive subscale scores predicted first-year to second-year retention. A logistic regression test was run to determine how each independent variable (e.g., SAT score, HSGPA, academic self-efficacy, academic engagement, campus engagement, educational commitment, social comfort, and resiliency) predicted first-year to second-year retention. Once the data were downloaded and coded in SPSS, the first step in the logistic regression analysis was to conduct assumption testing in each of the six areas addressed above. Once it was determined the data met the seven assumptions, the logistic regression results were interpreted. The interpretation of the results included an explanation of whether the independent variables had a statistically significant effect on the dependent variable, and how well the logistic regression model predicted the dependent variable (Laerd Statistics, 2017). An independent samples *t* test was conducted to determine whether there was any statistically significant difference between the retained and not retained groups. A *t* test for independent samples provides information on the mean differences between the two groups (Salkind, 2017).

Role of the Researcher

Although this is a quantitative study, it was critical to examine my positionality and role at the institution. I served as the Associate Provost for Enrollment Management and supervised the admissions process at Southeastern University. This position allowed me to access the demographic, admission information, and financial aid data of the sample included in this study. To protect the sample's identity and distance me from this information, SU’s Institutional Research office collected the data, de-identified all personal information, and provided a full data file to me for analysis. The intent of this was to limit the perceived impact that my position at the university could have on this study’s results. The data were stored on my personal computer, which is password protected and located in my home office. The Student Strengths Inventory was not administered solely for this study, but rather to begin gathering student information that could be used to predict academic success and retention. I became aware of this assessment through my research and then learned that SU administered it for the first time with the 2019 freshman cohort. Since the sample that completed the survey did not do so as part of this study and were not provided incentives for completing the instrument, there is a higher probability that students responded to items truthfully (Bickman & Rog, 2009; Merriam & Tisdell, 2016).

As noted earlier, the hypothesis that guided this study was that the scores on the SSI noncognitive subscales would have greater power to predict FYGPA and retention than the more commonly used SAT score and high school grade point average. This hypothesis was developed, in part, due to my positionality, as well as the many studies that have shown the importance of grit, self-efficacy, and motivation in achieving education attainment. My positionality has been developed over my twenty-year career in enrollment and because I performed below average on the SAT. However, I graduated with honors distinction for my bachelor’s degree and held multiple leadership positions during my undergraduate career. Quantitative research requires that researchers distance themselves from the study (Martin & Bridgmon, 2012). I needed to remain neutral when conducting the data analysis and hypotheses testing not to allow my bias and positionality to affect the results. I understood there was a likelihood that my assumptions would be proven false. If so, this would result in different recommendations for future research on noncognitive indicators of success.

Ethical Considerations

This study received approval from Abilene Christian University's Institutional Review Board (IRB). The IRB's purpose is to protect the anonymity of research participants, gather informed consent when required, minimize risk to research participants, and ensure that research procedures are administered fairly and equally (ACU, 2020). Even though this study used archival data, the IRB reviewed the research procedures to ensure the anonymity of the data, while also providing maximum benefits for the research study (ACU, 2020). Since this study analyzed data that was not initially collected for this study, this study did not involve human research participants. There are benefits of using archival data in quantitative studies. First, it is a convenient and cost-effective way to relatively easily access large amounts of data (Clarke & Cossette, 2000). Second, archived datasets pull information from multiple entities or systems, providing robust data for the analysis (Shultz et al., 2005). Regression analysis tends to use data that was previously collected and cannot be changed (Vogt, 2007).

At this juncture, it is important to discuss the difference between research and quality improvement. The Department of Health and Human Services defined research as "a systemic investigation, including research development, testing, and evaluation, designed to develop or contribute to generalizable knowledge" (DHHS as cited in Newhouse et al., 2006, p. 212). This study aimed to contribute to the knowledge of noncognitive factors that predict student success, so it was considered research. However, the study's results could improve institutional factors, such as retention and graduation rates. Because this study may have implications for quality improvement at Southeastern University, it was vital to have IRB oversight of the study, even though the application was exempt. Quality improvement is a process where "individuals work together to improve systems and processes with the intention to improve outcomes" (Newhouse et al., 2006, p. 212). A byproduct of this study may be quality improvement, depending on the results, which may improve outcomes for a specific population. The IRB at Southeastern University concluded that this study was exempt from oversight of this body because it used archival data that was de-identified. This process protected me from sample bias and manipulation of the results. No data were collected for this study until the ACU IRB review and approval process was completed.

Assumptions

The hypothesis guiding this study is that noncognitive attributes are better predictors of student success than are standardized test scores and high school GPA. To test this hypothesis, students completed a noncognitive questionnaire, and the answers were analyzed related to student success and retention indicators. This hypothesis assumed I would be able to gather enough student data to support this assumption. I also assumed that the instrument measured what it should, which was discussed earlier and confirmed through the internal consistency scores (Campus Labs, 2018; Gore et al., 2019). I assumed that students answered the questions honestly. Since the survey was completed anonymously and had no incentives for completion, this increased the likelihood that students answered truthfully (Merriam & Tisdell, 2016). Lastly, I assumed this study was relevant to the field of noncognitive research and the results would contribute additional knowledge to the phenomenon of college student success.

Limitations

It is important to note a few key limitations of this study. One limitation is the study site included just one institution, which could limit the generalizability of the results to other campuses, especially campuses with different institutional characteristics and student body differences. Another limitation is the sample. The sample only included those students who enrolled at SU, and not all those who were admitted or even applied. This could skew the generalizability of the results further as the enrolled population only includes one-quarter of all admitted students. The sample is also limited because it represented a smaller portion of the 2019 freshmen cohort, and the results might not be generalizable to the larger population. Whether the results can be generalized will depend on how much the sample mirrors the larger population in terms of gender, race/ethnicity, and other demographic characteristics. The last limitation is the use of a survey instrument. As with any survey, respondents might be less than truthful with their responses. The validity section addressed the SSI was not prone to socially desirable responses. However, that study pertained to one campus with a small sample of students. This may not be the case at Southeastern University.

Delimitations

Delimitations in a research study are boundaries or choices followed by the researcher, which could impact the study (Simon, 2011). One delimitation of this study is that it only included students who enrolled at Southeastern University and excludes the larger pool of applicants who were admitted to SU. Another delimitation is the choice to use the Student Strengths Inventory (SSI) survey instrument. There are a variety of noncognitive assessments that could have been utilized for this study. This assessment was initially chosen because it was already in use at the institution. However, additional research confirmed the SSI has strong construct validation, is used on college campuses, and has neutrality in the responses. As with any study, a different instrument might yield different results.

Summary

This study employed a quantitative methodology to examine how cognitive and noncognitive factors predict academic success in college. The noncognitive attributes were measured by the Student Strengths Inventory (SSI), which is a noncognitive questionnaire used on many college campuses and owned by Campus Labs. The cognitive attributes (standardized test score and HSGPA) were collected through the admissions application process. Participants in the study included a subset of first-year students enrolled at a comprehensive, regional university in the Southeastern United States in fall 2019 and completed the SSI either before enrolling or during their first year. Regression analyses were conducted to determine how well the cognitive and noncognitive factors predict FYGPA and first-year to second-year retention.

This study was a correlational predictive research design because I examined the relationship between variables, as well as how well the independent variables predict the dependent or outcome variable (Cohen et al., 2003). As defined in the research questions, the predictor variables were the SSI subscale scores, which include academic self-efficacy, academic engagement, educational commitment, resiliency, campus engagement, and social comfort, and HSGPA and SAT score. The outcome variables were FYGPA and first-year to second-year retention. I employed hierarchical multiple regression to answer the first research question and logistic regression to answer the second research question. A *t* test for independent samples examined the mean differences for the retained and not retained groups examined in the second research question. Chapter 4 presents the results of the statistical analysis. In the end, the findings of this study should hopefully contribute to the current literature on student success by examining whether noncognitive attributes can predict college student outcomes.

Chapter 4: Results

The purpose of this study was to examine whether cognitive or noncognitive factors were better predictors of first-year college student success, as indicated by first-year grade point average (FYGPA) and first-year to second-year retention. I conducted a series of quantitative analyses on each of the independent cognitive and noncognitive variables with the dependent variables, FYGPA and first-year to second-year retention, to determine whether the independent variables were statistically significant in predicting an outcome. This chapter summarizes the research approach and process and presents the results of the statistical analyses applied to conduct this study. This chapter concludes with a summary of the findings and a preview of Chapter 5.

Summary of the Research Focus and Process

Correlational predictive research was designed to examine the influence of the cognitive and noncognitive variables on FYGPA and first-year to second-year retention. I chose this research design because predictive research examines the impact that different variables have on an outcome (Cohen et al., 2003; Gall et al., 2007; Miles & Shevlin, 2007). In this study, the predictor variables were academic self-efficacy, academic engagement, educational commitment, resiliency, campus engagement, social comfort, high school grade point average, and SAT score. High school grade point average (HSGPA) and SAT score are cognitive factors, whereas the other variables are noncognitive. The outcome variables were FYGPA and first-year to second-year retention.

The dataset consisted of first-year students at Southeastern University who took the Student Strengths Inventory (SSI) in either summer or early fall 2019. The SSI is a noncognitive assessment that Southeastern University administered for the first time with the fall 2019 entering class. The same dataset was used to answer both research questions. The outcome variable in each research question determined the appropriate statistical analysis. To answer Question 1, I conducted a hierarchical multiple regression analysis to determine how each predictor variable influenced the outcome variable, FYGPA. To answer Question 2, I ran a logistic regression to determine how well the independent variables predicted first-year-to second-year retention. After the logistic regression was run, a *t* test for independent samples was conducted to determine whether there were statistically significant differences between the retained and not retained groups.

Presentation of the Findings

The design of this study was constructed around two research questions. I conducted two statistical analyses to test the null hypothesis for each research question. This section provides demographic information for the population under investigation and presents the results of the statistical tests used to answer each research question.

Description of Sample

A total of 1,461 in the entering class of fall 2019 at SU took the SSI assessment. Of this population, 189 were identified as transfer students and were excluded from the study. Since this study was focused on first-year college students, these students were excluded because they had prior completion of college coursework after graduating from high school. The final number of first-time freshmen students who took the SSI was 1,272. This represented 55% of the entire first-year class. Upon receiving IRB approval, I, the researcher, obtained the dataset. I removed 168 records from the original dataset. Nine records were removed because of a potential validity issue. I removed 61 records due to missing information, including missing noncognitive subscale scores, missing grade point average and SAT scores, or both. Additionally, I removed 98 student records because they left the institution after fall 2019. The final dataset included 1,104 first-year student records, which comprised 54% of the first-year students who remained enrolled through spring 2020.

The descriptive statistics for the dataset are presented in Table 3. The majority of students included in this study were female at 64% (*n* = 707). The majority of students in this study identified as non-Hispanic (*n* = 1,018) and White (*n* = 851); however, 13.2% (*n* = 146) identified as Black and 6.2% (*n* = 69) identified as either American Indian/Alaska Native, Asian, Hawaiian Native/Pacific Islander, or multiracial. There were 38 students who did not disclose their race. The average age was 18 at the time of assessment (*n* = 842). The study included a total of 463 in-state and 641 out-of-state students. A majority of students, 83.9% (*n* = 926), did not identify as a first-generation college student. A total of 1,037 students submitted the FAFSA, and 28.9% (*n* = 319) were eligible to receive a Pell grant, which designated them as a low socioeconomic status student.

Table 3

Descriptive Statistics by Demographic Information

Demographic	*n*	%
Ethnicity		
Non-Hispanic	1018	92.2
Hispanic	54	4.9
Unknown	32	2.9
Race		
American Indian/Alaska Native	7	0.6
Asian	16	1.4
Black	146	13.2
Hawaiian Native/ Pacific Islander	2	0.2
Multiracial	44	4.0
Unknown	38	3.4
White	851	77.1
Gender		
Female	707	64.0
Male	397	36.0
Age		
17	230	20.8
18	842	76.3
19	21	2.8
20	1	0.1
First Generation		
No	926	83.9
Yes	178	16.1
Student Type		
In-State	463	41.8
Out-of-State	641	58.1
FASFA		
Filed a FAFSA	1037	93.9
Did not file a FAFSA	67	6.1
Pell Grant		
Received Pell Grant	319	28.9
No Pell Grant	785	71.1

Before running statistics for the research questions, I analyzed skewness and kurtosis for each predictor and outcome variable. The results are presented in Table 4.

Table 4

Skewness and Kurtosis of Variables

Variable	*n*	Skewness	*SES*	Kurtosis	*SEK*
SAT	1104	.37	.07	.35	.15
HSGPA	1104	-.17	.07	-.91	.15
Academic Self-efficacy	1104	-.35	.07	-.07	.15
Academic Engagement	1104	-.42	.07	.19	.15
Educational Commitment	1104	-1.33	.07	2.17	.15
Resiliency	1104	-.29	.07	.14	.15
Campus Engagement	1104	-.58	.07	-.58	.15
Social Comfort	1104	-.47	.07	.10	.15
FYGPA	1104	-1.59	.07	-1.60	.15
Retention	1104	-1.77	.07	1.15	.15

Note. SES = Standard Error of Skewness. *SEK* = Standard Error of Kurtosis.

Skewness and kurtosis were measured to determine how the frequencies of each variable were different. A normal range for skewness is between 1 and -1, and a normal kurtosis range is between 2 and -2. Each of the variables, other than SAT score, displayed a negatively skewed distribution, which means there were more occurrences at the high end of the distribution (Salkind, 2017). Educational commitment, FYGPA, and retention exhibited negative skewness outside of the normal range. All the variables, except for educational commitment, fell within a normal kurtosis range, which means the distributions were not highly peaked or flat (Salkind, 2017). Skewness and kurtosis are important for determining the normality of the data (Field, 2018; Salkind, 2017) and will be discussed in the next section in the assumptions testing for hierarchical multiple regression.

Question 1

RQ1. To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and high school grade point average (HSGPA) predict first-year college grade point average (FYGPA)?

H_0: SAT score, HSGPA, and the six noncognitive subscale scores do not predict FYGPA.

H_1: SSI noncognitive subscale scores will be more predictive of FYGPA than HSGPA and SAT score.

Hierarchical multiple regression was run to predict FYGPA from the SSI subscale scores academic self-efficacy, academic engagement, educational commitment, resiliency, campus engagement, and social comfort, as well as SAT score and HSGPA. Table 5 shows the mean, standard deviation, and range for each of the variables analyzed in the hierarchical multiple regression.

Table 5

Mean Scores and Range Values of Variables

Variable	Range	Mean	*SD*
Academic Self-efficiency	24-48	40.74	4.38
Academic Engagement	14-48	37.62	5.40
Educational Commitment	25-48	43.70	3.82
Resiliency	8-48	31.86	5.21
Campus Engagement	15-48	38.75	5.21
Social Comfort	9-48	36.60	6.51
SAT Score	710-1500	1090	125.38
HSGPA	2.00-4.00	3.26	.44
FYGPA	.07-4.0	3.26	.70

The data displayed in Table 5 show measures of central tendency for the variables investigated in the first research question. The means in the table show the average for each variable, and the standard deviation indicates the extent to which the scores deviate from the mean (Gall et al., 2007; Salkind, 2017). The six SSI subscales were measured on a scale of 8 to 48, with each of the eight questions within the subscale having a score between 1 and 6 on the Likert scale. Both resiliency and social comfort displayed a wide range of scores, whereas the other SSI subscales showed a more compact range of scores. The SAT scale is measured from 400 to 1600. There were 260 students in the dataset who only submitted an ACT test score. I converted the ACT scores to the equivalent SAT scores (see Appendix B) for these students, and the converted scores are included in the SAT average score. The grade point average scales for both high school and first-year GPA ranged from 0.0 to 4.0.

Correlation examines the extent to which two variables are linearly related (Miles & Shevlin, 2007). The coefficient of correlation (*r*) is calculated when the independent and dependent variables are continuous (Hoy & Adams, 2016). The correlation coefficient will determine the strength of the relationship between variables, and whether the relationship is likely to do chance or not (Hoy & Adams, 2016; Salkind, 2017). Correlations range from 1 to -1 and show whether the relationship is positive or negative (Hoy & Adams, 2016; Salkind, 2017). A general rule in multiple regression is to look for correlation coefficients below $\pm$.7, which indicates that the correlation is moderate or low (Laerd Statistics, 2015; Salkind, 2017). None of the variables exhibited a correlation coefficient greater than $\pm$.7 (as shown in Table 6).

A bivariate correlation was conducted to determine which variables were related to FYGPA (as shown in Table 6). Academic self-efficacy, academic engagement, educational commitment, campus engagement, HSGPA, and SAT score showed a significant relationship with FYGPA.

Table 6

Correlation Matrix

	1	2	3	4	5	6	7	8	9
1. FYGPA		-.13	-.24	.01	.06	-.07	.03	-.57	-.34
2. Academic Self-Efficacy	-.13***		.46	-.48	.29	.41	.30	.24	.12
3. Academic Engagement	-.24***	.46		-.50	.27	.31	.16	.24	-.06
4. Educational Commitment	.01**	-.48	-.50		-.10	-.41	-.23	-.12	.06
5. Resiliency	.06	.29	.27	-.10		.13	.42	-.05	-.06
6. Campus Engagement	-.07*	.41	.31	-.41	.13		.47	.00	-.05
7. Social Comfort	.03	.30	.16	-.23	.42	.47		-.09	-.03
8. HSGPA	-.57***	.24	.24	-.12	-.05	.00	-.09		.45
9. SAT Score	-.34***	.12	-.06	.06	-.06	-.05	-.03	.45	

Note. 1 = First-year GPA, 2 = Academic Self-Efficacy, 3 = Academic Engagement, 4 = Educational Commitment, 5 = Resiliency, 6 = Campus Engagement, 7 = Social Comfort, 8 = HSGPA, 9 = SAT Score.

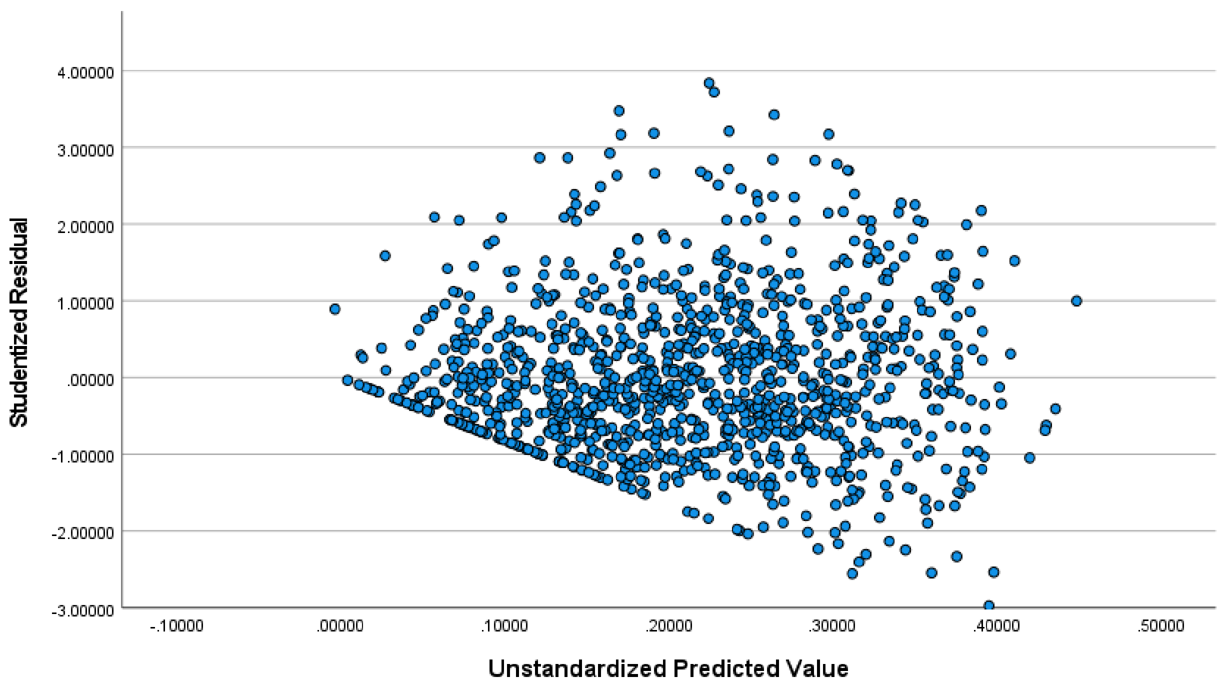
*$p < .05$. **$p < .01$; ***$p < .001$ (sig. 2-tailed).

Hierarchical multiple regression requires that assumptions are tested and satisfied before interpreting the results. The first assumption in hierarchical multiple regression is the dependent variable is continuous. First-year grade point average is continuous, so this assumption was satisfied. The second assumption is that there is more than one independent variable. There were eight independent variables included in this analysis, which satisfied this assumption. The other assumptions, described below, were tested and analyzed in the SPSS output of the results.

Residuals were independent, as assessed by a Durbin-Watson statistic of 1.84. The dependent variable, FYGPA, exhibited a negative skewness, which impacted the linearity of the scatterplots. One of the independent variables, educational commitment, also exhibited negative skewness. A visual inspection of a plot of studentized residuals versus unstandardized predicted values showed there was heteroscedasticity. To correct for both linearity, heteroscedasticity, and normality, a log 10 transformation with a reflection of the dependent variable (FYGPA) and one independent variable (educational commitment) was conducted (Grande, 2015). The log 10 transformation was conducted to correct the skewness, which impacted linearity, homoscedasticity, and normality (Grande, 2015). This transformation fixed the heteroscedasticity issue (as shown in Figure 3). The log transformation formula is displayed in the hierarchical regression tables in the notes. I confirmed the data were homoscedastic with a visual inspection of a scatterplot of studentized residuals against the unstandardized predicted values (Field, 2018).

Figure 3

Scatter Plot of Studentized Residuals by Unstandardized Predicted Value

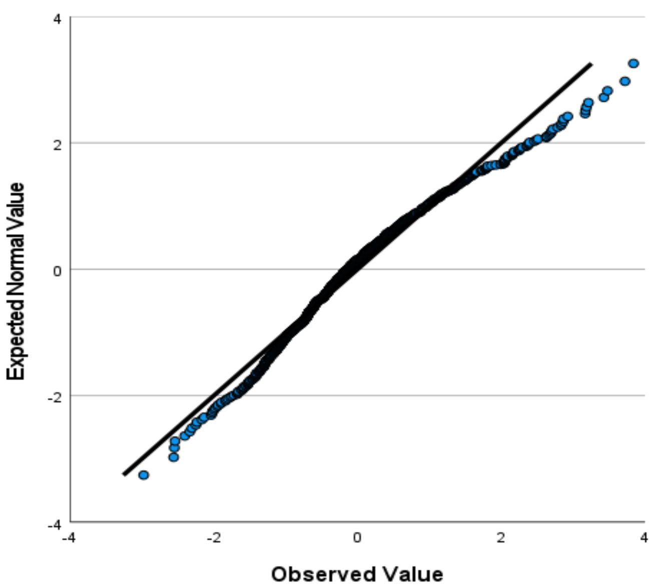


The dependent variable transformation also corrected the linearity issue. After the variable transformation, linearity was assessed by a partial regression plot of studentized residuals against the predicted values and a scatterplot of each independent variable against the dependent variable.

There was no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There were eight studentized deleted residuals greater than ±3 standard deviations. However, there were no leverage values greater than 0.2, and no values for Cook's distance above 1. For this reason, I left the eight records in the regression analysis. An assessment of a Q-Q Plot assessed the assumption that normality was met after transforming the dependent variable (as shown in Figure 4). Even though the distribution is slightly flat, the points are aligned close enough that the assumption of normality was met as multiple regression is robust against deviations from normality (Field, 2018).

Figure 4

Normal Q-Q Plot of Studentized Residuals



Hierarchical multiple regression was used to assess the noncognitive SSI subscales (e.g., academic self-efficacy, academic engagement, educational commitment, resiliency, campus engagement, and social comfort) and the cognitive factors (e.g., HSGPA and SAT score) to predict FYGPA. The hierarchical multiple regression was run in two blocks. The first block contained the six noncognitive subscale predictor variables: academic self-efficacy, academic engagement, educational commitment, resiliency, campus engagement, and social comfort. The second block contained the cognitive predictor variables: HSGPA and SAT score. Table 7 outlines the predictor variables used in each block and the resulting unstandardized β (regression) coefficient, the standard error of the coefficient, the standardized β coefficient, the significance, the R^2, the adjusted R^2, and the confidence intervals, along with the significance levels and variable transformation formulas.

Table 7

Results for Hierarchical Multiple Regression for FYGPA

	Variable: +FYGPA	*B*	95% CI for *B*		*SE B*	β	R^2	ΔR^2
			LL	UL				
Step 1	Constant	.50	.38	.63	.07		.07	.07***
	Academic Self-efficacy	-.00	-.01	.00	.00	-.07*		
	Academic Engagement	-.01	-.01	.00	.00	-.27***		
	++Educational Commitment	-.03	-.06	.01	-.06	-.06		
	Resiliency	.00	.00	.01	.00	.14***		
	Campus Engagement	.00	-.00	.00	.80	-.01		
	Social Comfort	.00	-.00	.00	.00	.02		
Step 2	Constant	1.06	.94	1.19	.06		.36	.29***
	Academic Self-efficacy	.00	.00	.01	.00	.09***		
	Academic Engagement	-.01	-.01	-.00	.00	-.17***		
	Educational Commitment	-.01	-.04	.02	.01	-.02		
	Resiliency	.00	-.00	.00	.00	.06*		
	Campus Engagement	-.00	-.00	.00	.00	-.06*		
	Social Comfort	-.00	-.00	.00	.00	-.02		
	HSGPA	-.17	-.19	-.15	.01	-.50***		
	SAT Score	.00	.00	.00	.00	-.13***		

Note. Model = “Enter” method in SPSS Statistics; *B* = unstandardized regression coefficient, CI = confidence interval with upper and lower limits, *SE* = standard error of the coefficient; β = standardized coefficient; R^2 = coefficient of determination; ΔR^2 = adjusted R^2.

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

+FYGPA = log10 (4.0 + 1 – FYGPA)

++Educational Commitment = log10 (48 + 1 – EC Score)

Within the first regression block, the SSI noncognitive subscales explained seven percent of the variance in FYGPA, $F(6,1097) = 15.28$, $p < .001$. There were three significant variables: academic self-efficacy, academic engagement, and resiliency. After entering the cognitive traits, HSGPA, and SAT score, the total variance in FYGPA explained by the model was 36%. The cognitive measures explained an additional 29% of the variance in FYGPA, R^2 change = .29, F change (2, 1095) = 246.97, $p < .001$. Both models were statistically significant in predicting FYGPA.

The full model of noncognitive and cognitive variables used to predict FYGPA was statistically significant, $R^2 = .364$, $F(8,1095) = 78.337$, adjusted $R^2 = .359$, $p < .001$. Due to this result, the null hypothesis was rejected. The full model showed that four of the noncognitive variables, academic self-efficacy, academic engagement, resiliency, campus engagement, and the two cognitive variables, HSGPA and SAT score, were statistically significant in predicting FYGPA. The addition of HSGPA and SAT score into the model increased the statistical significance of campus engagement in predicting FYGPA while decreasing the significance of resiliency but keeping the variable statistically significant. Educational commitment and social comfort were not statistically significant predictors of FYGPA in either model.

After an analysis of each independent variables' contribution to the regression model, a second hierarchical multiple regression was conducted. This regression test excluded the two nonsignificant variables: educational commitment and social comfort. Variables that are not statistically significant can reduce a regression model's precision (Field, 2018; Miles & Shevlin, 2007). Table 8 outlines the predictor variables used in each block and the resulting unstandardized β (regression) coefficient, the standard error of the coefficient, the standardized β coefficient, the significance, the R^2, the adjusted R^2, and the confidence intervals, along with the significance levels and variable transformation formula.

Table 8

Results for Hierarchical Multiple Regression for FYGPA Minus the Nonsignificant Variables

	Variable: +FYGPA	*B*	95% CI for *B*		*SE B*	β	R^2	ΔR^2
			LL	UL				
Step 1	Constant	.44	.35	.53	.05		.07	.07***
	Academic Self-efficacy	-.00	-.00	.00	.00	-.06		
	Academic Engagement	-.01	-.01	-.01	.00	-.25***		
	Resiliency	.00	.00	.01	.00	.14***		
	Campus Engagement	.00	-.00	.00	.00	.01		
Step 2	Constant	1.04	.94	1.14	.05		.36	.29***
	Academic Self-efficacy	.00	.00	.01	.00	.09**		
	Academic Engagement	-.01	-.01	-.00	.00	-.16***		
	Resiliency	.00	.00	.00	.00	.05		
	Campus Engagement	-.00	-.00	-.00	.00	-.07*		
	High School GPA	-.17	-.19	-.15	.01	-.49***		
	SAT Score	.00	.00	.00	.00	-.14***		

Note. Model = "Enter" method in SPSS Statistics; *B* = unstandardized regression coefficient, CI = confidence interval with upper and lower limits, *SE* = standard error of the coefficient; β = standardized coefficient; R^2 = coefficient of determination; ΔR^2 = adjusted R^2.

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

+FYGPA = log10 (4.0 + 1 – FYGPA)

Within the first regression block, the four SSI noncognitive subscales explained seven percent of the variance in FYGPA, $F(4,1099) = 22.21$, $p < .001$. Both academic engagement and resiliency were significant predictors of FYGPA. After entering the cognitive traits, HSGPA, and SAT score, the total variance in FYGPA explained by the model was 36%. The cognitive measures explained an additional 29% of the variance in FYGPA, R^2 change = .29, F change (2, 1097) = 248.59, $p < .001$. Both models were statistically significant in predicting FYGPA.

The full model of the four noncognitive and cognitive variables used to predict FYGPA was statistically significant, $R^2 = .36$, $F(6,1097) = 104.34$, adjusted $R^2 = .36$, $p < .001$. Due to this result, the null hypothesis was rejected. The full model showed that three of the noncognitive variables, academic self-efficacy, academic engagement, and campus engagement, and the two cognitive variables, HSGPA and SAT score, were statistically significant in predicting FYGPA. The addition of HSGPA and SAT score into the model increased the statistical significance of campus engagement in predicting FYGPA. The p-value for resiliency was .05 and cannot be considered significant because significance was measured with a p-value less than .05. However, due to resiliency's *p*-value being equal to .05, its contributions and effect on predicting first-year GPA will be included in the next chapter.

The regression equation for the full model is displayed as:

*FYGPA = (.09) (Academic Self-Efficacy) + (-.16) (Academic Engagement) + (.05) (Resiliency) + (-.07) (Campus Engagement) + (-.49) (High School GPA) + (-.14) (SAT Score)

*FYGPA = log10 (4.0 + 1 – FYGPA)

Question 2

RQ2: To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and HSGPA predict first-year to second-year college retention?

H_0: SAT score, HSGPA, and the six noncognitive subscale scores do not predict first-year to second-year college retention.

H_2: SSI noncognitive subscale scores will be more predictive of first-year to second-year retention than HSGPA and SAT score.

Logistic regression was performed to determine the effects of HSGPA, SAT score, and the six noncognitive subscales (e.g., academic self-efficacy, academic engagement, educational commitment, resiliency, campus engagement, and social comfort) on first-year to second-year retention on a sample of first-year students at Southeastern University. A Box-Tidwell procedure assessed the linearity of the continuous variables for the dependent variable's logit (Box & Tidwell, 1962). A Bonferroni correction was applied using all 16 terms in the model, which resulted in statistical significance being accepted when $p < .003125$ (Laerd Statistics, 2017; Tabachnick & Fidell, 2014). All continuous variables were found to be linearly related to the logit of the dependent variable (Miles & Shevlin, 2007).

There were no standardized residuals greater than ± 3 standard deviations. The logistic regression was statistically significant, $x^2(8) = 28.18$, $p < .001$ (as shown in Table 8). Since the model was statistically significant, I rejected the null hypothesis. The model explained 4% (Nagelkerke R^2) of the variance in retention and correctly classified 100% of the cases.

Table 9

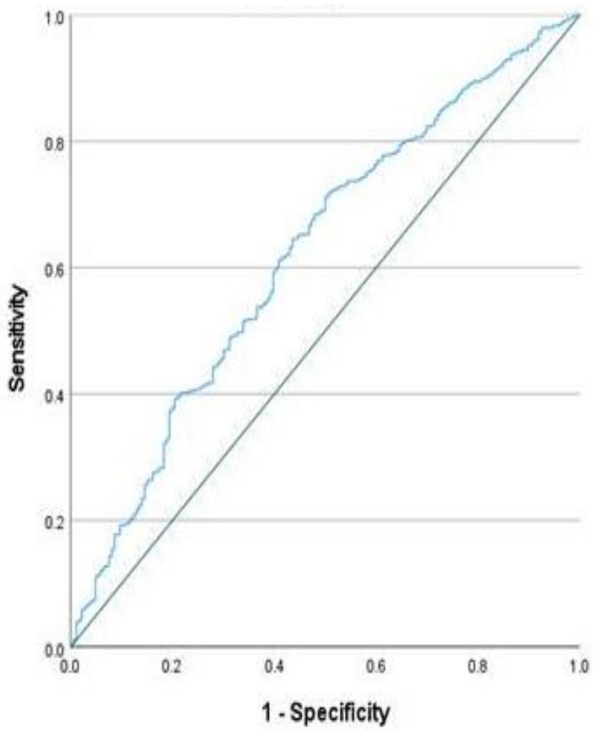
Logistic Regression Model Analysis

X^2	p	Cox & Snell R^2	Nagelkerke's R^2
28.18	.000	.03	.04

The area under the ROC curve (as shown in Figure 5) was .622, CI [.58, .67], which is a poor level of discrimination, according to Hosmer et al. (2013).

Figure 5

ROC Curve for Logistic Regression



Of the eight predictor variables, only high school grade point average (HSGPA) was statistically significant in predicting first-year to second-year retention (as shown in Table 9). Increased HSGPA was associated with an increased likelihood of retention into the second year of college. Table 9 displays the results of the logistic regression.

Table 10

Logistic Regression Results

	B	SE.	Wald	*df*	Sig. (*p*)	Odds Ratio	95% CI for *B*	
							LL	UL
High School GPA	.79	.22	12.78	1	.00	2.20	1.43	3.39
SAT Score	.00	.00	.91	1	.34	1.00	.99	1.00
Academic Self-Efficacy	-.04	.02	2.81	1	.09	.96	.92	1.01
Academic Engagement	.02	.02	1.11	1	.29	1.02	.98	1.06
Educational	.02	.03	.39	1	.53	1.02	.97	1.07
Commitment	-.02	.02	1.84	1	.18	.98	.95	1.01
Resiliency	.01	.02	.27	1	.60	1.01	.97	1.05
Campus Engagement	.01	.02	.13	1	.72	1.01	.98	1.04
Soc. Comf. Constant	-1.45	-1.30	1.24	1	.27	.25		

Note. *B* = unstandardized regression coefficient, *SE* = standard error of the coefficient, Wald = Wald Statistic, CI = confidence interval with upper and lower limits. $p < .05$. $p < .01$; $p < .001$.

An independent samples *t*-test was conducted to examine whether there were statistically significant differences between the retained and not retained groups. This analysis showed that there were no significant differences between the scores on the SSI noncognitive subscales and retention. The *t*-test revealed there were significant differences in HSGPA, SAT scores, and FYGPA between the retained and not retained groups. For HSGPA, there were statistically significant differences between retained students (n = 918, M = 3.29, SD = .43) and the not retained students (n = 186, M = 3.12, SD = .44): t (1104) = 4.61, p = .00, 95% CI [.09, .23]. For SAT score, there were statistically significant differences between the retained students (n = 918, M = 1094, SD = 128.24) and the not retained students (n = 186, M = 1069, SD = 107.94): t

(1104) = 2.85, p = .01, 95% CI [7.90, 43.24]. Lastly, FYGPA was examined for differences. There were statistically significant differences on FYGPA for retained students (n = 918, M = 3.36, SD = .57) and the not retained students (n = 186, M = 2.76, SD = .99): t (1104) = 8.10, p = .00, 95% CI [.46, .76]. The implications of the statistically significant differences in cognitive factors between these groups will be discussed in the next chapter.

Summary

Chapter 4 provided an overview of the data collected and the procedures utilized to analyze the data. The data consisted of both student demographic information, as well as the eight independent predictor variables (HSGPA, SAT score, SSI subscales: academic self-efficacy, academic engagement, educational commitment, resiliency, campus engagement, and social comfort) and the two outcome variables, FYGPA and first-year to second-year retention. Descriptive statistics were reported as well as the results from the hierarchical multiple regression and the logistic regression. The first hierarchical multiple regression statistical analysis found that academic self-efficacy, academic engagement, resiliency, campus engagement, HSGPA, and SAT score were statistically significant predictors of FYGPA. A second hierarchical multiple regression excluding the nonsignificant variables, educational commitment and social comfort, was conducted. The second hierarchical multiple regression statistical analysis found that academic self-efficacy, academic engagement, campus engagement, HSGPA, and SAT score were statistically significant predictors of FYGPA. I rejected the null hypothesis based on the findings of both hierarchical multiple regression tests. The logistic regression statistical analysis found that only HSGPA was a statistically significant predictor of first-year to second-year retention; therefore, I rejected the null hypothesis. An independent samples t-test found statistically significant differences in cognitive factors between the retained and not retained students. Chapter 5 will further discuss the results of the analysis related to the findings. The chapter will also discuss the limitations of the findings and conclude with a discussion of the implications of the study's findings for future research.

Chapter 5: Discussion, Recommendations, and Conclusions

Colleges and universities expend both human and fiscal resources in assisting that their first-year student cohorts have a successful transition from high school into college (Shaw & Mattern, 2013; Shaw & Rodeiro, 2019). A successful transition hinges, in part, on the student being college-ready (Shaw & Rodeiro, 2019), and also on the institution implementing sound admissions policies (Clinedinst, 2019) and investing in resources to support students once they arrive on campus (Raisman, 2013). These are critical factors that institutions must assess when examining contributing factors of student success. This examination becomes more critical considering research that predicts increased college enrollment (Shaw & Rodeiro, 2019). Yet, the projections show that just over half of all first-time, full-time students will graduate with a four-year degree (Kena et al., 2015).

In this study, student success was investigated by analyzing how various cognitive and noncognitive factors influenced first-year college grade point average (FYGPA) and first-year to second-year retention. The purpose of this correlational predictive study was to examine the effects of the SSI noncognitive subscale scores, the SAT score, and high school grade point average (HSGPA) on FYGPA and first-year to second-year retention, and to determine whether the SSI noncognitive subscale scores were better predictors of FYGPA and retention. This study adds to the existing body of research regarding noncognitive assessments to determine whether these assessments have value in the admissions process.

This study addressed two research questions: 1) To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and HSGPA predict FYGPA? 2) To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and HSGPA predict first-year to second-year college retention? First-year college students' application information, HSGPA and SAT scores, as well as the Student Strengths Inventory subscale scores, were analyzed to determine whether some relationships and patterns contributed to student success as measured by FYGPA and first-year to second-year retention.

This chapter discusses the key findings and implications of the results and the limitations of the study. The chapter ends with a discussion of the recommendations for future research and conclusions related to the study.

Key Findings and Theoretical Implications

As discussed in the literature review, current studies on the impact of noncognitive factors on student success have yielded contradictory results (Akos & Kretchmar, 2017; Thomas et al., 2007), and limited research has been conducted on the use of noncognitive assessments in the admissions process. This section will discuss the findings and implications for each research question and conclude with an in-depth discussion of the study's limitations. The key findings will be addressed through the lens of Tinto's student integration model and motivational theory.

Question 1

To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and HSGPA predict first-year college grade point average (FYGPA)?

This research question was constructed to investigate which factors best predict FYGPA. The analysis showed that both cognitive and noncognitive factors showed a correlation with FYGPA. These variables were examined as a block (noncognitive and cognitive) in the regression analysis to determine which better predicted FYGPA. This discussion includes the findings of the second hierarchical multiple regression, which omitted the two nonsignificant noncognitive variables: educational commitment and social comfort.

Noncognitive Factors Regression Block

The four SSI noncognitive subscales explained seven percent of the variance in FYGPA, $F(4,1099) = 22.21$, $p < .001$. This showed that the model was statistically significant in predicting FYGPA. Academic engagement and resiliency were significant predictors of FYGPA. Academic self-efficacy and campus engagement were not significant predictors of FYGPA in this regression analysis.

Noncognitive and Cognitive Factors Regression Block

The second regression, or full model, included HSGPA and SAT score, in addition to the four noncognitive variables: academic self-efficacy, academic engagement, resiliency, and campus engagement. The addition of the cognitive factors explained an additional 29% of the variance in FYGPA, showing that the model as statistically significant, $R^2 = .36$, $F(6,1097) = 104.34$, adjusted $R^2 = .36$, $p < .001$. The full model showed five statistically significant factors in predicting FYGPA: academic self-efficacy, academic engagement, campus engagement, FYGPA, and SAT score. For this study significance was measured with a *p*-value less than .05. Resiliency's p-value was equal to .05 and will be included in the discussion because *p*-values equal to .05 can be considered significant depending on sample size (Field, 2018). The impact of the statistically significant predictors, plus resiliency, is discussed below.

Academic Self-Efficacy. As a noncognitive construct, academic self-efficacy was a significant predictor of FYGPA in the full regression model but was not significant in the first block of only the four noncognitive variables. The average academic self-efficacy score was 40.74 ($n = 1104$, $SD = 4.38$). Academic self-efficacy was significantly related to FYGPA ($p <$

.001), Pearson's *r* = -.13. Academic self-efficacy was a significant predictor of FYGPA only in the full model. However, its contribution was minimal, as indicated by the standardized β coefficient (Block 1 β = -.06, Full Model β = .09). The addition of HSGPA and SAT into the model increased the significance of academic self-efficacy as a predictor. The implications for this finding in practice is that since academic self-efficacy is a predictor of FYGPA, institutions nurture and reinforce students' beliefs in their abilities to succeed, both for students who have low levels of academic self-efficacy and for those who have a high level, but struggle in adjusting to the demands of collegiate work (Tinto, 2017).

Academic Engagement. Academic engagement was a significant predictor of FYGPA. The average academic self-efficacy score was 37.62 (n = 1104, SD = 5.40), and was significantly related to FYGPA ($p < .001$), Pearson's *r* = -.24. The significance level of academic engagement did not change between the first block and the full regression model. Its contribution was minimal, as indicated by the standardized β coefficient (Block 1 β = -.25, Full Model β = -.16). This indicates that as FYGPA increases, academic engagement decreases. However, this decrease is minimal based on the model results. It is still critical for institutions to support pro-academic behaviors (Robbins et al., 2006) and develop interactions between students and faculty inside and outside the classroom (Hirschy, 2017; Tinto, 1975).

Resiliency. This noncognitive construct showed to be a statistically significant predictor of FYGPA in only the first regression model; however, its *p*-value equaled .05 in the second block. Some statistical analysis of p-values concludes that those equal to .05 can be considered significant depending on sample size (Field, 2018). Like the other noncognitive factors, resiliency's contribution was small, as indicated by the standardized β coefficient (Block 1 β = -.14, Full Model β = .05). Resiliency did not have a statistically significant correlation to FYGPA

($p > .05$), Pearson's $r = .06$. The average resiliency score was 31.86 ($n = 1104$, $SD = 6.45$), which was the lowest mean score of the SSI subscales. Eisenberg et al. (2016) posited that resilience has a direct effect on academic outcomes because it impacts how student respond to challenges in the college transition process and further posit that resilience directly influences academic success, based on how a student copes with these challenges in their first year of college. Resiliency is a malleable trait that can be developed and strengthened in adolescence (Eisenberg et al., 2016; Seligman, 2011; Yeager & Dweck, 2012).

Campus Engagement. In the first regression block, campus engagement was not a significant predictor of FYGPA. With the addition of HSGPA and SAT score into the model, the variable became significant. However, its contribution to predicting FYGPA was small as indicated by the standardized β coefficient (Block 1 $\beta = .01$, Full Model $\beta = -.07$). Campus engagement had a statistically significant correlation to FYGPA ($p < .01$), Pearson's $r = -.07$. The average campus engagement score was 38.75 ($n = 1104$, $SD = 5.21$). Engaging in the social environment of the campus creates a sense of belonging for students, which can increase levels of motivation, commitment to their classes, and commitment to the institution (Davis et al., 2019; Museus et al., 2017; Snyder et al., 2002). Further, institutional programs that focus on both social and academic development can positively influence a student's sense of belonging at key points during the first year of college.

HSGPA. Within the full regression model, HSGPA was a statistically significant predictor of FYGPA. HSGPA had a statistically significant correlation to FYGPA ($p < .001$), Pearson's $r = -.57$. The average HSGPA was 3.26 ($n = 1104$, $SD = .44$). HSGPA had the greatest significance in predicting FYGPA of all the variables as indicated by the standardized β coefficient (Full Model $\beta = -.49$). This finding confirms the results of previous studies

(Allensworth & Clark, 2020; Clinedinst, 2019; Galla et al., 2019; McCabe et al., 2020) that HSGPA is a strong predictor of FYGPA and, on average accounts for 30% or more of the variability in FYGPA. HSGPA is a measure of the day-to-day performance over four years of high school. It provides a glimpse into a student's academic ability, persistence, commitment, and motivation (Galla et al., 2019).

SAT Score. The full regression model indicated that the SAT was a statistically significant predictor of FYGPA. SAT score had a statistically significant correlation to FYGPA ($p < .001$), Pearson's $r = -.34$. The average SAT score was 1090 ($n = 1104$, $SD = 125.38$). The SAT score alone did not contribute much to the model, as indicated by the standardized β coefficient ($\beta = -.14$). To fully understand the contribution of SAT score to the model, I examined a regression of only HSGPA and SAT scores. Adding the SAT score to this model accounted for less than 1% of the variance (R^2 change = .002), whereas HSGPA explained 27% of the FYGPA variance. This indicates that, while significant in the full regression model, SAT scores offer very little predictive value for FYGPA.

Question 2

To what extent do the scores on the six noncognitive subscales of the Student Strengths Inventory (SSI), SAT scores, and HSGPA predict first-year to second-year college retention?

The second research question was analyzed with logistic regression with retention (1 = retained, 0 = not retained) as the dependent variable and the six SSI noncognitive subscales, HSGPA, and SAT scores as the independent variables. The average retention rate for the sample was 83.2%. HSGPA was the only significant predictor of retention. The odds ratio for HSGPA was 2.20, meaning that for each one-point increase in HSGPA, the change in the odds of being retained is 2.20 units. The other variables in the model had odds ratios around 1.00, meaning that an increase or decrease in those variables does not significantly change the odds of retaining.

An independent samples *t*-test was run to determine if there were any statistically significant differences between the retained and not retained groups. The *t*-test included FYGPA in the analysis. HSGPA, SAT score, and FYGPA showed statistically significant differences between the retained and not retained groups ($p < .01$). The noncognitive factors added no statistical significance to the differences in retention. This finding has implications because the first research question results showed four noncognitive characteristics (e.g., academic self-efficacy, academic engagement, resiliency, and campus engagement) were statistically significant predictors of FYGPA. Academic self-efficacy and resiliency were discussed as malleable (Eisenberg et al., 2016; Seligman, 2011; Tinto, 2017; Yeager & Dweck, 2012); whereas, institutions can impact campus and academic engagement through programmatic areas across campus. Institutions who are aware of the impact these factors have on first-year GPA can develop opportunities to increase these first-year students' attributes to increase first-year GPA, resulting in an increase in retention (Bean, 1980).

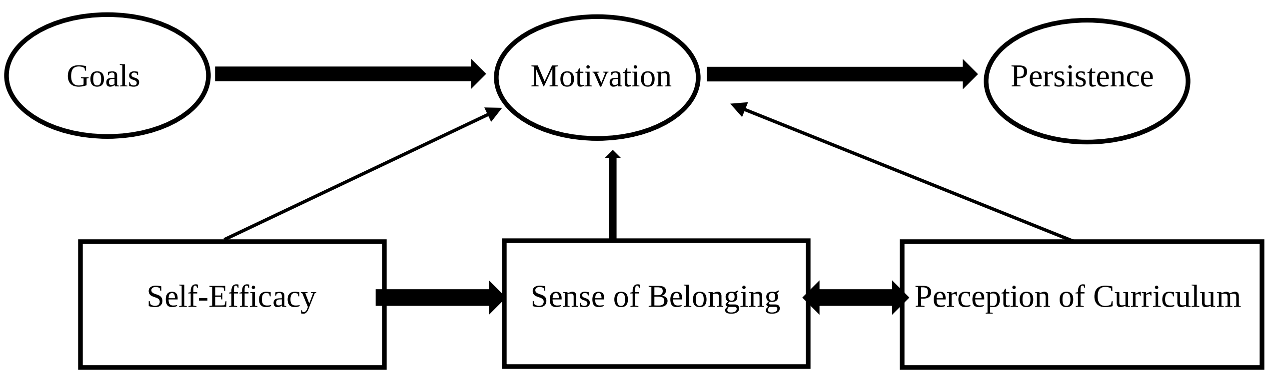
Theoretical Implications

Student retention in higher education has been the focus of research for decades. Tinto's (1975, 1993) student integration theory focused on the interactions between students and faculty in the academic setting, as well as the interactions between students and their peers in the social environment. Tinto (1975, 1993) postulated the more these interactions occur, the more likely a student is to retain. Post-Tinto retention scholars, namely Bean and Eaton (2001), focused on the confluence of social, psychological, and academic factors that influence student retention. Bean's (1980) research on student attrition concluded that college GPA was a strong predictor of retention, finding that students with higher GPAs had higher retention rates than students with lower GPAs.

More recent retention studies have focused on retention from a growth or motivational mindset rather than a deficit mindset (Bandura, 2001; Bean & Eaton, 2001; Wigfield & Eccles, 2000; Yeager & Dweck, 2012). Tinto (2017) built upon this research in "proposing a conceptual model of student motivation and institutional persistence," speculating that persistence is a manifestation of motivation (p. 255). Tinto's (2017) model of student motivation and persistence focused on how self-efficacy, sense of belonging, and perceptions of the curriculum that influence students' decision to stay or leave a college. This model is displayed in Figure 6.

Figure 6

A Model of Student Motivation and Persistence



Note. Adapted from “Through the Eyes of Students,” by V. Tinto, 2017, *Journal of College Student Retention, 19*(3), p. 256. (https://doi.org/10.1177/1521025115621917). Copyright 2017 by Sage.

The results of this study support the theoretical framework surrounding student retention and motivation. The underlying foundation for both theories is that a combination of student and institutional characteristics influence student success (Bandura, 2001; Bean & Eaton, 2001; Tinto, 1975, 1993, 2006, 2017; Wigfield & Eccles, 2000; Yeager & Dweck, 2012). Student noncognitive factors, such as academic self-efficacy, academic engagement, resiliency, campus engagement, and HSGPA, and to a limited extent, SAT score, help predict FYGPA. While only HSGPA was significant in predicting retention, FYGPA was statistically significant in comparing differences between students who were retained and not retained. By understanding this study's findings, institutions can better understand their students' motivations when developing programs that increase academic self-efficacy, academic and campus engagement, and resiliency. Institutions must also recognize the importance of HSGPA in predicting student success. While the results of the SSI represent a snapshot of students' noncognitive attributes and their relative strengths at the time of the assessment, the HSGPA provides a long-term overview not only of students' cognitive ability in the classroom, but also of their commitment to their education in high school. The findings of this study can assist institutions in refining their admissions criteria and strengthening their first-year programs through a deeper understanding of the various factors that contribute to the phenomenon of college student success.

Limitations

There are several limitations of this study that should be noted. First, in March 2020, the COVID-19 pandemic broke out worldwide, and upended education systems across the United States and the world (Bauman, 2020; Ellis, 2020; Patel, 2020). In response to the pandemic, Southeastern University ended in-person instruction in mid-March 2020, and students had to complete their spring classes online. SU implemented "emergency education," where classes quickly shifted online and were primarily taught asynchronously. This was both a paradigmatic and pedagogical shift for students. The institution implemented several exigency policies that impacted students, specifically, the first-year cohort. Namely, students had the option to choose to take their spring courses pass/fail, rather than receive letter grades.

Students could choose which classes they wished to take pass/fail after their grades were posted in mid-May. Classes taken pass/fail had no impact on the student's spring 2020 grade point average, and students were still able to earn credit for the course(s). Another policy change was that no student was put on probation or suspension at the end of the spring term. Given the unique policies related to the COVID-19 pandemic, as well as the long-lasting impacts on higher education, any findings from this study will be difficult to generalize to future studies of first-year college student success.

This study measured retention as positive when the student returned to Southeastern University. It did not measure whether a student simply dropped out of college or transferred to another institution, which is a limitation in measuring student success (Bowman et al., 2019). Southeastern University experienced a 5% increase in retention for the fall 2019 cohort. It is unknown whether this increase resulted from institutional-wide retention efforts or from the uncertainty of class modalities (i.e., online, hybrid, or face-to-face) leading to more students deciding to stay at SU rather than transfer. In contrast, there might have been students who wanted to return for their second year but could not due to personal or financial circumstances that drastically changed due to the COVID-19 pandemic. All these factors need consideration when generalizing about factors that relate to and predict retention and attrition.

A third limitation of the study is with the sample. The sample size was robust and comprised 54% of the total first-year cohort; however, the sample demographics did not entirely mirror the larger first-year student cohort. The sample had more females and slightly more White participants. The most noticeable difference was in the number of first-generation and Pell grant students. The total first-year student population was 27% first-generation and 36% Pell grant eligible. The sample was only 16% first-generation and 29% Pell grant eligible. Numerous extant literature shows that both first-generation and low socioeconomic status students face more significant barriers in their college transition and attaining a degree (Bowman et al., 2019; McCabe et al., 2020; Tinto, 2017). It is difficult to generalize this study's results to a larger population of first-year students or even the broader community of first-year students at SU because of the lower representation of first-generation and Pell grant students.

Another limitation of the study relates to student answers on the Student Strengths Inventory assessment. The previous chapter demonstrated the median scores, range of scores, and skewness for each noncognitive subscale. The mean scores for each of the subscales were high, and the mean of all the subscales was 38.2 out of 48. Each of the subscales was skewed with students more often endorsing higher scale responses than lower scale responses. Salkind (2017) posited that negative skewness is often an outcome when the test or assessment is "easy" (p. 168). Metz et al.'s (2015) study on the impact of socially desirable responses on the SSI is relevant to this limitation. As a reminder, social desirability is when students answer questions on self-reported surveys that present themselves in the best light, impacting the survey's validity (Metz et al., 2015). It appears that SU students may have demonstrated social desirability in their responses to the SSI based on the mean scores on each of the noncognitive subscales.

The fifth limitation of this study is that students were given the option to take the Student Strengths Inventory. It was not a required assessment as part of the new student orientation program or the first-year experience course. The sample of students who took the SSI was similar academically to the larger first-year cohort. The sample of students who took the assessment had almost equivalent SAT scores to the total first-year population, and the average HSGPA was equal, along with the average FYGPA, which was a 3.2 for both. The most obvious difference was the retention rate. The retention rate of the students who took the SSI was 10%

higher than the total first-year population (83% compared to 73%). This invites the question, why did a student choose to take the SSI? It is difficult to generalize this study's findings without fully understanding the motivation for taking the SSI.

The study's final limitation is related to FYGPA and the COVID-19 pandemic. The first research question results showed that FYGPA was overpredicted for many students, meaning that the actual earned FYGPA was less than the model predicted. As discussed in the previous chapter, these over predictions were not enough to remove any students from the study, but they warrant additional consideration. While upending the spring semester of their first year of college, this pandemic also impacted students' family and financial circumstances. The regression model does not account for the individual circumstances that students could have faced at home, nor how their mental health or commitment to academics were affected (Brown & Kafka, 2020).

Recommendations for Future Research

This study represents a critical first step in assessing cognitive and noncognitive factors that contribute to first-year student success in college. This study showed that both attributes, cognitive and noncognitive, were predictors of academic success as measured by first-year grade point average. While HSGPA and SAT scores were predictors of FYGPA, several noncognitive attributes contributed to a student's academic success: academic self-efficacy, academic engagement, resiliency, and campus engagement. Regarding retention, high school grade point average was the only statistically significant predictor. Looking beyond the first year of college, it is critical that colleges and universities research which factors contribute to students' academic success, persistence, and ultimately graduation from an institution. Success in college depends on more than academic skills. In combination with this study's findings, this research can guide enrollment leaders in redefining which admissions measures are both fair and equitable while supporting the institutional mission and meeting enrollment goals. The next section presents recommendations that enrollment leaders and higher education practitioners should consider in the admissions process.

Future of Standardized Testing

In summer 2020, the National Association for College Admissions Counseling's (NACAC) taskforce on Standardized Admission Testing for International and US Students released a report titled *Ensuring All Students Have Access to Higher Education: The Role of Standardized Testing in the Time of COVID-19 and Beyond*. The taskforce's original goal was to examine inequities in standardized testing; however, the charge expanded in response to the COVID-19 pandemic. This pandemic forced the cancellation of SAT and ACT tests for hundreds of thousands of students worldwide (Hoover, 2020; Jaschik, 2020). John Latting, chair of the task force, said, "This is a year to reexamine any mandatory use of testing as part of enrollment operations, for both practical but also ethical reasons. It is a year to be reminded of appropriate uses, and potential misuses, of standardized tests" (NACAC, 2020). According to NACAC's report, by the end of May 2020, approximately one million fewer 11th graders in the United States had taken the SAT for the first time compared to previous years. NACAC encouraged institutions to examine their testing policies. The findings in this study are both timely and relevant to the current admissions environment. A student's HSGPA proved to be the most significant predictor of both FYGPA and retention. While the SAT had some predictive power, it predicted less than two percent in the variance in first-year grade point average and was not statistically significant in predicting retention.

This finding is beneficial for less selective institutions as they consider adopting test-optional admissions policies in response to the continued cancellation of standardized tests. Many regional public institutions have grappled with adopting test-optional admissions policies for various reasons, including lack of support from state higher education organizations and concerns about having adequate staff to conduct a holistic admissions review in the absence of tests (Bastedo et al., 2018; NACAC, 2020; Shaw & Rodeiro, 2019). Throughout the entire year of 2019, 50 institutions announced a test-optional admissions policy (NACAC, 2020). As of the NACAC report's release in summer 2020, 318 institutions announced new test-optional admissions policies, including more than half of all four-year colleges and universities (NACAC, 2020). However, according to NACAC, over 100 public institutions, including some state systems, have not adjusted current admissions policies and still require submission of standardized tests (NACAC, 2020). While individual institutions should determine which factors add value to their admissions process, the results of this study can assist test-optional holdouts, especially public institutions, in adjusting current admissions practices.

Test-Optional Admissions Policies

During this study, Southeastern University implemented a test-optional admissions policy for students applying for fall 2021 admission. This policy was not implemented in response to the COVID-19 pandemic. The enrollment management office had been in discussions with the Provost and Faculty Senate about implementing this policy since fall 2019. SU adopted the test-optional policy in April 2020, making them the first public institution in the state to adopt such an approach. The other public institutions in the state quickly adopted temporary test-optional policies in response to COVID-19 and test cancellations. SU's test-optional policy requires that applicants have a 3.5 high school GPA to apply test-optional. Still, it does not require any additional supporting documents such as an essay, resume, or recommendation letters. SU conducted two studies that supported test-optional admissions. The first study was the Admitted Class Evaluation Services (ACES) through the College Board, which concluded for the fall 2017 first-year cohort that HSGPA had a .47 correlation with first-year GPA, while SAT score had a .37 correlation with FYGPA (ACES, 2018). The Institutional Research office conducted a second study focused on retention and graduation. A regression analysis using standardized test scores and HSGPA as predictors found that standardized tests had no relationship to retention or graduation rates across three cohorts of first-year. This study's findings support SU's previous research while also examining potential noncognitive attributes that predict student success. Additional research needs to explore the impact of noncognitive attributes beyond the first year of college and whether these attributes can be assessed in the admissions process.

Noncognitive Assessments

Noncognitive assessments provide students with opportunities to showcase their abilities outside of the cognitive domain. With the potential that standardized tests might be eliminated permanently (Jaschik, 2020) and the findings in this study that SAT score was not a strong predictor of student success, enrollment leaders must consider methods to assess skills and abilities outside of the cognitive domain for prospective students at their institutions. The four cognitive variables identified in this study, academic self-efficacy, academic engagement, resiliency, and campus engagement, warrant further studies to see how each predict student success. Each of these attributes significantly contributed to FYGPA, which made a statistically significant contribution to retention. Institutions can develop first-year experience programs that support the development of academic self-efficacy and resiliency, both attributes that are considered malleable in young adults (Bowman et al., 2019; Wilson et al., 2019). Tinto's (1975) model of student integration emphasized the importance of creating academic and social engagement opportunities. Engagement activities must be meaningful, occur early in the first year, and include interactions with peers and faculty across campus (Bowman et al., 2019). Early development of these noncognitive attributes can lead to higher FYGPAs, which can positively impact retention.

Character Collaborative. In 2016, the Character Collaborative was formed in response to David Holmes' article in the *Journal of College Admission* titled "Overdue Revolution: Character Strengths in the Admissions Equation." One of the Character Collaborative's visions is the "personal attributes and skillsets of resilience, perseverance, collaboration, and respect for others are more developed by our youth and demonstrated throughout society" (character-admission.org/our-vision). With a focus on noncognitive attributes, the Character Collaborative encourages enrollment leaders to recognize the limitations that too narrow a focus on cognitive factors creates in the admissions process and, instead, incorporate holistic admissions best practices. Enrollment leaders need to train admissions officers to evaluate and assess these documents when looking beyond a formulaic rubric when making decisions. Anderson and Weissbourd (2020) developed a best practice guide that can assist institutions in integrating and assessing these noncognitive traits as part of the admissions process while recognizing the difficulty of evaluating characteristics such as self-efficacy, motivation, grit, and resiliency creates in a high-stakes environment like admissions. Knowing the value that assessment of these noncognitive factors adds to the application review process is a critical first step that enrollment leaders can implement to improve the admission process's efficacy at their institution.

Student Groups

This study focused on the entire sample of students and did not disaggregate the findings based on student demographics such as race, gender, first-generation status, or socioeconomic status. This study included students who were honors students, regular admission, and provisional admission students. Future research could explore differences in student success by demographics and student groups. Longitudinal studies that follow students through graduation with a pre/posttest of noncognitive attributes could contribute to the phenomenon of noncognitive factors and student success. McCabe et al. (2020) posited that economically and socially at-risk undergraduates could benefit from targeted interventions aimed at fostering a growth mindset and helping them to believe in their ability to overcome challenges.

Future research should also explore the course-taking patterns of first-year students, and how the selection of majors and courses impacts academic outcomes and success. Berry and Sackett (2009) posited that FYGPA alone is not a good predictor of student success because the courses a student takes can contaminate FYGPA due to the differences the course discipline and/or the student’s major. Their research concluded that when course grades were considered with FYGPA, HSGPA and test scores accounted for between 44% and 64% of the variance in the individual course grade (Berry & Sackett, 2009). Institutions that better understand which student attributes predict success in a particular course or academic program could use these findings to modify admissions standards for applicants to specific programs.

Qualitative Studies

Studies that delve into students' perspectives and lived experiences can help institutions understand the attributes and characteristics that affect students’ success. Understanding why some students succeed and while some do not, despite indications to the contrary, was one of the original impetuses of Gore's work in the development of the SSI (Gore, 2012; Mendrinos, 2014). Furthermore, a qualitative analysis of first-year students' experiences during the COVID-19 pandemic could provide a rich analysis to explain why first-year grade point average was overpredicted in this study.

Final Conclusions

Several findings emerged from this study. First, the noncognitive variables assessed by the SSI did not predict first-year grade point average or retention better than traditional cognitive factors such as high school grade point average and SAT score. Academic self-efficacy, academic engagement, campus engagement, high school grade point average, and SAT were statistically significant predictors of first-year grade point average. SAT score did not add statistical value to the variability in predicting first-year grade point average. Finally, high school grade point average was the only statistically significant predictor of first-year to second-year retention.

Though this study was limited to a subset of first-year students at a single four-year public institution, the findings suggest that some noncognitive variables influence first-year college students' academic success. Enrollment leaders, especially those considering adopting test-optional admissions policies, could benefit from this study's findings regarding the importance of HSGPA as a significant predictor of both FYGPA and retention. Enrollment leaders can also benefit from recognizing the limited importance that standardized tests, specifically the SAT, have in predicting FYGPA and retention. Given the precarity of the future of standardized tests in the college admissions process, forward-thinking enrollment leaders need to look for useful supplements, or even replacements, for these tests. The importance of high school grade point average cannot be ignored and should be a primary focus in the application review process.

This study added to the phenomenon of noncognitive attributes as a predictor of student success. While this study did not find any groundbreaking conclusions related to which noncognitive factors best predict student success, it confirmed previous research about the vast array of noncognitive attributes and the variability in their utility pertaining to student success. Noncognitive attributes can assist admissions offices and enrollment leaders in deciding which students to admit. Carefully worded essay prompts asking applicants to share an experience overcoming a challenge or obstacle, or asking applicants to write about their belief in their ability to succeed in college, can provide admissions counselors a glimpse into applicants' resiliency and academic self-efficacy. Resumes and letters of recommendation can be analyzed to provide insights into applicants' commitment to scholarly and social engagement in their school and community. This deeper dive into the "whole" student becomes important for borderline applicants and applicants from marginalized and underrepresented backgrounds.

A focus on the "whole" student in the review process can provide enrollment leaders a glimpse into students' conscientiousness. HSGPA is one measure of conscientiousness (Galla et al., 2019). Conscientious can also be assessed through supplementary application materials like an essay, recommendation letters, and extra-curricular involvement. Individuals high in conscientiousness are predisposed to performing better academically (O'Conner & Paunonen, 2007), with numerous empirical research confirming that the personality trait "conscientiousness being the strongest overall predictor" of first-year college grade point average (Wilson et al., 2019, p. 62).

Throughout my 20-year career in admissions and enrollment, I often struggled in deciding which applicants to admit and which to deny. A compelling essay, a heartfelt recommendation, or an intriguing interview often swayed me to accept an applicant more than a high SAT score. I have seen students thrive in college who performed poorly on the SAT. I was one of these students—my SAT score indicated that I was not college-ready, despite graduating in the top ten percent of my high school class. I graduated Magna Cum Laude with my bachelor's degree and have pursued advanced degrees. Twenty-five years later, I need to thank the admissions officer who gave me the chance to pursue a college degree. I still wonder whether it was my essay, a letter of recommendation, or my GPA that provided me the opportunity to realize my dream.

As higher education is considered a public good, enrollment leaders must develop practices in their admissions offices that support a holistic admissions review of both cognitive and noncognitive factors. This is even more important today, given the precarity of standardized tests and their future in the college admissions process. This emphasis on holistic admissions also recognizes the changing demographics of college-aged students by 2026 (Grawe, 2018), and will provide greater access to higher education opportunities. Higher education institutions need to recognize the importance that HSGPA and the noncognitive factors (such as academic self-efficacy, academic engagement, resiliency, and campus engagement) have in predicting FYGPA and supporting retention. Enrollment leaders must then use this information to develop programs that connect students with academic and social resources on campus, foster connections with student support services, and build a foundation of high impact practices for engagement both in and out of the classroom. By creating a culture of student success, institutions can support their enrollment leaders who seek to admit qualified students who will be successful in and outside the classroom and, ultimately, will graduate from the institution.

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Appendix A: Student Strengths Inventory Sample Questions and Subscale Loading

All items are presented as statements with a 6-point Likert-scale response option escalating from *strongly disagree* to *strongly agree*.

Each page begins with the prompt:
Below are statements that describe various attitudes, opinions, and behaviors. Read each statement carefully and indicate how well it describes you by selecting the appropriate response.

Question	Subscale
I will succeed in my chosen major.	Academic Self-Efficacy
I am confident I will maintain a B average in college.	Academic Self-Efficacy
I am confident I will excel in college.	Academic Self-Efficacy
I often go to class without being fully prepared.	Academic Engagement
I strive for excellence in my schoolwork.	Academic Engagement
My parents often have to remind me to do my schoolwork.	Academic Engagement
School is a priority for me.	Educational Commitment
I see value in completing a college education.	Educational Commitment
Getting good grades is important to me.	Educational Commitment
I am quick to act emotionally	Resiliency
I manage stress well.	Resiliency
I am easily frustrated.	Resiliency
I plan to take part in many campus social activities.	Campus Engagement
I intend to seek volunteer or service-learning opportunities in college.	Campus Engagement
I plan to take on leadership roles when I'm in college.	Campus Engagement
I have many friends.	Social Comfort
I tend to work well with others.	Social Comfort
I never know what to say when meeting new people.	Social Comfort

Note. Adapted from "Student Strengths Inventory Assessment, by Campus Labs, 2018.

(www.campuslabs.com). Copyright 2018 by Campus Labs (Anthology).

Appendix B: ACT Composite to SAT Total

ACT Composite Score	SAT Composite Equivalent Score
36	1590
35	1540
34	1500
33	1460
32	1430
31	1400
30	1370
29	1340
28	1310
27	1280
26	1240
25	1210
24	1180
23	1140
22	1110
21	1080
20	1040
19	1010
18	970
17	930
16	890
15	850
14	800
13	760
12	710
11	670
10	630
9	590

Guide to the 2018 ACT®/SAT® Concordance
https://collegereadiness.collegeboard.org/pdf/guide-2018-act-sat-concordance.pdf.

Appendix C: IRB Approval

ABILENE CHRISTIAN UNIVERSITY
Educating Students for Christian Service and Leadership Throughout the World

Office of Research and Sponsored Programs
320 Hardin Administration Building, ACU Box 29103, Abilene, Texas 79699-9103
325-674-2885

September 2, 2020

Amanda Craddock
Department of Education
Abilene Christian University

Dear Amanda,

On behalf of the Institutional Review Board, I am pleased to inform you that your project titled "Noncognitive Attributes as a Measure for College Admission",

(IRB# 20-134)is exempt from review under Federal Policy for the Protection of Human Subjects as:

☐ Non-research, and
☑ Non-human research

Based on:
The data set will be de-identified prior to receipt.

If at any time the details of this project change, please resubmit to the IRB so the committee can determine whether or not the exempt status is still applicable.

I wish you well with your work.

Sincerely,

Megan Roth

Megan Roth, Ph.D.
Director of Research and Sponsored Programs