IDENTIFYING STUDENTS WHO NEED SUPPORT:

A LOGISTIC REGRESSION STUDY OF COMMUNITY

COLLEGE STUDENT SUCCESS PREDICTION

By

LORI A. COGGINS

Bachelor of Arts in American Studies
Oklahoma State University
Stillwater, Oklahoma
2004

Master of Science in Educational Leadership
Oklahoma State University
Stillwater, Oklahoma
2006

Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
July, 2019

IDENTIFYING STUDENTS WHO NEED SUPPORT:

A LOGISTIC REGRESSION STUDY OF COMMUNITY

COLLEGE STUDENT SUCCESS PREDICTION

Dissertation Approved:

Kerri S. Kearney

Dissertation Adviser

Stephen P. Wanger

John D. Foubert

Pamela M. Fry

ACKNOWLEDGEMENTS

I am grateful to my patient and kind Dissertation Chair and Advisor, Dr. Kerri Kearney, for her support and confidence in me. Thank you to Drs. Fry, Wanger and Foubert for their insightful guidance. It has been a privilege to work with such an experienced and knowledgeable group of educators.

Life presented more twists and turns than I can remember during the research and writing of this dissertation. Thank you to my husband, Scott Coggins, for appreciating my issues even when he sometimes did not fully understand them and for standing by me during this process. The encouraging words of my treasured daughters and fantastic family and friends carried me through to graduation.

Acknowledgements reflect the views of the author and are not endorsed by committee members or Oklahoma State University.

Name: LORI A. COGGINS

Date of Degree: JULY, 2019

Title of Study: IDENTIFYING STUDENTS WHO NEED SUPPORT: A LOGISTIC REGRESSION STUDY OF COMMUNITY COLLEGE STUDENT SUCCESS PREDICTION

Major Field: EDUCATIONAL LEADERSHIP AND POLICY STUDIES

Abstract: Ongoing questions exist about whether placement measures used by community colleges accurately predict students' potential for success in addition to assessing their academic achievement levels in reading, writing, and math. Research has shown that noncognitive measures can be effective tools for predicting student success and that success prediction has shown promise in improving the English and mathematics course placement process for community college students. More accurate placement can provide shorter time to degree and lower likelihood of dropping out. Subsequently, some community colleges have begun to implement success prediction as part of their placement processes to determine not only students' levels of academic preparation, but also their likelihood of succeeding in courses and staying in college. The purpose of this study was to evaluate the effectiveness, based on student performance and retention, of using a noncognitive assessment score to predict student success in English and math courses and retention from fall to spring semesters at a multi-campus, urban community college. Logistic regression was employed to determine the predictive value of SuccessNavigator, a noncognitive assessment, and that of other student information such as high school GPA, ACT scores, and writing and math placement tests. Data analysis demonstrated that although SuccessNavigator was a statistically significant predictor of student success and retention, a combination of high school GPA and ACT subject-area scores most accurately predicted success in writing and math courses, and that high school GPA was the best predictor of retention from fall 2016 to spring 2017. Findings from this study imply that more research is needed that applies new success theories that are specific to community college students to determine the best ways for community colleges to predict success and properly place their students.

TABLE OF CONTENTS

Chapter Page

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

CHAPTER I

INTRODUCTION

Community colleges are facing a completion crisis. Accountability for student success, including a sharp focus on graduation rates, has superseded higher education's focus on access for students from traditionally underrepresented groups (Goldrick-Rab, 2010; McClenney & Waiwaiole, 2005). According to the National Center for Educational Statistics or NCES (2016), the rate at which students at community college complete associate's degrees are significantly lower than the rate of students completing bachelor's degrees at four-year institutions. While there are multiple causes, one factor is the differences in college readiness of entering students at the two types of institutions. Community colleges are open access institutions. In addition to students who may *choose* community college, students who may not be admitted to four-year institutions also attend community colleges. This results in community college campuses that serve students of widely varying academic abilities and preparation levels. Because they are open access, community colleges educate higher percentages than four-year schools of students who require some developmental coursework to prepare them for the rigors of college courses. (Bailey, 2009).

Recent research studies in placement and developmental education found that placement tests used by community colleges are not accurate predictors of student success (Belfield & Crosta, 2012; Doyle, 2012; Saxon & Morante, 2014; Venezia & Hughes, 2013), and students who place into developmental courses are less likely to be retained each semester than their college level counterparts (Crisp & Delgado, 2014; Goldrick-Rab, 2010; McClenney, 2005). Some studies indicate that current placement processes tend to place too many students in developmental courses (Doyle, 2012; Belfield & Crosta, 2012). Addressing placement process issues to better serve students will ultimately improve community college completion rates. Effective placement will put more students in courses appropriate for them, removing the need for bored students to drop out of classes that are too basic (Crisp & Delgado, 2014; Goldrick-Rab, 2010; McClenney, 2005) and decreasing unneeded demands on community college resources during a time in which higher education finds itself in a widespread financial crisis.

Some community colleges worked to improve their placement processes by including multiple assessment measures; this has included a move away from using academic ability as the only criterion for placement. Studies on the usefulness of noncognitive, or affective, measures as indicators of future success have shown that some noncognitive factors can help determine which students are likely to succeed in college (Duckworth, Peterson, Matthews, & Kelly, 2007; Dweck, 2008; Pretlow & Wathington, 2013). While colleges work to improve placement, many educators are also creating student support services to assist developmental students in their journey to course success and program completion. Adding a noncognitive assessment to placement could help colleges identify which students could benefit most from additional supports such as tutoring, career exploration, and peer mentoring (Robbins, Oh, Le, & Button, 2009). Examples of noncognitive factors shown to predict college success are psychosocial factors such as self-regulation, positive mindset and self-efficacy, as well as external factors like social support and financial support (Robbins, et. al, 2009).

Statement of the Problem

Almost half of students entering community colleges in January, 2013, were considered not college ready because of their placement into developmental courses (U.S. General Accountability Office, 2013). These students purportedly arrived on college campuses underprepared to successfully complete college level coursework because of deficiencies in their reading, writing, and math skills. At community colleges, students are admitted prior to using assessment to determine whether their content knowledge reaches college level as determined by the state and the individual institution. I Education professionals struggle to determine whether unreasonable college expectations, inadequate high school preparation, or students' lack of ability or drive are at fault when students' test scores indicate that their skills or knowledge are below college level. The cause of the number of community college students who are ill- prepared for college is further problematized by ongoing questions about whether placement measures used by colleges accurately predict students' potential for success in addition to assessing their academic ability levels in reading, writing, and math.

Colleges and placement testing companies recently began to consider noncognitive factors instead of or in addition to standardized test scores to determine whether students are expected to succeed in the courses in which they are placed, shifting the emphasis from measuring academic achievement to predicting success in college courses (Robbins, Oh, Le, & Button, 2009). Studies have shown that students who are goal-directed, possess excellent study skills, and are comfortable asking for help succeed at higher rates even when their content test scores place them into developmental courses. Content test scores, while helpful in determining which students require additional academic preparation, are not believed to be the most accurate predictors of college success (Duckworth, et al., 2007; Robbins, et al., 2009). If content knowledge is not the only piece of information that is necessary to place students accurately in courses and additional academic supports, educators must determine what is missing and work to correct the placement problem. Given the positive outcomes reported by initial studies on the use of noncognitive factors for success prediction, further consideration of their role was needed.

Purpose of the Study

The purpose of this study was to evaluate the effectiveness, based on student performance and retention, of using a noncognitive assessment score to predict student success in English and math courses and retention from fall to spring semesters. For this study, success was defined as an earned grade of C or higher in English and math courses. Retention was defined as enrollment in the semester following the first semester of attendance at The College (a pseudonym).

Research Questions

1. Does a noncognitive assessment, SuccessNavigator, predict student success in freshman writing courses?
2. What combination of course placement information including SuccessNavigator, high school GPA, ACT and Accuplacer best predicts student success in freshman writing courses?

3. Does a noncognitive assessment, SuccessNavigator, predict student success in freshman mathematics courses?
4. What combination of course placement information including Success-Navigator, high school GPA, ACT, and Accuplacer best predicts student success in freshman mathematics courses?
5. Does a noncognitive assessment, SuccessNavigator, predict freshman student retention from fall to spring?
6. What combination of course placement information including Success-Navigator, high school GPA, and ACT best predicts freshman student retention from fall to spring?

Methodology

Study Site

The study was conducted at an urban community college (The College, a pseudonym) located in the central United States. The College enrolls nearly 24,000 students per year at its four primary instructional campuses and multiple, smaller, satellite campuses within its metropolitan area. The College offers university transfer and workforce development programs including associate's and applied associate's degrees and certificates.

Participants

Study participants were first semester freshmen students who had SuccessNavigator scores on file with The College. SuccessNavigator was used as a pilot placement tool during the fall 2016/spring 2017 academic year. Students who attended new student orientation, enrolled in The College's freshman student success course, or whose test scores placed them into developmental reading or writing were asked to complete SuccessNavigator, however, scores were not used to place students. Participants must have enrolled in the developmental or college level English or math course into which they placed in fall 2016.

Data Collection

Data were provided by The College's department of Institutional Research and consisted of student placement information, as well as information collected by The College that was not used in their placement process. Data that were used for placement purposes include ACT composite and sub-scores and ACCUPLACER English and math scores. Data collected that were not used in The College's placement process were high school GPA and SuccessNavigator sub-scores. Success outcomes included in data collection included developmental and college level English and math course grades and fall 2016 to spring 2017 retention.

Educational Testing Service (ETS) developed SuccessNavigator, which is a 30-minute, self-report psychosocial assessment that provides separate measures in four broad categories (including noncognitive factors): academic skills, commitment, self-management, and social support. The tool was developed to assist college personnel in placing students in English and math courses by indicating which students should be recommended for a higher-level placement based on their likelihood of success. SuccessNavigator is also promoted as providing assistance to academic advisors in identifying red flags that could hamper student success so that those can be addressed (Markle, et al., 2013).

The ACT is a standardized exam prominently used by colleges and universities in the United States to determine the academic readiness of students preparing to enter college. The ACT is designed to measure academic achievement in reading, writing, mathematics and science, producing sub-scores in each content area as well as a composite score (ACT, Inc., 2019; Bettinger, Evans & Pope, 2013). ACT scores are used by most colleges and universities in The College's state to make admission decisions, as well as to determine college readiness in reading, writing and math. The ACT exam was not designed to determine college-level versus developmental course placement for students but is frequently used in that capacity by community colleges.

The College's placement process for English and math courses began with ACT scores. Students who scored at least a 19 on the English and reading portions of the ACT were placed into college-level composition courses. Students whose ACT math scores were at least 20 were placed into college level math courses. Those students who submitted English and math scores under the minimums were required to take additional standardized subject area exams to determine their placement levels into one of several developmental English and math courses.

Subject area standardized placement testing is widely used in community colleges to determine students' levels of academic preparedness. ACCUPLACER is a set of computer adaptive reading, writing, and mathematics assessments from College Board, the company that is known for its SAT, AP, and CLEP exams. ACCUPLACER, the placement exams used for placement at The College, were administered at more than 2,000 high schools and colleges to assess students' readiness for college level courses (College Board, 2017).

Data Analysis

Binary logistic regression analyses were performed for each research question to examine the predictive value of independent, or predictor, variables on each of the three dependent, or outcome, variables that represent English and math course grades and retention from fall 2016 to spring 2017.

Significance of the Study

Research

This study contributed to our understanding of the usefulness of success prediction as part of a community college's placement process. Findings from this research also improved our knowledge of the effectiveness of using noncognitive assessments, specifically SuccessNavigator, as a tool for success prediction in a community college – currently a weak area of the research literature.

Theory

The research findings strengthen our understanding of the success theories behind noncognitive measures. Evaluations were made among theories behind noncognitive measures and their usefulness for success prediction compared to measures of academic preparedness as well as the applicability of theory to the potential use of multiple measure to predict student success.

Practice

The findings of this study help advance efforts to make the placement process specific to The College more meaningful to students. This research study also more broadly contributes to refining educators' understanding of the effectiveness of using noncognitive assessments to determine which students need additional supports to help them succeed in their coursework and complete their educational programs. The comparison of SuccessNavigator's predictive value to that of other placement data such as high school GPA, ACT subject area scores, and Accuplacer subject scores will assist educators in their search for a more accurate placement process.

Summary

Many students are underprepared for college coursework upon their arrival at community college. Colleges have traditionally required developmental reading, writing, and math education to academically prepare students for college. However, students in developmental education are less successful than their college-ready counterparts. Traditionally, the placement process attempts to measure academic preparedness, but does not attempt to measure noncognitive traits that have been shown to contribute to academic success and retention. This study seeks to determine the predictive effectiveness of a noncognitive assessment when added to the current placement process at a community college.

Chapter Two examines literature related to community college student success, developmental education, and noncognitive assessments. Chapter Three describes the study methodology. Chapter Four highlights the findings of the study, and Chapter Five provides a detailed discussion of the findings.

CHAPTER II

REVIEW OF LITERATURE

A review of scholarly literature established the solid foundation from which the problem statement and research questions that guide this study were developed. This examination of literature begins in the first section with a discussion of various postsecondary education options. In the second section, the focus narrows to community colleges including literature related to student success rates and institutional outcomes. The third section highlights student preparedness followed by the final section on developmental education and student placement. A brief summary concludes the chapter.

Postsecondary Education Options

Each year, a new cohort of high school graduates enters the next phase of their development. Students decide their paths from among a number of postsecondary options, choosing whether they will work, enter military or volunteer service, or seek job training or higher education. While these choices are all viable options that can each provide fulfillment and success, only one of these options is typically promoted to students as the best path to personal and career success. That best path is higher education, specifically a bachelor's degree.

Rosenbaum, Stephan, and Rosenbaum (2010) assert that a shift has taken place over the last several decades in how postsecondary options are presented to high school students resulting in an increase in the numbers of high school graduates who choose to pursue bachelor's degrees. Most high school graduates enter two-year and four-year institutions intending to earn bachelor's degrees, but comparatively few students actually earn degrees. Students' intentions have changed, but their completion rates have not improved significantly.

One theme that Rosenbaum, et al. (2010) identified through years of research in the health and education fields is that "withholding potentially discouraging information from youth appears to be a widespread societal problem" (p. 3). The researchers propose that the Bachelor of Arts degree has been idealized by society. This idealization has become prominent in K-12 schools. Children as young as kindergarten are encouraged to focus on college as their educational end goal. Rosenbaum, et al. (2010) propose a three-pronged remedy to this idealization that leads many students to college when they do not need or want to earn a degree. Their solution for society, parents, and high school counselors is "realizing that many good jobs do not require a BA, fully informing students about their options, and, as students select goals, honestly telling them what it will take to succeed" (Rosenbaum, et al., 2010, p. 3).

The blame for too many students choosing college while ignoring other options is placed not on students, but is spread among society, our K-12 school system, and high school counselors, although no one entity itself is the cause of this situation, according to Rosenbaum, et al. (2010). When the source of a problem cannot be identified, it becomes more difficult to solve the problem. Higher education scholars and practitioners continue to conduct research and identify theories around issues related to low college completion rates. Stern (2013) found a disconnect in high school teachers' understanding of the skills needed for success in college from those success skills that college professors actually require, primarily the ability of students to focus in some depth on a subject rather than learn at a surface level. Identifying how to realign the focus on all students earning a bachelor's degree will help reroute students into other postsecondary options that can also provide stable successful lives. Much research, however, highlights the success of students who complete college while little research exists on the success of students who take alternative paths after high school (Lee, Almonte, & Youn, 2013).

One example of such a study found that people with college degrees are less likely to lose their jobs and incomes during economic downturns and earn higher wages over a lifetime than people with only a high school diploma or less (Hout, 2012). Non-economic benefits of college completion include family stability and healthier lifestyles, resulting in reduced divorce rates, better child-rearing practices, and improved health outcomes. These outcomes are attractive to students, parents, and high school counselors, so the guidance to complete a bachelor's degree remains. Completion of a degree or transfer to a four-year institution is not realized by most community college students, however, so while all may enter, few exit successfully (Hout, 2012).

Schudde and Goldrick-Rab (2015) examined sociological research on higher education institutions and synthesized applications of sociological theory to community colleges, specifically looking at social stratification. Community colleges offer students open access to a college education while perpetuating low student transfer and graduation rates. Community colleges permit almost everyone who wants to pursue a degree or certificate to enter and try, but access does not guarantee completion for most students. It is within these contexts that sociologists study community colleges.

Critical education theorists examine community colleges as "a contested site in which inequality is simultaneously ameliorated by increasing educational opportunity and exacerbated by failing to improve equity in college completion across key demographics, such as race and socioeconomic status" (Schudde & Goldrick-Rab, 2015, p. 28). While open access community colleges permit all students to enter college, an achievement gap remains in the success and completion of students from various demographic groups.

Community colleges unwittingly participate in social stratification through addressing inequality by providing open access admission and low-cost tuition (Schudde & Goldrick-Rab, 2015). These aspects of community college attract a more ethnically and economically diverse student population comprised of people who would not otherwise attend a four-year university because of higher admission standards and cost. Students who attend community college tend to be older than their university counterparts (Schudde & Goldrick-Rab, 2015). Many community college students need to work and remain at home due to the high cost of living away from family or in order to care for children or elderly or disabled family members. This results in students who would benefit most from completing college instead attending institutions that provide the least opportunity for completion (Hout, 2012; Lucas, 2001; Schudde & Goldrick-Rab, 2015).

Labaree (2013) goes a step further than Schudde & Goldrick-Rab by asserting that community colleges contribute to social stratification by sorting students, which protects privilege in higher education. "Students are sorted into tiers of higher education that have become increasingly segmented in terms of fields of study, degrees conferred, and returns to credentials" (Schudde & Goldrick-Rab, 2015, p. 31). For Horace Mann, education was considered “the great equalizer of the conditions of men – the balance-wheel of social machinery” (Mann, 1868). Social stratification between community colleges and bachelor’s degree granting institutions, however, presents a barrier to Mann’s idea of equalization.

Large number of students continue to choose community colleges to pursue higher education because of the low cost and ease of access. A 2016 study applied the college choice conceptual framework to the post-secondary decisions made by a group of low-income, African-American and Latino students from inner-city high schools (Cox, 2016). Cox examined the Hossler & Gallagher (1987) college choice model which asserts that students maneuver three phases of the college choice process, developing aspirations/preparing for application, searching/applying, and choosing from among colleges to which students are admitted. Cox (2016) asserts that this model is inadequate for understanding the post-secondary paths of students from underrepresented groups.

The college choice framework does not account for the low-income experience faced by students in Cox’s (2016) study. Complicating factors such as lack of adequate housing and food impact students’ ability to have their most basic needs met and render the college choice model inadequate for understanding what these students do after high school (Cox, 2016). The types of students in Cox’s study are those most likely to choose community college over university.

One group of researchers examined college choice specifically with community college students. Somers, et al. (2014) developed their Theory of Choice through focus group research with 223 community college students from multiple institutions located in one state. Their findings indicated that the choice to attend community college is complex. Their theory includes 10 factors that fit into three categories, aspirations and encouragement, institutional characteristics, and finances. Study participants reported deciding to attend community colleges for reasons such as needing to be close to home and a job, improving future economic opportunities for themselves and their dependents, and proving wrong people who had discouraged them in the past, primarily teachers and high school counselors (Somers, et al., 2014).

The literature on postsecondary education options revealed that students who choose community college are likely to face more challenges to their success than students who choose universities to begin their college education. This presents unique challenges to community colleges as educators work tirelessly to find the most effective ways to support their students. The scope and causes of the completion crisis are described in the next section.

Community College Completion Crisis

Community colleges enroll almost half of all undergraduate students in the United States, but they also have the lowest graduation rates of all institution types. Only 20% of the 2011 cohort of full-time, first-time, public community college students graduated within three years (National Center for Educational Statistics, 2016). In addition to the implications for colleges and for students, this phenomenon negatively impacts our larger society. Schneider and Yin (2012) projected that if U.S. community college dropouts had been reduced by half for the academic years 2006 through 2009, 160,000 new graduates would have increased overall personal income in the United States by over $30 billion and paid additional federal taxes of more than $4 billion.

The potential positive economic impact of more college graduates has not gone unnoticed by policy makers. President Barrack Obama addressed the downward pull on the U.S. economy created by a lack of college educated citizens in 2009. During a speech at Macomb Community College in Michigan, the president introduced the American Graduation Initiative. This initiative was designed to help community college students complete five million new degrees and certificates by the year 2020 (Obama, 2009).

While community colleges have become the doorway to higher education for many students, graduation rates are the standard by which student success is measured by governmental agencies (Wild & Ebbers, 2002). In addition to completing associate's degrees and other credentials at community colleges, many students take community college courses as steps on their way to completing bachelor's degrees; these students may spend a few semesters or even years at a community college campus before moving on to a four-year university. Students who completed four-year degrees after transferring from community colleges are successful by their own definition because they accomplished what they intended at the community college but, when degrees are not completed at the community college, their success is not reflected in graduation rates for the institution (Wild & Ebbers, 2002). Some colleges are beginning to report transfer rates to provide a more accurate picture of student success, but graduation rates continue to the primary indicator of student success (Crisp & Mina, 2012; Wild & Ebbers, 2002).

In 2015, while the six-year graduation rate for public, four-year universities was disappointing at 58%, the three-year graduation rate for public, two-year colleges was less than half of the university rate at 20% (NCES, 2016). The timeframes reported in these findings represent completion rates for students who take 1.5 times the traditional number of years to complete their degrees. Even using these extended timeframe completion statistics, community college graduation rates are far behind those of four-year institutions and, as a result, are of continuing concern for policymakers, higher education, and the general public.

Given the institutional and student differences between community colleges and four-year institutions, higher education stakeholders might be tempted to conclude that low community college student success rates are an issue only for those directly associated with community colleges. In reality, however, low community college success rates impact all of higher education. While some people continue to think of the stereotypical college undergraduate as someone who is 18 to 22 years old, who lives on a university campus, and who depends on their parents for financial support, in reality, 45% of all undergraduates attended community colleges in fall 2014 (American Association of Community Colleges, 2016). With community colleges educating almost half of all undergraduates, many of whom intend to transfer to four-year universities, the need to improve student success at community colleges is evident. Students who are not successful at community colleges will not move on to study at four-year institutions. Everyone has a stake in the success of community college students.

Contributing Factors

Inadequate student retention by colleges produces low student graduation rates. Vincent Tinto (1993) researched student-focused persistence in developing his Institutional Departure Model rather than taking an institution-focused retention perspective. Tinto (1993) identified the three phases of his model as separation, transition and integration. Tinto's theory placed the accountability for student attrition on students based on their own poor decision making and personal character issues. Bean's (1980) early retention work took the opposite perspective of Tinto's research by examining institutional factors that impacted student retention. Bean's Student Attrition Model provided a framework for institutions to examine their parts in low student retention outcomes (1980). Tinto's and Bean's theories served college for decades until subsequent researchers began to look at the more complex reasons why students leave college early.

One of those complex reasons for low retention and graduation rates at community colleges is that community colleges maintain open door admission policies (Crisp & Mina, 2012). These policies are in line with the mission of the community college, which includes serving as many community members as possible through offering lower division, developmental, and vocational coursework. The practice of open door admission, by its nature, encourages an increased presence of nontraditional students, and research has shown that student demographic differences are one reason for the disparity in completion rates between community college students and university students (Crisp & Mina, 2012).

Students over 25 years old and students of color enroll at higher percentages in community colleges than in four-year universities. These same students also tend to be first generation, low socio-economic status, employed, and commuters; current measures also indicate that they are academically underprepared at higher levels than university students (Crisp & Mina, 2012; Fike & Fike, 2008; Townsend & Twombly, 2007; Wild & Ebbers, 2002). Community college students were grouped into the following six categories by Crisp and Mina (2012); transfer, vocational, developmental, community education, dual enrollment, and English as a second language students. Community college students may fall into one or more of these categories (Crisp & Mina, 2012; Wild & Ebbers, 2002). The characteristics of community college students generally place them in groups that have shown to be at higher risk of dropping out than traditional university students (Caporrimo, 2008; Cox, Reason, Nix & Gillman, 2016; Crisp & Mina, 2012).

In addition to considering barriers to success faced by the nontraditional student, other focus areas for research on community college student success shift away from student attributes and toward institutional concerns. Most scholarly literature on institutional characteristics affecting student success is concentrated in the university context (Goldrick-Rab, 2010). In a review of academic and policy research literature, however, Goldrick-Rab (2010) identified six community college practices that affect student success: pedagogical practices not linked to real world situations, insufficient academic advising, a lack of data-driven decision making, inadequate professional development, the reliance on adjunct faculty, and the noncredit bearing nature of developmental coursework. Goldrick-Rab (2010) reported these practices as institutional barriers to community college student success.

Students who are placed into developmental coursework realize that their work in these courses provides no college credit, so they may feel discouraged by the cost and length of time that developmental courses add to their educational programs. Additionally, placement processes that only include content area tests tend to place students who would have otherwise succeeded in college level coursework into developmental courses (Goldrick-Rab, 2010). Community colleges that are serious about addressing the completion crisis should address reading, writing, and mathematics placement and support services. The issue of the lack of preparation for college level coursework of many community college students is addressed in the next section.

College Readiness

Understanding the issue of underprepared college students can be challenging. When a student graduates from high school, the student should be academically prepared for college, career, and life. Many underprepared students who do not meet minimum university admission requirements begin their studies at community colleges (Community College Survey of Student Engagement, 2016). According to the Community College Survey of Student Engagement, or CCSSE, 68% of all students entering community colleges are underprepared to be successful in college level mathematics and English courses. This is significant because the percentage of undergraduate students served by community colleges is rising. A 2013 report by the United Stated General Accountability Office (GAO) to the House of Representatives indicated that community colleges served 39% of all undergraduate students in the U.S. In only three years, the percentage of all undergraduates attending community colleges rose to 45% (AACC, 2016).

A logical solution to the issue of so many students being underprepared for college might be to redirect those students away from higher education and into adult basic education programs. ABE programs, however, are primarily designed for students who did not finish high school or those who struggle with reading, writing and math because of a significant gap in their master of the English language (National Skills Coalition, 2019). ABE programs in the state in which The College operates fit this description and are situated within the career and technical schools (separate from community colleges) and in community-based programs, many of which are situated in PreK-12 schools. Given that approximately two-thirds of new students entering The College each year require developmental reading, writing or math courses and because these students have already graduated from high school or received a GED, ABE programs are neither designed for nor appropriate for students who require developmental courses to prepare them for college level coursework.

The first step in the college admission process for many students is the completion of a high-stakes college entrance exam such as the SAT or the ACT. The state in which The College is situated uses the ACT, American College Testing, exam as the first measure of college readiness. The ACT is comprised of exams in four academic areas, mathematics, English, reading, and science. Students earn a composite score as well as subscores in the four subject areas. The ACT composite score was used during fall 2016 for overall admission purposes in The College's state as mandated by the state's higher education governing body. ACT subject area scores were used to determine whether students must take additional placement tests for referral into college level courses or one of several levels of developmental English and math courses. The purpose of the ACT exam is primarily to assess a student's level of content knowledge in four subject areas, not necessarily to place students into developmental coursework (ACT, Inc., 2019). Recent research findings, however, indicate that ACT scores and thereby content knowledge, may not be the best predictors of college success (Bettinger, Evans & Pope, 2013). The College's use of a content knowledge measure, ACT, to determine whether students were prepared to begin college level coursework, likely contributes to students' incorrect placement.

Successful scores on the ACT exam allow students in The College's state automatic admission to its community colleges, research universities and regional institutions. Low ACT scores require entering students to complete additional placement testing such as Accuplacer subject tests in reading, writing, and math. Accuplacer is a CollegeBoard product. CollegeBoard is the organization that provides the SAT, AP, and CLEP tests (Accuplacer, 2019).

Community colleges rely heavily on placement tests such as the Accuplacer to determine into which developmental or college level writing and math courses students should initially be placed. This is a high stakes decision that can mean more time to degree and additional tuition for students who place into developmental coursework. Accuplacer, like the ACT, is meant to measure academic achievement for placement. It is not meant to be used to predict student success (Saxon & Morante, 2015). These two assessments, however, are the tools currently used by The College to determine writing and math placement.

Students who are referred to developmental education upon admission to a community college do not always enroll in or complete the developmental coursework prescribed. The CCRC report found that less than half of students who place into developmental education actually complete their developmental course sequences (Bailey, Jeong, & Cho, 2009). In fact, approximately 30% of students referred to developmental education never enroll in a developmental course (Bailey, Jeong, & Cho, 2009). Some of these students enroll in courses that have no reading, writing or math prerequisites and put off their developmental courses until later semesters, and some leave community college.

When students leave because of the results of the placement process, developmental education becomes a barrier rather than an academic support as intended (Bailey, 2009). Based on low community college success rates, simply being referred to developmental courses is not enough support for underprepared students. Those students need additional academic as well as non-academic supports to succeed (Saxon & Morante, 2015).

Placement and Success Prediction

A placement test is "a test usually given to a student entering an educational institution to determine specific knowledge or proficiency in various subjects for the purpose of assignment to appropriate courses or classes" (Merriam-Webster, 2019). For many years, colleges relied on measures of academic preparation such as the ACT, SAT and standardized placement tests such as Accuplacer to determine whether students were prepared for college level coursework and, if not, the tests were also used to determine at which developmental level students should be placed. More recently, however, studies determined that academic achievement measures are not the best methods of placing students. Institutions began shifting their focus toward success prediction instead of or in addition to academic achievement to more accurately place students (Bailey, Jaggars, & Jenkins, 2015; Belfield & Crosta, 2012; Doyle, 2012; Nakajima, Dembo, & Mossler, 2012; Saxon & Morante, 2014; Venezia & Hughes, 2013).

Recent research studies in placement and developmental education found that placement tests used by community colleges are not accurate predictors of student success in academic coursework (Belfield & Crosta, 2012; Doyle, 2012; Saxon & Morante, 2014; Venezia & Hughes, 2013). Students who place into developmental courses were less likely to be retained each semester than their college level counterparts (Crisp & Delgado, 2014; Goldrick-Rab, 2010; McClenney, 2005), and some studies indicated that placement processes tended to place too many students in developmental courses (Doyle, 2012; Belfield & Crosta, 2012). Only 65% to 70% of community college students who placed into developmental math and English courses (68% of all community college students nation-wide) believed that they were appropriately placed (Community College Survey of Student Engagement, 2016). The abundance of incorrect placement could indicate that measuring academic preparation indicated by test scores alone was not effective for proper placement of students in math and English courses.

Adding success prediction to the placement process to better serve students would ultimately improve community college completion rates. Effective placement would put more students in courses that are appropriate for them, removing the need for bored students to drop out of classes that are too basic, as well as for overwhelmed students to drop out of courses that are too challenging (Crisp & Delgado, 2014; Goldrick-Rab, 2010; McClenney, 2005). Some community colleges worked to improve their placement processes by including some element of success prediction such as high school course grades, high school grade point average, SAT or ACT scores, and noncognitive assessments that measure traits such as mindset and motivation. Some institutions attempted to measure other variables such as socio-economic status and levels of financial and social support that have been shown to predict student success. Using multiple measures or alternatives to measurements of academic ability became consistent trends in higher education math and English course placement (Saxon & Morante, 2014; Woods, Park, Hu, & Jones, 2019).

A prominent developmental education researcher and practitioner, Hunter R. Boylan, former Director of the National Center for Developmental Education, asserted that for educators to more accurately predict student success, “we have to measure something more than [students’] cognitive ability. We also have to measure their affective characteristics. We have to look at life circumstances…Right now, we are not doing this very often or very well” (Levine-Brown & Anthony, 2017, p. 20). Boylan warned that policy makers should stop focusing on finding ways to place fewer students into developmental courses and work instead on determining the best use of multiple measures for more accurate initial placement and assignment to support services. Noncognitive factors related to student success are examined in the next section.

Noncognitive Issues and Student Success

William Sedlacek was a pioneer in the area of exploring the use of noncognitive measures in predicting student success (Sedlacek & Brooks, 1976; Tracey & Sedlacek, 1982). His work grew out of the need to improve retention rates for students from underrepresented groups. Sedlacek’s research was conducted at universities, but his focus on nontraditional and minority student success made his work relevant in a discussion of community college student success.

Sedlacek and Brooks (1976) identified seven variables related to college student success specifically for ethnic minority students: “positive self-concept, realistic self-appraisal, understanding of and ability to deal with racism, preference for long-range goals over short-term or immediate needs, availability of a strong support person, successful leadership experience and demonstrated community service” (Tracey & Sedlacek, 1982, p. 6). Tracey and Sedlacek (1982) developed the Noncognitive

Questionnaire or NCQ and tested it for content validity in 1979 and 1980. The questionnaire was administered to 2,122 incoming freshmen at the University of Maryland, College Park during summer orientation. The study found the instrument to be both reliable and valid and that different variables were related to success measures for white students than those for African-American students (Tracey & Sedlacek, 1982).

Tracey and Sedlacek (1982) found that the noncognitive variables of "self-confidence, preference for long-range goals over short-term or immediate needs, and realistic self-appraisal were most strongly related to grade point average" (p. 1) for white students. For African-American students, positive self-concept and realistic self-appraisal were related to grade point average. Study findings indicated that the questionnaire was significantly related to grades for white students, and to grades and retention for African-American students.

By 1993, Sedlacek shifted his terminology for describing students from underrepresented groups away from negative terms such as minority to the more neutral "nontraditional applicant/student" (Sedlacek, 1993, p. 33). Nontraditional is the term most commonly used today by educators to describe students who are "people who have had different experiences than white middle/upper middle class, mostly male people in U.S. society" (Sedlacek, 1993, p. 33). This is generally an accurate description of community college students. By 1993, Sedlacek also identified an eighth noncognitive variable required for nontraditional college student success: knowledge acquired in a field. The term for this trait was not as self-explanatory as the first seven traits; Sedlacek defined knowledge acquired in a field as "unusual and/or culturally related ways of obtaining information and demonstrating knowledge." (Sedlacek, 1993, p. 34).

In subsequent decades, Sedlacek continued to advocate for the use of noncognitive variables in college admissions as well as for scholarship selection. Kalsbeek, Sandlin, and Sedlacek (2013) assert that the Gates Millennium Scholars, or GMS, program applied the Sedlacek method of noncognitive assessment for selection. The results in 2008 were that the six-year graduation rate for program participants was 90% compared to 57% overall for students at four-year institutions (Kalsbeek, Sandlin, & Sedlacek, 2013).

By 2004, Sedlacek's descriptions of noncognitive variables that predict student success evolved into positive self-concept, realistic self-appraisal, understands and knows how to handle the system, prefers long-range to short-term or immediate needs, availability of strong support person, successful leadership experience, demonstrated community service, and nontraditional knowledge acquired (Kalsbeek, Sandlin, & Sedlacek, 2013). The use of Sedlacek's method of including noncognitive variables in the admissions or selection process continued to show positive results (Kalsbeek, Sandlin, & Sedlacek, 2013), particularly for increasing admission and selection of nontraditional students into selective and competitive universities and programs. However, Sedlacek's work has not been a focus for use in placement at open access institutions.

Theorists subsequent to Sedlacek studied traits that predict success in various areas including academic success for college students. These theorists focused more narrowly on traits related to the noncognitive variables Sedlacek identified. One example is grit theory developed by Angela Duckworth (2007) to explain why some people are more successful than others who possess equal intelligence. Duckworth defined grit as a noncognitive character strength that is defined as perseverance and passion for long-term goals (Duckworth, et al., 2007). Grit compares to Sedlacek's noncognitive variable, prefers long-range to short-term or immediate needs.

Another theorist whose work is related to Sedlacek's is Carol Dweck (2008). Dweck's growth mindset is similar to Sedlacek's noncognitive traits, positive self-concept and realistic self-appraisal. Dweck's studies demonstrated that people who possessed the growth mindset were more successful than those who had fixed mindsets. People with growth mindset demonstrated the ability to bounce back from setbacks and failures (Dweck, 2008).

Sedlacek, Duckworth, and Dweck are success theorists who developed instruments or methods for effectively predicting success and tested their methods extensively, demonstrating the validity and reliability of the instruments. Success prediction is one purpose of a more recently developed instrument called SuccessNavigator from Educational Testing Service or ETS.

SuccessNavigator

SuccessNavigator is a computer-delivered assessment developed by ETS for use as a placement instrument and success prediction tool. SuccessNavigator marketed itself as an instrument that could assist placement decision-makers in determining which students could be accelerated in placement because of their predicted levels of success. The assessment was also meant to assist advisors in identifying the types of academic and non-academic supports students should be offered upon their entry into college study. SuccessNavigator was successfully adopted by a number of colleges and universities including Montgomery College, Saginaw Valley State University, Iowa Western Community College and University of New Mexico. These institutions primarily used the assessment to tailor support for each student (Markle, Olivera-Aguilar, Jackson, Noeth, & Robbins, 2013), however, not for math and English placement decisions.

SuccessNavigator is an instrument grounded partially in the theory of conscientiousness, which was also studied by Duckworth (MacCann, Duckworth, & Roberts, 2009). The personality trait of conscientiousness was identified, along with openness to experience, extraversion, agreeableness, and neuroticism, in the five factor model of personality (McCrae & Costa, 1987). Conscientiousness is defined as "organization, timeliness, effort, and drive to achieve goals" (Markel, et al., 2013).

Three of the skills measured by SuccessNavigator were identified by Markle, et al. (2013) as facets of conscientiousness (MacCann, Duckworth, & Roberts, 2009) and include academic skills, commitment, and self-management. A fourth SuccessNavigator skill, social support, was identified as related to academic success by Robbins, Allen, Casillas, Peterson, & Le (2006). Within the context of SuccessNavigator, social support included connectedness, institutional support, and barriers to success (family pressures and the presence of a support person). Although Markle, et al. (2013), did not identify Sedlacek's theory as a basis for SuccessNavigator, the instrument's four general skills contained subskills that were similar to Sedlacek's eight noncognitive variables based on my comparison of descriptions provided by the researchers (Markle, et al., 2013; Sedlacek, 2011). Figure 2.1 demonstrates the similarities between SuccessNavigator's subskills and Sedlacek's noncognitive variables.

Figure 2.1

Comparison Between SuccessNavigator's Subskills and Sedlacek's Noncognitive Variables

SuccessNavigator Subskill	Sedlacek's Noncognitive Variable
Organization	Prefers Long-Range to Short-Term or Immediate Needs
Meeting Class Expectations	Prefers Long-Range to Short-Term or Immediate Needs
Commitment to College Goals	Prefers Long-Range to Short-Term or Immediate Needs
Institutional Commitment	Understands and Knows How to Handle the System
Sensitivity to Stress	Positive Self-Concept/Realistic Self-Appraisal
Academic Self-Efficacy	Positive Self-Concept/Realistic Self-Appraisal
Test Anxiety	Positive Self-Concept/Realistic Self-Appraisal
Connectedness	Successful Leadership Experience/Demonstrated Community Service/Nontraditional Knowledge Acquired
Institutional Support	Understands and Knows How to Handle the System
Barriers to Success	Availability of Strong Support Person

Two primary differences exist between Sedlacek's theory and SuccessNavigator. One difference is that although the SuccessNavigator instrument is reliable and valid as explained in Chapter III, it has not had the benefit of being employed over decades and in as many studies as Sedlacek's success prediction instrument. The second difference is that the purpose of Sedlacek's work was strictly success prediction for purposes such as awarding prestigious scholarships while SuccessNavigator's assessment is meant to be used, in part, to provide recommendations for accelerating placement in English and math courses for students who demonstrate a strong likelihood of success.

The overlap in the two theories of success is demonstrated in the categories that organize the assessment items. The overlap of factors in the recently designed

SuccessNavigator with those of Sedlacek's well-established success prediction instrument supported the exploration of the predictive effectiveness of SuccessNavigator. SuccessNavigator purported to extend the use of a theory similar to Sedlacek's from success prediction to placement. SuccessNavigator used success prediction to enhance and accelerate the placement process, so SuccessNavigator's ability to accurately predict success required confirmation.

Summary

A thorough examination of the relevant literature was conducted in this chapter. Studies related to students' postsecondary options, the community college completion, college readiness, course placement, and theories related to noncognitive issues and student success were discussed. Chapter III will introduce the study methodology.

CHAPTER III

METHODOLOGY

This chapter provides an overview of the study methodology. The first sections of this chapter describe the problem statement, purpose statement, and research question. The next section provides context for the study, followed by a section addressing study procedures and methods. The final section is a chapter summary.

Statement of the Problem

Almost half of students entering community colleges in January, 2013, were considered not college ready because of their placement into developmental courses (U.S. General Accountability Office, 2013). These students purportedly arrived on college campuses underprepared to successfully complete college level coursework because of deficiencies in their reading, writing, and math skills. At community colleges, students are admitted prior to using assessment to determine whether their content knowledge reaches college level as determined by the state and the individual institution. It is difficult to determine whether unreasonable college expectations, inadequate high school preparation, or students' lack of ability or drive are at fault when students' test scores indicate that their skills or knowledge are below college level. The cause of the number of community college students who are ill prepared for college is further problematized by ongoing questions about whether placement measures used by colleges accurately predict students' potential for success in addition to assessing their academic ability levels in reading, writing, and math.

Colleges and placement testing companies recently began to consider noncognitive factors instead of or in addition to standardized test scores to determine whether students are expected to succeed in the courses in which they are placed, shifting the emphasis from measuring academic achievement to predicting success in college courses (Robbins, Oh, Le, & Button, 2009). Studies have shown that students who are goal-directed, possess excellent study skills, and are comfortable asking for help succeed at higher rates even when their content test scores place them into developmental courses. Content test scores, while helpful in determining which students require additional academic preparation, are not believed to be the most accurate predictors of college success (Duckworth, et al., 2007; Robbins, et al., 2009). If content knowledge is not the only piece of information that is necessary to place students accurately in courses and additional academic supports, educators must determine what is missing and work to correct the placement problem. Given the positive outcomes reported by initial studies on the use of noncognitive factors for success prediction, further consideration of their role was needed.

Purpose Statement

The purpose of this study was to evaluate the effectiveness, based on student performance and retention, of using a noncognitive assessment score to predict student success in English and math courses and retention from fall to spring semesters. For this study, success was defined as an earned grade of C or higher in English and math courses. Retention was defined as enrollment in the semester following the first semester of attendance at The College (a pseudonym).

Research Questions

The following research questions guided this study.

1. Does a noncognitive assessment, SuccessNavigator, predict student success in freshman writing courses?
2. What combination of course placement information including SuccessNavigator, high school GPA, ACT and Accuplacer best predicts student success in freshman writing courses?
3. Does a noncognitive assessment, SuccessNavigator, predict student success in freshman mathematics courses?
4. What combination of course placement information including Success-Navigator, high school GPA, ACT, and Accuplacer best predicts student success in freshman mathematics courses?
5. Does a noncognitive assessment, SuccessNavigator, predict freshman student retention from fall to spring?
6. What combination of course placement information including Success-Navigator, high school GPA, and ACT best predicts freshman student retention from fall to spring?

Null Hypotheses

The null hypotheses tested in this study are as follows.

1. A noncognitive assessment, SuccessNavigator, does not predict student success in freshman writing courses.

2. No combination of course placement information including SuccessNavigator, high school GPA, ACT and Accuplacer predicts student success in freshman writing courses.
3. A noncognitive assessment, SuccessNavigator, does not predict student success in freshman mathematics courses.
4. No combination of course placement information including SuccessNavigator, high school GPA, ACT and Accuplacer predicts student success in freshman mathematics courses.
5. A noncognitive assessment, SuccessNavigator, does not predict freshman student retention from fall to spring freshman student retention.
6. No combination of course placement information including SuccessNavigator, high school GPA and ACT predicts freshman student retention from fall 2016 to spring 2017.

Context for the Study

The College (a pseudonym) is an open-access community college located in the central United States. The College enrolls nearly 24,000 students at its four primary instructional campuses and multiple, smaller, satellite campuses within one of the two major metropolitan areas in the state. The College offers university transfer and workforce development programs.

In 2014, The College formed a group of faculty, staff and administrators to work on creating a more accurate new student placement process, a process that used ACT sub-scores and ACCUPLACER content area scores for student placement. The group made a number of recommendations to The College that were or were intended to be implemented. Most of these recommendations were related to the type of standardized content area placement test to be used, cut score determinations for various developmental level and college level course placement, and the number of placement tests in English and math that students were permitted to take in the same day. In an effort to try using multiple measures to more accurately place students, the group also recommended that The College pilot a noncognitive assessment alongside the current placement process in an effort to determine whether success prediction is helpful in placing students in developmental courses and in determining the academic supports meant to encourage success for students in those courses.

Beginning in spring 2016, The College asked students to take SuccessNavigator (in addition to ACCUPLACER) as part of their onboarding process, a process which included admission, English and math course placement, new student orientation, and enrollment. Students were also encouraged, and many were required, to take the assessment as part of their freshman student success course. The College was working to determine the effectiveness of SuccessNavigator for success prediction.

Procedures and Methods

This study used data provided by the institution but not connected to any studies, related or unrelated, currently being conducted by The College. Educators involved in student retention efforts were examining a number of alternatives for cognitive (ACT, new versions of ACCUPLACER, faculty developed assessments) and noncognitive measures (SuccessNavigator, faculty-developed noncognitive questions) for the purpose of more accurately determining student placement and success prediction. The College was also considering placement process changes such as preventing students from taking

English and math placement exams on the same day and requiring test preparation. This study considered the effectiveness of the SuccessNavigator assessment, as well as other admission and placement data collected by The College in success prediction.

Participants

Study participants were first semester freshmen students in fall 2016 who had SuccessNavigator scores on file with The College. Participants were enrolled in the English or math course into which they placed in fall 2016. SuccessNavigator was used in a pilot for all incoming students who required Accuplacer placement testing because their ACT sub-scores in English and mathematics were under 19, as well as for all students enrolled in The College's required first semester student success course.

Data Collection

De-identified data were provided by The College's department of Institutional Research. The College provided high school GPA, ACT, ACCUPLACER, and SuccessNavigator scores and sub-scores for each participant, as well as grades earned in fall 2016 math and English courses and retention from fall 2016 to spring 2017. Demographic information for gender, race, and age was also provided.

Variables

Variables used in six separate regressions are listed in Figures 3.1, 3.2, and 3.3. The variables listed in Table 3.1 were used to address research questions 1 and 2 related to writing course success. Likewise, the variables listed in Figure 3.2 were used to address research questions 3 and 4 related to math course success. Variables listed in Figure 3.3 were used to address research questions 5 and 6 related to retention from fall 2016 to spring 2017.

Figure 3.1

Predictor Variables and Associated Outcome Variable for English

Predictor (independent) variable	Outcome (dependent) variable
SN_ENGL_PLCMT_INDX SuccessNavigator English Placement Index Score	WRTG_SUCCESS Successful completion or non-completion of writing course. Course success is defined as an earned grade of C or better in highest level writing course attempted.
ACCUPLACER_SENT_SKILLS Accuplacer English Sentence Skills Placement Test Score	
ACT_ENGL ACT English Sub-score	
HS_GPA High School Grade Point Average	

Note. All predictor variables are continuous. The outcome variable WRTG_ SUCCESS is categorical.

Figure 3.2

Predictor Variables and Associated Outcome Variable for Math

Predictor (independent) variable	Outcome (dependent) variable
SN_MATH_PLCMT_INDX SuccessNavigator Math Placement Index Score	MATH_SUCCESS Successful completion or non-completion of math course. Course success is defined as an earned grade of C or better in highest level math course attempted.
ACCUPLACER_ELEM_ALG Accuplacer Elementary Algebra Test Score	
ACT_MATH ACT Math Sub-score	
HS_GPA	

Note. All predictor variables are continuous. The outcome variable MATH_ SUCCESS is categorical.

Figure 3.3

Predictor Variables and Associated Outcome Variable for Retention

Predictor (independent) variable	Outcome (dependent) variable
SN_RET_INDX SuccessNavigator Retention Index Score	RETENTION_SPR_2017 Retention from fall 2016 to spring 2017
ACT_COMPOSITE ACT Composite Score	
HS_GPA	

Note. All predictor variables are continuous. The outcome variable RETENTION_ SPR_2017 is categorical.

Instrument

SuccessNavigator is an assessment developed by Educational Testing Service, or ETS, the nonprofit company that also produces the GRE and TOEFL exams. Markle, Olivera-Aguilar, Jackson, Noeth, and Robbins (2013) described SuccessNavigator as follows:

> The *SuccessNavigator*™ assessment is an online, 30-minute self-assessment of psychosocial and study skills designed for students entering postsecondary education. In addition to providing feedback in areas such as classroom and study behaviors, commitment to educational goals, management of academic stress, and connection to social resources, it is also designed to predict a range of early academic outcomes. (p. 1)

SuccessNavigator assessment items fall into fourteen subskill categories that are grouped within four broader general skills. The general skills scores are then configured into recommendations in an advisor report that provides, among other recommendations, an English placement index, a math placement index, and a retention index for each student.

The English and math placement indices are meant to be used by advisors to recommend whether a student should be bumped from their current English or math placement into a higher-level course. Students may view score reports to help inform the discussion with their advisors and so that students may make informed decisions around placement and support service options. If the placement indices predict a probability of success for a particular student, SuccessNavigator recommends to the student's advisor that the student enroll in an English or math course one level higher than the course into which the student placed based on academic performance on the ACCUPLACER exam. This is meant to address the issue of students being required to complete numerous developmental courses before reaching college level coursework. The Retention Success Index is designed to notify the advisor of the student's likelihood of being retained to the next semester. The purpose of this information is to assist advisors in recommending a set of academic supports and even appropriate courses based on the needs of each student. Table 3.4 demonstrates the organization of the subskills within each general skill.

Reliability and Validity

Educational researchers at ETS tested reliability for each of the ten subskills measured by SuccessNavigator through Cronbach's alpha. Nunnally (1978) suggested that standard reliability values for a low-stakes self-report assessment such as SuccessNavigator should exceed an alpha of .70. All scales exceeded the suggested .70, ranging from the lowest alpha score of .78 on the subskill Barriers to Success to .90 on Institutional Commitment.

Substantive validity was achieved by aligning SuccessNavigator's skill categories and assessment items to theory and to practice. The four general skills are based on theories about the relationship to success of personality, conscientiousness, emotional stability, academic self-efficacy, and the tendency to connect with others. SuccessNavigator's general skills and subskills (Figure 3.4) were designed to address the same areas of student needs that the student affairs or student service areas of colleges are designed to serve. Assessment developers examined programs and services and the literature in these topic areas. When ETS had developed a map of the general skills and subskills, they presented the maps to faculty, staff, and students from 50 colleges and universities who confirmed the relevance of the design (Markle, et.al. 2013).

Figure 3.4

General Skills and Subskills Measured by the SuccessNavigator Assessment (Markle, et al., 2013, Appendix)

General Skill	Subskill	Definition	Example Item
Academic Skills Tools and strategies for academic success	Organization	Strategies for organizing work and time	I write a daily to-do list. I use a calendar to plan my school day.
	Meeting Class Expectations	Doing what's expected to meet the requirements of courses including assignments and in-class behaviors	I am on time for class. I complete my assignments on time.
Commitment Active pursuit toward an academic goal	Commitment to College Goals	Perceived value and determination to succeed in and complete college	One of my life goals is to graduate college. The benefit of a college education outweighs the cost.
	Institutional Commitment	Attachment to and positive evaluations of the school	This is the right school for me. I'm proud to say I attend this school.
Self-Management Reactions to academic and daily stress	Sensitivity to Stress	Tendency to feel frustrated, discouraged or upset when under pressure or burdened by demands	I get stressed out easily when things don't go my way. I am easily frustrated.
	Academic Self-Efficacy	Belief in one's ability to perform and achieve in an academic setting	I'm confident that I will succeed in my courses this semester. I can do well on tests if I apply myself.
	Test Anxiety	General reactions to test-taking experiences, including negative thoughts and feelings (e.g., worry, dread)	When I take a test, I think about what happens if I don't do well. The night before a test, I feel troubled.
Social Support Connecting with people and student resources for success	Connectedness	A general sense of belonging and engagement	I feel connected to my peers. People understand me.
	Institutional Support	Attitudes about and tendency to seek help from established resources	If I don't understand something in class, I ask the instructor for help. I know how to find out what's expected of me in classes.
	Barriers to Success	Financial pressures, family responsibilities, conflicting work schedules and limited institutional knowledge	Family pressures make it hard for me to commit to school People support me going to college.

Strong structural validity of SuccessNavigator was ensured through extensive testing of the psychometric properties of the assessment items during summer and fall of 2012. The initial 125 items were administered to students from multiple institutions in various parts of the United States. The final sample consisted of 5,120 students who complete all of the 125 assessment items. Confirmatory factor analyses were used to judge the fit of the items within subskill categories. Items with standardized loadings great than 0.2 and communality values greater than 0.1 were kept, although a few that did not meet that criteria were retained as well. The Organization and the Barriers to Success subskills contain some assessment items that fall below the minimum loadings and communalities score (Markle, et.al., 2013).

Data Analysis

Binary logistic regression. The purpose of binary logistic regression is to determine the probability of individual cases being assigned to one of two groups represented by an outcome variable. Another explanation of the purpose is that binary logistic regression "specifies the probabilities of the particular outcomes (e.g., "pass" and "fail") for each subject or case involved" (Mertler & Vannatta, 2005, p. 313). The probability being predicted ranges from 0 to 1.

Conditions required for binary logistic regression. Conditions that must be present for binary logistic regression are related to the outcome variable and the number of cases included in the study. The first condition for the use of binary logistic regression is that the outcome variable is a single, dichotomous variable (Leech, Barrett, & Morgan, 2011). The three outcome variables used for this study are dichotomous variables. Predictor variables may be a combination of continuous and categorical. All predictor variables in this study were continuous. Next, the categories of the outcome variable must be mutually exclusive, meaning that each case must be classified in either category represented by the outcome variable, but not both categories (Leech, et. al., 2011). This condition was met for all six regressions. Finally, Leech, Barrett, & Morgan (2011) assert that a minimum of 20 cases per predictor with a minimum of 60 total cases must be present for binary logistic regression. The number of cases in each subset of the sample in this study surpassed this minimum requirement.

Analysis. Each of the three outcome variables was regressed onto the corresponding predictor variables, as well as every possible combination of corresponding predictor variables in separate regressions. Separate logistic regressions were conducted to determine which combinations of predictor variables (SuccessNavigator English Placement, Math Placement, and Retention Indices; Accuplacer Sentence Skills and Accuplacer Elementary Algebra; ACT English, math, and composite; and high school GPA) were the strongest predictors of success in English courses, math courses, and retention to the spring 2017 term.

Data Coding

To prepare the data for analysis, categorical outcome variables were coded as follows. The outcome variables WRTG_SUCCESS and MATH_SUCCESS, were coded 1 for participants who earned A, B, or C in their fall 2016 English course and 0 for participants who earned D or F. Participants who received grades of audit (AU), withdraw (W), or incomplete (I) were also coded 0 because they did not successfully complete their writing or math course during the fall 2016 term. Students at The College were required to earn a C or better in each English and math course in the developmental and introductory course sequence to progress to the next level course. In the rare case that a participant attempted two English or math courses during the fall 2016 semester, either because the participant completed a corequisite course model (enrollment in both the college-level course and a developmental course as a support workshop throughout the same term) or because they completed multiple short-term courses during fall 2016, the grade from only the highest level English or math course attempted was used in the analysis.

The categorical outcome variable, RETENTION_SPR_2017 was coded 1 for participants who returned to The College and attended classes in spring 2017 and 0 for participants who did not return for the spring 2017 semester.

Limitations of the Study

The overall study sample did not include all fall 2016 incoming freshmen. SuccessNavigator was administered by The College as part of a pilot program to examine the usefulness of a noncognitive assessment as part of the placement process. SuccessNavigator was not administered across the board to all incoming students. Although the number of cases for each regression met the threshold for conditions required for a valid regression study, the number of study participants was considerably less than the entire incoming freshman class for fall 2016.

Another limitation of this study is that not all student placement data was collected by The College to be used for placement or success prediction. This eliminated the possibility of using such additional data for this study. An example of data not available is high school transcript information such as English and mathematics courses taken and grades earned in those courses.

Additionally, the results of this study are not meant to be generalized to a larger student population or to other higher education institutions because of the limitation of different student populations. Freshman classes vary from institution to institution, especially for community colleges. Rural residential colleges, urban commuter colleges, regional universities and research institutions matriculate groups of students with differing demographics and life situations. While this study could be used to inform other higher education professionals who seek to improve their students' educational experiences, these results are not meant to be generalized. Each institution should determine, based on working with their own students, the best use of data to predict student success.

Summary

The purpose of this study was to evaluate the effectiveness of adding a noncognitive assessment score to a community college's current placement process for predicting student success in English and math courses and retention to the next semester. By incorporating success prediction into the placement process, community colleges may be able to identify students for whom additional academic supports could improve success and retention. Regressions including scores from a noncognitive assessment, SuccessNavigator, test scores from ACT and Accuplacer, and high school GPA were run to determine which available student data might most effectively predict success in English and math courses and retention from fall 2016 to spring 2017. Chapter four will detail the results of the study.

CHAPTER IV

RESULTS

The purpose of this study was to evaluate the effectiveness, based on student performance and retention, of using a noncognitive assessment score (SuccessNavigator) to predict student success in English and math courses and retention to the next semester. For this study, success was defined as an earned grade of C or higher in English and math courses. Retention was defined as enrollment in the semester following the first semester of attendance at The College, an open access community college.

A logistic regression study was conducted to determine the predictive value of a noncognitive assessment and other placement data currently available to The College for success in English and math courses and retention to the following semester. Data analyses were conducted using the following process based on the “Checklist for Conducting Binary Logistic Regression” (Mertler & Vannatta, 2005, p. 329).

1. Data with missing SuccessNavigator scores were removed from the dataset.
2. Remaining data were prepared for analysis.
3. Predictor variables were tested for model fit.
4. Outliers were identified and removed from the dataset.
5. Predictor variables were tested for multicollinearity.

6. Logistic regressions were run for each predictor variable and each possible combination of predictor variables.

Binary logistic regression analyses were employed to address each research question. The outcome, or dependent variable in each regression, was a binary categorical variable. Predictor, or independent variables in each regression, were continuous. After discussions of sample subsets, assumptions, and the model selection process, results of the analyses follow. Sections are organized by research question.

Sample subsets

From the overall sample, subsets of participants were included in the English and math analyses because not all students in the sample took English or math courses during the fall 2016 semester. Additionally, some students were only required to take either the English or the math placement tests, but not both, based on their ACT English or math subject area scores upon admission to The College. Subject area scores or 19 or above in English and 20 or above in math automatically placed students at the college level in those subjects, eliminating the need for additional testing. All study participants from the overall sample were included in the retention analysis for Research Questions 5 and 6. Demographic data are presented in each section for the particular subsets of participants represented.

Assumptions

Binary logistic regression does not require that assumptions regarding the distributions of predictor variables be met, so normal distribution, linear relationships, and equal variances of predictor variables were not examined.

Three assumptions must be addressed in binary logistic regression. First, no outliers may be present in the data. An examination of the data indicated several outliers in each subset determined by the outcome variable being examined. Outliers were removed prior to running the logistic regressions. The second assumption, absence of multicollinearity, was checked and met for each subset of the data. Third, predictor variables must be linearly related to the logit of the outcome variable. This assumption was checked and met for each data subset (Leech, et. al., 2011).

Model selection process

Comparisons among a number of regression models were examined for Research Questions 2, 4, and 6 to determine the model with the highest level of predictive value for student success in writing and math courses and retention. Three pieces of data output, overall model fit, classification table, and summary of model variables, were interpreted and compared to determine the best regression model (Mertler & Vannatta, 2005).

Research Question One

Research question one addressed writing course success prediction using the SuccessNavigator English Placement Index.

Research Questions 1 and its corresponding null hypothesis follow.

Does a noncognitive assessment, SuccessNavigator, predict student success in freshman writing courses?

H_0. A noncognitive assessment, SuccessNavigator, does not predict student success in freshman writing courses.

The subset of the original data sample included data for students who took entry level English courses (low- and mid-level developmental writing and freshman composition) and who completed the SuccessNavigator with a valid English Placement Index score. This data subset was comprised of 752 (n = 752) first time in college students who entered The College in fall 2016. More than half of the sample subset, 58.6% (n = 441), were female. Males made up 41.4% (n = 311) of participants. The ages of participants ranged from 18 to 54 years. First-time students aged 18 and 19 made up 84.7% (n = 637) of the sample subset. Only 15.3% (n = 115) of participants from the sample subset were older than 19 years. Table 4.11 summarizes the reported race of students included in the sample subset.

Table 4.11

Race of Students Who Completed English Courses

Race	Number	Percentage
American Indian or Alaska Native	n=52	6.9
Asian	n=21	2.8
Black or African American	n=51	6.8
Hispanic of any race	n=84	11.2
More than one race reported	n=87	11.6
Native Hawaiian or Other Pacific Islander	n=1	0.1
Non-resident alien	n=22	2.9
Not reported	n=32	4.3
White	n=402	53.5

Data Analysis

Initial data screening led to the elimination of two outliers with large squared Mahalanobis distance values. Simple logistic regression was performed on the outcome variable writing course success (WRTG_SUCCESS) using SuccessNavigator English Placement Index) SN_ENGL_PLCMT_INDX as a predictor variable to determine whether SuccessNavigator scores predicted writing course success. The score range for SuccessNavigator English Placement Index scores ran from 66.97 to 132.21 with a mean score of 104.43 and included 752 student scores (*n=752)*. Descriptive statistics for the predictor variable are displayed in Table 4.12.

Table 4.12

Descriptive Statistics for Predictor Variable

Predictor Variable	*n*	*M*	*SD*	*SE*	Min	Max
SN_ENGL_PLCMT_INDX	752	104.43	11.56	.42	66.97	132.21

A test of the regression model against a constant-only model was statistically significant, $\chi^2 = 51.85$, $df = 1$, $p < .001$ (Table 4.13).

Table 4.13

Regression Model Fit

Model	-2 Log Likelihood	Chi-Square	*df*	*p*
Final	864.158	51.85	1	.000

The regression model classification table, displayed in Table 4.14, indicates that the regression model correctly classified 70.3% of the cases. For comparison, constant model case classification information is presented in Table 4.15. The constant model correctly classified 70.2% of cases by predicting that all students would be successful in their writing courses. The regression model correctly predicted that 29 students would not be successful in writing courses. While only 12.9% of students predicted to be unsuccessful were observed to be unsuccessful, the constant only model did not correctly classify any of the students who would be unsuccessful. While overall accuracy of predicted versus observed cases is important, the purpose of this study was to identify the best method of predicting success so that students who are predicted to be unsuccessful can begin their college studies with appropriate academic support, giving them the best chance for success.

Table 4.14

Regression Model Classification

	Predicted		
Observed	Unsuccessful	Successful Completion	Percent Correct
Unsuccessful	29	195	12.9%
Successful Completion	28	500	94.7%
Totals and Overall Percentage	57	695	70.3%

Table 4.15

Constant Model Classification

	Predicted		
Observed	Unsuccessful	Successful Completion	Percent Correct
Unsuccessful	0	224	0%
Successful Completion	0	528	100%
Totals and Overall Percentage	0	752	70.2%

The summary of the model variable is presented in Table 4.16. The odds ratio (e^B = 1.052, p < .001) demonstrated that students were 1.052 times more likely to be successful in writing courses for every one-point increase in SuccessNavigator scores, a statistically significant increase.

Table 4.16

Summary of Model Variable

Variable	*β*	*SE*	*Wald*	*Odds ratio*	*p*
SN_ENGL_PLCMT_INDX	.051	.007	48.156	1.052	.000

Data analysis revealed a questionable but statistically reliable model fit with an extremely high -2 Log Likelihood = 864.158. The regression model was significantly different from the constant-only model, $\chi^2(1) = 51.850$, $p < .001$ and correctly classified 70.3% of cases. Although the model fit was questionable, the regression model did affirmatively answer Research Question 1. SuccessNavigator English Placement Index scores did predict student success in freshman writing courses. The null hypothesis was rejected.

Research Question Two

Research Question 2 asked what combination of student placement data, available at the time of students' matriculation to The College, was most effective for predicting whether students were successful in their freshman writing courses. The data analysis for Research Question 1 used only SuccessNavigator English Placement Index as the predictor variable. To address Research Question 2, regressions were run using each of the four writing course success predictor variables individually, as well as in every possible combination. Because SuccessNavigator English Placement Index is one of the four predictor variables, it was also included in the analysis for Research Question 2.

Data Analysis

Results of each regression were compared to determine the most effective use of available placement data for predicting writing course success. Logistic regressions were performed using the following predictor variables: SuccessNavigator English Placement Index (SN_ENGL_ PLCMT_INDX), high school grade point average (HS_GPA), ACT English sub-score (ACT_ENGL) and Accuplacer Sentence Skills (ACCUPLACER_SENT_SKILLS).

Research Question 2 and its corresponding null hypothesis follow.

What combination of course placement information including Success-Navigator, high school GPA, ACT, and Accuplacer best predicts student success in freshman writing courses?

H_0. No combination of course placement information including Success- Navigator, high school GPA, ACT, and Accuplacer predicts student success in freshman writing courses.

Cases that did not include scores for the predictor variable being analyzed were eliminated from the initial dataset before each regression was conducted. Outliers with large squared Mahalanobis distance values were also eliminated from each data subset before regressions were conducted. Fifteen logistic regressions were performed on writing course success (WRTG_SUCCESS) as the outcome variable using each predictor variable in separate regressions and in regressions using every possible combination of predictor variables. Results of the regression using the predictor variable SuccessNavigator English Placement Index were reported in the previous section and are repeated in this section so that comparisons can be made among the regression models to determine the model that best predicts writing course success.

The first four regressions that were conducted were the four simple logistic regressions on WRTG_SUCCESS using each of the predictor variables in separate regressions. Descriptive statistics for the first four regressions, including SN_ENGL_PLCMT_INDX, are presented in Table 4.21.

Table 4.21

Descriptive Statistics for Regressions Using Each Predictor Variable

Predictor Variable	*n*	*M*	*SD*	*SE*	Min	Max
SN_ENGL_PLCMT_INDX	752	104.43	11.56	.42	66.97	132.21
HS_GPA	698	3.06	.54	.02	1.37	4.00
ACT_ENGL	582	19.62	4.74	.20	9	32
ACCUP_SENT_SKILLS	337	79.59	17.57	.96	29	120

Subsequent regressions using each combination of predictor variables were conducted. The model fit statistics for all 15 regression models are displayed in Table 4.22.

Model Fit

Table 4.22

Model Fit Research Question Two

Model	-2 Log Likelihood	Chi-Square	*df*	*p*
SN_ENGL_PLCMT_INDX	864.158	51.85	1	.000
HS_GPA	765.737	74.113	1	.000
ACT_ENGL	683.682	0.850	1	.357*
ACCUP_SENT_SKILLS	418.685	1.005	1	.316*
SN_ENGL_PLCMT_INDX & HS_GPA	749.700	80.649	2	.000
SN_ENGL_PLCMT_INDX & ACT_ENGL	637.606	46.282	2	.000
SN_ENGL_PLCMT_INDX & ACCUP_SENT_SKILLS	394.525	24.408	2	.000
HS_GPA & ACT_ENGL	583.665	83.958	2	.000
HS_GPA & ACCUP_SENT_SKILLS	340.653	22.412	2	.000
ACT_ENGL & ACCUP_SENT_SKILLS	228.552	1.444	2	.486*
SN_ENGL_PLCMT_INDX, HS_GPA & ACT_ENGL	579.479	82.863	3	.000
SN_ENGL_PLCMT_INDX, HS_GPA & ACCUP_SENT_SKILLS	328.673	31.307	3	.000
SN_ENGL_PLCMT_INDX, ACT_ENGL & ACCUP_SENT_SKILLS	204.389	25.608	3	.000
HS_GPA, ACT_ENGL & ACCUP_SENT_SKILLS	197.501	24.875	3	.000
SN_ENGL_PLCMT_INDX, HS_GPA, ACT_ENGL & ACCUP_SENT_SKILLS	187.542	32.239	4	.000

Note. * indicates non-significant model fit at $p < .05$.

Model Selection Process

The first step in determining the best prediction model for writing course success was elimination of models based on non-significant model fit. Three models were initially eliminated from consideration as the best predictor model because they were not significantly different than their constant models according to the *p* values displayed in Table 4.22. The three models that were initially eliminated through this process were the models using singular predictor variables ACT_ENGL ($\chi^2(1) = 0.850$, $p = .357$) and ACCUP_SENT_ SKILLS ($\chi^2(1) = 1.005$, $p = .316$), as well as the model that included both predictor variables ACT_ENGL and ACCUP_SENT_SKILLS ($\chi^2(2) = 1.444$, $p = .486$). After initially eliminating three of the regression models from consideration for best prediction model, remaining regressions were examined and eliminated based on classification tables and summary of model variables (Mertler & Vanatta, 2005).

The next step in determining the best model for success prediction was to compare classification tables of the remaining regression models to those of their constant models. The constant model classification table in each regression predicts that all students will be successful. If a regression model classifies fewer students correctly than its corresponding constant model, the default constant model is the better predictor of success, eliminating the need for the regression model. After examining classification tables for the remaining regression models, the following three models were eliminated from consideration; the model using the single predictor variable, HS_GPA (regression model correctly classified 69.8% of cases, constant model correctly classified 71.1% of cases); the model using both SN_ENGL_PLCMT_INDX and HS_GPA (regression model correctly classified 70.4% of cases, constant model correctly classified 71.2% of cases); and the model using HS_GPA and ACCUP_SENT_SKILLS (regression model correctly classified 67.2% of cases, constant model correctly classified 68.9% of cases). The regressions for the three models accurately classified fewer cases than the constant models, so the models were eliminated from consideration for best predictor model.

Finally, the summaries of model variables for the remaining models were examined. Models were removed from consideration if the Wald statistic was non-significant for one or more predictor variables in the model. The Wald is a measure of significance for the unstandardized regression coefficient, or β, and "represents the significance of each variable in its ability to contribute to the model" (Mertler & Vanatta, 2005, p. 320). A significance level of $p < 0.05$ was applied in each case. Table 4.23 displays the models that were eliminated from consideration based on predictor variables with nonsignificant Wald statistics.

Table 4.23

Summary of Model Variables with Non-Significant Wald

Variable	*β*	*SE*	*Wald*	*Odds ratio*	*p*
SN_ENGL_PLCMT_INDX	.058	.009	41.549	1.060	.000
& ACT_ENGL	-.013	.021	.416	.987	.519*
SN_ENGL_PLCMT_INDX	.051	.011	21.736	1.052	.000
& ACCUP_SENT_SKILLS	-.009	.007	1.759	.991	.185*
SN_ENGL_PLCMT_INDX	.019	.011	2.827	1.019	.093*
& HS_GPA	1.694	.283	35.932	5.443	.000
& ACT_ENGL	-.058	.023	6.165	.943	.013
SN_ENGL_PLCMT_INDX,	.077	.017	20.493	1.081	.000
& ACT_ENGL	-.075	.073	1.054	.928	.304*
& ACCUP_SENT_SKILLS	-.010	.012	.619	.990	.431*
HS_GPA,	1.820	.416	19.151	6.171	.000
& ACT_ENGL	-.107	.075	2.040	.899	.153*
& ACCUP_SENT_SKILLS	-.012	.013	.912	.988	.340*
SN_ENGL_PLCMT_INDX,	.065	.022	8.406	1.067	.004
& HS_GPA	.885	.505	3.071	2.423	.080*
& ACT_ENGL	-.091	.076	1.435	.913	.231*
& ACCUP_SENT_SKILLS	-.013	.013	1.059	.987	.303*

Note. * indicates non-significant Wald statistic at $p < .05$

After eliminating the six models displayed in Table 4.23, three regression models remained. Comparisons of the remaining three models were conducted based on overall model fit, classification tables, and the summary of model variables. Descriptive statistics for the remaining three models are displayed in Table 4.24.

The numbers of cases included in each regression were reduced as additional predictor variables were included in the regression models. Model 1, using only SN_ENGL_PLCMT_INDX as the predictor variable, included n = 752 cases with scores ranging from 66.97 to 132.21 with a mean score of 104.43. Model 2 included two predictor variables, HS_GPA and ACT_ENGL, and included n = 574 cases with HS_GPA scores ranging from 1.48 to 4.00 (mean 3.15) and ACT_ENGL sub-scores ranging from 9 to 32 (mean 19.62). Model 3 included three predictor variables, SN_ENGL_PLCMT_INDX, HS_GPA and ACCUP_SENT_SKILLS and used n = 291 cases. In the Model 3 regression, scores for the predictor SN_ENGL_PLCMT_INDX ranged from 71.43 to 132.21 with a mean score of 101.27. HS_GPA scores ranged from 1.47 to 3.96 with a mean score of 2.86. ACCUP_SENT_SKILLS scores ranged from 29 to 120 with a mean score of 78.96.

Table 4.24

Descriptive Statistics for Remaining Models

Model/Predictor Variable	*n*	*M*	*SD*	*SE*	Min	Max
1/SN_ENGL_PLCMT_INDX	752	104.43	11.56	.42	66.97	132.21
2/HS_GPA	574	3.15	.50	.02	1.48	4.00
& ACT_ENGL	574	19.62	4.72	.20	9	32
3/SN_ENGL_PLCMT_INDX	291	101.27	11.62	.68	71.43	132.21
& HS_GPA	291	2.86	.53	.03	1.47	3.96
& ACCUP_SENT_SKILLS	291	78.96	17.51	1.03	29	120

All three of the remaining models had high -2 Log Likelihood statistics, but all indicated significant model fit at $p < .001$, as displayed in Table 4.25.

Table 4.25

Model Fit for Remaining Models

Model	-2 Log Likelihood	Chi-Square	*df*	*p*
1/SN_ENGL_PLCMT_INDX	864.158	51.850	1	.000
2/HS_GPA & ACT_ENGL	583.665	83.958	2	.000
3/SN_ENGL_PLCMT_INDX HS_GPA & ACCUP_SENT_SKILLS	328.673	31.307	3	.000

The Summary of Model Variables, displayed in Table 4.26, indicates that all predictor variables for each model are statistically significant contributors to the model at $p < .05$. A separate examination of each remaining model follows.

Table 4.26

Summary of Model Variables for Each Remaining Model

Variable	*β*	*SE*	*Wald*	*Odds ratio*	*p*
1/SN_ENGL_PLCMT_INDX	.051	.007	48.156	1.052	.000
2/HS_GPA	1.980	.238	69.237	7.244	.000
2/ACT_ENGL	-.059	.023	6.288	.943	.012
3/SN_ENGL_PLCMT_INDX	.042	.013	9.927	1.043	.002
3/HS_GPA	.664	.303	4.808	1.943	.028
3/ACCUP_SENT_SKILLS	-.017	.008	4.765	.983	.029

Model 1, SuccessNavigator English Placement Index Only

When considering the number of cases included in each analysis and model fit from among the three remaining models, Model 1 (SN_ENGL_PLCMT_INDX only) included the highest number of cases (n = 752) and revealed a questionable model fit with an extremely high -2 Log Likelihood = 864.158. The regression model was significantly different from the constant-only model at $\chi^2(1) = 51.850$, $p < .001$. The classification table, Table 4.27, indicates that regression Model 1 correctly classified 70.3% of cases, which outperformed the constant model by .1%. Because the focus of this research study was on accurate success prediction to determine which students should receive additional academic support, the breakdown of numbers of students accurately predicted to be unsuccessful by each regression model is notable. Of the 224 students who were observed to be unsuccessful (earned a grade lower than C) in their writing courses, Model 1 accurately predicted that 29, or 12.9%, would be unsuccessful. The odds ratio (e^B = 1.052, p < .001) demonstrated a statistically significant increase in the likelihood of success in writing courses when the SuccessNavigator score increased by 1.

Table 4.27

Regression Model Classification Table for Model 1, SN_ENGL_PLCMT_INDX

	Predicted		
Observed	Unsuccessful	Successful	Percent Correct
Unsuccessful	29	195	12.9%
Successful	28	500	94.7%
Totals and Overall Percentage	57	695	70.3%*

Note. *Constant model percent correct = 70.2%

Model 2, High School GPA and ACT English

The number of cases included in the analysis for Model 2 was n = 574. Analysis revealed a questionable model fit with a high -2 Log Likelihood = 583.665. The regression model was significantly different from the constant-only model, $\chi^2(2)$ = 83.958, p < .001. The classification table, Table 4.28 indicated that Model 2 correctly classified 73.9% of cases, outperforming the constant model by .7%. Of the 154 students who were observed to be unsuccessful (earned a grade lower than C) in their writing courses, Model 2 accurately predicted that 37, or 24.0%, would be unsuccessful. The odds ratio for the predictor variable HS_GPA (e^B = 7.244, p < .001) in Model 2 indicated a strong success predictor, increasing the likelihood of success 7.244 times for each one point increase in HS_GPA. in writing courses when high school GPA increased by one point. The odds ratio for ACT English revealed a small, negative change in the likelihood of success in writing courses (e^B = .943, p < .05) for every one point increase in ACT English sub-scores. These data taken together indicate a fairly strong model for success prediction in writing courses.

Table 4.28

Regression Model Classification Table for Model 2, HS_GPA & ACT_ENGL

	Predicted		
Observed	Unsuccessful	Successful	Percent Correct
Unsuccessful	37	117	24.0%
Successful	33	387	92.1%
Totals and Overall Percentage	70	504	73.9%*

Note. *Constant model percent correct = 73.2%

Model 3, SuccessNavigator English Placement Index, High School GPA and Accuplacer Sentence Skills

The fewest number of cases were included in the analysis for Model 3, n = 291. Analysis revealed a questionable model fit with a high -2 Log Likelihood = 328.673. The regression model was significantly different from the constant-only model, $\chi^2(3)$ = 31.307, p < .001. Model 3 correctly classified 69.8% of cases, outperforming the constant model by .7% as displayed in Table 4.29. The odds ratio for SN_ENGL_PLCMT_INDX GPA (e^B = 1.043, p < .01) indicated that using Model 3, a one point increase in SN_ENGL_PLCMT_INDX score increased likelihood for success by 1.043. The odds ratio for HS_GPA (e^B = 1.943, p < .05) revealed a substantial change in the likelihood of success in writing courses when High School GPA increased by 1. The odds ratio for Accuplacer Sentence Skills revealed a slight negative change in the likelihood of success in writing courses (e^B = .983, p < .05) when the Accuplacer Sentence Skills score increased by 1.

Table 4.29

Regression Model Classification Table for Model 3, SN_ENGL_PLCMT_INDX, HS_GPA & ACCUP_SENT_SKILLS

	Predicted		
Observed	Unsuccessful	Successful	Percent Correct
Unsuccessful	19	71	21.1%
Successful	17	184	91.5%
Totals and Overall Percentage	69	452	69.8%*

Note. *Constant model percent correct = 69.1%

A thorough examination of the final three regression models determined that Model 2, HS_GPA and ACT_ENGL, was the most accurate prediction model. The deciding factors among the final three models were the odds ratios of the predictor variables and their significance levels as well as the accuracy of the classification table predictions. Model 2 was determined to be the best model for writing course success prediction because HS_GPA (e^B = 7.244, $p < .001$) and ACT_ENGL (e^B = .943, $p < .05$) best met the standard of highest odds ratios and lowest significance levels among the three models. Additionally, classification tables for each model indicated that Model 2 most accurately predicted success in writing courses (73.9% correct overall), especially in predicting which students would be unsuccessful (24.0% correct). The answer to Research Question 2 that addressed the combination of course placement information that best predicts student success in freshman writing courses, were the predictor variables high school GPA and ACT English sub-score. The null hypothesis was rejected.

Research Question Three

Research question three addressed math course success prediction using the SuccessNavigator Math Placement Index.

Research Question 3 and its corresponding null hypothesis follow.

Does a noncognitive assessment, SuccessNavigator, predict student success in freshman mathematics courses?

H_0. A noncognitive assessment, SuccessNavigator, does not predict student success in freshman mathematics courses.

The subset of the original data sample included data for students who took entry level math courses (low- and mid-level developmental math or any college level math course) and who completed the SuccessNavigator with a valid Math Placement Index score. This data subset is comprised of 844 (n = 844) first time in college students who entered The College in fall 2016. More than half of the sample subset, 58.1% (n = 490), was female. Males made up 41.9% (n = 354) of participants. The ages of participants ranged from 18 to 55 years. First-time students aged 18 and 19 made up 80.7% (n = 681) of the sample subset. Only 19.3% (n = 163) of participants from the sample subset were older than 19 years. Table 4.31 summarizes the reported race of students included in the sample subset.

Table 4.31

Race of Students Who Completed Math Courses

Race	*n*	Percentage
American Indian or Alaska Native	52	6.2
Asian	25	3.0
Black or African American	57	6.8
Hispanic of any race	76	9.0
More than one race reported	113	13.4
Native Hawaiian or Other Pacific Islander	1	0.1
Non-resident alien	21	2.5
Not reported	41	4.9
White	458	54.3

Data Analysis

Initial data screening led to the elimination of four outliers with large squared Mahalanobis distance values. Simple logistic regression was performed on math course success (MATH_SUCCESS) as the outcome variable and SuccessNavigator Math Placement Index (SN_MATH_PLCMT_INDX) as predictor variable to determine whether SuccessNavigator scores predicted math course success. The score range for SuccessNavigator Math Placement Index scores ran from 58.23 to 132.21 with a mean score of 103.90 and included 844 student scores (n = 844). Descriptive statistics for the predictor variable are displayed in Table 4.32.

Table 4.32

Descriptive Statistics for Predictor Variable

Predictor Variable	*n*	*M*	*SD*	*SE*	Min	Max
SN_MATH_PLCMT_INDX	844	103.90	11.74	.40	58.23	132.21

A test of the regression model against a constant-only model was statistically significant, χ^2 = 61.20, *df* = 1, *p* < .001 as displayed in Table 4.33.

Table 4.33

Regression Model Fit

Model	-2 Log Likelihood	Chi-Square	*df*	*p*
Final	1014.162	61.20	1	.000

The regression model classification table, displayed in Table 4.34, indicated that the regression model correctly classified 66.6% of cases. For comparison, constant model case classification information is presented in Table 4.35. The constant model also correctly classified 66.6% of cases by predicting that all students would be successful in their math courses. The regression model correctly predicted that 47 students would be unsuccessful in math courses. While only 16.7% of students predicted to be unsuccessful were observed to be unsuccessful, the constant only model did not correctly classify any of the students who would be unsuccessful. While overall accuracy of predicted versus observed cases is important, the purpose of this study was to identify the best method of predicting success so that students who are predicted to be unsuccessful can begin their college studies with appropriate academic support, giving them the best chance for success.

Table 4.34

Regression Model Classification

	Predicted		
Observed	Unsuccessful	Successful Completion	Percent Correct
Unsuccessful	47	235	16.7%
Successful Completion	47	515	91.6%
Totals and Overall Percentage	94	750	66.6%

Table 4.35

Constant Model Classification

	Predicted		
Observed	Unsuccessful	Successful Completion	Percent Correct
Unsuccessful	0	282	0%
Successful Completion	0	562	100%
Totals and Overall Percentage	0	844	66.6%

The summary of the model variable is presented in Table 4.36. The odds ratio (e^B = 1.051, p < .001) demonstrated that students were 1.051 times more likely to be successful in math courses for each point increase in SuccessNavigator scores, a statistically significant increase.

Table 4.36

Summary of Model Variable

Variable	*β*	*SE*	*Wald*	*Odds ratio*	*p*
SN_MATH_PLCMT_INDX	.050	.007	55.631	1.051	.000

Data analysis revealed a questionable model fit with an extremely high -2 Log Likelihood = 1014.162. The regression model was significantly different from the constant-only model, $\chi^2(1) = 61.2$, $p < .001$ and correctly classified 66.6% of cases. Although the model fit was questionable, the regression model did affirmatively answer Research Question 3. SuccessNavigator Math Placement Index did predict student success in freshman math courses. The null hypothesis was rejected.

Research Question Four

Research question 4 asked what combination of student placement data, available at the time of students' matriculation to The College, was most effective for predicting whether students were successful in their freshman math courses. The data analysis for Research Question 3 used only SuccessNavigator Math Placement Index as the predictor variable. To address Research Question 4, regressions were run using each of the four math course success predictor variables individually as well as in every possible combination. Because SuccessNavigator Math Placement Index was one of the four predictor variables, it was also included in the analysis for Research Question 4.

Data Analysis

Results of each regression were compared to determine the most effective use of available placement data for predicting math course success. Logistic regressions were performed using the following predictor variables: SuccessNavigator Math Placement Index (SN_MATH_ PLCMT_INDX), high school grade point average (HS_GPA), ACT Math sub-score (ACT_MATH) and Accuplacer Elementary Algebra (ACCUPLACER_ELEM_ALG).

Research question four and its corresponding null hypothesis follow.

What combination of course placement information including Success-Navigator, high school GPA, ACT, and Accuplacer best predicts student success in freshman mathematics courses?

H_0. No combination of course placement information including Success- Navigator, high school GPA, ACT, and Accuplacer predicts student success in freshman math courses.

Cases that did not include scores for the predictor variable being analyzed were eliminated from the initial dataset before each regression was conducted. Outliers with large squared Mahalanobis distance values were also eliminated from each data subset before regressions were conducted. Fifteen logistic regressions were performed on math course success (MATH_SUCCESS) as the outcome variable using each predictor variable in a separate regression and in regressions using every possible combination of predictor variables. Results of the regression using the predictor variable SuccessNavigator Math Placement Index were reported in the previous section and are repeated in this section so that comparisons can be made among the regression models to determine the model that best predicts math course success.

The first four regressions that were conducted were the four simple logistic regressions on MATH_SUCCESS using each of the predictor variables in separate regressions. Descriptive statistics for the first four regressions, including SN_MATH_PLCMT_INDX, are presented in Table 4.41.

Table 4.41

Descriptive Statistics for Regressions Using Each Predictor Variable

Predictor Variable	*n*	*M*	*SD*	*SE*	Min	Max
SN_MATH_PLCMT_INDX	844	103.90	11.74	.40	58.23	132.21
HS_GPA	768	3.05	.54	.02	1.25	4.00
ACT_MATH	620	19.11	3.70	.15	11	30
ACCUP_ELEM_ALG	507	52.63	21.35	.95	21	120

Subsequent regressions using each combination of predictor variables were conducted. The model fit statistics are displayed in Table 4.42.

Model Fit

Table 4.42
Model Fit Research Question 4

Model	-2 Log Likelihood	Chi-Square	*df*	*p*
SN_MATH_PLCMT_INDX	1014.162	61.195	1	.000
HS_GPA	878.866	88.827	1	.000
ACT_MATH	764.006	1.747	1	.186*
ACCUP_ELEM_ALG	642.781	4.021	1	.045
SN_MATH_PLCMT_INDX & HS_GPA	854.943	102.072	2	.000
SN_MATH_PLCMT_INDX & ACT_MATH	708.453	58.037	2	.000
SN_MATH_PLCMT_INDX & ACCUP_ELEM_ALG	623.499	21.666	2	.000
HS_GPA & ACT_MATH	645.505	100.718	2	.000
HS_GPA & ACCUP_ELEM_ALG	529.452	29.936	2	.000
ACT_MATH & ACCUP_ELEM_ALG	383.211	1.036	2	.596*
SN_MATH_PLCMT_INDX, HS_GPA & ACT_MATH	643.490	100.335	3	.000
SN_MATH_PLCMT_INDX, HS_GPA & ACCUP_ELEM_ALG	514.419	38.755	3	.000
SN_MATH_PLCMT_INDX, ACT_MATH & ACCUP_ELEM_ALG	368.552	15.695	3	.001
HS_GPA, ACT_MATH & ACCUP_ELEM_ALG	339.152	33.331	3	.000
SN_MATH_PLCMT_INDX, HS_GPA, ACT_MATH & ACCUP_ELEM_ALG	334.679	37.097	4	.000

Note. * indicates non-significant model fit at $p < .05$

Model Selection Process

The first step in determining the best prediction model for math course success was elimination of models based on non-significant model fit. Two models were initially eliminated from consideration as the best predictor model because they were not significantly different than their constant models according to the p values displayed in Table 4.42. The two models that were initially eliminated through this process were the models using the singular predictor variables ACT_MATH ($\chi^2(1) = 1.747$, $p = .186$) and the model that included both predictor variables ACT_MATH and ACCUP_ELEM_ALG ($\chi^2(2) = 1.036$, $p = .596$). This parallels two of the three models that were initially eliminated for success in writing course prediction, ACT_ENGL and ACT_ENGL & ACCUP_SENT_SKILLS. After initially eliminating two of the regression models from consideration for best prediction model, remaining regressions were examined and eliminated based on classification tables and summary of model variables (Mertler & Vanatta, 2005).

The next step in determining the best model for success prediction was to evaluate the classification tables of the remaining regression models versus their constant models. The constant model classification table in each regression predicts that all students will be successful. If a regression model classifies fewer students correctly than its corresponding constant model, the default constant model is the better predictor of success, eliminating the need for the regression model. After examining classification tables for the remaining regression models, the following three models were eliminated from consideration, SN_MATH_PLCMT_INDX (Regression Model = 66.6%; Constant Model = 66.6%), ACCUP_SENT_SKILLS (Regression Model = 66.5%; Constant Model

= 66.5%) and the model using both HS_GPA and ACCUP_ELEM_ALG (Regression Model = 67.2%; Constant Model = 67.2%). The regressions for all three models accurately classified the same number of cases as the constant models.

Finally, the summaries of model variables for the remaining models were examined. Models were removed from consideration if the Wald statistic was non-significant for one or more predictor variables in the model. The Wald is a measure of significance for the unstandardized regression coefficient, or β, and "represents the significance of each variable in its ability to contribute to the model" (Mertler & Vanatta, 2005, p. 320). Because the Wald statistic is conservative, a liberal significance level ($p < 0.1$) was applied in each case. Table 4.43 (page 71) displays the models that were eliminated from consideration based on predictor variables with nonsignificant Wald statistics.

Table 4.43

Summary of Model Variables with Non-Significant Wald

Variable	*β*	*SE*	*Wald*	*Odds ratio*	*p*
SN_MATH_PLCMT_INDX	.060	.009	49.422	1.062	.000
& ACT_MATH	.002	.025	.009	1.002	.924*
SN_MATH_PLCMT_INDX	.003	.008	17.214	1.034	.000
& ACCUP_ELEM_ALG	.007	.005	2.031	1.007	.154*
SN_MATH_PLCMT_INDX,	.014	.011	1.712	1.014	.191*
& HS_GPA	1.871	.285	43.229	6.495	.000
& ACT_MATH	-.075	.028	7.010	.928	.008
SN_MATH_PLCMT_INDX,	.009	.010	.739	1.009	.390*
& HS_GPA	1.236	.272	20.701	3.440	.000
& ACCUP_ELEM_ALG	-.006	.005	1.119	.994	.290*
SN_MATH_PLCMT_INDX,	.042	.011	13.966	1.043	.000
& ACT_MATH	-.079	.098	.657	.924	.418*
& ACCUP_ELEM_ALG	.004	.007	.345	1.004	.557*
HS_GPA	1.706	.320	28.418	5.508	.000
& ACT_MATH	-.155	.104	2.222	.857	.136*
& ACCUP_ELEM_ALG	-.002	.008	.058	.998	.809*
SN_MATH_PLCMT_INDX,	.009	.014	.443	1.009	.506*
& HS_GPA	1.712	.387	19.545	5.541	.000
& ACT_MATH	-.170	.105	2.635	.844	.105*
& ACCUP_ELEM_ALG	-.003	.008	.169	.997	.681*

Note. * indicates non-significant Wald statistic at $p < .1$

After eliminating the seven models displayed in Table 4.43, three regression models remained. Comparisons of the remaining three models were conducted based on overall model fit, classification tables, and the summary of model variables. Descriptive statistics for the remaining three models are displayed in Table 4.44.

The numbers of cases included in each regression differed based on how many and which predictor variables were used in the regression. Model 1, using only HS_GPA as the predictor variable, included $n = 768$ cases with scores ranging from 1.25 to 4.00 with a mean score of 3.049. Model 2 included two predictor variables, SN_MATH_PLCMT_INDX and HS_GPA and used $n = 760$ cases. SN_MATH_PLCMT_INDX scores ranged from 61.76 to 130.59 with a mean score of 102.49 and HS_GPA scores ranged from 1.47 to 4.00 with a mean score of 3.06. Model 3 also included two predictor variables, HS_GPA and ACT_MATH and used $n = 609$ cases. In the Model 3 regression, scores for the predictor HS_GPA ranged from 1.59 to 4.00 with a mean score of 3.14. ACT_MATH scores ranged from 11 to 32 with a mean score of 19.17.

Table 4.44

Descriptive Statistics for Remaining Models

Model/Predictor Variable	*N*	*M*	*SD*	*SE*	Min	Max
1/HS_GPA	768	3.049	.54	.02	1.25	4.00
2/SN_MATH_PLCMT_INDX	760	102.49	11.93	.43	61.76	130.59
& HS_GPA	760	3.06	.52	.02	1.47	4.00
3/HS_GPA	609	3.14	.50	.02	1.59	4.00
& ACT_MATH	609	19.17	3.75	.15	11	32

All three of the remaining models had high -2 Log Likelihood statistics, but all indicated significant model fit at $p < .001$ as displayed in Table 4.45.

Table 4.45

Model Fit for Remaining Models

Model	-2 Log Likelihood	Chi-Square	*df*	*p*
1/HS_GPA	878.866	88.827	1	.000
2/SN_MATH_PLCMT_INDX & HS_GPA	854.943	102.072	2	.000
3/HS_GPA & ACT_MATH	645.505	100.718	2	.000

The Summary of Model Variables, displayed in Table 4.46, indicates that all predictor variables for each model were statistically significant contributors to the model at $p < .05$. A separate examination of each remaining model follows.

Table 4.46

Summary of Model Variables for Each Remaining Model

Variable	*β*	*SE*	*Wald*	*Odds ratio*	*p*
1/HS_GPA	1.430	.163	76.870	4.179	.000
2/ SN_MATH_PLCMT_INDX	.018	.009	4.469	1.018	.035
& HS_GPA	1.332	.203	42.852	3.787	.000
3/HS_GPA	2.097	.233	80.870	8.139	.000
3/ACT_MATH	-.079	.028	7.901	.924	.005

Model 1, SuccessNavigator Math Placement Index Only

At this point, a view of various statistics from the data output was most helpful in determining the best model for writing course success prediction. The three final models had a comparable number of cases included in each analysis. Model 1 (High School GPA only) included 768 cases ($n = 768$), but also revealed a questionable model fit with an extremely high -2 Log Likelihood = 878.866. The regression model was significantly different from the constant-only model, $\chi^2(1) = 88.827$, $p < .001$. The classification table, Table 4.47, indicates that regression Model 1 correctly classified 69.8% of cases, outperforming the constant model by 2.2%. The percentage of students who were both predicted by the model and observed to be unsuccessful was 26.1%. The odds ratio (e^B = 4.179, $p < .001$) demonstrated a statistically significant increase in the likelihood of success in math courses when high school GPA increased by 1 point.

Table 4.47

Regression Model Classification Table for Model 1, HS_GPA

	Predicted		
Observed	Unsuccessful	Successful	Percent Correct
Unsuccessful	65	184	26.1%
Successful	48	471	90.8%
Totals and Overall Percentage	113	655	69.8%*

Note. *Constant model percent correct = 67.6%

Model 2, SuccessNavigator Math Placement Index and High School GPA

The number of cases included in analysis for Model 2 was $n = 760$. Analysis revealed a questionable model fit with a high -2 Log Likelihood = 854.943. The regression model was significantly different from the constant-only model, $\chi^2(2)$ = 102.072, $p < .001$. The classification table, Table 4.48 indicated that Model 2 correctly classified 71.1% of cases, outperforming the constant model by 3.5%. The percentage of students who were both predicted by the model and observed to be unsuccessful was 30.5%. The odds ratio for the predictor variable SN_MATH_PLCMT_INDX (e^B =

1.018, $p < .05$) revealed a slight but significant change in the likelihood of success in math courses when SuccessNavigator Math Placement Index scores increased by 1. The odds ratio for the predictor variable HS_GPA revealed that students were 3.787 times more likely to be successful in their math course ($e^B = 3.787$, $p < .001$) for each one point increase in high school GPA.

Table 4.48

Regression Model Classification Table for Model 2, SN_MATH_PLCMT_INDX & HS_GPA

	Predicted		
Observed	Unsuccessful	Successful	Percent Correct
Unsuccessful	75	171	30.5%
Successful	49	465	90.5%
Totals and Overall Percentage	124	636	71.1%

Note. *Constant model percent correct = 67.6%

Model 3, High School GPA and ACT Math

The number of cases included in the analysis for Model 3 was $n = 609$. Analysis revealed a questionable model fit with a high -2 Log Likelihood = 645.505. The regression model was significantly different from the constant-only model, $\chi^2(2) = 100.718$, $p < .001$. Model 3 correctly classified 74.9% of cases, outperforming the constant model by 5.1% as displayed in Table 4.49. The percentage of students who were both predicted by the model and observed to be unsuccessful was 36.4%. The odds ratio for the predictor variable HS_GPA ($e^B = 8.139$, $p < .001$) revealed a substantial change in the likelihood of success in math courses when high school GPA increased by 1 point.

The odds ratio for ACT_MATH (e^B = .924, $p < .01$) revealed a slight negative change in the likelihood of success in math courses when ACT math scores increased by 1.

Table 4.49

Regression Model Classification Table for Model 3, HS_GPA & ACT_MATH

	Predicted		
Observed	Unsuccessful	Successful	Percent Correct
Unsuccessful	67	117	36.4%
Successful	36	389	91.5%
Totals and Overall Percentage	103	506	74.9%*

Note. *Constant model percent correct = 69.8%

A thorough examination of the final three regression models determined that Model 3 was the best model for math course success prediction because HS_GPA (e^B = 8.139, $p < .001$) and ACT_MATH (e^B = .924, $p < .01$) best met the standard of highest odds ratios and lowest significance levels. According to the classification tables for each of the final three regression models, Model 3 provided the most accurate success prediction as well as the most accurate prediction of which students would be unsuccessful. The answer to Research Question 4, the combination of course placement information including SuccessNavigator, high school GPA, ACT, and Accuplacer that best predicts student success in freshman math courses, was high school GPA and ACT Math. The null hypothesis was rejected.

Research Question Five

Research question five addressed prediction of student retention from fall 2016 to spring 2017 using the SuccessNavigator Retention Index.

Research Question 5 and its corresponding null hypothesis follow.

Does a noncognitive assessment, SuccessNavigator, predict freshman student retention from fall to spring?

H_0. SuccessNavigator, does not predict retention from fall 2016 to spring 2017.

The subset of the original data sample included data for students who completed the SuccessNavigator assessment with a valid Retention Index score. This data subset was comprised of 1,014 (*n*=1,014) first time in college students who entered The College in fall 2016. More than half of the sample subset, 58.2% (*n*=590), was female. Males made up 41.8% (*n*=424) of participants. The ages of participants ranged from 18 to 64 years. First-time students aged 18 and 19 made up 85.8% (*n*=870) of the sample subset. Only 14.2% (*n*=144) of participants from the sample subset were older than 19 years. Table 4.51 summarizes the reported race of students included in the sample subset.

Table 4.51

Race of Students Who Submitted Valid SuccessNavigator Retention Index Scores

Race	*n*	Percentage
American Indian or Alaska Native	62	6.1
Asian	30	3.0
Black or African American	68	6.7
Hispanic of any race	91	9.0
More than one race reported	135	13.3
Native Hawaiian or Other Pacific Islander	2	0.2
Non-resident alien	24	2.4
Not reported	39	3.8
White	563	55.5

Data Analysis

Initial data screening led to the elimination of three outliers with large squared Mahalanobis distance values. Simple logistic regression was performed on retention (RETENTION_SPR_2017) as the outcome variable using SuccessNavigator Retention Index) SN_RET_INDX as predictor variable to determine whether SuccessNavigator scores predicted retention from fall 2016 to spring 2017. The scores for SuccessNavigator Retention Index ranged from 62.08 to 138.24 with a mean score of 101.32 and included 1,014 students scores (n = 1,014). Descriptive statistics for the predictor variable are displayed in Table 4.52.

Table 4.52

Descriptive Statistics for Predictor Variable

Predictor Variable	*n*	*M*	*SD*	*SE*	Min	Max
SN_RETENTION_INDX	1014	101.32	13.19	.41	62.08	138.24

Table 4.53 reveals that a test of the regression model against the constant-only model was statistically significant, χ^2 = 18.43, df = 1, p < .001.

Table 4.53

Regression Model Fit

Model	-2 Log Likelihood	Chi-Square	*df*	*p*
Final	974.378	18.434	1	.000

The regression model classification table, displayed in Table 4.54, indicates that the regression model correctly classified 80.8% of cases. The constant model also correctly classified 80.8% of cases by predicting that all students would be retained. The regression model and constant model classification tables are identical.

Table 4.54

Regression Model Classification

Observed	Predicted		
	Not Retained	Retained	Percent Correct
Not Retained	0	195	0.0%
Retained	0	819	100.0%
Totals and Overall Percentage	0	1014	80.8%

The summary of the model variable is presented in Table 4.55. The odds ratio (e^B = 1.027, p < .001) demonstrated that students were 1.027 times more likely to be retained from fall 2016 to spring 2017 for each point increase in SuccessNavigator scores, a statistically significant increase.

Table 4.55

Summary of Model Variable

Variable	*β*	*SE*	*Wald*	*Odds ratio*	*p*
SN_RET_INDX	.026	.006	17.966	1.027	.000

Data analysis revealed a questionable model fit with an extremely high -2 Log Likelihood = 974.378. The regression model was significantly different from the constant-only model, $\chi^2(1) = 18.43$, $p < .001$ and correctly classified 80.8% of cases. The odds ratio (e^B = 1.027, $p < .001$) demonstrated a slight but statistically significant increase in the likelihood of retention when SuccessNavigator score increased by 1. Classification tables revealed that the SuccessNavigator Retention Index score was no better at predicting retention than the constant model. Because the regression model was significant, the conclusion is that the model did affirmatively answer Research Question 5. SuccessNavigator does predict student retention from fall 2016 to spring 2017. The null hypothesis was rejected.

Research Question Six

Research question 6 asked what combination of student placement data, available at the time of students' matriculation to The College, was most effective for predicting whether students would be retained from fall 2016 to spring 2017. The data analysis for Research Question 5 used only SuccessNavigator Retention Index as the predictor variable. To address Research Question 6, regressions were run using each of the three retention predictor variables individually as well as in every possible combination. Because SuccessNavigator Retention Index was one of the four predictor variables, it was also included in the analysis for Research Question 6.

Data Analysis

Results of each regression were compared to determine the most effective use of available placement data for predicting retention. Logistic regressions were performed using the following predictor variables: SuccessNavigator Retention Index (SN_RETENTION_INDX), high school grade point average (HS_GPA) and ACT composite score (ACT_COMPOSITE).

Research question six and its corresponding null hypothesis follow.

What combination of course placement information including Success-Navigator, high school GPA, and ACT best predicts freshman student retention from fall to spring.

H_0. No combination of course placement information including Success- Navigator, high school GPA and ACT predicts freshman student retention from fall to spring.

Cases that did not include scores for the predictor variable being analyzed were eliminated from the initial dataset before each regression was conducted. Outliers with large squared Mahalanobis distance values were also eliminated from each data subset before regressions were conducted. Seven logistic regressions were performed on Spring 2017 Retention (RETENTION_SPR_2017) as the outcome variable using each predictor variable in a separate regression and in every possible combination. Results of the regression using the predictor variable SuccessNavigator Retention Index were reported in the previous section and are repeated in this section so that comparisons can be made among the regression models to determine the model that best predicts retention.

The first three regressions that were conducted were the three simple logistic regressions on RETENTION_SPR_2017 using each of the predictor variables in separate regressions. Descriptive statistics for the individual regressions using each of the three predictor variables are presented in Table 4.61.

Table 4.61

Descriptive Statistics for Regressions Using Each Predictor Variable

Predictor Variable	*n*	*M*	*SD*	*SE*	Min	Max
SN_RETENTION_INDX	1014	101.32	13.19	.41	62.08	138.24
HS_GPA	960	3.11	.54	.02	1.47	4.00
ACT_COMPOSITE	813	20.54	3.85	.14	12	32

Subsequent regressions using each combination of predictor variables were conducted. The model fit statistics for all seven regression models are displayed in Table 4.62.

Model Fit

Table 4.62

Model Fit Research Question Four

Model	-2 Log Likelihood	Chi-Square	*df*	*p*
SN_RETENTION_INDX	974.378	18.434	1	.000
HS_GPA	878.041	3.664	1	.000
ACT_COMPOSITE	766.914	7.580	1	.006
SN_RETENTION_INDX & HS_GPA	872.832	34.670	2	.000
SN_RETENTION_INDX & ACT_COMPOSITE	745.856	28.638	2	.000
HS_GPA & ACT_COMPOSITE	695.843	47.267	2	.000
SN_RETENTION_INDX, HS_GPA & ACT_COMPOSITE	689.452	52.875	3	.000

Model Selection Process

The regression models were all significantly different than their constant models at $p < .01$. Additionally, the models all indicated questionable model fit because of extremely high -2 Log Likelihood statistics, so classification tables were examined as the next step in eliminating models. Classification tables for four of the regression models correctly classified the same percentage of cases as the constant models. Classification tables for three of the models correctly classified fewer cases than the constant model.

According to model fit statistics and classification tables, none of the seven models accurately predicted retention (Mertler & Vanatta, 2005).

Because the regression models were all significantly different than their constant models, and none of the classification tables correctly classified more cases than the corresponding constant models, the remaining step in determining the best model for retention prediction was to examine the summaries of model variables for the seven models. Models were removed from consideration if the Wald statistic was non-significant for one or more predictor variables in the model. The Wald is a measure of significance for the unstandardized regression coefficient, or *B*, and "represents the significance of each variable in its ability to contribute to the model" (Mertler & Vanatta, 2005, p. 320). A significance level of $p < 0.1$ was applied in each case. Table 4.63 displays the summaries of model variables for all seven regression models.

Table 4.63

Summary of Model Variables

Variable	*β*	*SE*	*Wald*	*Odds ratio*	*p*
1/SN_REGRESSION_INDX	.026	.006	17.966	1.027	.000
2/HS_GPA	.849	.155	29.984	2.338	.000
3/ACT_COMPOSITE	.066	.024	7.359	1.069	.007
4/SN_RETENTION_INDX,	.013	.008	2.675	1.013	.102*
& HS_GPA	.700	.189	13.712	2.013	.000
5/SN_RETENTION_INDX,	.036	.008	20.300	1.036	.000
& ACT_COMPOSITE	.018	.027	.447	1.018	.504*
6/HS_GPA	1.250	.204	37.687	3.490	.000
& ACT_COMPOSITE	.002	.027	.006	1.002	.941*
7/SN_RETENTION_INDX,	.020	.009	4.548	1.020	.033
& HS_GPA	1.044	.231	20.422	2.842	.000
& ACT_COMPOSITE	-.015	.028	.275	.985	.600*

Note. * indicates non-significant Wald statistic, $p > .1$

An examination of the seven regression models ruled out models 4, 5, 6 and 7 because one or more of the variables had nonsignificant Wald statistics. Deciding factors among models 1, 2, and 3 were the odds ratios of the predictor variables and their significance levels. Model 2 was determined to be the best model for retention prediction because HS_GPA (e^B = 2.338, $p < .001$) best met the standard of highest odds ratio and lowest significance levels. The answer to Research Question 6, the combination of course placement information including SuccessNavigator, high school GPA, and ACT that best predicted student retention from fall 2016 to spring 2017 was high school GPA. The null hypothesis was rejected. Descriptive statistics are displayed for the high school GPA only model in Table 4.64. The regression model classification table for the best predictor model is displayed in Table 4.65

Table 4.64

Descriptive Statistics for Remaining Model

Model/Predictor Variable	*n*	*M*	*SD*	*SE*	Min	Max
HS_GPA	960	3.108	.54	.017	1.47	4.00

Table 4.65

Regression Model Classification Table for Model 1, HS_GPA

	Predicted		
Observed	Unsuccessful	Successful	Percent Correct
Unsuccessful	0	174	0.0%
Successful	0	786	100.0%
Totals and Overall Percentage	0	960	81.9%

**Constant model percent correct = 67.6%*

Summary

Data analysis revealed that SuccessNavigator did predict student success in writing and math courses in fall 2016 and retention from fall 2016 to spring 2017. Study results also revealed that other student admission information predicted success and retention more effectively than SuccessNavigator, and that the most effective success predictors differed among writing, math and retention. Chapter V includes a discussion of the results and implications for future research.

CHAPTER V

DISCUSSION

This study sought to evaluate the effectiveness, based on student performance and retention, of using a noncognitive assessment score (SuccessNavigator) to predict student success in writing and math courses and retention to the next semester. An earned grade of C or higher in writing and math courses indicated success. Retention was defined as enrollment in the semester following the first semester of attendance. The study site was an open-access community college located in the central United States. The population selected for study consisted of first semester freshman students in fall 2016 who completed the SuccessNavigator assessment as part of a pilot program to improve effectiveness of the initial English and math course placement process. Logistic regression determined the effectiveness of using a noncognitive assessment as a part of the placement process to predict student success in writing and math courses and student retention from fall 2016 to spring 2017.

The research questions that guided the study were:

1. Does a noncognitive assessment, SuccessNavigator, predict student success in freshman writing courses?
2. What combination of course placement information including SuccessNavigator, high school GPA, ACT and Accuplacer best predicts student success in freshman

writing courses?

3. Does a noncognitive assessment, SuccessNavigator, predict student success in freshman mathematics courses?
4. What combination of course placement information including SuccessNavigator, high school GPA, ACT, and Accuplacer best predicts student success in freshman mathematics courses?
5. Does a noncognitive assessment, SuccessNavigator, predict freshman student retention from fall to spring?
6. What combination of course placement information including SuccessNavigator, high school GPA, and ACT best predicts freshman student retention from fall 2016 to spring 2017 student.

The null hypotheses tested in this study were:

1. A noncognitive assessment, SuccessNavigator, does not predict student success in freshman writing courses.
2. No combination of course placement information including SuccessNavigator, high school GPA, ACT and Accuplacer predicts student success in freshman writing courses.
3. A noncognitive assessment, SuccessNavigator, does not predict student success in freshman mathematics courses.
4. No combination of course placement information including SuccessNavigator, high school GPA, ACT and Accuplacer predicts student success in freshman mathematics courses.

5. A noncognitive assessment, SuccessNavigator, does not predict freshman student retention from fall to spring freshman student retention.
6. No combination of course placement information including SuccessNavigator, high school GPA and ACT predicts freshman student retention from fall 2016 to to spring 2017.

This discussion of study results begins with a summary of findings followed by a detailed discussion section. The implications section provides implications for research, theory and practice in higher education and is followed by a brief conclusion.

Summary of Findings

Overall, data analysis demonstrated that high school GPA and ACT subject area scores were more effective success predictors in first-year English and math courses than SuccessNavigator. The single noncognitive assessment tool, with its additional cost, did not substantially improve the accuracy of the placement process intended to identify students who needed support services such as writing and math tutoring at The College. The no-cost data already available to The College (high school GPA and ACT) more accurately predicted student success and retention.

Research questions 1, 3, and 5 addressed the effectiveness of the noncognitive assessment, SuccessNavigator, in predicting student success and retention. Study findings demonstrated that SuccessNavigator *did* predict student writing and mathematics course success and retention from fall 2016 to spring 2017. Although analysis revealed that the regression model fits were questionable for research questions 1, 3, and 5, they were statistically significant. Thus, research questions 1, 3, and 5 were answered affirmatively, and their corresponding null hypotheses were rejected.

While SuccessNavigator was a statistically significant predictor of success and retention, the small difference between the predictive capability of the assessment and that of the constant models for each research question indicated that the cost to The College of using the noncognitive assessment, approximately $5.00 for each administration, may not be the best use of funds. Rather, academic advisors would be almost as effective placing students without SuccessNavigator while saving The College a substantial amount of money.

Combination of Course Placement Information

Research questions 2, 4, and 6 asked what combination of available course placement information best predicted student success in writing and math courses and retention from fall 2016 to spring 2017. Results indicated that at least one combination of available course placement information significantly predicted success for each research question, so the null hypotheses were rejected. None of the regression models that answered questions 2, 4, and 6 included SuccessNavigator as one of the significant predictors of success. While the cost to The College is $5.00 per test administration for SuccessNavigator, there is no cost to The College to obtain high school GPA scores and ACT scores, so using the no-cost information available to admissions personnel and advisors would provide more effective success and retention prediction and cost thousands of dollars less than using the SuccessNavigator noncognitive assessment.

Writing Course Success Prediction

SuccessNavigator accurately predicted writing course success for over two-thirds of students included in the analysis. While accurate success prediction would help college personnel and new freshmen tremendously, the ability to identify which students are most likely to be *unsuccessful* would be most helpful to in identifying which students required the most support upon entry to The College. SuccessNavigator English Placement Index accurately predicted which students would be unsuccessful in writing courses at a low rate, only 12.9% of all unsuccessful students. If SuccessNavigator had been used in placement, 29 students who would not have otherwise received additional supports would have received that help, but 195 students who also needed additional supports would have been missed because SuccessNavigator predicted that they would successfully complete writing courses and they did not.

Data analysis for research question 2 revealed that the combination of high school GPA and ACT English sub-score was the most accurate model for predicting writing course success among all the models including the SuccessNavigator only model. This model also most accurately predicted which students would be *unsuccessful*. Using the high school GPA/ACT English model, 24% of all unsuccessful students were correctly predicted to be unsuccessful. The high school GPA and ACT English model more accurately predicted success in writing courses than SuccessNavigator and incurred no cost to The College.

Math Course Success Prediction

SuccessNavigator accurately predicted math course success for two-thirds of students included in the analysis. As with writing courses, accurate prediction of students who were most likely to be *unsuccessful* would be most helpful to in identifying which students required additional support upon entry to The College. SuccessNavigator Math Placement Index accurately predicted which students would be unsuccessful in math courses at a low rate, only 16.7% of all unsuccessful students.

Data analysis for research question 4 revealed that the combination of high school GPA and ACT math sub-score was the most accurate model for predicting math course success. This model also most accurately predicted which students would be *unsuccessful*. Using the high school GPA/ACT math model, 36.4% of all unsuccessful students were correctly predicted to be unsuccessful. The high school GPA and ACT math model more accurately predicted success in math courses than SuccessNavigator and incurred no cost to The College.

Upon evaluating the effectiveness of all the possible predictor models for success in writing and math courses, the combination of high school GPA and the appropriate ACT sub-score was the most accurate model for prediction for both subjects.

Retention Prediction

The results of retention prediction portion of the study were the most intriguing related to the use of SuccessNavigator. The predictive value of the regression model and constant model were identical, accurately predicting which students would be retained at 80.8% of students included in the analysis. This result indicated that The College could eliminate the cost of using SuccessNavigator along with requiring students to take another test because SuccessNavigator provided no new information to academic advisors and other admissions and placement staff. SuccessNavigator Retention Index added no value to retention prediction.

Upon evaluation of all possible combinations of placement data, the model using only high school GPA was determined to be the most accurate predictor of retention. Data analyses related to retention seem to indicate that, using the data currently available to The College, the most accurate way to predict retention was to assume that all students will be retained. A discussion of these findings, as they are situated within the literature, follows.

Discussion of Findings

Research findings are discussed within the context of the related literature in each of the following sections.

Postsecondary Education Options

Several options for education and career training are available to students upon completion of high school. The literature indicates that some students who might appreciate workforce training options continue to choose to go to college because of societal pressure to do so. This ensures that students who might excel in vocational programs will continue to enter community colleges to pursue associate's and bachelor's degrees (Hout, 2012; Rosenbaum, et al., 2010).

The low cost and open access of community colleges is especially attractive to students who need to remain at home to be near work and care for family members. These sorts of pressures help maintain the steady pipeline of underprepared students moving from high school into community colleges. This situates community colleges as a sort of funnel for postsecondary learners with a heavy emphasis on serving students from underrepresented groups, which tend to be disproportionally made up of underprepared students (Crisp & Mina, 2012; Fike & Fike, 2008; Townsend & Twombly, 2007; Wild & Ebbers, 2002). The characteristics of community college students generally place them in groups that have shown to be at higher risk of dropping out than traditional university students (Crisp & Mina, 2012).

Some students, whether placed into developmental or college level coursework, may have been more engaged in their postsecondary studies if they had chosen a vocational program or apprenticeship rather than an academic course of study. For students who are better suited to something different than college academics, this could lead to disengagement, subsequent poor performance, and dropping out (Schudde & Goldrick-Rab, 2015). The admission and placement process at The College, like most other community colleges, did not provide an avenue for students to explore or validate their reasons for choosing to attend community college. Because colleges and universities compete for a limited number of students that appears to be in decline in recent years, most colleges understandably stay away from suggesting to students that there are multiple good postsecondary options for consideration. This piece of the higher education process is not in students' best interests, however, and likely contributes to lower success rates.

Cox's (2016) application of the college choice framework seems to be consistent with this study's findings that, while some measures do significantly predict success, the data available to The College failed to accurately predict which students would be *unsuccessful* at rates higher than 34.9%. Cox found that complicating factors such as lack of adequate food and housing were issues affecting postsecondary choice, as well as success and retention, for students from underrepresented groups. Nothing in the current admission and placement data available to The College evaluates the existence of such complicating factors for new freshmen.

Community college student focus groups identified three primary themes that comprised the Theory of Choice by Somers, et al. (2014). The three primary categories that reasons for choosing community college fell into were needing to be close to home and a job, improving future economic opportunities for themselves and their dependents, and proving wrong people who had discouraged them in the past, primarily teachers and high school counselors (Somers, et al., 2014). If we look through the lens of the Theory of Choice, this study's findings seem to indicate that while SuccessNavigator attempted to get at the true noncognitive issues that would impact success, it must be missing some pieces in how it attempts to identify which students need the most support. Regardless of the reasons that students choose community college, success and completion will likely remain elusive if we fail to understand who needs help before failing grades are assigned and students drop out.

Community College Completion Crisis

Course success and retention are vital for students to graduate from community college and/or to transfer to university. Because 45% of all undergraduates attend community colleges at some point during their college career, student success at four-year institutions and community colleges is connected (National Center for Educational Statistics, 2016). Students who are unsuccessful in community college will not be able to transfer and complete bachelor's degrees.

This study's findings indicate that SuccessNavigator did not add enough value to success prediction to support the institution's cost of testing every incoming student. For a success prediction instrument to have a significant role in the admission and placement process, it must provide substantial benefit to the institution while being a minimal barrier to college access. Students generally tend to see the requirement to take another test, even though it is a noncognitive assessment, as another step in the process that could potentially hinder their placement and slow their ability to move through their general education courses. Additionally, the cost to The College to administer SuccessNavigator is $5.00 per administration. In a typical fall term, the cost to test 3,500 new incoming students would be $17,500. Without a significant difference being made by the use of SuccessNavigator, these are funds that could be redirected to student support such as tutoring, bookstore credits for low income students, and other such supports.

Nontraditional students, such as those found in high numbers at community colleges, are more likely to be from underrepresented groups, working, financially responsible for themselves and their families, and over 25. Many community college students fall into more than one of those and other categories that put students at higher risk for dropping out of college.

Nontraditional students' characteristics are not in themselves the things that hold down success rates at community colleges; rather it is higher education's lack of ability to adapt to meet the needs of these students (Goldrick-Rab, 2010). This study's findings indicate that SuccessNavigator did not go far enough in its ability to identify which students would be *unsuccessful* and need additional support. It also was not helpful in identifying which supports would be needed by each student. Results such as these prevent even the most dedicated of higher education professionals from being able to provide the right solutions to the right students. Findings seem to indicate that relying on a more individualized approach to each student's success rather than a standardized test could be the most effective method of determining needed support.

Community colleges measure student success at the institutional level in part through course pass rates and retention. Academic issues such as lack of adequate preparation and noncognitive issues such as low self-confidence, lack of family and financial support, and more practical issues, such as absence of adequate transportation or access to wi-fi, can influence both course pass rates and retention. Students may be adequately prepared for coursework but not be retained because of external pressures typically related to lack of resources. The use of SuccessNavigator was an attempt to identify which students were likely to succeed in writing and math courses and which students were likely to be retained by measuring noncognitive traits rather than academic preparedness. Study findings seem to suggest that using a measure of academic achievement to predict success was most effective, especially when a longer-term assessment, high school GPA, was used as a predictor variable.

Study findings demonstrated that for writing and math course success prediction, the combination of high school GPA and ACT subject-area scores were the most accurate predictors of success. Practically, however, that combination of data only accurately identified one-quarter (writing) to one-third (math) of students who went on to fail their courses. While the high school GPA and ACT model is better at success prediction than SuccessNavigator and is also free to the college, it still leaves out most students who could benefit from additional support. Viewed through the lens of the community college completion crisis literature, accurate course success and retention prediction is still elusive for The College.

College Readiness

College readiness has traditionally been measured by standardized tests such as SAT and ACT. Findings from this study indicate that those tests, used exclusively, are not significant predictors of student success. While some colleges and universities are moving away from using SAT and ACT scores as admission criteria, most institutions still use these measures for admission and placement. Low community college student success rates, however, tend to indicate that college readiness may not be the best measure for determining whether a student will be successful.

In addition to SuccessNavigator, two of the student data pieces that this study examined for effectiveness in success prediction were ACT and Accuplacer. Neither instrument on its own accurately predicted writing or math course success, but ACT when paired with high school GPA did accurately predict which students would be successful. Accuplacer was not an accurate success prediction tool. Neither the ACT nor Accuplacer were designed to predict success, however this study's findings indicate that high school GPA paired with ACT subject area scores did accurately predict success in writing and math courses at The College. This model's ability to predict who would be *unsuccessful*, however, was statistically significant but not accurate enough to be practically reliable.

Placement and Success Prediction

The literature indicates that community colleges should work toward identifying affective student characteristics that are barriers to success and address those barriers at admission and placement. Rather than focus on placing fewer students into developmental education so that fewer students experience the barrier of developmental courses, Boylan asserts that we should address students' life circumstances that serve as barriers to their success (Levine-Brown & Anthony, 2017). SuccessNavigator attempts to identify affective characteristics that could hinder success, but the findings of this study indicate that it could be measuring the wrong characteristics or is not measuring them accurately, or that a standardized noncognitive measurement is not effective at success and retention prediction.

Findings from this study indicate that high school GPA should be incorporated into the placement process at The College. High school GPA scores were available but The College did not use them in their placement process in 2016-2017. Study findings indicated that high school GPA paired with ACT sub-scores accurately predicted which students would be successful in writing and math courses, so incorporating GPA will improve success prediction at The College.

Noncognitive Issues, Student Success and SuccessNavigator

William Sedlacek's Noncognitive Questionnaire, or NCQ (1993), has been used to successfully predict success for students who are nontraditional but who are also entering selective admission universities. Students entering these types of institutions have established a history of high academic achievement, so they are not typically students who would encounter placement testing. While Sedlacek's NCQ has a history of accurate success prediction, it has not been used in community colleges with enough frequency to determine its predictive ability with students who perform lower academically than students who traditionally take the NCQ. Likewise, the traits measured by the NCQ leave out practical personal issues such as transportation and child care that could be success barriers for community college students.

Grit (Duckworth, et al., 2007) and Mindset (Dweck, 2008) also measure students' propensity to persist toward long-term goals and to bounce back from setbacks, but neither these measures nor the NCQ seek to measure specific situations that could cause nontraditional students to fail or drop out of college early in their educational process. An extensive overlap exists in the traits measured by the NCQ and those measured by SuccessNavigator. Because study findings indicate that SuccessNavigator is not an accurate success predictor, it is reasonable to wonder if NCQ may perform similarly to SuccessNavigator in predicting student success and retention for community college students.

Implications

Implications for research, theory, and practice are defined in this section. Suggestions for future research are included.

Research

This study found that SuccessNavigator was not the most accurate predictor of course success and retention for students at The College. These findings imply that the shift in focus from assuring access to promoting student success may not have a simple solution. Community college success prediction using noncognitive measures has become a focus of researchers to find ways of identifying which students need support to be successful (for example, see Belfield & Crosta, 2012; Doyle, 2012; Saxon & Morante, 2014; Venezia & Hughes, 2013). Based on findings from the current study, it seems that the time has come to focus research efforts on finding more holistic approaches to success prediction, especially in identifying students who are likely to fail and drop out. Particularly in the community college setting, this may include ways of identifying and addressing success barriers such as low self-confidence, lack of positive support system, and limited access to a computer and wi-fi connection. This study's findings support previous research findings in this area.

Future research. Accurately predicting student success as part of the placement process may seem a logical starting point for supporting student success; however, the more elusive, and perhaps critical, piece of student success prediction is determining which students are most likely to fail and drop out. In addition to predicting which students are likely to drop out or fail, future research should seek to identify effective methods for determining specific supports needed by incoming freshmen. While study findings indicated that a combination of high school GPA and ACT subject area scores most accurately predicted which students would be successful in writing and math courses and that high school GPA most accurately predicted which students would be retained from fall 2016 to spring 2017, none of these measures were effective at predicting lack of success.

Based on the results of this study and Hunter Boylan's (Levine-Brown & Anthony, 2017) assertion that educational institutions should help students overcome the life circumstances that serve as success barriers, I recommend qualitative and quantitative studies to determine incoming freshman students' needs and how institutions may best address those needs. The possibility exists that SuccessNavigator could be helpful in identifying needed support structures rather than focusing on informing course placement. Additionally, institutions that implement assistance to address students' life barriers such as housing assistance, transportation, daycare, and social services on campus should longitudinally evaluate the success of students who were referred to those services. These types of studies could help improve initial success prediction and placement by following students through the entire first year and beyond to see if and how identified non-academic supports worked for students.

Theory

Study findings imply that the theory behind SuccessNavigator, which overlaps with Sedlacek's Non-cognitive Questionnaire, was not useful for success prediction with the population of students at The College. Because SuccessNavigator was least helpful in identifying students who were likely to fail, its framework appears to have a gap in the area of identifying barriers to success. Because community college students are heavily nontraditional, practical and logistical issues such as lack of enough food, a place to live, reliable child care, transportation, access to a computer and wi-fi, and money for textbooks and supplies are needs that are not identified through either Sedlacek's or SuccessNavigator's frameworks. These are needs that are typical of nontraditional students, however.

The Theory of Choice (Somers, et al., 2014), developed by researchers through their work with community college students, seemed to provide the most promise for community college student success prediction. If this theory is an accurate representation of the reasons that students choose community college, it could also serve as a framework for identifying which students need additional non-academic support. The theory includes 10 factors that fit into three categories, aspirations and encouragement, institutional characteristics, and finances. The third category, finances, is not specifically represented in Sedlacek's or SuccessNavigator's frameworks, but is a category that likely covers many of the barriers encountered by community college students. Study findings imply that a theory that includes categories that more accurately represent community college students should be applied to success prediction. The Theory of Choice could be adapted for that purpose.

Practice

Implications for practice include more involvement from academic advisors in the placement process by tasking them with determining which students need nonacademic support to be successful their first semester. This could involve covering a predetermined set of questions with each student during their advising appointment to determine where barriers to success exist and working together to find solutions. Responsibility would fall to the institution to provide funding for needed supports. Predicting which students are likely to be successful and which are not likely to be successful is a logical beginning, but this also requires community colleges to find ways to pay for needed supports. If supports cannot be funded, it doesn't matter whether or not we are able to predict which students are likely to fail and drop out. Institutions must be able to take action to support course success and retention. Study findings provide an effective way to identify future successful students, but until we have a useful method of determining which students will struggle, one-on-one advising appears be the most effective method of identifying barriers to success.

The cost of using advisors to administer noncognitive questions should add minimal, if any, cost to the placement process. Most institutions, including The College, require students to see an academic advisor each semester, so an implication for practice is for advisors to add several questions to their advising visits with students that seek to discover whether any noncognitive issues exist that might hamper success. They should follow up on students' replies with suggesting available supports. This type of individualized noncognitive assessment paired with the most accurate prediction models identified in this study should be examined through institutional or other research to determine whether it adds predictive value.

Conclusions

This study sought to determine the accuracy of SuccessNavigator as a factor in identifying the most accurate method of predicting success, or lack of success, in writing and math courses, as well as retention from fall to spring for students entering in fall 2016 at The College. Data analysis revealed that the combination of high school GPA and ACT subject area scores were the most accurate predictors of success in writing and math courses. High school GPA was the most accurate predictor of retention. The identified models predicted success more accurately than SuccessNavigator alone, as well as all other combinations of predictor variables that included SuccessNavigator, high school GPA, ACT subject area scores, Accuplacer Sentence Skills, and Accuplacer Elementary Algebra. Findings from this study imply that more research is needed that applies new success theories that are specific to community college students to determine the best ways for community colleges to predict success and properly place their students.

REFERENCES

ACT, Inc. (2019). Retrieved from http://www.act.org/content/act/en/products-and-services/the-act-postsecondary-professionals.html.

Accuplacer (2019). Retrieved from https://accuplacer.collegeboard.org/.

American Association of Community Colleges (2016). *Community College Fast Facts.* Retrieved from http://www.aacc.nche.edu/AboutCC/Documents/AACCFactSheetsR2.pdf.

Bailey, T. (2009). Challenge and opportunity: Rethinking the role and function of developmental education in community college. *New Directions for Community Colleges, 145*, 11–30. doi: 10.1002/cc.352

Bailey, T., Jeong, D. W., & Cho, S. (2009). Referral, enrollment, and completion in developmental education sequences in community colleges. *Community College Research Center CCRC Working Paper 15.*

Bailey, T. R., Jaggars, S. S., Jenkins, D. (2015). *Redesigning America's Community Colleges.* Cambridge, MA: Harvard University Press.

Barnett, E. A. (2011). Validation experiences and persistence among community college students. *The Review of Higher Education, 34*(2), 193-230.

Bean, J. (1980). Dropouts and turnover: The synthesis and test of a causal model of student attrition. *Research in Higher Education, 12*(2), 155-187.

Belfield, C. R. & Crosta, P. M. (2012). Predicting success in college: The importance of placement tests and high school transcripts. *Community College Research Center CCRC Working Paper 42.*

Bettinger, E. P., Evans, B. J., & Pope, D. G. (2013). Improving college performance and retention the easy way: Unpacking the ACT exam. *American Economic Journal: Economic Policy 2013, 5*(2), 26-52. Retrieved from http://dx.doi.org/10.1257/pol.5.2.26.

Caporrimo, R. (2008). Community college students: Perceptions and paradoxes. *Community College Journal of Research and Practice, 32*, 25-37.

College Board (2017). Retrieved from https://accuplacer.collegeboard.org/educator/why-accuplacer.

Community College Survey of Student Engagement (2016). *Expectations meet reality: The underprepared student and community colleges 2016 national report.* Retrieved from http://www.ccsse.org/docs/Underprepared_Student.pdf.

Cox, B. E., Reason, R. D., Nix, S., & Gillman, M. (2016). Life happens (Outside of college): Non-college life events and students' likelihood of graduation. *Research in Higher Education, 57*(7), 823-844.

Cox, R. D. (2016). Complicating conditions: Obstacles and interruptions to low-income students' college "choices." *The Journal of Higher Education, 87*(1), 1-26.

Crisp, G., & Mina, L. (2012). The community college: Retention trends and issues. *The ACE Series on Higher Education: College Student Retention, 2nd ed.* Alan Seidman, ed

Doyle, W. R. (2012). Playing the numbers: Remediation: No easy answers. *Change, 44*(6), 60-63. doi: 10.1080/00091383.2012.728956

Duckworth, A. L., Peterson, C., Matthews, M. D., and Kelly, D. R. (2007). Grit: Perseverance and passion for long-term goals. *Journal of Personality and Social Psychology 92*(6), 1087-1101.

Duckworth, A. L., & Quinn, P. D. (2009). Development and Validation of the Short Grit Scale (Grit-S). *Journal of Personality Assessment, 91*(2), 166-174.

Dweck, C. S. (2008). *Mindset: The new psychology of success.* New York, NY: Ballantine.

Fike, D. S. & Fike, R. (2008). Predictors of first-year student retention in the community college. *Community College Review, 36*(2), 68-88.

Goldrick-Rab, S. (2010). Challenges and opportunities for improving community college student success. *Review of Educational Research, 80*(3), 437-469.

Goodwin, B. & Miller, K. (2013). Grit + talent = student success. *Educational Leadership 71*(1).

Hossler, D., & Gallagher, K. S. (1987). Studying student college choice: A three phase model and the implications for policymakers. *College and University, 62,* 207-221.

Hout, M. (2012). Social and economic returns to college education in the United States. *Annual Review of Sociology, 38,* 379-400. doi:10.1146/annurev.soc.012809.102503

Kalsbeek, D., Sandlin, M., & Sedlacek, W. (2013). Employing noncognitive variables to improve admissions and increase student diversity and retention. *Strategic Enrollment Management Quarterly 1*(2), 132-150. doi: 10.1002.sem3.20016

Labaree, D. (2013). A system without a plan: Emergence of an American system of higher education in the twentieth century. *Bildungsgeschichte: International Journal for the Historiography of Education 3*(1), 46-59.

Lee, K. A., Almonte, J. L. J, Youn, M. (2013). What to do next: an exploratory study of the post-secondary decisions of American students. *Higher Education: The International Journal of Higher Education and Educational Planning, 66*(1), 1-16. doi: 10.1007/s10734-012-9576-6

Leech, N. L., Barrett, K. C., & Morgan, G. A. (2011). *IBM SPSS for intermediate statistics: Use and interpretation, Fourth Edition.* New York, NY: Routledge.

Levine-Brown, P. & Anthony, S.W. (2017). The Current State of Developmental Education: An Interview with Hunter R. Boylan. *Journal of Developmental Education, 41*(1), 18-22.

Lucas, S. (2001). Effectively maintained inequality: Education transitions, track mobility, and social background effects. *American Journal of Sociology, 106,* 1642-1690. doi:10.1086/321300

MacCann, C., Duckworth, A. L., & Roberts, R. D. (2009). Empirical identification of the major facets of conscientiousness. *Learning and Individual Differences 19*, 451-458.

Mann, H. (1868). Twelfth annual report to the Massachusetts State Board of Education, 1848. *Life and Works of Horace Mann, ed. Mrs. Mary Mann, vol.3, p. 669.* Available from http://www.bartleby.com/73/498.html

Markle, R., Olivera-Aguilar, M., Jackson, T., Noeth, R., & Robbins, S. (2013). *Examining evidence of reliability, validity, and fairness for the SuccessNavigator™ assessment* (Report No. ETS RR-13-12). Retrieved from https://www.ets.org/research/policy_research_reports/publications/report/2013/jqob.

McClenney, K. M., & Waiwaiole, E. N. (2005). Focus on student retention: Promising practices in community college. *Community College Journal, 75*(6), 36-41.

McCrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality and Social Psychology, 51,* 81-90.

Merriam-Webster (2019). Retrieved from https://www.merriam-webster.com/dictionary/placement%20test on February 22, 2019.

Mertler, C. A., & Vannatta, R. A. (2005). *Advanced and multivariate statistical methods: Practical application and interpretation.* Glendale, CA: Pyrczak

Nakajima, M. A., Dembo, M. H., Mossler, R. (2012). Student persistence in community colleges. *Community College Journal of Research and Practice. 36*(8), 591-613. doi: 10.1080/1066892090305-4931

National Center for Education Statistics. (2016). *The Condition of Education.* Retrieved from https://nces.ed.gov/programs/coe/indicator_ctr.asp.

National Skills Coalition. (2019). Retrieved from https://www.nationalskillscoalition.org/federal-policy/adult-basic-education on February 22, 2019.

Nunnally, J. C. (1978). *Psychometric theory* (2nd ed.). New York, NY: McGraw-Hill.

Obama, B. (2009). *Remarks by the president on the American Graduation Initiative.* Washington, DC: The White House, Office of the Press Secretary. Available from http://www.whitehouse.gov/the_press_office/Remarks□by□the□President□on□the□American□Graduation□Initiative□in□Warren□MI/

Pretlow, J. & Wathington, H. D. (2013). Who places into developmental education and why. *Community College Journal of Research and Practice, 37*(10), 794-799. doi: 10.1080/10668926.2012.719482

Robbins, S. B., Oh, I.-S., Le, H., & Button, C. (2009). Intervention effects on college performance and retention as mediated by motivational, emotional, and social control factors: Integrated meta-analytic path analyses. *Journal of Applied Psychology, 94*(5), 1163-1184. doi:10.1037/a0015738

Rosenbaum, J. E., Stephan, J. L., & Rosenbaum, J. E. (2010). Beyond one-size-fits-all college dreams: Alternative pathways to desirable careers. *American Educator, Fall 2010,* 2-13.

Rutschow, E. Z., Richburg-Hayes, L., Brock, T., Orr, G., Cerna, O., Cullinan, D., Kerrigan, M. R., Jenkins, D., Gooden, S., & Martin, K. (2011). *Turning the tide: Five years of achieving the dream in community colleges.* New York: MDRC.

Saxon, D. P., & Morante, E. A. (2014). Effective student assessment and placement: challenges and recommendations. *Journal of Developmental Education, 37*(3), 24-31.

Saxon, D. P., & Morante, E. A. (2015). Student assessment and placement: Most colleges oversimplify the process. *Research in Developmental Education, 26*(2), 1-3.

Schneider, M., & Yin, L. M. (2012). Completion matters: The high cost of low community college graduation rates. *American Enterprise Institute for Public Policy Research (2): Education Outlook.*

Scott-Clayton, J., & Stacey, G. W. (2015). Improving the accuracy of remedial placement. New York, NY: Columbia University, Teachers College, Community College Research Center.

Sedlacek, W. E. (1993). Employing noncognitive variables in admissions and retention in higher education. *Achieving diversity: Issues in the recruitment and retention of underrepresented racial/ethnic students in higher education*, 33-39. Alexandria, VA: National Association of College Admission Counselors.

Sedlacek, W. E. (2011). Using noncognitive variables in assessing readiness for higher education. *Readings on Equal Education, 25*, 187-205.

Sedlacek, W. E. & Brooks, G. C., Jr. (1976). *Racism in American education.* Chicago: Nelson-Hall.

Somers, P., Haines, K., Keene, B., Bauer, J., Pfeiffer, M., McCluskey, J., … Sparks, B. (2006). Towards a theory of choice for community college students, *Community College Journal of Research and Practice, 30*(1), 53-67. doi: 10.1080/10668920500248886

Stern, G. M. (2013). Study explores why many high school graduates are not ready for college. *The Hispanic Outlook in Higher Education 23*(21), 20-21.

Tinto, V. (1993). *Leaving college : Rethinking the causes and cures of student attrition. Second edition.* Chicago : University of Chicago Press.

Townsend, B. K., Twombly, S. B., & Association for the Study of Higher Education. (2007). Community college faculty: Overlooked and undervalued [Monograph]. *ASHE Higher Education Report, 32*(6).

Tracey, T. J., & Sedlacek, W. E. (1982). *Noncognitive variables in predicting academic success by race.* Paper presented at the Annual Meeting of the American Educational Research Association, New York, NY. March 19-23, 1982.

U.S. General Accountability Office (2013). *Community colleges: New federal research center may enhance current understanding of developmental education. A report to the ranking member, committee on education and the workforce, U.S. House of Representatives* (Report No. GAO-13-656).

Venezia, A. and Hughes, K. L. (2013). Acceleration strategies in the new developmental education landscape. *New Directions for Community Colleges, 164*(Winter 2013). doi: 10.1002/cc.20079

Von Culin, K. R., Tsukayama, E., & Duckworth, A. L. (2014). Unpacking grit: Motivational correlates of perseverance and passion for long-term goals. *The Journal of Positive Psychology, 9*(4), 306-312. Retrieved from http://dx.doi.org/10/1080/17439760.2014.898320.

Wild, L. & Ebbers, L. (2002). Rethinking student retention in community colleges. *Community College Journal of Research and Practice, 26*(6), 503-519.

Woods, C. S., Park, T., Hu, S., & Jones, T. B. (2019). Reading, writing, and English course pathways when developmental education is optional: Course enrollment and success for underprepared first-time-in-college students. *Community College Journal of Research and Practice, 43*(1), 5-25. doi: 10.1080/10668926.2017.139114

VITA

Lori A. Coggins

Candidate for the Degree of

Doctor of Philosophy

Dissertation: IDENTIFYING STUDENTS WHO NEED SUPPORT: A LOGISTIC REGRESSION STUDY OF COMMUNITY COLLEGE STUDENT SUCCESS PREDICTION

Major Field: Educational Leadership and Policy Studies

Biographical:

Education:

Completed the requirements for the Doctor of Philosophy in Educational Leadership and Policy Studies at Oklahoma State University, Stillwater, Oklahoma in July, 2019.

Completed the requirements for the Master of Science in Educational Leadership at Oklahoma State University, Stillwater, Oklahoma in 2006.

Completed the requirements for the Bachelor of Arts in American Studies at Oklahoma State University, Stillwater, Oklahoma in 2004.

Experience:

Tulsa Community College, Assistant Professor and Coordinator of First Year Experience Seminar January 2014 through present.

Tulsa Community College, Interim Associate Dean of Communications Division at Southeast Campus August 2015 through May 2016.

Oklahoma State University-Tulsa, Manager of Graduate Student Services Center, October 2007 through September 2010.