ROADBLOCKS TO MOMENTUM: AN ANALYSIS OF COLLEGE MAJOR GPA RESTRICTIONS AND STRANDED STUDENTS

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Abstract

College retention, persistence, and completion are key indicators of a successful institution, but six-year degree completion has remained stagnant in recent years (National Student Clearinghouse Research Center, 2022). Despite institutional efforts through success initiatives to keep students retained, one set of barriers to degree completion may be due to established major GPA restrictions and policies that prevent students from being able to declare their majors. Accordingly, students who are unable to declare their major but keep enrolling in courses may be in danger of becoming “stranded.” This quantitative examination of student data from one large public four-year college aims to identify the characteristics of stranded students and consider how they compare to non-stranded students. The Academic Momentum Model by Cliff Adelman (1999, 2006) provides a lens to identify academic factors that may predict stranded status.

The results of the analysis found that stranded students demonstrate indicators of academic momentum (Adelman, 2006), however, decreased levels of academic performance increased the likelihood of becoming stranded. A student’s choice of major was found to be related to the likelihood of becoming stranded, along with other academic characteristics such as summer term enrollment, second-year GPA, changing of majors, and continuous enrollment. The study confirmed that major GPA admission restrictions were associated with a lower likelihood of a positive outcome for students.

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Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

College student retention, persistence, and completion have been well-established areas of research to assist colleges in determining the effectiveness of their degree programs and to help understand why students may not complete their intended major. Retention support is critical for the student and the institution and for society. Dr. Dursen Delen, a Regents Professor at Oklahoma State and retention researcher, described how improving college retention benefits everyone in the community. Public economic benefits include increased tax revenue and individual economic benefits through higher salaries. Higher retention also offers public social benefits (reduced crime rates) and individual social benefits (increased quality of life), which are too great to be ignored (Spears School of Business, 2017, para. 5). Dr. Delen further stated that "by increasing retention just by one percent, we can save millions of public dollars," and the institution itself also benefits from increased retention efforts through higher rankings, reputation, and financial well-being (Spears School of Business, 2017, para. 5).

The benefits and improved quality of life through earning a college degree are well-documented. College graduates can earn more than one million dollars throughout their lifetime and have an average income 65% higher than high school-only graduates. The personal benefits to students are also enhanced through higher education, such as advanced intellectual skills, personal health benefits, social and emotional benefits, and effective citizenship. Students earning bachelor's degrees have higher employment rates, greater career mobility, and more opportunities to work independently (Cueso et al., 2020, pp. xxiii-xxiv).

The national retention data trends also suggest the need to examine phenomena that can affect degree attainment rates. Recent six-year rates have slightly increased but have remained stagnant nationally. The six-year completion rate for the incoming fall 2016 cohort was 62.3%, unchanged from the 2015 cohort (62.2%). This infinitesimal increase followed a gain of 1.2% in the preceding year (National Student Clearinghouse Research Center, 2022, p. 1). The inability to complete a degree on time is also costing students financially, and the rising costs of college have made the next generation of students more debt-averse than previous generations. Research shows that the Generation Z proportion of prospective students who believed they would finance at least part of their college education with student loans, in contrast to the actual percentage of student loans awarded, was much lower compared to Millennials (Trovato, 2021, para. 3). The College Savings Foundation found that 54% of high school students were concerned about their ability to pay back college debt (Romney, 2018). The costs of college have continued to rise, with a 175% increase in tuition and fees over the past 20 years for public national universities, significantly outpacing inflation (Kerr & Wood, 2022). Given the high costs associated with attending college and their aversion to debt, students may be less inclined to stay in college than previous generations. The national retention data and financial burden demonstrate a need to develop support for students who may be in danger of not completing a degree.

One key contributing factor to inert national student retention rates is the Grade Point Average (GPA) restrictions that colleges implement for declaring specific majors (Bleemer et al., 2023; Bleemer & Mehta, 2021; Koshland & King Liu; Schmidt, 2021). Some students who persist to their third or fourth year may not achieve the required cumulative GPA to gain acceptance into a major. This could result in the student taking superfluous classes and earning inapplicable credits to improve their GPA. These extra courses would increase the time to graduation, increase the financial burden for the student, and lower the institution's retention rates. Students unable to gain acceptance to a major after their fifth term of enrollment are defined as stranded students for this study. The group status stranded or non-stranded serves as the key variable of interest in the study of pre-major students and students accepted into their major. To effectively examine the stranded students, “undeclared” or “exploring” majors are not included in the study as they have not indicated a major (or benchmark) GPA they are working towards. This is not to say that undeclared students are not becoming stranded as well, but their stranded story will not fully emerge until a pre-major is indicated.

While GPA restrictions may be an indication of a barrier to degree completion, becoming stranded is hypothesized to be an indication that a student has the academic momentum to persist through college and earn a degree. A student enrolled in their third consecutive academic year, despite not having been accepted to their major, demonstrates academic commitment and intention to complete their degree. This hypothesis is tested by examining measures of academic momentum benchmarks. Understanding the prevalence of stranded students, identifying the type of student who may become stranded, and learning if certain majors are strongly correlated with stranded status motivates the purpose of the study.

Purpose of the Study

The three main purposes of the study are to describe the characteristics of stranded students to examine the effect of major restrictions, provide recommendations to enhance early detection and intervention, and support degree completion leading to improved institutional retention rates. The issue of becoming stranded for undeclared third-year college students motivates the study’s purpose. Major GPA restrictions have been shown to reduce the likelihood that a pre-major student can successfully declare their intended major (Bleemer & Mehta, 2021; Bleemer et al., 2023; Schmidt, 2021). The results of the study will inform the prevalence of the stranded student issue, specifically what percentage of each cohort is becoming stranded and from which majors. Understanding the effect of meritocratic GPA policies on student success may be the impetus to drive institutional policy and improve institutional six-year retention rates.

Until policy changes are implemented, advisors must work within the regulations established to intervene and guide students to an obtainable and economically beneficial degree path. Support for students with stranded status motivates the proposed study's purpose, which first aims to help administrators identify students at risk of not gaining acceptance into their major. A student taking additional credits that do not apply to a degree will increase the effort spent, time to graduation, and financial burden. However, before spending resources on an intervention for at-risk students it would be pertinent to understand if the student is less likely to graduate (Singell & Wadell, 2010, p. 565). An important finding in the literature is that a targeted intervention through academic advising has been effective in improving future academic success (Aljets, 2018; Chen & Upah, 2018; Elrich & Russ-Eft, 2013; King, 2015; Mu & Fosnacht, 2013; Young-Jones et al., 2013). If an undeclared student is informed of their likelihood to declare their intended major during academic year three, it may help prevent a student from continuing down an unobtainable degree path and becoming stranded. Institutional efforts to help students find a path to degree completion can be considered an initiative designed to improve retention rates. The main goals of the study are to inform on the development of an early intervention with students that could help reduce their future financial burden, support degree attainment, and improve university retention rates.

College Major GPA Restrictions

The relevant history and background of college major GPA restrictions revealed that colleges can decide to implement such policies for assorted reasons, including preventing students from entering a career field in which they may not be successful and ensuring that students are intellectually and socially prepared to enter the workforce (Schmidt, 2021; Koshland & King Liu, 2018). College major restrictions may come in three forms:

> (1) In-major mechanical restrictions require students to achieve a GPA in the major's introductory courses above a minimum threshold,
>
> (2) Overall mechanical restrictions require students to achieve an overall GPA in their first year or two of college above a certain threshold and
>
> (3) Discretionary restrictions require students to submit a competitive application to the department; what criteria departments use to review the applications varies and is often not transparent (Bleemer & Mehta, 2023, para. 9).

This study will focus on part (2), noted above, by examining the effect of mechanical restrictions (cumulative GPA thresholds) on the likelihood of becoming stranded. Including part (1) in-major mechanical restrictions would require a more detailed analysis of each student's course history, as this analysis only seeks sample data that includes academic achievement at the semester level (GPA and cumulative GPA) to examine group differences. Also, part (3) discretionary restrictions are not included in the analysis as this data is often housed within departments, and students who are at the point in their academic career to submit an application to the major would likely meet the GPA restriction set by that major. The non-inclusion of part one and part three of Bleemer and Mehta's (2023) definition of GPA restrictions may be considered a limitation of the study.

Impact of Meritocratic Major Restrictions

To provide context to the study, examining the implications of GPA requirements on a student's ability to progress into their intended major program is essential. Among the few researchers who have examined college major GPA restrictions, Schmidt (2021) describes how a liberal arts college implemented core course grade policies based on high demand for the Economics major. When department resources are scarce, there are limited ways to regulate the number of students admitted to a major (p. 107). In an examination of their college's major restriction policies, Koshland and King Liu (2018) of the UC Berkeley Academic Senate Committee on Educational Policy, found some major restrictions dated back to 1938, when Economics required a minimum grade point average of 3.0 (p. 5). With institutional policies implemented based on the preferences of each university, it is difficult to determine the specific origin of major restriction policies. The adoption of such policies appears to be a combination of demand, resources, student preparedness, and university prestige. The impact of meritocratic major requirements has been efficient in limiting the number of students who can declare their intended major.

The GPA major restrictions implemented at colleges and universities appear to have little to no benefit for the student. Research shows that low-GPA students are no less likely to graduate if they were permitted to seek a restricted major, the labor market value of degrees awarded by restricted majors is no higher than it had been before the restriction was implemented, and restrictions ultimately exclude the students who have the most to gain (Bleemer et al., 2023). Schmidt (2021) examined policies implemented at a liberal arts college and found the major restrictions were effective in decreasing demand by limiting the number of students who are eligible for admission to the Economics major, while also increasing student effort and learning in core pre-major courses. Their study also notes previous work by Professor Eshragh Motahar, whose survey of 32 top liberal arts colleges revealed that all but one limited access based on grades in either introductory or core courses (p. 107).

Bleemer and Mehta (2021) examined the enrollment of underrepresented minority students following the implementation of major GPA restrictions at national public research universities. A review of the five highest-premium majors at the top 25 schools found that three-quarters had university course GPA restrictions, including every Nursing major and nearly all Mechanical Engineering and Finance majors (p. 2). The findings also indicate that "major restrictions reduce the number of students who declare the restricted major," and underrepresented minority students are over twice as likely to exit the major than non-underrepresented minority students (p. 13). Major restrictions also decreased the likelihood by 15% that students who intend to enter the restricted major can successfully declare their intended restricted major.

Major restrictions appear to have a greater impact on underrepresented minority students (URM). Bleemer et al. (2023) later examined major restrictions at 106 public universities with R1 research status and found that URM students were three times more likely to leave a major once a restriction was imposed, compared to their non-URM peers (para. 15). The results of these restrictions force URM into less lucrative majors. The authors also found that 55% of students needed to overcome major restrictions to graduate and 20% needed to overcome a mechanical (cumulative GPA) restriction (para 13). Bleemer et al. (2023) also note that when low-GPA students are admitted to their major, they achieve greater long-run employment benefits. Therefore, GPA restrictions are not "employer-friendly and do not meaningfully enhance the earnings of graduates in those majors" (para. 19). This study will build upon the Bleemer (2023) study by examining the rates of major change of minority and non-minority students.

The literature validates that college major GPA requirements can be a challenge for undergraduate students to overcome and declare their major (Bleemer et al., 2023; Bleemer & Mehta, 2021; Schmidt, 2021). The restrictions do appear to have the effect of limiting the number of students who can enter a specific career field. The studies related to GPA requirements highlight the recent interest in institutional policies and how these relate to broader inequality (e.g., Bleemer's recent work). As major restrictions become continually ubiquitous, students are forced to navigate a series of barriers that have a greater impact on low-GPA and underrepresented minority students. Research has also indicated a student's decision of college major, in either a STEM or non-STEM, can affect their ability to persist (King, 2015; Whitcomb et al., 2022).

Persisting to Intended Major

The rate of student persistence has exhibited a correlation to the type of degree selected. Students who enroll in STEM majors have been shown to have lower persistence rates compared to other business or non-STEM majors. Spight (2022) examined a population of 4,489 full-time, first-time college undergraduates from a Western research university and discovered that early declaration of a pre-major did not have a significant effect on graduation rates. Whether a student matriculated as undeclared versus with a major declared, neither population had a significantly greater likelihood of graduating on time (Spight, 2022, p. 954). Whitcomb et al. (2022) investigated trends in the undergraduate majors that students are declaring, dropping, or completing their degrees at a public high-research institution. A binary flag analysis of 18,319 undergraduate students from a large public research university found that students in majors such as psychology, computer science, and non-STEM were the least likely to drop their major. Most of the students who dropped STEM majors did not earn a degree or moved to non-STEM majors (2022).

In a logistic regression analysis of 12,144 responses from the *National Education Longitudinal Study*, King (2015) examined the persistence rates of physical science/engineering (PS/E) majors compared to students in majors from all other disciplines. The results indicated that students in business, education, and humanities have higher persistence rates than students in PS/E, and social science had a lower rate of persistence (p. 48). Despite being more prepared for college, students in the PS/E had lower persistence rates. College achievement is more directly correlated with PS/E students persisting than non-PS/E degree students. This research is important for the study as it helps to understand the type of majors that are less likely to persist, which is also examined as part of the study.

Switching majors may also be a factor in becoming a stranded student. Schudde et al. (2020) conducted a regression analysis of 22,532 student records from the *BPS:12/17* national survey and found nearly 40% of students changed their major at least once, and 59.6% of undeclared students were still undeclared three years later. Students who sought advice from an academic advisor or who did not stop out were less likely to change majors (p. 210). The findings related to third-year students are particularly insightful for this study, as students who remain undeclared after three years may become stranded if they are not accepted to their intended major.

The time needed to graduate may not be impacted by an early declaration of a major. However, declarations of STEM-based majors may be more likely to drop their major, resulting in more time to complete, or the possibility of becoming stranded (King, 2015; Spight, 2022; Whitcomb et al., 2022). Meeting with an academic advisor can help students stay on track with their intended major and lower the odds of becoming stranded (Faulconer et al., 2014; Gordanier et al., 2019; Hanover Research, 2014; Schudde et al., 2020; Tampke, 2013; Zhang et al., 2014). Becoming stranded in their third academic year should be a central data point that academic advisors use for targeted intervention. Further, students who are still enrolled in their third academic year are displaying an ability to persist, despite not yet receiving acceptance into their major. This study seeks to understand if stranded students display the academic momentum indicators to persist in their major and complete their degree. Stranded students with characteristics of academic momentum justify specialized support and resources devoted to their academic success. The literature on early alert, advising intervention, and completion initiatives are all examples of the higher education field's focus on early momentum, but there are students who may still be stranded despite those efforts. The theoretical framework of academic momentum, developed by Cliff Adelman (1999, 2006), provides several indicators that can inform the type of students who will become stranded.

Academic Momentum

Cliff Adelman (1999, 2006) theorized that a student's academic momentum can help explain degree completion. Since it is hypothesized that a stranded student is exhibiting signs of completing their degree, Adelman's (2006) theory of Academic Momentum informs the study by providing a lens through which to view the story of a stranded student. While Academic Momentum Theory is applied to explain degree completion, the ability to declare a major is a critical milestone in that process. This link further explains the connection to the study. The inclusion of academic momentum variables in the analysis, such as GPA benchmarks and continuous enrollment, will support the justification of a targeted intervention by demonstrating if academic momentum benchmarks exist for stranded students. A review of the literature on college retention, GPA major restrictions, and early intervention motivates the research topic and informs the study's rationale and significance.

Study Rationale and Significance

The study aims to contribute to the limited amount of research on GPA restrictions and will also subsidize the growing research on academic momentum, student retention, and at-risk college students. The study seeks to increase awareness regarding the stranded student issue facing second and third-year college students, which is a relatively unexplored area of research. The analysis will examine how major restrictions contribute to the likelihood of becoming stranded in numerous ways. For example, if both a student who has been accepted into their program and a "pre-major" student has 70 cumulative credits, are there significant differences in their academic momentum benchmarks or other student characteristics? The application of certain academic variables will contribute to Adelman's (2006) findings on the relationship between academic momentum benchmarks and degree completion. The study will extend the work of Adelman (2006) by including academic probation, consistently low academic performance, choice of college, and choice to change pre-major as potential indicators of academic momentum.

The study will also contribute to the limited amount of research on the influence of GPA restrictions by determining if major restrictions are impacting certain groups of students, including underrepresented minority students (Bleemer et al., 2023; Bleemer & Mehta, 2021). The study will also support the findings on the relationship between the type of major and student persistence (King, 2015; Spight, 2022; Whitcomb et al., 2022).

The research will illuminate the phenomenon of stranded students and generate ideas for future research avenues. The significance of the findings could lead to institutional policy changes or added support initiatives. For example, suppose a group of students within a college are in a situation where they are unable to declare a major. In that case, this is critical information for the department administrators to either enact intervention or policy change to support degree completion. The impact of meaningful intervention is further discussed in the literature review. A set of research questions has been developed to guide the examination of GPA restrictions and stranded status.

Research Questions

To achieve the study's goal and determine if a student with stranded status can realistically be identified, predicted, and supported there are three main research questions.

1(a). What are the demographic and academic characteristics of students who have "stranded status"?

1(b). To what extent are there differences in academic momentum indicators of the stranded status group and the non-stranded status group?

2. Which majors are more associated with stranded status?

3(a). What academic and demographic indicators are predictive of stranded status?

3(b). Do these relationships vary across colleges?

The research questions are examined through a quantitative design approach.

Overview of Research Design

The inability of motivated students to otherwise declare a major due to meritocratic GPA restrictions can lead to the completion of courses not applicable to the intended degree and a student becoming stranded without working toward specific degree requirements. Obtaining a sample of the stranded students is the first step in the research.

Sample

Employing a quantitative approach, the analysis will first determine which students would be considered "stranded" for this study. A non-probability sample from the 2013-2016 incoming student cohorts at a Southwestern university are identified through specific criteria relevant to the study (credits earned and acceptance, or not, into a major program). A descriptive statistics analysis will determine the stranded status group (SS) and non-stranded status group (NSS) for comparison.

Table 1

Stranded Status Group Membership

Student Characteristics	SS	NSS
Indicate a Pre-Major	X	X
Earned >70 Credits by Term 8	X	X
Declared Major by Term 5		X

Note. SS = Stranded Status and NSS = Non-Stranded Status.

As discussed, there may be other requirements that prevent a student from declaring or being part of the "stranded" group, such as a minimum grade in an introductory course or application process, but those requirements are beyond the scope of the analysis. For the data analysis in the study, SS membership is defined by the student's decision to choose a pre-major and reach the accumulation of 70 credits without a declared major by the fifth term (Table 1). A 70-credit benchmark used for the study is based on the 15-to-finish initiatives established by academic advising centers (Complete College America, 2022; University of Maine, 2023). The advising initiatives suggest students should be completing their pre-major requirements, or at least 60 credits, by the conclusion of the second academic year. To capture the diverse range of course-taking behaviors such as earning fewer than 15 credits per semester, enrolling in remedial courses, or repeating courses, data is gathered through the student's third academic year. This ensures differences in students' decisions are adequately accounted for.

Data Analysis and Methods

The analysis of stranded and non-stranded students will follow similar methodologies of group comparison studies (Eveland, 2019; Hall & Ponton, 2005; Ngamsiriudom et al., 2022). Once the sample is established through data collection, a descriptive statistical analysis will report the variable frequencies and mean differences of GPA variables between the SS and NSS groups. A Chi-square test of Independence will determine if students who are considered "stranded" are also significantly associated with academic momentum benchmarks such as course withdrawal rates, continuous enrollment, and summer term enrollment. An Independent t-test is used to examine the association of scale variables such as First-year GPA, Second-Year GPA, and cumulative GPAs. A two-column chart is provided, including academic and demographic variables, along with the averages for each group to describe the sample. The variables with significant differences are indicated.

Next, a comparative analysis will demonstrate if the meritocratic GPA policies of specific majors and colleges are significantly associated with stranded students. A binary logistic regression will provide the odds of students becoming stranded based on their selection of certain majors and colleges. A frequency distribution of SS and NSS students in each major will illuminate the impact of each major's restrictions on a student becoming stranded. To initiate institutional policy changes or enact a robust intervention program, a critical starting point will be identifying which majors and colleges are contributing more to the stranded student issue. This links GPA restrictions and their relationship to the stranded student.

Academic and demographic differences between the stranded status group and the rest of the cohort are further examined in the final part of the analysis. The analysis will determine which academic and demographic characteristics are significant predictors of stranded status group membership. A logistic regression analysis method is modeled by the methodological approaches of research on at-risk students (Del Prette et al., 2012; Gilstrap, 2020; Glynn et al., 2011; Nichols et al.,1998; Singell & Waddell, 2010; Zhang & Rangwala, 2018). This methodology has been used to examine if a set of defined independent variables can predict a future at-risk student. Some of the key student variables in the analysis include a student's academic probation status, history of academic performance, choice of major, and decision to change a major. The study will use theoretical variables from Adelman (2006) and explanatory designed variables to determine if certain characteristics can be used to help academic advisors predict a student who may be at risk of becoming stranded. Interactions by College type will also be utilized to examine if a combined set of student choices and characteristics is more likely to predict SS. The quantitative research design and analysis procedures in Chapter 3 will further provide details of the study's methodology. A set of definitions are included for the analysis.

Definition of Terms

The study will utilize specific language that should be defined for the reader for a better understanding of the analysis.

Pre-major students - students who have not been accepted by a college into a major program but chose a pre-major program.

Declared students - students who have been accepted by the college into a major program.

College Type – The schools within the institution where major types are contained, such as the College of Engineering, or College of Education.

Major Type – The specific major selected by the student within a college such as Accounting, or Computer Science.

GPA Restrictions - cumulative GPA admission requirements that are set forth by the colleges that serve as a benchmark to gain acceptance into the major program.

Stranded Students - pre-major students who did not declare a major by term 5 and accumulated 70 credits by term 8.

Non-Stranded Students - pre-major students who declared a major by term 5 and accumulated 70 credits by term 8.

Non- or Not-applicable Credits - any credits earned by students that will not have a direct application on their degree requirement worksheet; a completed course that ends up valueless.

Summary

Finding new ways to identify at-risk college students is critical to the success of the institution's retention efforts and its students. The quantitative analysis will seek to determine if GPA restrictions affect a student's likelihood of becoming stranded. An examination of student variables will help college administrators identify variables that can be used to predict a student who is at risk of stranded status. Helping students achieve academic success through an obtainable degree path will improve retention, persistence, and completion rates for the institution, as well as lower the financial burden for the student and improve their chances for higher lifelong earnings. To add context to the type of stranded student, Adelman's (2006) theories on academic momentum provide a series of benchmarks to be examined throughout the postsecondary career. The theoretical framework and explanatory designed variables are discussed in the next chapter.

Chapter 2: Literature Review

Introduction

An extensive focus in higher education literature has been directed toward understanding the factors contributing to college students' postsecondary success. Research has shown the importance of student success initiatives to support degree completion such as summer bridge programs (Howard & Sharp, 2019; Stolle-McAllister, 2011), tutoring support (Batz et al., 2017; Hockings et al., 2008; Stranger-Hall et al., 2010), peer-led supplemental instruction (Malm et al., 2018; Skoglund et al., 2018), faculty to student mentoring (Chelberb & Boseman, 2019; Law et al., 2020; Lisberg & Woods, 2018), peer mentoring (Dennehy & Dasgupta, 2017; Flores & Estudillo, 2018), and first-year seminar programs (Cueso, 2015; Jenkins-Guarnieri, 2015; Krsmanovic, 2019; Swanson, 2017). Simultaneously, policies have been enacted, sometimes in response to research findings, to enhance retention, persistence, and graduation rates.

For example, 15-to-finish initiatives have been designed to keep students motivated toward a goal, keeping them on a path to degree completion (Complete College America, 2022; University of Maine, 2023). Additionally, early alert systems have been designed to identify at-risk students, which guide intervention strategies (Faulconer et al., 2014; Gordanier et al., 2019; Hanover Research, 2014; Tampke, 2013; Zhang et al., 2014). Targeted interventions are designed to assist in overcoming challenges progressing toward degree completion and *not* becoming a stranded student. This review highlights and summarizes the research on the intervention avenues developed, such as academic advising early alerts, and the impact of targeted academic advising on retention. An overlooked area is the issue of stranded students, defined above as students in their third academic year who were unable to declare a degree. The literature also suggests that college major GPA restrictions have the opposite effect as student success initiatives and limit students' ability to declare a major (Bleemer et al., 2023; Bleemer & Mehta, 2021; Schmidt, 2021). An intervention by academic advisors of students at risk of becoming stranded can help support retention, persistence, and degree completion.

The literature review process began with a drafted outline of the concepts associated with student retention and persistence and how these relate to college major GPAs, including major declaration and major restrictions, research related to at-risk students, and student momentum theories. Search terms were input into the university libraries database, which included searches of ERIC, EBSSOhost, and SAGE databases for relevant topic terms, and included a filter for peer-reviewed journals. Google Scholar was also utilized with the same search terms and parameters. Recent and relevant articles were searched using criteria of 2013-present, including expanded year ranges to increase search results when needed, and with the year filter removed for searches on theoretical frameworks. Some of the key search terms utilized in the process included: *college major GPA admission requirements, college major GPA restrictions, college major declaration, at-risk college students, academic momentum, college student momentum*, *academic advising and student success, college student early alert, college student intervention, and academic advising intervention.*

With a key purpose of the study to provide intervention to students regarding their likelihood to complete their intended degree, a discussion of the literature begins with an overview of the types of systems that institutions have implemented to target at-risk students early in their postsecondary careers. An examination of intervention results will provide an understanding of their impact on student success.

Early Alert Systems

An early alert system can be a critical component for administrators to improve student achievement and retention rates. Early detection and intervention of at-risk students are shown to be effective in supporting student retention (Faulconer et al., 2014; Gordanier et al., 2019; Hanover Research, 2014; Tampke, 2013; Zhang et al., 2014). Early Alert systems use "software to provide a formal, proactive feedback structure through which university faculty alert students and their campus support agents to issues impacting academic performance" (Faulconer et al., 2014, p. 45). Approaches to following up with students could include multiple contacts by faculty and staff through traditional methods of e-mail, cell phone, text messaging, or through an online learning system.

A report by Hanover Research (2014) found that early alert systems are most effective when targeting specific student populations, such as at-risk students, and nearly 90% of four-year institutions have an early alert system (p. 3-5). Also, an effectual intervention strategy is critical to achieving results. Institutions may not require action by the student after an alert is received; however, an "intrusive posture of this sort may be necessary to facilitate full effectiveness" (p. 4). The Hanover Report (2014) also found that the early alert system's efficacy in improving retention has been mixed, with a need for more empirical evidence with conclusive results (p. 7).

Assessing retention efforts includes the examination of students who are considered "at risk" of dropping out of school, or students who are in danger of "educational failure either by failing to learn while in school or by dropping out of school altogether" (Kaufman, Bradbury, & Owings, 1992, p. 1). Students from low socioeconomic backgrounds, from minority groups, and whose parents did not attend college are at higher risk of dropping out (p. 1). By identifying at-risk students early in their academic careers through an alert system, institutions can enhance areas of student support and improve institutional retention rates. Assisting at-risk students to an obtainable degree path will also help limit the financial burden associated with attending college. Early alert systems and targeted intervention have been effective overall in supporting students who may be considered at-risk (Faulconer et al., 2014; Gordanier et al., 2019; Hanover Research, 2014; Tampke, 2013; Zhang et al., 2014). It is essential to examine the effectiveness of early alert systems that have previously been implemented.

Supporting Degree Completion with Early Alert Interventions

Student outcomes within institutions have been examined to determine the impact of early alert programs. Vilano et al. (2018) examined an early alert system's relation to student retention at a regional university. The institution implemented a customized early alert system called Automated Wellness Engine (AWE), which used "student-level information from a data warehouse to analyze, flag and report students deemed at risk of disengaging from their studies" (p. 905). A total of 34 triggers of demographic, institutional, student performance, and workload variables were used to identify at-risk students. Data points included alternate admission, residency, enrollment credits, portal usage, and failing grades received. The survival analysis approach of 16,142 students found that an early alert system was effective in identifying students with significantly higher risks of discontinuing their studies (p. 908).

Tampke (2013) examined the implementation of an early alert system at a large, public university in the Southwest through a mixed-method approach. Students were identified by instructors using the system PeopleSoft. Indicators for early alerts included attendance, class performance, class participation, and concerns over major, among others (p. 529). Comparing academic outcomes between alerted and non-alerted students, the analysis of 255 referrals by 87 instructors found the intervention with the faculty had a significant impact on student success, and to a lesser degree meeting with staff from the Early Alert Referral System (EARS) also improved student success (p. 527-531). Tampke (2013) found EARS contributes to targeted interventions, allowing students to receive support before their academic struggles escalate. The article also highlights the importance of continuous EARS assessment to ensure effectiveness in predicting at-risk students.

Faulconer et al. (2014) examined survey data of faculty, advisors, students, and network administrators to determine the effectiveness of an early alert system. Their institution implemented the Starfish Retention Solutions system designed to provide early alert flags, student monitoring, reporting, and a student support network (p. 46). The system used analytics related to student grades and absences to create over 28,000 student notifications during the Spring and Fall semesters. Through the course of one academic year in 2011, flag notifications were directed to students regarding their academic status by 38% of the campus faculty. The results indicated that more than 80% of faculty considered early alerts to be effective and 85% of students who received an academic difficulty flag acted on the notification (p. 47). The success of an early alert system depends on the intervention's timeliness to support student retention.

Zhang et al. (2014) employ quantitative methods, including regression analysis and t-tests, to assess the impact of a targeted intervention of at-risk business students at a minority-serving institution. The data point of failing midterm grades was used to identify the students considered at-risk. The logistic regression analysis of 128 at-risk students indicated that students who participated in an intervention with academic advising achieved higher GPAs, received passing grades at a higher rate, and had lower withdrawal rates (p. 4). The regression analyses demonstrated a positive relationship between intervention and future academic success.

Gordanier et al. (2019) also examined a targeted early intervention of 640 at-risk economics students at the University of South Carolina. Based on the criteria of a 70% score in the courses, 18% of the group was targeted for intervention. A sharp regression discontinuity design found that students “performed 6.5% to 7.5% better on a set of questions on the final exam than students who were just above the threshold” and students who were least prepared to enter college benefited the most from the intervention (p. 28). A review of the literature on early alert interventions demonstrates some of the efforts that have been tried to affect degree completion and persistence. The research validates that a well-targeted and timely intervention can improve the chances of future academic success. Oftentimes, academic advisors are tasked with providing these timely interventions to students. An issue could arise when students are not promptly notified of their academic challenges by their advisors, potentially increasing their likelihood of becoming stranded. A review of the literature has revealed a positive relationship between impactful academic advising and future academic success.

Academic Advising Impact on Retention

As students advance through their first two years of postsecondary education, academic advisors play a critical role in the retention, persistence, and completion efforts of the university. Advisors can identify systemic barriers, share knowledge on cross-campus student success initiatives, and make impactful connections with the students (Aljets, 2018). Through working with students daily, advisors inherit an understanding of the barriers to academic success. This area of student support must be addressed as poor academic advising can potentially be a factor in a student becoming stranded.

Young-Jones et al. (2013) evaluated academic advising from the perspective of student needs, expectations, and success. The three-part quantitative analysis of 611 undergraduate students at a Midwestern university found that academic advising can “impact all facets of a student’s academic experience, ranging from the development of self-efficacy to practical applications of study skills” (p. 15). The results further indicated that advising effectively supports the institution’s retention efforts (p. 15). Chen and Upah (2018) examined the influence of predictive analytics on academic advising. In their quasi-experimental study of 125 first-year first-term, undeclared engineering students at a large Midwestern university, logistic regression analysis discovered that students who received analytics-informed advising were significantly more likely to change majors. Also, the authors discovered that student characteristics of first-term credits completed, and ACT scores were significant predictors of changing a major (Chen & Upah, 2018). This finding supports the idea that targeted intervention can direct a student to a more obtainable degree path and avoid becoming stranded.

The impact of academic advising was also examined by Mu and Fosnacht (2019), who reviewed survey data from the 2014 National Student Survey of Engagement (NSSE). The multivariate analysis of 26,516 senior undergraduates from 156 bachelor-granting colleges and universities determined that students’ self-reported gains increased with each academic advising visit (p. 1294). Also, their analysis indicated a “significant and positive correlation between the number of advising meetings and grades” (Mu & Fosnacht, 2019, p. 1299). Elrich and Russ-Eft (2013) further assessed student experience with academic advising to identify possible changes in students' self-efficacy and self-regulated learning-strategy levels following academic advising. Utilizing a post-advising sessions survey of 120 community college students, the results suggested that students who participated in academic advising experienced increased levels of self-efficacy and self-regulated learning strategy. A review of the literature on the impact of academic advising and targeted interventions has shown to have positive effects on students’ academic success and university retention efforts. Academic advisors are often guided by institutional completion programs to keep students on track such as the Fifteen to Finish, Finish in Four, and Think 30 (University of Maine, 2023).

Institutional Completion Programs

Guided by today's "15 to Finish" initiatives in advising centers, motivated students work to complete the suggested number of credits each semester. Completing 12 credit units instead of the recommended 15 in the first term and fewer than 30 credits within the first year hinders future degree completion (Attewell & Monaghan, 2016; Belfield et al., 2016; Davidson & Blankenship, 2017). Additionally, a lack of pathway classes or inadequate guidance by the academic advisors could lead to becoming stranded, despite the students' best efforts to remain on a "15 to Finish" track. Currently, over 25 states and 200 institutions have implemented a 15-to-finish policy initiative to encourage students to remain on track for graduation (Complete College America, 2022). This suggested plan would require students to complete 60 credits by the end of their second academic year.

Despite progressing as advised, the ability to declare a major can be a critical factor that affects momentum toward degree attainment. While students may have earned a substantial number of credits, GPA restrictions within specific majors could impede their advancement toward degree completion. To determine if students who are stranded exhibit signs of momentum to complete their degree, Cliff Adelman's (2006) work on academic momentum provides a theoretical framework for the analysis.

Theoretical Framework

The theoretical framework of Adelman's (2006) academic momentum model will first be discussed as the guiding framework for the study, followed by a review of the literature on the ways academic momentum has been used in higher education research to explain degree completion. It is hypothesized that students with strong indicators of academic momentum, but who are also at risk of not gaining acceptance into a major, could be in danger of becoming stranded. Adelman (2006) notes that academic momentum is best examined following at least two academic years. This analysis will assess academic momentum during the third academic year, following Adelman's suggested approach to examining academic progress. Stranded students should be of critical importance to administrators as exhibiting signs of academic momentum implies, they have the characteristics to achieve a degree.

Attewell et al. (2012) note the speed with which undergraduates initially progress in college significantly affects their likelihood of completing a degree, an effect separate from those of high school academic preparation and family socioeconomic status (para. 1). However, Adelman (2006) also suggested that student choices such as summer-term credit generation, meeting the challenge of college-level mathematics, the effort required to yield a rising GPA, and remaining continuously enrolled, all reflect continuing leverage of attainment (p. 80). A student's academic momentum will position them for a greater likelihood of degree completion, but it also may contribute to future credit loss if certain benchmarks are not attained during their first three postsecondary years.

Academic Momentum Model

Cliff Adelman first introduced the concept of academic momentum in 1999 and later revised it in 2006. There is no clear definition for academic momentum, however, several researchers have adapted the core components to create their own definition (Davidson & Blankenship, 2017, p. 467). Adelman's (2006) academic momentum perspective "suggests that the speed with which undergraduates progress during the early phase of college significantly affects their likelihood of completing a degree" (Attewell et al., 2012, p. 39). As a variation of the human capital "investment model," Adelman's "investment behaviors" suggest that students invest in their education and future through academic commitment of time and effort (p. 80). Each positive investment action can serve as a foundation, creating momentum toward achieving academic goals. The academic momentum perspective also assumes that institutional opportunity plays a role in the student's story where provided there is opportunity, the choices made by students provide subsequent leverage (p. xxiv). Adelman's (2006) study focuses on the moments where "student choice intersects the structures of opportunity offered by institutions" (Adelman, 2006, p. 84).

Tracking a national sample of millions of 10th-grade students, Adelman's (1999) original regression analysis of a national 10th-grade cohort used high school and college transcripts, test scores, and surveys to determine that academic resources and continuous enrollment were significant factors related to degree completion. A key point in Adelman's (1999) original analysis notes that the amount and type of intervention matters concerning a student's degree completion. Targeted intervention is the purpose of this research study to help administrators identify students at risk of becoming stranded and provide them with a realistic probability of degree completion. Adelman (2006) later revisited the academic momentum model using *National Education Longitudinal Survey* data of 12,000 students from eighth grade in 1988 to December 2000 (p. 3). The results mirrored his original study's findings and determined postsecondary benchmarks (credits earned at the end of the calendar year), students' use of time (summer courses, continuous enrollment), and academic performance (GPA ranks) as the critical components of academic momentum.

The academic momentum model also guides the use of three specific variables to strengthen the GPA rank variable, including first calendar year GPA, cumulative GPA for the first two calendar years, and GPA as of the last date of attendance, whether a degree was earned (p. xxii). Both the speed of progression (continuous enrollment) and student choices (summer classes, completing college-level math, financial aid) are utilized as variables in the analysis. It is imperative to evaluate how each of the academic momentum independent variables adapted for the analysis is related to student retention and the dependent variable of stranded status.

First-Year GPA

Researchers have utilized GPA after the first academic year in student retention analysis as a predictor of academic achievement, demonstrating that first-year GPA scores are correlated with student persistence rates (Adelman 1999, 2006; Clovis & Chang, 2021; Collings & Eaton, 2021; Ishitani, 2016; Martin et al., 2013; Muller et al., 2017; Singell & Waddell, 2010). Students who can earn grades in the top 40% of their cohort exhibit strong indicators of academic momentum and degree completion (Adelman, 2006, p. xxii). GPA can assess student effort, which contributes positively to degree completion (Adelman, 2006; DesJardins et al., 2002). The application of a first-year GPA variable in the analysis will compare stranded status students with non-stranded status students to determine if there are significant differences between the groups. For example, if the stranded status group has significantly lower first-year GPAs, it may be considered a significant predictor of stranded status. If a considerable number of the stranded status students' first-year GPAs are found in the top 40% of the cohort, it will also demonstrate signs of academic momentum.

Second-Year GPA

A full perspective of the student's progress can be assessed by examining their academic success at certain points in time. Adelman (2006) notes that a student's second academic year offers the opportunity to recapture any lack of momentum of the first, and the second year maybe even more important than the first (p. 53). The analysis shows substantial differences in graduation rates between students with higher second-year GPAs compared to students with lower second-year GPAs (p. 55). Including the second-year GPA variables provides context to the student's reasoning for stranded status. For example, a strong second-year GPA could demonstrate academic momentum, but poor academic performance in first-year GPA could also prevent the student from gaining acceptance to a major due to cumulative GPA restrictions. A poor second-year GPA could potentially lead students to retake classes or complete non-major classes to improve their cumulative GPA, which could lead to stranded status.

Cumulative GPA

Stranded status may occur when the student has completed the pre-major course requirements, but the cumulative GPA does not meet the requirement for the major. This data point is critical to explore as it provides a fuller assessment of the quality of student effort throughout an entire undergraduate career. By the end of the second academic year, the students who can earn more credits and higher GPAs are more likely to graduate (Adelman, 2006, p. 61). Slanger et al. (2015) used cumulative GPA as part of the definition of student success and the key variable of interest in their analysis (para. 1). Cumulative GPA has been utilized as a variable to examine correlations to retention (Adelman, 2006; Blekic et al., 2020; Cochran et al., 2014; Farmer et al., 2016) as well as assessing the persistence of at-risk students (Gilstrap, 2020). The use of the cumulative GPA variable provides context to the student's trend toward academic success by examining grade point averages at three points in time, compared to only two points in time in Adelman's (1999) original *Toolbox* (p. 69). The cumulative GPA requirement is utilized to determine stranded status group membership.

Continuous Enrollment

Academic Momentum considers the student's use of time, including continuous enrollment and summer term enrollment. When controlling for all other factors, Adelman (2006) found that continuous enrollment increased the probability of degree completion by 43% (p. xxi). As noted by Adelman (2006), continuous enrollment is a key indicator for analyses of postsecondary careers (Carroll 1989; Astin 1993; Horn 1998; Berkner, He, & Cataldi, 2002) (p. 73). Continuous enrollment has also exhibited a positive correlation with degree completion (Auburn University, 2008; Chen and Carroll, 2005; Offenstein et al., 2010). As a benchmark for the study, the indicators of continuous enrollment will include students with less than one and less than two semesters of dropout. Students continuously enrolled in their third academic year without acceptance into a major may be at risk of stranded status.

Summer Term Enrollment

Adelman describes how a student's use of the summer term can be a degree completion lever, and more students are maximizing this opportunity (p. 109). A student who enrolls in courses over the summer term is demonstrating a positive sign of academic momentum. Students who earn summer credits are 11.2% more likely to graduate and earning more than four summer credits has a considerable influence on degree completion (Adelman, 2006). Summer term enrollment has been used as a variable to examine degree completion (Adelman, 2006; Atwell, et al., 2012; Davidson, 2014; Offenstein et al., 2010, Wang et al., 2015). As an indicator of academic momentum, the summer term enrollment variable is included in the analysis to analyze differences in summer term enrollment between the stranded students and non-stranded students.

For example, a stranded student who has completed a summer class is still exhibiting signs of academic momentum.

Remedial Courses

Dichotomous variables used by Adelman (2006) included whether a student took any remedial courses in the first academic year and whether the student earned any credits in college-level mathematics during the calendar year following first enrollment, where college-level mathematics was defined as college algebra, finite math, statistics, pre-calculus, and calculus (p. 18). In the Toolbox Revisited, Adelman's (2006) remedial variable is referred to as the "Remedial Problem," in which any remedial courses in the first calendar year are categorized as a dichotomous variable. The remedial problem is highlighted by Jimenez et al. (2016), who found that students paid approximately $1.3 billion in yearly out-of-pocket costs for remediation in all 50 states and the District of Columbia (p. 2).

Research has been varied on the outcomes of students who enrolled in remedial courses. While some literature shows that remedial coursework does not lead to positive student outcomes (Jimenez et al., 2016; Martorell & McFarlin, 2011), additional research found that "remediation appears to increase student persistence, but that increased persistence has only a minimal impact on degree completion" (Calcagno & Long, 2008, p. 31). Scott-Clayton and Rodriguez (2015) found that remedial courses did not discourage persistence and remedial work appears to be diversionary, where students "generally enroll and persist at the same rates but simply take remedial courses instead of college-level courses" (p. 6).

This study does not separate Math and English remedial, which replicates Adelman's (2006) findings where any remedial course taken in the first two years was the only "minimal statistical criteria for entrance into the stepwise logistic model" allowing to "track any association of early remediation with degree completion" (p. 187). Enrolling in remedial courses during the first academic year would result in a great accumulation of credits not applicable to a degree, and a student becoming stranded.

Academic Momentum in Relation to Stranded Status

Attewell et al. (2012) describe the three parts of academic momentum as the student's initial academic course load and progress, which set a trajectory that strongly influences subsequent degree completion. Next, early momentum is associated with degree attainment over a student's sociodemographic background and high school academic preparation. Lastly, enrolling in summer courses may provide practical interventions for improving completion rates (p. 27). A key component of the research study examines the student's progress following the accumulation of at least 70 total credits. Adelman (2006) describes how academic histories cannot be fully assessed until after the second year, following college entry and examining the extent to which students have completed their pre-major courses. At this point, the student's postsecondary story fully emerges and provides an opportunity to set benchmarks for academic advice and intervention (p. xix). The analysis will examine if any of the academic momentum benchmarks from years one and two are predictive of becoming stranded in year three.

It is hypothesized that students who continue to matriculate through their second year of college without declaring must possess characteristics of academic momentum to remain enrolled, despite not making progress toward their intended major. A comparative analysis of academic momentum characteristics between stranded and non-stranded students will assess this correlation hypothesis. Alternatively, it may be the case that students who do not demonstrate traditional characteristics of academic momentum may be more likely to be stranded. For example, it may be possible that students with consistently low GPAs are more likely to be stranded by not meeting a GPA admission requirement. This will be informed by the inclusion of framework-designed explanatory variables, beyond the academic momentum indicators, to determine if different academic characteristics are significantly correlated with stranded status, such as a low GPA, Pell Grant status, or other student demographics.

Stranded students with strong academic momentum should be a focus for administrators to help the student continue on an educational path and improve the institutional six-year retention rates. However, little is known about this population of students and what academic experiences they had in their first two years of college that may have led them to the stranded situation. Academic momentum has been used by previous researchers to explain progress toward degree attainment and degree completion (Adelman, 1999, 2006; Attewell et al., 2012; Clovis & Chang, 2021; Davidson & Blankenship, 2016; Martin et al., 2013, Wang et al., 2015). Given its focus on milestones in a student's academic journey, the Academic Momentum model can also serve as a framework for advancing this study of stranded students. Examples of the theory applied as a theoretical framework in higher education research are further discussed.

Academic Momentum as Theoretical Framework in Research

Higher Education researchers have adopted parts of Adelman's (2006) Academic Momentum model to examine degree completion among first and second-year college students. Attewell et al. (2012) examined eight years of student data from the *NELS:88/2000* national survey. Their growth-curve analysis of the 1988 incoming cohort found that enrollment in fewer than 12 credits in the first semester and taking summer classes after the first academic year affected degree attainment. Attewell et al. (2012) adapted Adelman's model of academic momentum to include credit hours *attempted* in the first semester as an additional indicator of academic momentum. The findings are consistent with Adelman (2006), demonstrating that early academic success predicts subsequent academic success and degree completion (Attewell et al., 2012).

Davidson and Blankenship (2017) examined 172,827 student records from two-year and four-year public institutions in Kentucky to examine the relationship between initial academic momentum and credits earned, persistence, degree completion, and socioeconomic status. Their definition of academic momentum included *earned* college-level credit hours and enrollment in remedial education courses was not included. The results of the descriptive statistics analysis found that students who earned 30 credits in their first academic year had a higher chance of persistence and an 80% chance of completing their degree within six years (p. 474). Wang et al. (2015) defined academic momentum by including *total attempted credits during the first year* and *delayed entry*, along with summer enrollment, and first-term grade point average. Their path analysis of 15,000 first-time postsecondary students at Wisconsin technical schools discovered that students who participated in a dual enrollment program were correlated with more attempted credits, higher rates of summer term enrollment, and strong academic performance (Wang et al., 2015).

Clovis and Chang (2021) examined the effects of academic momentum on degree attainment for students who attended a two-year college only and for students who transferred to a four-year college. The researcher's definition of academic momentum included first-year credits, first-year GPA, and months attended college from high school. The analysis examined 41,000 student records from the *ELS:2002* national student data file and learned that students who transferred to a four-year college had higher rates of first-year completed credits, higher first-year GPA, and lower rates of delayed college entry. Martin et al. (2013) examined levels of a student's academic momentum by focusing on specific areas of prior learning (high school grades), life experience, and ongoing achievement (college grades). Various forms of momentum (pre-college courses, college course load, and early achievement) were associated with future academic success. The longitudinal analysis of 904 students indicated that high school achievement was a significant predictor of achievement in each semester in years 1 and 2—but on a diminishing basis (p. 659). An additional longitudinal path analysis showed that high school achievement and ongoing university achievement predicted subsequent achievement through university (p. 661).

The literature on applying academic momentum to explain degree completion has incorporated parts of Adelman's (2006) perspective but also modified the model to include other benchmarks. Similarly, this study will use conceptualized explanatory variables related to a student's academic performance as indicators of academic momentum. The study will test if stranded students exhibit significant academic momentum indicators. While the theoretical framework provides an understanding of the type of student who exhibits academic momentum, previous quantitative research on independent sample analysis and at-risk students offers a methodology to analyze the stranded student phenomenon further.

Conceptual Methodology for Analysis

The conceptual design of this study requires data analysis of two separate (independent groups), which are declared students and pre-major students. To compare the GPAs of the population samples identified for the study, the quantitative methodological approach is first based on the framework of similarly designed research using independent samples (Eveland, 2019; Hall & Ponton, 2005; Ngamsiriudom et al., 2022). Second, the framework to guide the predictive analysis has been established from previous research that sought to identify a student who is considered at risk of not completing a degree (Del Prette et al., 2012; Gilstrap, 2020;

Glynn et al., 2011; Nichols et al.,1998; Singell & Waddell, 2010; Zhang & Rangwala, 2018). The methods identified provide the foundation for researching students in stranded status by attempting to verify if academic or demographic characteristics can predict a student who is at risk of becoming stranded. The data points identified through the theoretical framework and explanatory interaction terms will permit an estimation of the predicted stranded status probability at a particular point in time and will seek to confirm prior work that student attributes, measured performance, and student choices are crucial factors in retention (Singell & Wadell, p. 594).

Several studies provide the framework to conduct a comparative analysis between two identifiable student groups. Ngamsiriudom et al. (2022) used the t-test analysis to test significant differences between male and female students in different majors in terms of their academic performance and attitudes in a statistics course. Similarly, Eveland (2019) used the t-test method to examine differences in average GPA between first- and later-generation college students. Hall and Ponton (2005) also used an independent t-test to examine differences in math self-efficacy of students enrolled in two different math courses. The methods used in these studies will inform the analysis to test group differences in academic performance benchmarks between students accepted into a major and pre-major students.

To further examine the association between the variables and stranded students, there are several advantages to using a Chi-square including its robustness concerning the distribution of the data, its ease of computation, the detailed information that can be derived from the test, and handling data from both two group studies (McHugh, 2013, p. 143). The analysis will also provide information on group differences in specific student populations by utilizing a series of demographic variables, similar to the studies identified.

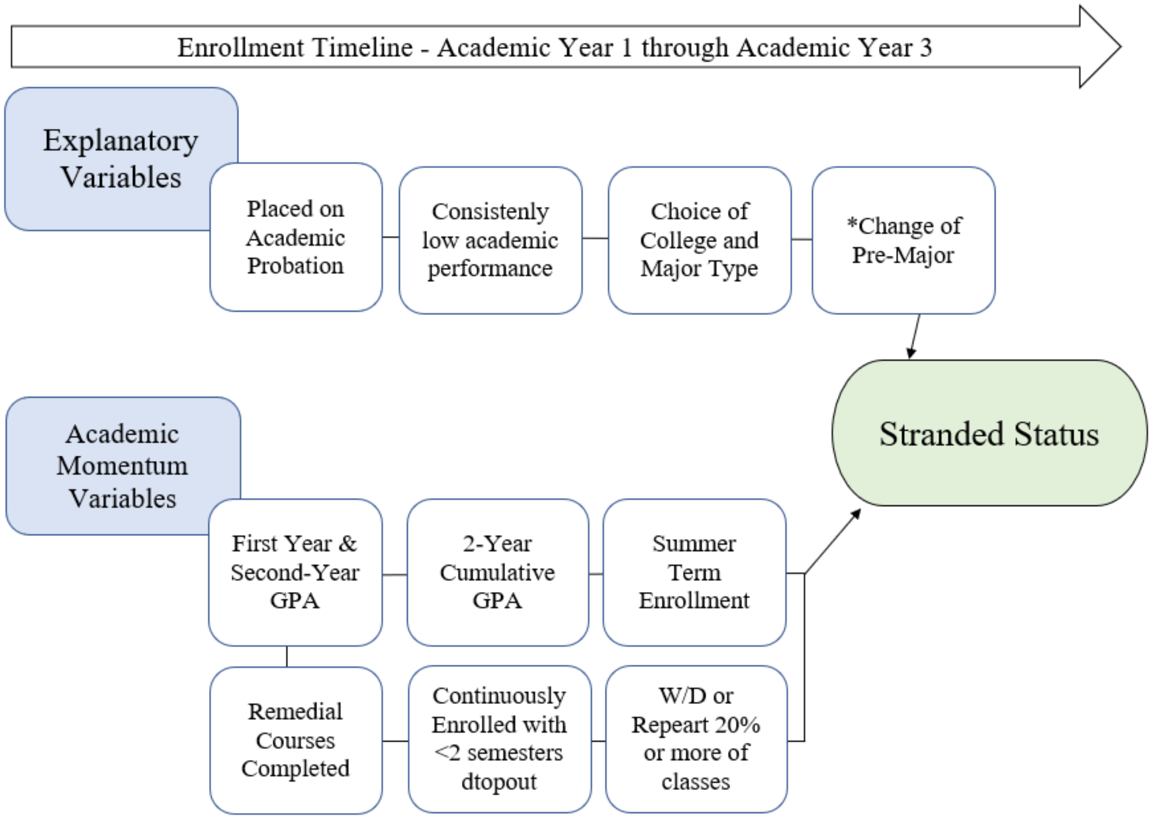
In the research paradigm of at-risk students, logistic regression analysis has been conducted as a common methodology for this type of predictive research. The predictive portion of the analysis aims to replicate the logistic regression methodology to accurately predict factors that contribute to becoming stranded. Nichols et al. (1998) used logistic regression analysis to examine students who persisted or did not return (at risk) for their second year of college. Their analysis of 1,116 persisters and 123 non-persisters at the University of Miami determined if students who enrolled before or after an application deadline were more or less likely to persist. Singell and Waddell (2010) examined 2,848 first-time full-time University of Oregon students to identify who may be considered at-risk and would benefit from targeted retention efforts. The regression analysis, "predicted retention probability at a particular point in time that serves as a measure of 'at-risk status' and confirms prior work that student attributes, measured performance, and financial aid are important factors in retention" (p. 549). Singell and Waddell (2010) claim the study was able to identify students who are most vulnerable to not being retained (p. 556). The model utilized for the study can provide the framework to compare students' accumulated credits who are declared or undeclared at a particular point in time.

Glynn et al. (2011) also examined at-risk student persistence of 5,221 student responses from two national and four in-house surveys. The logistic regression analysis found that nine variables and seven distinct factors are the most likely predictors of future student matriculation, including gender, off-campus employment, concern for financial education, and institutional commitment (p. 82). In subsequent work, Zhang and Rangwala (2018) also employ a logistic regression approach to predict if a student is at risk of dropping out of school. Their use of historical student records data such as high school GPA, gender, race, and school/department while admitted, their model effectively predicted students at risk of dropping out in future semesters. Gilstrap (2020) examined persistence among 35,239 at-risk students at an urban college utilizing a multiple regression model approach followed by a network analysis. The results indicated that loans were the greatest indicator of attainment, and any type of financial aid will contribute to persistence. Gilstrap (2020) also notes that utilizing more than 10 variables in a multiple linear regression analysis will inevitably result in high multicollinearity results, meaning two or more independent variables will have a high correlation with one another (p. 473). It is important to note that general student demographics such as gender and race will also be included.

The methods identified in the literature on comparative analysis and predicting at-risk students inform the conceptual framework of the study to examine factors associated with academic momentum and stranded status. Following these methodologies, the analysis of stranded students will use several variables to identify SS group membership (see Figure 1), and the main objective is to determine if SS group membership can be predicted by various demographic variables, academic momentum benchmarks, and explanatory variables drawn from the review of the literature on retention and persistence.

Figure 1

Conceptualization of Stranded Status



Note: *Change of Major Adapted from Adelman (2006) to specify if a student changed their pre-major in their first three academic years.

Key variables such as first-year college GPA, cumulative GPA, remedial courses, withdrawn courses, summer term enrollment, and continuous enrollment are adopted from Adelman’s (2006) academic momentum model framework. Additional explanatory variables identified as key terms will also be considered along with socioeconomic status indicators and demographic characteristics (Appendix B). Understanding how the independent variables selected are related to the dependent variable of the study (SS group membership) is further discussed in Chapter 3. There are additional factors that may contribute to a student becoming stranded that are less quantifiable or measurable such as inadequate knowledge of campus resources, lack of focus, or indecision on a future major. These types of factors could be tested through qualitative analysis or student surveys. However, these are outside the scope of the study. Additional factors that may affect stranded status are further discussed in the limitations of the study.

Summary

Academic advising and student intervention are critical components of the institution's retention efforts. Early alert systems can be utilized to identify students who may be at risk of becoming stranded and provide support to degree completion. The analysis will support the existing research on early alerts and advising interventions by identifying potential student variables that can be used to identify at-risk students. The analysis is designed to add to the limited research on GPA requirements by examining their impact on a student's ability to declare a major. The key contribution to the literature on degree completion is the introduction of the stranded student phenomenon as a key data point for institutional retention efforts.

The academic momentum model describes how events and milestones in the early part of a student's academic trajectory have implications for subsequent academic outcomes. The components of Cliff Adelman's (2006) academic momentum model have been identified as the appropriate framework to advance the study of the research topic on stranded students. This study is necessary as a student with strong academic momentum who does not meet the pre-major meritocratic GPA requirements demonstrates academic commitment and deserves an increased level of support from the institution. The identified theoretical framework variables and conceptualized explanatory variables of the study will inform the type of student who may become stranded. The study will build upon Adelman's (2006) theory by including stranded status as a factor associated with academic momentum. Identifying a student at risk of becoming stranded will serve as a mechanism to improve six-year retention rates, which is the study's motivation. The analysis methodology for this study, modeled from the identified conceptual frameworks, is further discussed in Chapter Three.

Chapter 3: Methods

Research Approach, Design, and Procedures

The idea of a student in stranded status has been a relatively unexplored phenomenon. An approach using varied quantitative methods has been chosen to examine stranded status group membership, signs of academic momentum, contributing factors to group membership, and the impact of major restrictions on becoming a stranded student through the following research questions: ***Research Question 1(a)*****:** What are the demographic and academic characteristics of students who have "stranded status"? ***1(b)*****:** To what extent are there differences in academic momentum indicators of the stranded status group and the non-stranded status group? ***Research Question 2*****:** Which majors and colleges are more associated with stranded status? ***Research Question 3(a)*****:** What academic and demographic indicators are predictive of stranded status? ***3(b).*** Do these relationships vary across colleges?

A basic descriptive statistics approach is employed for RQ1 and identifies the characteristics of students in stranded status (SS). Descriptive statistics analysis can find "patterns in data to answer questions about who, what, where, when, and to what extent" (NCEE, 2017, pp. 1-2). To answer RQ1(b), a comparative analysis approach using the Chi-Square Test of Independence will examine if students in the stranded status group exhibit indicators of academic momentum (McHugh, 2013). This analysis will establish if the academic momentum benchmarks are significantly associated with SS group membership.

The comparative analysis in RQ2 helps to understand the association between students' choice of major and college on stranded status. Data is included from students of all majors with "pre-major" designations established by the colleges and will seek to examine if the GPA restrictions for certain majors, colleges, and pre-majors are more significantly associated with stranded status. If certain majors have more students in a stranded status, this could be the impetus for policy changes at the college level. To understand the significance of the observed differences between the majors and which categories account for any differences, a binary logistic regression will determine the odds of becoming stranded based on the choice of major and college. Understanding which majors are significantly associated with stranded status will further support targeted interventions for students.

Binary logistic regression analysis is also used for RQ3 to determine if certain indicators and college choices are correlated with stranded status. To predict stranded status, variables identified from Academic Momentum Theory (Adelman, 2006), and theorized explanatory variables are included. In addition to the demographic and academic characteristics, an interaction term of college choice is added to further understand the stranded status story and determine if certain colleges paired with student characteristics can predict SS group membership. Predictive research is aimed at the development of systems to predict criteria of interest (stranded status) by utilizing information from one or more predictors (independent variables) (Pedhauzur & Schmelkin, 1991, p. 305). The purpose of previous studies on at-risk students is to assist college administrators with identifying students early in their academic careers to lower dropout rates and increase future retention. Similarly, following the research paradigm of at-risk students (Del Prette et al., 2012; Gilstrap, 2020; Glynn et al., 2011; Nichols et al.,1998; Singell & Waddell, 2010; Zhang & Rangwala, 2018), this study aims to help administrators identify students early on, who may be at risk of entering a stranded status. An intentional intervention could encourage students to change their academic approach, seek campus support resources, or consider another obtainable degree path. Criteria to establish the population sample for the analysis are discussed in the following section.

Data for Sample

The data was collected from the Southwestern University, which is a large, four-year institution, classified as a doctoral university with high research activity. The university is also considered an AANAPISI, HSI, and MSI-serving institution with a Fall 2023 enrollment of 31,094 (25,797 undergraduates), including 21,956 minority students. Also, 87% of the population is considered an in-state resident.

Data Collection and Instruments

Data was received from the Southwestern University data warehouse office. The data collected did not contain identifiable data and was stored in a password-protected drive. There is little to no potential risk for the students identified in the sample population. The study was approved by IRB on November 15th, 2023, which determined the research does not meet the definition of 'research with human subjects' according to federal regulations, and there is no further requirement for IRB review. The software analysis tool, IBM SPSS Statistics, was utilized to conduct the quantitative analysis.

Sampling

The quantitative research design does not require student recruitment; however, specific criteria must be used to establish the student population who may be entering a stranded status. The total population sample includes undergraduate students at a four-year research university in the Southwestern United States. The data collection procedures for this study required support from the institution's data office, which provided five spreadsheets with the requested student information from the incoming student cohorts of 2013-2016, excluding students who entered college as "undeclared," or undecided. Only students from majors with "pre-major" designations were included in the study. For example, Psychology major students are admitted to their degree upon entry to the university and do not require pre-major designations with major GPA admission requirements. The raw data spreadsheets included full academic records of course enrollment variables (course term, year, subject, withdraw, remedial), financial variables (scholarship recipient, loans received), semester variables (cumulative grade point averages, term enrollment, term grade point averages, semester credits, major, college), student population demographics (gender, race, Pell grant status, parent's education level), and degrees conferred. The total sample provided included 12,734 individual student records, found in Table 2.

Table 2

Full Sample Year and Term Frequency

First Year and Term	Count
2011 Fall	1
2013	48
2013 Fall	3002
2013 Summer	11
2014	25
2014 Fall	3163
2014 Spring	7
2014 Summer	19
2015	3
2015 Fall	3219
2015 Spring	15
2015 Summer	32
2016	8
2016 Fall	3034
2016 Spring	7
2016 Summer	24
2017 Fall	9
2017 Spring	16
2017 Summer	2
2018 Fall	4
2018 Spring	7
2018 Summer	1
2019 Spring	2
2020 Fall	2
2020 Spring	2
2020 Summer	1
2021 Spring	2
No Value	68
Total	12734

The data was cleaned to remove missing records, incomplete records, students who began classes in a Spring or Summer term, or students who entered a cohort after Fall 2016. Only students beginning in the Fall term are selected for consistency across the sample. This brought the population to 12,418 students entering cohorts Fall 2013, Fall 2014, Fall 2015, and Fall 2016, which can be found in Table 3. The non-probability sampling method for the study was used to obtain the stranded status group (SS) and the non-stranded status group (NSS) samples for analysis. Non-probability sampling is required to identify the students who meet well-defined criteria. For these comparative samples, "randomization is not important in selecting a sample from the population of interest. Rather, subjective methods are used to decide which elements are included in the sample" (Etikan et al., 2015, p. 1). When utilizing specific criteria to identify a sample population, a sub-method of purposive sampling, homogeneous sampling, may be used to focus the sample on a "precise similarity and how it relates to the topic being researched" (Etikan et al., 2015, p. 3).

Table 3

Full Sample Cohort Years

Year and Term	Frequency	Percent	Valid Percent	Cumulative Percent
2013 Fall	3002	24.2	24.2	24.2
2014 Fall	3163	25.5	25.5	49.6
2015 Fall	3219	25.9	25.9	75.6
2016 Fall	3034	24.4	24.4	100
Total	12418	100	100	

The conditions established to identify the SS group include students who have (a) accumulated at least 70 credits by term 8 and (b) remain in "PRE" major status through enrollment in term 5. For the comparison group (NSS), students must have (a) accumulated at least 70 credits through enrollment term 8 but (b) declared a major by enrollment term 5. The purposive sample for analysis was further defined with a pre-determined set of parameters, including earning 70 or more credits by term eight. Term 8 was established as the benchmark to ensure all students captured in the sample are in their third academic year, considering most institutional majors require 60 general education (pre-major) course credits, by which point a major should be declared. The institution's main advising center recommends that students should have a declared major by the end of their second academic year. Utilizing term 5 major declaration status for the analysis ensures the sample included students following their second academic year, accounting for summer term enrollment. The purposive sampling method to identify a diverse cross-section of students will allow for concentration on students with "particular characteristics who will better be able to assist with the relevant research" (Etikan et al., 2015, p. 3). The data shows that 7,535 students (60.7%) indicated a pre-major, and 7,056 students (56.8%) had accumulated at least 70 credits by term 8. These values can be found in Table 4 for the full sample population. This overall approach ensures the population sample includes students who may be in stranded status.

Table 4

Frequency Table of Sample Criteria

Pre-Major Student		Frequency	Percent	Valid Percent	Cumulative Percent
	No Pre-Major	4883	39.3	39.3	39.3
	Pre-Major	7535	60.7	60.7	100
	Total	12418	100	100	

Credit Accumulation		Frequency	Percent	Valid Percent	Cumulative Percent
	Less than 69 Credits by Term 8	5362	43.2	43.2	43.2
	More than 70 Credits by Term 8	7056	56.8	56.8	100
	Total	12418	100	100	

Filters were then added to the data for a Pre-major indicated in the student's major plan description, bringing the sample to 7,535, followed by a filter for achievement of 70 total credits by term eight, resulting in the final sample population to 4,149, described in Table 5. A grouping variable was then added to distinguish the "Stranded Status" group (SS) and the "Non-Stranded Status" group (NSS). If a student has not declared a major by term 5, they are part of the SS group (2,520 students), or if a declared major was detected they are part of the NSS group (1,629 students), described in Table 6.

Table 5

Sample Population of Pre-Majors

Achieved 70 Credits by Term 8		Frequency	Percent	Valid Percent	Cumulative Percent
	No	3386	44.9	44.9	44.9
	Yes	4149	55.1	55.1	100
	Total	7535	100	100	

Table 6

Comparison Groups for Analysis

Declared a Major by Term 5		Frequency	Percent	Valid Percent	Cumulative Percent
	Non-Stranded Status	1629	39.3	39.3	39.3
	Stranded Status	2520	60.7	60.7	100
	Total	4149	100	100	

The cohort distribution of the sample includes 964 from Fall 2013, 1055 from Fall 2014, 1087 from Fall 2015, and 1043 from Fall 2016, as found in Table 7. A critical piece of the study is the examination of GPA major restrictions. As part of the analysis, the final pre-major indicated by each student was identified in Appendix A, along with the GPA requirement to enter the intended college. The distribution of GPA restrictions for stranded and non-stranded groups can be found in Table 8 with GPA restriction levels of 2.00, 2.50, 2.75, and 3.00.

Table 7

Cohort Year and Stranded Status

	Non-Stranded		Stranded		Total
Year and Term	Count	Row N %	Count	Row N %	Count
2013 Fall	338	35.10%	626	64.90%	964
2014 Fall	379	35.90%	676	64.10%	1055
2015 Fall	441	40.60%	646	59.40%	1087
2016 Fall	471	45.20%	572	54.80%	1043
Total	1629	39.30%	2520	60.70%	4149

Table 8

GPA Requirements and Stranded Status

Major Admission Requirement	Non-Stranded	Stranded	Total
2.00	503	620	1123
2.50	122	224	346
2.75	807	1239	2046
3.00	197	437	634
Total	1629	2520	4149

Research Questions and Hypotheses

1(a). What are the demographic and academic characteristics of students who have "stranded status"?

1(b). To what extent are there differences in academic momentum indicators of the stranded group and the non-stranded group?

Hypotheses 1: Students in the SS group will exhibit indicators of academic momentum.

2. Which majors and colleges are more associated with stranded status?

Hypothesis 2: Students in majors with higher GPA restrictions are more likely to have stranded status.

3(a). What academic and demographic indicators are predictive of stranded status?

Hypothesis 3: Academic and explanatory variables will demonstrate significance in predicting stranded status group membership (e.g., changing of major will be a significant predictor of SS).

3(b). Do these relationships vary across colleges/departments?

Hypothesis 4: Relationships will vary across colleges and departments.

These hypotheses are informed by the literature on predicting at-risk students and the academic momentum model. Established explanatory variables, along with variables identified by Adelman (2006), are input into the data analysis software to test these hypotheses and examine which academic momentum and explanatory factors are significantly associated with SS and predictive of stranded status group membership.

Theoretical Variables

Cliff Adelman's (2006) model of academic momentum identifies several key variables that are indicators of students with positive academic momentum. These variables were included in the analysis to determine if stranded status students exhibit similar characteristics of academic momentum benchmarks as non-stranded status. Throughout the analysis for a Yes or No outcome in the variable, a 1 was assigned for Yes, and a 0 was assigned for No.

Remedial Courses

Remedial courses completed were identified in two parts, (a) remedial course in the first two terms (*Any Remedial in First Two Terms*) and (b) remedial course identified within the first 25 course records (*Any Remedial in First 25 Courses*). The 25-course benchmark was chosen to represent a timeframe of around two academic years, as many courses with labs or discussion components were displayed as two separate rows in the raw data. A Yes or No dichotomous variable was added to indicate if a student's record showed a remedial course within the given timeframes.

Withdraw in 20% or More of Courses

Next, the course history provided data to determine if a student withdrew from 20% or more of their courses (*Withdraw 20% or more in First 25 Courses)*. Using the same benchmark as remedial courses, a Yes or No dichotomous variable was added to indicate if a student withdrew from 20% or more of their first 25 course records.

Summer Term Enrollment

Following the same parameters, a variable was constructed to indicate if a student enrolled during a summer term (*Any Summer Course in the First 25 Courses*). A Yes or No dichotomous variable was added to indicate if a student enrolled in a summer course within their first 25 course records.

First-Year, Second-Year, and Cumulative GPA

A student's early academic benchmarks are also associated with subsequent academic momentum and degree completion (Adelman, 2006, p. xxii). The variables for First-Year GPA (*First-Year GPA*), the cumulative GPA of term 1 and term 2, and Second-Year GPA (*Second-Year GPA*), [term 3 GPA + term 4 GPA / 2] were calculated for analysis. Additionally, cumulative GPA after Term 4 was also included as a variable (*Cumulative GPA through Term 4*).

Continuous Enrollment

The next variable identified by Adelman (2006) was continuous enrollment. He followed the approach of “NCES postsecondary transcript-based grade-cohort studies, where noncontinuous enrollment was defined as more than one semester” without enrollment (Adelman, 2006, p. 19). For this variable, any two consecutive terms missed though the initial six terms were considered non-continuous enrollment[1]. A Yes or No dichotomous variable (*Continuous Enrollment in First Six Terms (< 2)*) was added to indicate if a student had a continuous enrollment value of less than 1.5.

Additional Explanatory Variables

While Adelman’s theory offers some important variables that explain academic momentum, stranded status is a unique phenomenon that may not only be explained by academic momentum variables. Therefore, a series of additional explanatory variables were also theorized to examine stranded status. It is hypothesized that students may encounter many different circumstances that may lead to becoming stranded. To account for the variations in academic careers, the conceptualized variables include (a) students who may encounter one poor academic semester of academic probation, (b) students who may consistently demonstrate poor academic performance, (c) students who decide to change their pre-major during the first five terms of postsecondary education, (d) students who withdraw from courses, and (e) student’s choice of

[1] For continuous enrollment, a new variable calculates the value differences between each term where Fall value = n, Spring value = n + 1, and Summer value = n + 1.5. After assigning a value to each term, any difference in term values greater than 1.5 (term B - term A, term C - term B, etc.) is considered a term of non-continuous enrollment. For example, if a student enrolled in Fall 2013 (value = 1) and did not return until Fall 2014 (value = 3), the difference in values (2) is greater than (1.5), which equals non-continuous enrollment. The summation of the computed values distinguishes a student with continuous enrollment.

college and major type. The criteria used to establish these variables provide further context on their inclusion and relation to stranded status.

Academic Probation

A student may struggle academically in their transition from high school to college, which could result in a poor academic semester early in their postsecondary career. Alternatively, unforeseen circumstances can arise for students that may result in a poor academic semester later in their postsecondary career. Constructing a misinformed schedule with difficult courses during the same semester could also result in poor academic performance. Despite a student performing well academically in all semesters, it is theorized that one poor academic semester can significantly impact a student's cumulative GPA to the degree that declaring their intended major may be unobtainable. With extensive variability in causes of poor academic performance, a student earning less than a 2.00 in *any* semester during their first six terms in postsecondary education has been added as an explanatory variable to inform the stranded status student. This benchmark is representative of the 2.00 semester GPA established by Southwestern University to designate a student who receives academic probation status.

Varying definitions in the literature describe academic probation as an institutional policy "designed to help students improve their grades, stay enrolled, and eventually receive a degree" (Bowman & Jang, 2015, p. 1286). Research has shown that being placed on academic probation has a negative effect on retention and degree completion (Dong, 2019; Bowman & Jang, 2015; Sneyers & De Witte, 2018; Wright, 2020). However, some studies have shown no significant relationship between academic probation and retention (Albert & Wozny, 2019; Casey et al., 2018). A Yes or No dichotomous variable was added (*Academic Probation Received*) to indicate if a student was placed on academic probation status. Similar to going on academic probation, consistently lower academic performance may be a contributing factor to a future stranded status.

Consistently Low Academic Performance

It is theorized that consistently low academic performance can keep a student's cumulative GPA below the threshold of major declaration. A student may be performing well enough academically to remain enrolled at the university, but not consistently achieving a GPA to surpass the cumulative GPA restrictions for major declaration. The consistently low academic performance variable criteria include students with *two* or more semesters below a 2.50 GPA. Any meaningful results related to consistently low academic performance will build upon the findings of previous literature, which utilizes cumulative GPA (performance across multiple terms) as a predictor of student outcomes (Adelman, 2006; Blekic et al., 2020; Cochran et al., 2014; Farmer et al., 2016; Gilstrap, 2020). A Yes or No dichotomous variable was calculated (*Consistently Low Academic Performance*) to indicate if a student has more than two semesters of low academic performance. This additional explanatory variable has been identified as a key indicator to predict students in a stranded status.

Student's Choice of College and Major Type

The GPA requirements established by Southwestern University vary between colleges, and even within colleges, certain majors require higher cumulative GPAs to gain acceptance into the major. For example, within the College of Engineering, an Electrical Engineering major requires a 2.00 cumulative GPA, while a Mechanical Engineering major requires a 2.50, and a Computer Science major requires a 2.75. It is hypothesized that a student's choice of major is significantly correlated to stranded status group membership. The addition of the variables for students' choice of college and major will determine if there are differing relationships of group membership by college.

To factor student choice into the analysis, a set of variables was established to determine if a student declared their intended major by term five, if a student declared any major by term five, or if a student remained undeclared by term five. These criteria were also used to establish the group samples for SS and NSS. Given the raw data's inclusion of summer term enrollment, term five is used to ensure that all student records are captured following at least their second academic year. To create the Declared Major string variable, any term that did not contain a "PRE" after the final "PRE" was detected, indicated a major declaration. The variables established for the analysis described the students' (First Major) and (Final Major) through term 8 indicated, (First College) and (Final College) through term 8 indicated, and (Last Pre-major) designation. The impact of these student decisions on stranded status is further examined in RQ(2) and RQ(3).

Changing of PRE-Major

In addition to student performance, a decision by a student to change their pre-major during their first three academic years may also be a contributing factor. The general education requirements for each college within the university are unique. A student who changes their pre-major may be required to take different general education courses, potentially leaving some of the credits previously earned to be lost. Therefore, it is theorized that a student who changes their pre-major within the first five terms of postsecondary education may be at risk of becoming stranded. An explanatory variable has been developed to account for student decision variations. Modeled from Adelman's (2006) Academic Momentum perspectives, the change of major variable is adapted to include a student changing their *pre-major* before declaring a major. This variable is intended to capture student's indecision or shifting interests that may lead to a change in their academic goals. Utilizing the newly established major declaration variables, a Yes or No dichotomous variable was calculated (*Changed Major by Term 5*) to indicate if a student changed their pre-major during the first five terms. With the assumption that each student should have one change in their major record (pre-major to declared major) if a non-declared student had more than one change across their data responses for major, or a declared student had more than two changes across their data responses for major, a designation of changed major was added for analysis.

GPA Restriction Difficulty Level

The study seeks to examine if GPA restrictions impact a student becoming stranded and potentially earning credits that will not apply to a degree. A categorical variable was designed to assess if a particular major GPA restriction difficulty level affects stranded status (*Major GPA Requirement*), which is categorized as 2.00 = 1, 2.50 = 2, 2.75 = 3, and 3.00 = 4. The GPA admission requirement of 2.00 was used as the reference category for the analysis.

Academic Momentum Variables Extended

Building upon Adelman's (2006) variables, a continual enrollment explanatory variable was created to determine if there is an association with stranded status. Yes or No dichotomous variables were created to identify several additional theorized indicators. Students having continuous enrollment without any semester dropouts within the first six terms (*Continuous Enrollment in First Six Terms (< 1)*), cumulative GPA after term 5 (*Cumulative GPA through Term 5*), any withdrawal in first two terms (*Any Withdraw in First Two Terms*) and any withdraw in the initial 25 courses (*Any Withdraw in First 25 Courses*) were also added to build upon Adelman's (2006) variables. Each of the explanatory variables identified should be included in the predictive analysis to further explain the story behind a stranded student. The connection of the explanatory variables to stranded status is outlined in Figure 1 and a full list of the variables utilized for the study and corresponding research question is found in Table 9.

Table 9

Variables Identified for Analysis

Student Variables	RQ 1(a)	RQ 1(b)	RQ 2	RQ 3(a)	RQ 3(b)
Explanatory					
Academic Probation Received	X	X		X	X
Changed Major by Term 5	X	X		X	X
Consistently Low Academic Performance	X	X		X	X
Continuous Enrollment in First Six Terms (< 1)	X	X		X	X
Any Withdraw in First Two Terms & 25 courses	X	X		X	X
Cumulative GPA through Term 5	X	X		X	X
Major and College Type			X		X
Pre-Major Choice			X		
Theoretical					
Any Remedial in First Two Terms & 25 Courses	X	X		X	X
Withdraw 20% or more in First 25 Courses	X	X		X	X
Any Summer Course in First 25 Courses	X	X		X	X
Continuous Enrollment in First Six Terms (< 2)	X	X		X	X
First-Year GPA	X	X		X	X
Second-Year GPA	X	X		X	X
Cumulative GPA through Term 4	X	X		X	X
Demographic					
Gender	X			X	X
Race/Ethnicity	X			X	X
Scholarship Received	X			X	X
Student Loans Received	X			X	X
Pell-grant eligible	X			X	X
Parent's Education Level	X			X	X

Demographic Variables

As a staple in most quantitative studies, the inclusion of student demographics helps to examine important between-group differences in the likelihood of stranded status. The demographic information collected is modeled from Adelman's (2006) research, but certain variables are excluded for relevance to the study. The inclusion of gender, race/ethnicity, and socioeconomic status variables will enhance the analysis by providing insight into the types of students who may become stranded. For example, a student's social status origins are shown to affect his or her college experiences and outcomes (Walpole, 2003, p. 63). Although Adelman used the socioeconomic quartile as a measure of SES, these data were not available. This study uses a set of indicators related to Pell-grant status, if the student has accepted loans to support the costs of tuition if the student received a scholarship, and the parent's college education level.

The demographic and socioeconomic variables received were prepared for analysis including Gender (Male = 1, Female = 0), Race (AIAKN - American Indian or Alaskan Native; ASIAN - Asian; BLACK - African American or Black; HISPA - Hispanic; MULTI - more than one race/ethnicity; NONRS - International; PACIF - Hawaiian or other Pacific Islander; UNKWN - Unknown; WHITE - White.), Pell-Grant Eligible (Y/N), Received Scholarship (Y/N), Received Student Loans (Y/N), Parents No Bachelor Degree (Y/N), Parents No College (Y/N). A Yes or No dichotomous variable was calculated for each demographic variable. Dummy variables were developed for race to include as part of the regression analysis. Appendix B and C show the full list of descriptive statistics for each independent variable included in the quantitative analysis. The data analysis section will provide details on the steps to examine the variables for analysis.

Data Analysis

To answer the research questions, various forms of quantitative analysis are employed through each stage. Descriptive statistics are first used to identify the group samples. Chi-square test of Independence and Independent t-tests then examine academic momentum differences between the SS and NSS groups. Next, a binary logistic regression determines the odds of becoming stranded from the choice of a student's major. Binary logistic regression analysis also examines if there are student variables (demographic, academic momentum, explanatory, student choice) that are significant in predicting stranded status group membership. The types of analysis needed for the raw data were confirmed through a hypothesis testing guide (Haq & Nazir, 2016). The data analysis process for each research question will be further outlined below.

Research Questions 1(a) & 1(b)

To begin the examination of GPA restrictions and stranded students, a basic descriptive analysis of pre-major students with 70 or more credits (total population sample) has identified our comparison groups samples of SS and NSS (Table 6). The establishment of students in the comparative groups will provide the answer to RQ1(a). This question is designed to describe the sample by reporting each group's descriptive frequencies. To conduct the data analysis for RQ1(b) both a Chi-square test of Independence (for dichotomous variables) as well as an Independent t-test (for scale variables) will test group differences in academic momentum indicators by comparing associations between two groups, where there are unique subjects in each group (TexaSoft, 2021, para. 3). These types of quantitative analysis can determine if an association exists between categorical variables, or whether the variables are independent or related (Kent State University Library, 2023).

The Chi-Square Test of Independence has been used in educational research to examine differences in student groups (Connolly et al., 2017; Kimbark et al., 2016; Soria et al., 2013).

This type of analysis will require two categorical variables (number of SS and NSS students in each major), two or more categories for each variable (e.g., any remedial course), and independence of observations (each categorical count is independent). The number of students within each major and college is distributed in a frequency distribution table (Kent State University Library, 2023). To assess the strength of an association between two categorical variables, the Phi coefficient is included in the results (Akoglu, 2018). The explanatory variables are also examined for association with SS. The Independent t-test on GPA variables will assess the size of the effect by using Cohen's *d,* with the values 0.2 = small effect, 0.5 = moderate effect, and 0.8 = large effect (National University, 2024).

Results are reported in a table presenting the group differences of all included variables for the SS and NSS groups. A comparative analysis will establish if students with stranded status exhibit similar characteristics of academic momentum as declared students. It is hypothesized that there will not be significant group differences in academic momentum benchmarks between the SS and NSS groups. This analysis will determine if academic momentum indicators are significantly associated with SS group membership.

Research Question 2

A quantitative analysis of different majors and colleges will determine if there are significant odds of becoming stranded due to student choice. As pertains to the analysis of RQ2, it is hypothesized that there will be significant group differences in the percentage of students with stranded status from within different majors and colleges. To examine this hypothesis, a binary logistic regression analysis will examine the odds of group membership (SS and NSS). The binary logistic regression is used to predict the "probability that an observation falls into one of two categories of a dichotomous dependent variable based on one or more independent variables that can be either continuous or categorical" (Laerd Statistics, 2018). The null hypothesis indicates that all coefficients in the model are equal to zero, or "none of the predictor variables have a statistically significant relationship with the response variable, *y*" (Statology, 2021).

A significant coefficient with a p-value $\leq .05$ is used as the probability of the event occurring (SS or NSS) and will determine if the model is statistically significant. The significance is examined along with the odds ratio to ascertain if there are higher odds of becoming stranded because of a student's choice of college and major. An additional step is taken to manually calculate the predicted odds to better understand the model results, using the formula: odds = P/(1-P). For example, if the odds ratio has a value of 1.505, students who respond 1 to that variable will have 50.5% higher odds of becoming stranded (Grace-Martin, n.d.).

Research Question 3(a)

A binary logistic regression analysis will also be used to determine if a defined set of variables can be significant predictors of stranded status group membership. It is hypothesized that some independent variables will be more significantly correlated to stranded status than other variables. Along with the explanatory variables previously identified, additional categorical and dichotomous variables are included in the predictive analysis, reflecting the academic momentum variables used by Adelman (2006). Since the dependent variable is binary, the equation is expressed as the probability that $Y = 1$ given X, the values of the predictors, or:

$$\text{Prob}\{\text{STRANDED STATUS}\} = \beta_0 + \beta_1(\text{Demographic}) + \beta_2(\text{Explanatory}) + \beta_3(\text{Momentum}).$$

The predicted dichotomous dependent variable (SS or NSS) is a function of the probability that a particular student is in one of the categories (Hasan, 2020). In this analysis, Y is the dependent variable (SS), which denotes the occurrence of the event of interest. This equation is used rather than the conventional linear regression equation, as a linear model cannot fit the data over the entire range of predictors. A purely linear model would permit the probability of stranded status group membership to exceed one or fall below zero (Harrell, Jr. & Harrell, 2015). A logistic regression on the GPA admission requirement is examined as a predictor of stranded status. An area that will also be explored is the student's choice of college type. The pre-major status variables will allow for comparing students within colleges to identify predictive differences.

Research Question 3(b)

Building upon the logistic regression model, adding in the interaction of college type (College of Education, College of Engineering, etc.) with each of the significant explanatory variables will examine to what extent the likelihood of stranded status varies by college. The expanded equation for RQ3(b) includes the college-type variable:

Prob{STRANDED STATUS}= β_0+β_1(Demographic) + β_2(Explanatory) + β_3(Momentum) + β_4(Demographic x CollegeType) + β_5(Explanatory x CollegeType) + β_6(Momentum x CollegeType).

For example, if the interaction between academic probation and college type is significant and positive for the College of Business, this suggests that Business students on academic probation in the first two years are more likely to be stranded in year three than those on probation in other colleges.

The analysis will seek to establish if certain independent variables (both theoretical and explanatory) are reliable predictors of stranded status group membership. To enhance the analysis, depending on if there are significant differences in variation by college, interaction terms will also be added to conclude if certain combined characteristics are more predictive of stranded status. The analysis results are in the Results section prepared in a journal submission format that includes tables and graphs for each quantitative analysis. The quantitative analysis types described have been identified as the most logical methodology to answer each research question. To confirm that the study accurately investigates the intended outcome, it is crucial to address issues related to validity and reliability.

Validity and Reliability

To ensure the study is examining what is intended to be examined, there are validity and reliability issues that must be addressed. First, stranded status will not emerge until after the second year of postsecondary academics when the student should be accepted into their major. To account for this timeline, the analysis applies a purposive non-probability sample of students with 70 or more accumulated credits. This will improve the validity of the study by ensuring the sample characterizes a reasonable cross-section of the entire population and that the students selected are representative of the population (Lawson & Philpott, 2008, p. 70-71). By including students who are pre-major only, and not "undeclared," the analysis considers that stranded status can only be achieved if the student is making progress toward a defined goal (intended major). The sampling criteria established will also limit selection bias. The study is reliable in the sense that it can be replicated at other higher education institutions by applying similar sample parameters. The variables collected for the study are common data points collected by institutional data warehouses. The methodology and instruments used for the study allow for consistency of measurement of stranded status students and will permit the same results to be produced in the future (Lawson & Philpott, 2008, p. 2). Effect size interpretation will also confirm if the variable is measuring the phenomena correctly.

A threat to the validity is that students are not enrolled in courses for personal enrichment purposes, which are unobservable in the administrative data set. However, even if a course is taken as personal enrichment, exploring a subject area for a potential major, or taking a class to improve their cumulative GPA, taking classes that do not apply to the degree or being indecisive on major decisions may still lead to a stranded status. There are factors to consider that may affect the analysis's conclusions, including the use of enough predictor variables. Also, a threat to the validity could be that the independent variables selected for analysis might be capturing the effect of something unobservable that is correlated with the dependent variable. This omitted variable bias can occur if an omitted third variable causes the dependent and independent variable. The causal assertion holds only when all other potential explanations are eliminated (Wilms et al., 2021). The study will seek to provide descriptive insight into the factors that lead to stranded status, however, the model may not capture all factors associated with stranded status, which would be considered a limitation of the study.

Summary

The phenomenon of stranded college students is examined through a quantitative analysis approach based on the theoretical framework of Adelman (2006) and the methodology of studies on at-risk students. The results of the analysis will determine if stranded students exhibit qualities of academic momentum and confirm if certain major requirements are likely to contribute to stranded status. The quantitative approach will also inform on which college majors are more associated with stranded status. The explanatory variables were created to support the analysis to determine if certain student characteristics accurately predict stranded status. The methods identified are designed to reach the study's goal to examine the effect of major restrictions on stranded status and support degree completion through early detection and intervention.

Chapter 4: Results

This analysis describes the characteristics of students in a stranded status, examines the effect of major restrictions, and determines if certain demographic or academic characteristics can predict a student with a stranded group status. The analysis will also examine the association of college and major choice to stranded status. This chapter will outline the results of the analysis beginning with the first research question. Each research question is addressed by providing the quantitative analysis results.

Research Question 1(a) and 1(b)

The first step of the comparative analysis sought to provide the demographic and academic characteristics of students in a stranded status. Utilizing the grouping variable of "stranded status," the descriptive statistics provided between the SS and NSS groups include the in-group percentages, total percentage of the sample, and percentage of the total sample.
Each variable percentage provided is from the total defined population sample of 4,149 students. The second part of RQ1 seeks to ascertain to what extent there are differences in academic momentum benchmarks of the stranded group and the non-stranded group. The results suggest a statistically significant relationship exists between stranded status and remedial courses completed, summer term enrollment, first-year GPA, second-year GPA, and cumulative GPA after enrollment in term 4.

Demographic Characteristics

A basic descriptive statistical analysis provides the gender, race, and financial-related characteristics (Pell Grant status, scholarships, student loans, parent's education level) of the sample population at the Southwestern University.

Student Demographics

For gender, the stranded status group includes 56.90% female and 43.10% male, where 59.87% of females are stranded and 61.93% of males are stranded. For the nine Race/Ethnicity variables, American Indian or Alaskan Native is reported as 20.00% stranded (.04% of stranded). Asian is reported as 63.49% stranded (23.81% of stranded). African American or Black is reported as 59.35% stranded (5.79% of stranded). Hispanic is reported as 61.17% stranded (29.76% of stranded). More than 1 Race/Ethnicity is reported as 60.36% (10.75% of stranded). International is reported as 50.00% stranded (.67% of stranded). Hawaiian or other Pacific Islander is reported as 64.45% stranded (1.43% of stranded). Unknown is reported as 58.82% stranded (.40% of stranded). White is reported as 58.79% stranded (27.34% of stranded).

Financial Aid Status

For the financial-related variables, the stranded status group has 36.50% of students who are Pell Grant eligible, and the results showed that for the sample population, 61.34% of Pell Grant-eligible students were stranded. The stranded status group reported 86.63% of students received a scholarship, and for the sample, 60.55% of the students who received a scholarship were stranded. The stranded status group also showed 48.77% of students received student loans, and for the sample, 62.42% of students who received a scholarship were stranded. Related to the parent's education level, 49.17% of stranded students' parents do not have a bachelor's degree. Also, for the sample, 60.26% of students whose parents do not have a bachelor's degree were stranded. The stranded status group reported 24.95% of student's parents did not attend college, and for the sample, 58.80% of students whose parents did not attend college were stranded. The counts and percentages for the demographic variables can be found in Appendix D.

Academic Momentum Benchmark Variables

To understand if stranded students are exhibiting signs of academic momentum, Adelman's (2006) Academic Momentum model variables are compared between the two sample groups. The results of the test suggest that a statistically significant association exists between stranded status and students who enrolled in remedial courses, enrolled in a summer term, first-year GPA, second-year GPA, and cumulative GPA following term 4. The descriptive statistics for the stranded group's academic momentum variables and additional explanatory variables can be found in Appendix E.

Remedial Courses

Results from the Chi-square test indicate a statistically significant association between variable stranded status and their likelihood of enrolling in remedial courses within the first two terms, $\chi^2(1, N = 4149) = 24.331$, $p < .001$. The strength of this association, as measured by the Phi coefficient, is $\Phi = .077$. Within the first two terms, 20.95% of stranded students enrolled in a remedial course, compared to only 14.68% of non-stranded students. The results further indicated that 68.75% of students who took a remedial course in the first two terms became stranded.

Significance was also shown for remedial courses within the first 25 courses, $\chi^2(1, N = 4149) = 21.006$, $p < .001$. The strength of this association is $\Phi = .071$. Within the first 25 courses, 23.37% of stranded students enrolled in a remedial course, compared to only 17.43% of non-stranded students. The results further indicate that 67.47% of students who took a remedial course in their first 25 courses became stranded. The findings show there is a difference in the proportion of SS compared to NSS, however, the overall effect size is low for both remedial variables (Akoglu, 2018). The association, although moderate for each, indicates that SS is more likely to have enrolled in remedial courses within their first two terms and within the first 25 courses compared to NSS, where SS represented a greater proportion of students enrolling in remedial courses. The overall findings indicate that students who enrolled in remedial courses are more likely to become stranded.

Withdrawal in 20% or More of Courses

The relationship between course withdrawal from 20% or more of the first 25 courses was not significant, $\chi^2(1, N = 4149) = .012, p = 1.000$. The strength of this association is $\Phi = .002$. Within the first 25 courses, 0.52% of Stranded students withdrew from less than 20% of their courses, compared to 0.59% of non-stranded students. The results further indicate that 61.90% of students who withdrew from 20% or more of their first 25 courses became stranded. A difference is shown in the proportion of SS compared to NSS; however, the overall effect size is negligible for withdrawing from 20% or more of courses. The very weak association indicates that withdrawing from 20% or more of courses does not impact the likelihood of becoming stranded. SS group membership cannot be directly associated with higher withdrawal rates within the first 25 courses. The findings indicate this academic momentum benchmark is not able to help determine if students will become stranded.

Summer Term Enrollment

The relationship between summer term enrollment within the first 25 courses was significant, $\chi^2(1, N = 4149) = 51.983, p < .001$. The strength of this association is $\Phi = .112$. Within the first 25 courses, 52.02% of stranded students enrolled in a summer course, compared to only 40.58% of non-stranded students. The results further indicate that 66.48% of students who enrolled in a summer term became stranded. A difference is shown in the proportion of SS compared to NSS; however, the overall effect size is small for summer term enrollment. The association, although moderate, indicates that SS are more likely to enroll in summer courses within their first 25 courses compared to NSS, where SS represented a greater proportion of students enrolling in summer term courses. The finding indicates students enrolling in a summer term are more likely to become stranded.

Continuous Enrollment with <2 Dropout Semesters

The relationship between continual enrollment (less than 2 dropouts) within the first six terms was not significant, $\chi^2(1, N = 4149) = 1.756$, $p = .191$. The strength of this association is $\Phi = .021$. Within the first six terms, 98.41% of stranded students demonstrated continual enrollment of less than 2 dropout semesters, compared to 97.85% of non-stranded students. The results also indicate that 60.87% of students who had continuous enrollment (<2 dropouts) became stranded. A difference was shown in the proportion of SS compared to NSS; however, the overall effect size is negligible for continual enrollment (less than 2 dropouts). The very weak association indicates that continual enrollment (less than 2 dropouts) does not impact the likelihood of becoming stranded. SS group membership cannot be directly associated with continual enrollment (less than 2 dropouts). The non-significant association confirms that continuous enrollment with less than two dropout semesters is not able to help determine if students are more likely to become stranded. The results of the Chi-Square tests for Adelman's (2006) adapted academic momentum variables can be found in Table 10.

Table 10

Chi-Square Test Results of Academic Momentum Variables by Stranded Status

Academic Momentum Variables	χ2 Value (df = 1)	Level of Significance	Phi Value
Any Remedial Course in First Two Terms	24.331	.001***	0.077
Any Remedial Course in First 25 Courses	21.006	.001***	0.071
Withdraw 20% or more in First 25 Courses	0.012	1.000	0.002
Any Summer Course in First 25 Courses	51.983	.001***	0.112
Continuous Enrollment in First Six Terms (< 2)	1.756	0.191	0.021

Note. Variables are significant at *p<.05**p<.01 ***p<.001. Sample size (N) = 4149

First-Year GPA

To measure the association of the final academic momentum variables, first-year GPA, second-year GPA, and cumulative GPA (Appendix C), an Independent samples t-test was conducted to compare SS and NSS students. The Welch's test values are reported as Levene's test indicated the homogeneity of variances assumption was not met for each variable. The relationship between students first-year GPA was significant, revealing differences in the variance of scores for non-stranded (M = 3.13, SD = .60) and stranded students (M = 3.01, SD = .56); $t(3300.78) = 6.857$, $p < .001$, suggesting that non-stranded performed significantly better on first-year GPA than stranded students. The effect size for the difference in first-year GPA performance between the two groups was calculated as Cohen's $d = 0.221$, indicating a small effect (National University, 2024). The results designate that NSS is associated with slightly higher academic performance in the first year, although the overall difference between the two groups is not substantial. The GPA variables used for analysis can be found in Appendix F. The findings confirm that a student is more likely to become stranded as their first-year GPA decreases.

Second-Year GPA

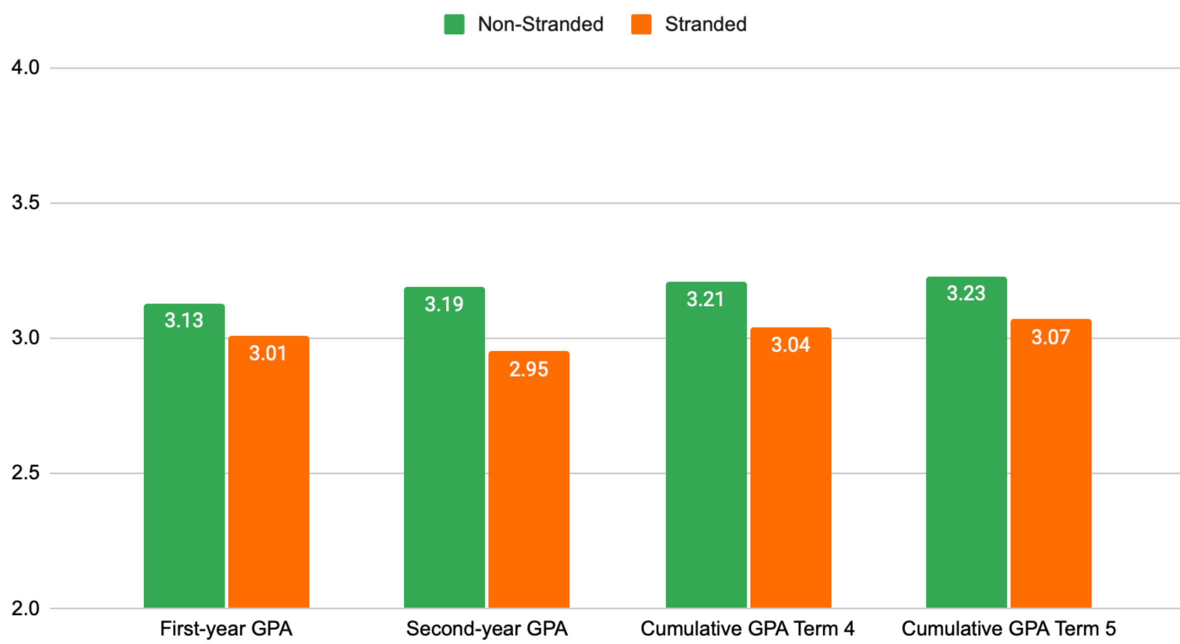
The relationship between students' second-year GPA was significant. For second-year GPA, revealing differences in the variance of scores for non-stranded ($M = 3.19$, SD = .63) and stranded students ($M = 2.95$, SD = .65); $t(3559.83) = 11.943$, $p < .001$, suggesting that non-stranded performed significantly better on second-year GPA than stranded students. The effect size for the difference in second-year GPA performance between the two groups was calculated as Cohen's $d = 0.377$, indicating a small effect. The results indicate that non-stranded students are associated with slightly higher academic performance in the second year, although the overall difference between the two groups is not substantial. The findings confirm that a student is more likely to become stranded as their second-year GPA decreases.

Cumulative GPA Term 4

For cumulative GPA after term 4, the analysis revealed a significant difference in the scores for non-stranded ($M = 3.21$, SD = .49) and stranded students ($M = 3.04$, SD = .47); $t(3374.40) = 10.759$, $p < .001$, suggesting that non-stranded performed significantly better on second-year GPA than stranded students. The effect size for the difference in cumulative GPA after term 4 between the two groups was calculated as Cohen's $d = 0.345$, indicating a small effect. Student GPA mean averages for the academic performance variables included in the analysis are in Figure 2. The findings confirm that a student is more likely to become stranded as their overall cumulative GPA decreases across the first four terms.

Figure 2

Average GPA Means for SS and NSS



The results indicate that non-stranded students are associated with slightly higher cumulative academic performance through four terms, although the overall difference between the two groups is not substantial. The results of the Independent t-tests for the GPA variables can be found in Table 11.

Table 11

Stranded Status Comparisons of GPA Variables

	Non-Stranded		Stranded					
	M	*SD*	*M*	*SD*	*df*	*t*	*p*	Cohen's d
First-year GPA	3.13	0.60	3.01	0.56	3300.78	6.857	.001***	0.221
Second-year GPA	3.19	0.63	2.95	0.65	3559.83	11.943	.001***	0.377
Cumulative GPA Term 4	3.21	0.49	3.04	0.47	3374.40	10.759	.001***	0.345
Cumulative GPA Term 5	3.23	0.46	3.07	0.45	3364.38	10.810	.001***	0.348

Note. Variables are significant at *p<.05**p<.01 ***p<.001. Welch's test values are reported as Levene's test indicated the homogeneity of variances assumption was not met for each variable. Sample size (N) = 4149.

Explanatory Variables

To expand on the analysis, Chi-square tests were also conducted on the additional explanatory variables established for the study to determine if there is a significant association with stranded status group membership. The results of the test suggest that a statistically significant association exists between stranded status and students placed on academic probation, changing of major, consistently low academic performance, continual enrollment (<1 dropout), withdrawing from a course, and cumulative GPA after term 5.

Academic probation

The relationship between students who were placed on academic probation within their first six terms was significant, $\chi^2(1, N = 4149) = 33.472$, $p < .001$. The strength of this association, as measured by the Phi coefficient, is $\Phi = .090$. Within the first six terms, 34.68% of stranded students were placed on academic probation, compared to only 26.15% of non-stranded students. The results also showed that 67.23% of students who were placed on academic probation became stranded. A difference was shown in the proportion of SS compared to NSS; however, the overall effect size is small for students placed on academic probation. The association, although moderate, indicates that SS are more likely to be placed on academic probation within their first six terms compared to NSS, where SS represented a greater proportion of students being placed on academic probation. The findings demonstrate that students who receive academic probation are more likely to become stranded.

Change of Major

The relationship between students who changed their major by term 5 was significant, $\chi^2(1, N = 4149) = 24.453$, $p < .001$. The strength of this association, as measured by the Phi coefficient, is $\Phi = .077$. Within the first five terms, 31.75% of stranded students changed their major, compared to only 24.62% of non-stranded students. The results also indicated that 66.61% of students who changed their major by term 5 became stranded. A difference was shown in the proportion of SS compared to NSS; however, the overall effect size is small for changing a major by term 5. The association, although weak to moderate, indicates that SS are more likely to change their major within their first five terms compared to NSS, where SS represented a greater proportion of students who changed their major. The findings show that students who change their major are more likely to become stranded.

Consistently Low Academic Performance

The relationship between students with consistently low academic performance was significant, $\chi^2(1, N = 4149) = 60.235$, $p < .001$. The strength of this association is $\Phi = .120$. Within the first six terms, 36.63% of stranded students demonstrated consistently low academic performance, compared to only 25.11% of non-stranded students. The results also indicated that 69.29% of students who demonstrated consistently low academic performance became stranded.

A difference was shown in the proportion of SS compared to NSS; however, the overall effect size is small for students with consistently low academic performance. The association, although moderate, indicates that SS is more likely to demonstrate consistently low academic performance compared to NSS, where SS represented a greater proportion of students who performed consistently low academically. The findings show that students with consistently low academic performance are more likely to become stranded.

Continuous Enrollment with <1 Dropout Term

The relationship between students with continual enrollment was significant, $\chi^2(1, N = 4149) = 15.242$, $p < .001$. The strength of this association is $\Phi = .061$. Within the first six terms, 87.62% of stranded students demonstrated continual enrollment with less than one dropout, compared to only 83.30% of non-stranded students. The results also indicated that 61.94% of students who had continuous enrollment (<1 dropout) became stranded. The findings show there is a difference in the proportion of SS compared to NSS, however, the overall effect size is small for students with less than one term of dropout. The association, although weak, indicates that SS is more likely to have continual enrollment compared to NSS, where SS represented a greater proportion of students with less than one dropout term. The findings indicate that students with continual enrollment of less than one dropout semester are more likely to become stranded.

Withdraw from Any Course Two Terms

The relationship between students with any course withdrawal in their first two terms was not significant, $\chi^2(1, N = 4149) = 2.780$, $p = .101$. The strength of this association is $\Phi = .026$. Within the first two terms, 21.87% of stranded students withdrew from a course, compared to only 19.71% of non-stranded students. The results also indicated that 63.19% of the students who withdrew from a course in their first two terms became stranded. A difference was shown in the proportion of SS compared to NSS; however, the overall effect size is negligible for any course withdrawal in the first two terms. The very weak association indicates that withdrawal in the first two terms does not impact the likelihood of becoming stranded. SS group membership cannot be directly associated with withdrawal in the first two terms. The findings indicate that withdrawing from any course within the first two terms is not able to help determine if students will become stranded.

Withdraw from Any Course in the First 25

The relationship between students with any course withdrawal in their first 25 courses was significant, significance was shown for students with any course withdrawal in their first 25 courses, $\chi^2(1, N = 4149) = 4.455$, $p = .035$. The strength of this association is $\Phi = .033$. Within the first 25 courses enrolled, 35.91% of stranded students withdrew from a course, compared to 32.72% of non-stranded students. The results also indicated that 62.93% of students who withdrew from one of their first 25 courses became stranded. The findings show there is a difference in the proportion of SS compared to NSS, however, the overall effect size is small for students with any course withdrawal in their first 25 courses. The association, although weak, indicates that SS is more likely to withdraw within their first 25 courses compared to NSS, where SS represented a greater proportion of students who had any course withdrawal in their first 25 courses. The findings indicate that when including the first 25 courses, students withdrawing from any course will increase their likelihood of becoming stranded. Table 12 shows the results of the Chi-Square tests for the additional explanatory variables.

Table 12

Chi-Square Test Results of Academic Momentum Variables by Stranded Status

Explanatory Variables	$\chi 2$ Value (df = 1)	Level of Significance	Phi Value
Academic Probation Received	33.472	.001***	0.09
Changed Major by Term 5	24.453	.001***	0.077
Consistently Low Academic Performance	60.235	.001***	0.12
Continuous Enrollment in First Six Terms (< 1)	15.242	.001***	0.061
Any Withdraw in First Two Terms	2.780	0.101	0.026
Any Withdraw in First 25 Courses	4.455	0.035*	0.033
Major GPA Admission Requirement	34.577	.001***	0.091

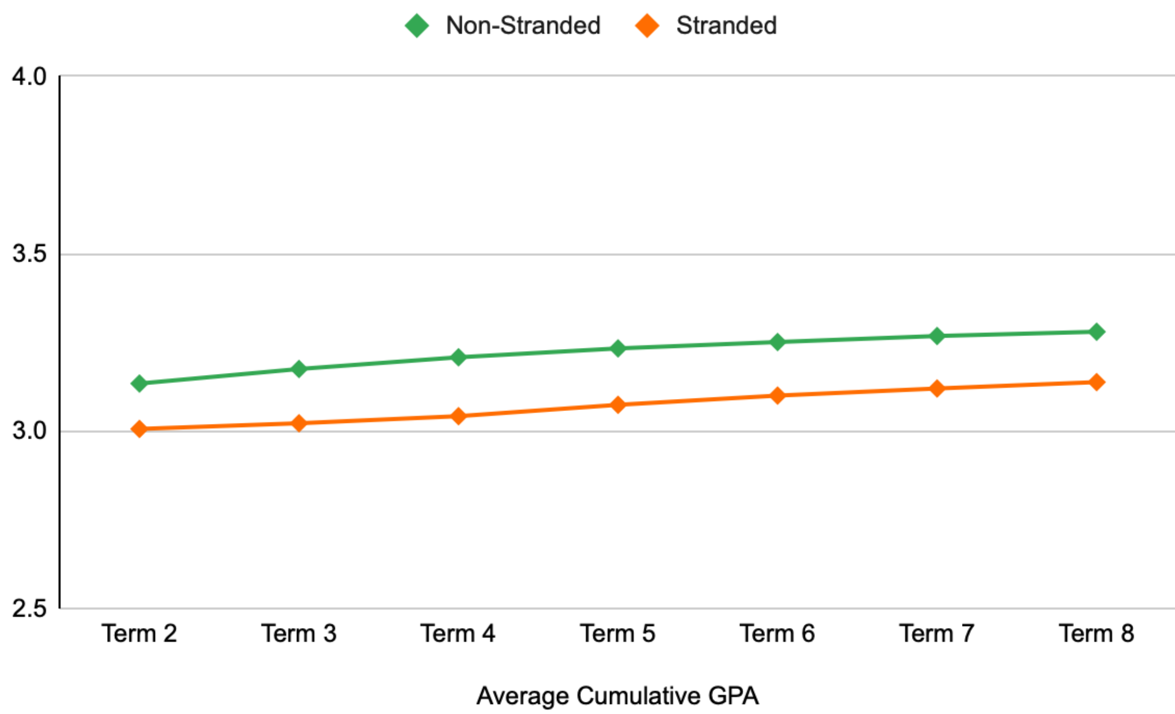
Note. Variables are significant at *p<.05, **p<.01, ***p<.001. Sample size (N) = 4149.

Cumulative GPA Term 5

The Independent samples t-test was used to calculate the final explanatory variable. For cumulative GPA after term 5, the analysis revealed a significant difference in the scores for non-stranded (M = 3.23, SD = .46) and stranded students (M = 3.07, SD = .45); $t(3364.38) = 10.810$, $p < .001$, suggesting that non-stranded performed significantly better on second-year GPA than stranded students. The effect size for the difference in cumulative GPA after term 5 between the two groups was calculated as Cohen's $d = 0.348$, indicating a small effect (Table 11). A review of the average cumulative GPA from term 2 through term 8 shows NSS students with higher average scores (Figure 3).

Figure 3

Average Cumulative GPA Performance of SS and NSS



The results indicate that non-stranded students are associated with slightly higher cumulative academic performance through five terms, although the overall difference between the two groups is not substantial. The findings confirm that a student is more likely to become stranded as their overall cumulative GPA decreases across the first five terms. A summary and interpretation of these results are discussed in the next chapter. The associations between college major choices and stranded status are examined through RQ2.

Major GPA Requirements

A Chi-square was also used to examine associations between GPA major restriction levels and stranded status. The relationship between students' major GPA admission requirements was significant, $\chi^2(1, N = 4149) = 34.577$, $p < .001$. The strength of this association is $\Phi = .091$. For students with a 2.00 GPA requirement, 55.21% are SS and 44.79% are NSS. The analysis found that 24.60% of stranded students are seeking a 2.00 GPA major. For students with a 2.50 GPA requirement, 64.74% are SS and 35.26% are NSS. The analysis found that 8.89% of stranded students are seeking a 2.50 GPA major. For students with a 2.75 GPA requirement, 60.65% are SS and 39.44% are NSS. The analysis found that 29.86% of stranded students are seeking a 2.75 GPA major. For students with a 3.00 GPA requirement, 68.93% are SS and 31.07% are NSS. The analysis found that 17.34% of stranded students are seeking a 3.00 GPA major. The findings show there is a difference in the proportion of SS compared to NSS, however, the overall effect size is small for students' major GPA restriction levels. The association, although weak, indicates that SS is more likely to be in a restrictive major compared to NSS, where SS represented a greater proportion of students attempting to enter each GPA restriction level. The findings indicate that a student's choice of major can impact their likelihood of becoming stranded. The major GPA restrictions' Chi-square test results are also found in Table 10.

Research Question 2

The second research question sought to examine which majors and colleges are associated with stranded status group membership. The first step in measuring stranded association to college choice is analyzing the descriptive statistical frequencies of student's choice of first pre-major, final major, first college, final college, and final pre-major.

Student's Major Choices

The top five first pre-majors by total count include Business PRE (N = 905), Nursing PRE (N = 609), Criminal Justice PRE (N = 339), Computer Science PRE (N = 261), and Mechanical Engineering PRE (N = 201). The top five first pre-majors by the percentage of stranded students are Nutrition PRE (77.40%), Civil Engineering PRE (72.50%), Electrical Engineering PRE (70.80%), Engineering/Computer Sci PRE (69.80%), and Computer Engineering PRE (68.90%). It is important to note that some students entered as "Computer Science PRE" rather than "Engineering/Computer Sci PRE." The Computer Science PRE is reported at (58.60% stranded). The top 20 first pre-major selections can be found in Appendix G.

The top five final student major choices through term 8 by count include Criminal Justice BA (N = 363), Nursing BS (N = 231), Accounting BSBA (N = 204), Nursing PRE (N = 185), and Kinesiological Sciences BS (N = 161). The top five final majors by the percentage of stranded students ($n > 50$) are Mechanical Engineering (96.97%), Nursing PRE (95.68%), Comprehensive Med Imaging BS (94.12%), Business PRE (90.28%), Computer Science PRE (89.65%). The top 75 final pre-major selections can be found in Appendix H.

Student's College Choices

The top five choices of first college, which have pre-majors, by total count include College of Business (N = 905), College of Engineering (N = 785), College of Nursing (N = 609), College of Urban Affairs (N = 576), and College of Health Sciences (N = 315). The top five first college choices, which have pre-majors, by the percentage of stranded students are the College of Nursing (66.80%), College of Engineering (64.80%), College of Education (62.80%), College of Health Sciences (59.40%), and College of Business (52.90%). The first college selections can be found in Appendix I.

The top five choices of final college choice through term 8 include College of Business (N = 888), College of Urban Affairs (N = 793), College of Engineering (N = 597), College of Nursing (N = 416), and College of Health Sciences (N = 359). The College of Education also had a large population of (N = 343). The top five final colleges by the percentage of stranded students are the College of Nursing (81.49%), the College of Engineering (75.21%), the College of Education (72.89%), the College of Business (64.08%), and the College of Public Health (54.00%). The final college selections can be found in Appendix J.

The top five final pre-major choices include Business PRE (N = 1,086), Nursing PRE (N = 634), Criminal Justice PRE (N = 438), Computer Science PRE (N = 308), and Mechanical Engineering PRE (N = 209). The top five final pre-major by percentage of stranded students (with N > 50) are Comprehensive Medical Img PRE (75.20%), Secondary Education PRE (72.80%), Civil Engineering PRE (72.00%), Elementary Education PRE (71.50%), and Social Work PRE (70.40%). The final pre-major selections can be found in Appendix K. The significance of the association between stranded status and student choices is further examined through logistic regression analysis.

Significance of College and Pre-major Choice

The College of Education is used as the reference category as it has a similar rate of stranded (62.80%) as the average stranded percentage across all majors (61.29%) and will serve as a benchmark to determine how likely are students from other colleges to be stranded.

First College Choice

A binary logistic regression[2] was performed to identify the effects of first college choice on the likelihood of SS group membership. The model was statistically significant, $\chi^2(10) = 242.110$, $p < .001$. The model explained 7.7% (Nagelkerke R^2) of the variance in stranded status,

[2] The binary logistic regression analysis aims to assess the effect of a student's initial choice of college and the final college as indicated by term 8. In the raw data, these responses were provided as string variables, which were then converted into 11 numeric categories for both the first and final college.

denoting a minimal explanatory power, with the Hosmer-Lemeshow test confirming a satisfactory fit, (p = 1.000). The results correctly classified 63.0% of cases. This finding allows for differentiation of first college choice based on their stranded status. Among the 11 re-coded *First College* categories, with College of Education serving as the reference, four categories: College of Sciences, ($p < .001$), College of Urban Affairs ($p < .001$), College of Business (p = .004), and the College of Public Health (p = .003) emerged as significant predictors of SS group membership (Table 13). When considering the first college choice alone for the significant colleges, the odds of being in SS are 300.1% higher for the College of Sciences, 55.6% lower for the College of Urban Affairs, 33.5% lower for the College of Business, and 72% lower for the College of Public Health. Additionally, the odds of being in SS are higher for all other majors except the College of Health Science, although the differences were not statistically significant. The findings indicate that certain student choices of first college are more likely to become stranded.

Table 13

Logistic Regression Predicting Stranded Status from First College Choice

							Confidence Interval	
First College	β	SE β	Wald χ^2	*df*	*p*	Exp(B)	Lower	Upper
College of Engineering	0.087	0.147	0.355	1	0.552	1.091	0.819	1.455
College of Fine Arts	0.203	0.225	0.815	1	0.367	1.225	0.789	1.902
College of Hospitality	0.314	0.325	0.933	1	0.334	1.368	0.724	2.586
College of Liberal Arts	0.239	0.216	1.227	1	0.268	1.27	0.832	1.937
College of Sciences	1.387	0.208	44.455	1	<.001***	4.001	2.662	6.014
College of Urban Affairs	-0.811	0.152	28.618	1	<.001***	0.444	0.33	0.598
College of Health Sciences	-0.146	0.171	0.73	1	0.393	0.864	0.619	1.208
College of Business	-0.407	0.143	8.158	1	0.004**	0.665	0.503	0.88
College of Nursing	0.176	0.153	1.325	1	0.25	1.192	0.884	1.608
College of Public Health	-1.272	0.424	9.005	1	0.003**	0.28	0.122	0.643

Note. Variables are significant at *p<.05, **p<.01, ***p<.001. College of Education is the reference group. Exp(B) = Odds Ratio.

Final College Choice

Next, a logistic regression was performed on the student's final college choice through term 8. The model was statistically significant, $\chi^2(10) = 390.949$, $p < .001$. The model explained 12.2% (Nagelkerke R^2) of the variance in stranded status, denoting a minimal explanatory power, with the Hosmer-Lemeshow test confirming a satisfactory fit, ($p = 1.000$). The results correctly classified 65.3% of cases. The results of the analysis can be found in Table 14. This finding allows for differentiation of final college choices based on their stranded status. Among the 11 re-coded *Final College* categories, with College of Education serving as the reference, 10 categories - College of Fine Arts (p <.001), College of Hospitality ($p < .001$), College of Liberal Arts ($p < .001$), College of Sciences, ($p < .001$), College of Urban Affairs ($p < .001$), College of

Health Sciences (p = .002) College of Business (p = .003), College of Nursing (p = .005), and the College of Public Health (p < .001) emerged as significant predictors of SS group membership.

When considering final college choice alone, the odds of being in SS are 74.5% lower for the College of Fine Arts, 89.4% lower for the College of Hospitality, 81.7% lower for the College of Liberal Arts, 63.4% for the College of Sciences, 61.4% lower for Urban Affairs, 39% lower for College of Health Sciences, 33.6% lower for the College of Business, 63.8% higher for the College of Nursing, and 56.3% lower for the College of Public Health. Although the difference is not statistically significant, the odds of being in SS are 12.9% higher for the College of Engineering. The findings indicate that certain student choices of final college are more likely to become stranded.

Table 14

Logistic Regression Predicting Stranded Status from Final College Choice

							Confidence Interval	
Final College	β	SE β	Wald χ^2	*df*	*p*	Exp(B)	Lower	Upper
College of Engineering	0.121	0.154	0.616	1	0.432	1.129	0.834	1.526
College of Fine Arts	-1.367	0.22	38.585	1	<.001***	0.255	0.166	0.392
College of Hospitality	-2.242	0.246	82.822	1	<.001***	0.106	0.066	0.172
College of Liberal Arts	-1.698	0.176	93.117	1	<.001***	0.183	0.13	0.258
College of Sciences	-1.005	0.216	21.597	1	<.001***	0.366	0.24	0.559
College of Urban Affairs	-0.951	0.141	45.682	1	<.001***	0.386	0.293	0.509
College of Health Sciences	-0.494	0.163	9.191	1	0.002**	0.61	0.443	0.84
College of Business	-0.41	0.14	8.564	1	0.003**	0.664	0.504	0.873
College of Nursing	0.493	0.175	7.93	1	0.005**	1.638	1.162	2.309
College of Public Health	-0.829	0.235	12.478	1	<.001***	0.437	0.276	0.692

Note. Variables are significant at *p<.05, **p<.01, ***p<.001. College of Education is the reference group. Exp(B) = Odds Ratio.

Final Pre-Major Choice

A logistic regression was performed on the student's final pre-major on record. The model was statistically significant, $\chi^2(28) = 164.175$, $p < .001$. The model explained 5.3% (Nagelkerke R^2) of the variance in stranded status, denoting a minimal explanatory power, with the Hosmer-Lemeshow test confirming a satisfactory fit, ($p = 1.000$). The results correctly classified 62.2% of cases. The results of the analysis can be found in Table 15. This finding allows for the differentiation of final pre-major choices based on their stranded status. Among the 11 re-coded Final Pre-major categories, with Athletic Training PRE serving as the reference, 12 pre-majors with significance ($p < .001$) including Business PRE, Civil Engineering PRE, Comprehensive Medical Img PRE, Computer Engineering PRE, Computer Science PRE, Electrical Engineering PRE, Elementary Education PRE, Mechanical Engineering PRE, Nursing PRE, Nutrition PRE, Secondary Education PRE, and Social Work PRE. An additional seven pre-majors showed significance including Communication PRE ($p = .003$), Early Childhood Education PRE ($p = .016$), Entertainment Engr Design PRE ($p = .003$), Health Care Admin PRE ($p = .023$), Human Services PRE ($p = .011$), Kinesiological Science PRE ($p = .016$), and Special Education PRE ($p = .049$). These 17 final pre-major indicators emerged as significant predictors of SS group membership. The findings section will further examine the likelihood of becoming stranded based on the student's choices.

When considering the significant final pre-major designation alone, with Athletic PRE as the reference group, the odds of being in SS are higher for 20 different pre-majors, with the highest odds of becoming stranded coming from Kinesiology Sciences (628%), Comprehensive Medical Img (451.4%), and Secondary Education (387.4%). The only major with lower odds of becoming stranded compared to Athletic PRE was Public Health PRE (8.9%). Although the analysis provided high percentages for other majors compared to Athletic PRE, the overall findings indicate that certain PRE majors are more likely to become stranded.

Table 15

Logistic Regression Predicting Stranded Status from Final Pre-Major Choice

							Confidence Interval	
Final Pre-Major Indicated	β	SE β	Wald χ^2	*df*	*p*	Exp(B)	Lower	Upper
Business PRE	0.904	0.243	13.829	1	<.001***	2.469	1.533	3.977
Civil Engineering PRE	1.542	0.34	20.533	1	<.001***	4.672	2.399	9.102
Communication Studies PRE	0.882	0.302	8.541	1	0.003**	2.416	1.337	4.366
Comprehensive Medical Img PRE	1.707	0.302	31.93	1	<.001***	5.514	3.05	9.968
Computer Engineering PRE	1.364	0.331	16.981	1	<.001***	3.913	2.045	7.486
Computer Science PRE	1.035	0.263	15.538	1	<.001***	2.815	1.683	4.709
Construction Management PRE	1.544	0.504	9.396	1	0.002**	4.684	1.745	12.571
Criminal Justice PRE	0.49	0.254	3.722	1	0.054	1.632	0.992	2.685
Early Childhood Education PRE	0.983	0.409	5.766	1	0.016*	2.671	1.198	5.957
Electrical Engineering PRE	1.516	0.394	14.795	1	<.001***	4.554	2.103	9.859
Elementary Education PRE	1.52	0.292	27.163	1	<.001***	4.573	2.582	8.1
Engineering/Computer Sci PRE	0.04	0.669	0.004	1	0.952	1.041	0.28	3.866
Entertainment Engr Design PRE	1.254	0.415	9.123	1	0.003**	3.503	1.553	7.901
Health Care Admin PRE	0.841	0.369	5.179	1	0.023*	2.318	1.124	4.782
Human Services PRE	1.11	0.434	6.536	1	0.011*	3.036	1.296	7.112
Journalism & Media Studies PRE	0.339	0.276	1.505	1	0.22	1.404	0.817	2.413
Kinesiological Science PRE	1.986	0.825	5.797	1	0.016*	7.286	1.447	36.691
Mechanical Engineering PRE	1.243	0.277	20.192	1	<.001***	3.466	2.015	5.96
Nuclear Medicine PRE	0.6	0.584	1.054	1	0.305	1.821	0.58	5.721
Nursing PRE	1.396	0.25	31.104	1	<.001***	4.04	2.473	6.6
Nutrition PRE	1.293	0.351	13.532	1	<.001***	3.643	1.829	7.254
Public Health PRE	-0.094	0.897	0.011	1	0.917	0.911	0.157	5.287
Secondary Education PRE	1.584	0.304	27.133	1	<.001***	4.874	2.686	8.844
Social Work PRE	1.466	0.323	20.618	1	<.001***	4.334	2.301	8.161
Special Education PRE	0.91	0.461	3.888	1	0.049*	2.484	1.005	6.136

Note: Significance Level = *p<.05, **p<.01, ***p<.001. Athletic Training PRE is the reference group. Health Physics PRE, Healthcare Admin PRE, Public Administration PRE, and Radio Technology PRE have less than 5 total students. Exp(B) = Odds Ratio.

Research Question 3(a)

The final research question, divided into two parts, seeks to determine if stranded status group membership can be predicted by a student's demographic and academic characteristics. Part (a) of the analysis begins with a binary logistic regression using the stranded status grouping variable as the dichotomous outcome variable. The independent variables (Table 9) are utilized as the predictor variables. Before analyzing the predictor variables, a key phenomenon in question is the varying GPA requirements established by each major.

Major GPA Requirement

A logistic regression was conducted to understand the association between GPA requirement levels and the likelihood of SS group membership. Utilizing the GPA requirement identified by the student's last pre-major on record, a logistic regression was performed on the student's GPA requirement level for entry into the intended major. With a 2.00 GPA serving as the reference category, the logistic regression model was statistically significant, $\chi^2(3) = 34.952$, $p < .001$. The model explained 1.1% (Nagelkerke R^2) of the variance in stranded status, denoting a minimal explanatory power, with the Hosmer-Lemeshow test confirming a satisfactory fit, (p = 1.000). The results correctly classified 60.7% of cases. This finding allows for the differentiation of GPA restriction levels based on the student's stranded status. Among the four categories, with the (2.00) GPA requirement level serving as the reference, each remaining level, including 2.50 GPA ($p = .002$), 2.75 GPA ($p = .003$), and 3.00 GPA ($p < .001$) emerged as significant predictors of SS group membership. When considering GPA requirement alone, the odds of being in SS are 49% higher for students with a 2.50 GPA requirement, 24.6% higher for students with a 2.75

GPA requirement, and 80% higher for students with a 3.00 GPA requirement. The results of the regression analysis can be found in Table 16.

Table 16

Logistic Regression Predicting Stranded Status from GPA Requirement

							Confidence Interval	
GPA Requirement	β	SE β	Wald χ²	*df*	*p*	Exp(B)	Lower	Upper
2.50	0.398	0.128	9.765	1	0.002**	1.490	1.16	1.913
2.75	0.22	0.075	8.54	1	0.003**	1.246	1.075	1.443
3.00	0.588	0.105	31.487	1	<.001***	1.800	1.466	2.21

Note. Variables are significant at *p<.05, **p<.01, ***p<.001. 2.00 is the reference group. Exp(B) = Odds Ratio.

Demographic Characteristics

It is also hypothesized that a student's demographic and academic characteristics may also be associated with SS group membership. The three-stage analysis will begin with analyzing the demographic characteristics, then the Academic Momentum model-based variables are added, and lastly, the theorized explanatory variables are added to the full analysis. Utilizing the demographic variables identified for each record, a logistic regression was performed on the student's demographic characteristics, including gender, race, Pell Grant eligibility, scholarship recipient, student loan recipient, and parent's education level of no bachelor and no college. First, logistic regression was performed on gender, race, and financial variables alone to understand their relationship to stranded status.

Gender Variables Alone

The model for gender alone was not statistically significant, $\chi^2(1) = 1.808$, $p = .179$. The model explained .10% (Nagelkerke R^2) of the variance in stranded status, denoting gender as a very low explanatory of variance in SS. The results correctly classified 60.7% of cases. When considering gender alone, the odds of being in SS are 9.1% higher for males, although the difference is not statistically significant.

Race Variables Alone

Next, the model for race variables alone was not statistically significant, $\chi^2(8) = 10.839$, $p = .211$. The model explained .40% (Nagelkerke R^2) of the variance in stranded status, denoting race as a very low explanatory of variance in SS, with the Hosmer-Lemeshow test confirming a satisfactory fit, ($p = 1.000$). The results correctly classified 60.8% of cases. Only Asian ($p = .028$) emerged as a significant predictor of stranded status. When considering race alone, the odds of being in SS are 21.9% higher for Asians. Also, although not significant, the odds of becoming stranded are 2.3% higher for African American or Black, 10.5% higher for Hispanic, 6.7% higher for More than 1 race, 29.9% lower for International, and 32.8% higher for Hawaiian or other Pacific Islander compared to White students.

Financial-related Variables Alone

Next, the model for financial variables alone was not statistically significant, $\chi^2(5) = 7.205$, $p = .206$. The model explained .20% (Nagelkerke R^2) of the variance in stranded status, denoting the financial characteristics (Pell status, scholarship, parents' education level) as a very low explanatory of variance in SS, with the Hosmer-Lemeshow test confirming a satisfactory fit, ($p = .305$). The results correctly classified 60.7% of cases. None of the financial variables emerged as a significant predictor of stranded status. When considering financial characteristics alone, the odds of being in SS are 5.1% higher for Pell Grant eligible students, 4.4% lower for scholarship recipients, 13.2% higher for students with loans, 1.2% higher for students whose parents do not have a bachelor, and 11.2% lower for students with parents who did not complete college, although the difference is not statistically significant for each financial variable.

Combined Gender and Race Variables

For the second part of the demographics model, combining gender and race variables in one model was not statistically significant, $\chi^2(6) = 12.583$, $p = .785$, which means gender and race combined as a whole, do not significantly predict SS. The model explained .40% (Nagelkerke R^2) of the variance in stranded status, denoting combined demographics as a very low explanatory of variance in SS, with the Hosmer-Lemeshow test confirming a satisfactory fit, ($p = .785$). The results correctly classified 60.7% of cases. Similar to the race-only regression, the category of Asian emerged as the only significant predictor of SS group membership ($p = .027$). When considering gender and race combined, the odds of being in SS are identical to race alone, although the differences again are not statistically significant.

Combined Gender, Race, and Financial Variables

The final part of the demographic analysis, combining gender, race, and financial characteristics in one model was not statistically significant, $\chi^2(14) = 20.602$, $p = .112$, which means the demographics categories only, combined as a whole, do not significantly predict SS. The model explained .70% (Nagelkerke R^2) of the variance in stranded status, denoting race as an exceptionally low explanatory of variance in SS, with the Hosmer-Lemeshow test confirming a satisfactory fit, ($p = .829$). The results correctly classified 60.8% of cases. Similar to the previous regressions, the category of Asian ($p = .024$) and student loan recipient ($p = .044$) emerged as the only significant predictor of SS group membership ($p = .027$).

When considering the demographic characteristics combined, the odds of being in SS are 22.7% higher for students identifying as Asian and 14.1% lower for student loan recipients. Although not significant, when combining demographic characteristics the odds of becoming stranded are 9.0% higher for males, 1.5% lower for African American or Black, 14.1% higher for Hispanic, 4.9% higher for More than 1 race, 25.0% lower for International students, and 26% higher for Hawaiian or other Pacific Islander compared to White, 5.1% higher for Pell Grant eligible students, 14.1% higher for students with loans, 2.5% higher for students whose parents do not have a bachelor, and 13.0% lower for students with parents who did not complete college. The results of the logistic regressions on demographic variables can be found in Appendix L.

Academic Momentum Characteristics

The next stage of the analysis examines if a student's academic momentum characteristics, as outlined by Adelman (2006), are significant predictors of stranded status group membership.

Academic Momentum Benchmark Variables Alone

A logistic regression of the Academic Momentum variables only was statistically significant, $\chi^2(8) = 225.337$, $p < .001$, which means the Academic Momentum indicators combined as a whole, significantly predict SS. The model explained 7.2% (Nagelkerke R^2) of the variance in stranded status, denoting the Academic Momentum characteristics as a small explanatory of variance in SS, with the Hosmer-Lemeshow test showing a poor model fit, (p = .001). The results correctly classified 64.7% of cases. Among the eight variables, three were statistically significant including if a student was enrolled in a summer term within the first 25 courses ($p < .001$), continual enrollment with less than two dropout semesters ($p = .022$), and second-year GPA ($p < .001$). When considering the academic momentum variables alone the odds of being in the SS group were 71.6% higher for students who enrolled in a summer course, 77.3% higher for students with continual enrollment, and for each one-unit increase in second-year GPA (moving from 2.0 to 3.0) the odds of becoming stranded decrease by 37.1%. Although not statistically significant, the odds of being in SS are 51.2% higher for students taking remedial courses in the first two terms, 12.6% lower for students taking remedial courses within their first 25 combined courses, 29.9% lower for students who withdrew 20% or more of their courses, for each one-unit increase in first-year GPA the odds of becoming stranded increased by 6.4%, and for each one-unit increase in cumulative GPA after term 4 the odds of becoming stranded decreased by 26.3%.

Demographic and Academic Momentum Variables Combined

For the second stage of the analysis to answer RQ3(a), a combined logistic regression of all variables in one model was conducted. The analysis showed the combination of the demographic and academic momentum variables was statistically significant, $\chi^2(22) = 250.931$, $p < .001$, which means the demographic characteristics and Academic Momentum indicators combined as a whole, significantly predicted SS. The model explained 8.0% (Nagelkerke R^2) of the variance in stranded status, with the Hosmer-Lemeshow test showing a poor model fit, ($p = .002$). The results correctly classified 64.4% of cases. Among the 22 variables, five were statistically significant including if a student identified as American Indian or Alaskan Native ($p = .04$), Asian ($p = .011$), if a student was enrolled in a summer term within the first 25 courses ($p < .001$), demonstrated continual enrollment with less than two dropouts ($p = .030$), and second-year GPA ($p < .001$). When considering the academic momentum variables plus the demographic characteristics the odds of being in the SS group were 89% lower for students who identify as American Indian or Alaskan Native, 26.7% higher for students who identify as Asian, 72.9% higher for students who enrolled in a summer course, 73.2% higher for students with continual enrollment, and for each one-unit increase in second-year GPA (ex. moving from 2.0 to 3.0) the odds of becoming stranded decrease by 36.9%. The analysis demonstrates that these variables can be considered significant predictors of stranded status group membership. The logistic regression results for Adelman's (2006) Academic Momentum variables and combination analysis can be found in Appendix M.

Explanatory Variables

The final stage of the logistic regression in RQ3(a) incorporates the theorized explanatory variables that may contribute to stranded status group membership.

Explanatory Variables Alone

First looking at the explanatory variables alone, the logistic regression was statistically significant, $\chi^2(7) = 167.625$, $p < .001$, which means the explanatory variables, significantly predicted SS. The model explained 5.4% (Nagelkerke R^2) of the variance in stranded status, denoting the explanatory variables as a small explanatory of variance in SS, with the Hosmer-Lemeshow test confirming a satisfactory fit, ($p = .549$). The results correctly classified 62.7% of cases. Among the seven variables included, three were statistically significant including if a student changed their major in the first five terms ($p < .001$), if a student had continual enrollment with less than one dropout ($p < .001$), and cumulative GPA after term 5 ($p < .001$). When considering the explanatory variables alone the odds of being in the SS group were 44.5% higher for students who changed their major, 66.1% higher for students with a continual enrollment of less than one dropout, and each one-unit increase in cumulative GPA after term 5 (e.g. moving from 2.0 to 3.0) the odds of becoming stranded decreased by 52.6%. Although not statistically significant, the odds of being in SS are 1.5% lower for students who receive academic probation, 12.5% higher for students with consistently low academic performance, 3.5% higher for students who withdraw in any of the first two terms, and 6% lower for students who withdraw in any of the first 25 courses.

Demographic, Academic Momentum, and Explanatory Variables Combined

Next, a combined logistic regression analysis is designed to incorporate each of the demographic, momentum, and explanatory variables into one model for the analysis. A combination analysis of all variables was statistically significant, $\chi^2(29) = 305.698$, $p < .001$, which means the combined demographic characteristics, academic momentum benchmarks, and explanatory variables as a whole, significantly predicted SS. The model explained 9.7% (Nagelkerke R^2) of the variance in stranded status, denoting the combined characteristics as a small explanatory of variance in SS, with the Hosmer-Lemeshow test showing a poor model fit, ($p = .018$). The results correctly classified 65.3% of cases. Among the 29 variables included, five were statistically significant including if a student identified as Asian ($p = .011$), if a student enrolled in a summer course ($p < .001$), second-year GPA ($p < .001$), if a student changed their major in the first five terms ($p < .001$), and if a student had continual enrollment with less than one dropout ($p < .001$). When considering the combined variables, the odds of being in the SS group were 27.4% higher for students who identify as Asian, 78.2% higher for students who enrolled in a summer term, 52.2% higher for students who changed their major, 61.3% higher for students with continual enrollment of less than one dropout, and for each one-unit increase in second-year GPA (e.g. moving from 2.0 to 3.0) the odds of becoming stranded decrease by 39.6%.

Although not statistically significant, the odds of being in SS are higher for students who identify as Male, as well as students who identify as Hispanic, More than 1 race/ethnicity, Hawaiian or other Pacific Islander, and Unknown, compared to students who identify as White. While also not significant, the odds of SS group membership are higher for students who are Pell Grant eligible, receive student scholarships, receive student loans, take any remedial course in the first two terms, have continual enrollment (<2 dropouts), withdraw from a course in their first two terms. Also, for each one-unit increase in the First-year GPA the odds of becoming stranded decrease by 1.4%, for each one-unit increase in cumulative GPA after term 4 the odds of becoming stranded decrease by 6.8%, and for each one-unit increase in cumulative GPA after term 5 the odds of becoming stranded decrease by 22.1%. The non-significant results also indicate that the odds of SS group membership are lower for female students, and students who identify as Black or International, along with students whose parents did not attend college, took a remedial course in the first 25 courses, withdrew from 20% or more of courses, receive academic probation, students with consistently low academic performance, students who withdraw in any of the first 25 courses. The results of the full logistic regression of the demographic, momentum, and explanatory variables can be found in Appendix N.

Research Question 3(b)

The final part of the study seeks to examine to what extent the likelihood of stranded status varies by college. Utilizing the significant characteristics identified in the first part of RQ3 (if a student identified as Asian, if a student enrolled in a summer course, second-year GPA, if a student changed their major in the first five terms, and if a student had continual enrollment with less than one dropout), interaction terms were created by multiplying the value of the significant variables by student's choice of College in term 8. Dummy variables for each College were created, using the College of Education as the reference category. When adding the interaction terms into the full logistic regression with the original variables, the combination analysis was statistically significant, $\chi^2(79) = 861.352$, $p < .001$, which means the combined demographic characteristics, Academic Momentum benchmarks, explanatory variables, and interaction terms as a whole, significantly predicted SS. The model explained 25.6% (Nagelkerke R^2) of the variance in stranded status, denoting the combined characteristics with interaction terms as a small explanatory of variance in SS, with the Hosmer-Lemeshow test confirming a satisfactory fit, ($p = .050$). The results correctly classified 70.1% of cases. Among the 29 original variables included, only three of the five were statistically significant including if a student enrolled in a summer course ($p = .035$), second-year GPA ($p = .011$), and if a student had continual enrollment with less than one dropout ($p < .001$). When considering the combined variables, the odds of being in the SS group were 162.5% higher for students who enrolled in a summer term, 269.5% higher for students with continual enrollment of less than one dropout, and for each one-unit increase in second-year GPA (ex. moving from 2.0 to 3.0) the odds of becoming stranded decrease by 35.9%.

Among the 50 interaction variables included, eight were statistically significant including Asian * College of Fine Arts ($p = .004$), Asian * College of Liberal Arts ($p = .038$), Second-year GPA * College of Nursing ($p < .001$), Changed Major * College of Fine Arts ($p = .014$), Cont Enroll * College of Fine Arts ($p = .009$), Cont Enroll * College of Hospitality ($p = .002$), Cont Enroll * College of Nursing ($p = .031$), and Cont Enroll * College of Public Health ($p = .032$). When considering the combined variable and interaction terms the odds of being in the SS group were 90.6% lower for Asian students in the College of Fine Arts, 77.2% lower for Asian students in the College of Fine Arts, for each one-unit increase in second-year GPA (ex. moving from 2.0 to 3.0) the odds of becoming stranded for students in the College of Nursing increase by 62.8%. Additionally, the odds of being in the SS group are 75% lower for College of

Fine Arts students who change their major, 80.5% lower for College of Fine Arts students with continual enrollment (<1), 87.8% lower for College of Hospitality students with continual enrollment (<1), 65.7% lower for the College of Nursing students with continual enrollment (<1), and 78.9% lower for College of Public Health students with continual enrollment (<1). The results of the full logistic regression of the student variables and interaction terms can be found in Appendix O. These findings demonstrate that while some individual academic characteristics may be predictors of stranded status, the likelihood of group membership does vary by the student's choice of College type.

Conclusion

The analysis showed that there are significant group differences related to the stranded and non-stranded groups. A descriptive analysis of the SS and NSS was able to show the demographic characteristics, Academic Momentum Theory indicators, and explanatory variable outcomes between the samples. A closer examination of the Academic Momentum benchmarks showed significant differences for some, but not all of Adelman's (2006) indicators. A significant relationship was demonstrated between the student's initial choice for college type, the college choice in term 8, and the final pre-major on record to their likelihood of becoming stranded. While several variables (demographic, academic momentum, explanatory) were not statistically significant in predicting group membership, the analysis nonetheless demonstrated that students who can declare their major by term five with strong academic performance through their second year have lower odds of becoming stranded. When college choice was added as an interaction term, the significant predictor variables were shown to vary by college type. The findings of the analysis are further discussed in the next chapter.

Chapter 5: Discussion

The issue of stranded students has been an unexplored phenomenon in higher education, yet many students find themselves unable to declare a major due to GPA admission requirements. These students continue to pursue additional college credits and spend more time, money, and effort in hopes of being able to move forward. This study sought to describe the prevalence of stranded students and to expand on the higher education research of at-risk college students and major GPA restrictions. The study was guided by an academic momentum model (Adelman, 1999; 2006) to understand if stranded students are exhibiting benchmarks indicative of future degree attainment. The analysis sought to identify student characteristics that may be predictive of future stranded status, with the goal of early detection to provide support for stranded students during their academic journey.

This chapter will present the major findings from the quantitative analysis and their conclusions. Future implications and recommendations for higher education administration will be presented with the goal of supporting degree completion of stranded students. Suggestions for future research will be discussed to expand on this study and further understand the issue of stranded students.

Major Findings and Conclusions

As discussed, the study examines the relationship between academic momentum, other explanatory variables, and the likelihood of becoming a stranded student. The study is designed around three research questions, each aimed at understanding the stranded status outcome.

***Research Question 1(a)*:** What are the demographic and academic characteristics of students who have "stranded status"? ***1(b)*:** To what extent are there differences in academic momentum indicators of the stranded status group and the non-stranded status group?

***Research Question 2*:** Which majors and colleges are more associated with stranded status?

Research Question 3(a)*:** What academic and demographic indicators are predictive of stranded status? ***3(b). Do these relationships vary across colleges?

The first noticeable indication of the prevalence of stranded students was discovered through obtaining the sample for the study, finding that 2520 pre-major students had not successfully declared a major by their fifth term and later accumulated at least 70 total credits, or 20% of the full population sample. This was compared to only 1629 pre-major students who declared a major in the same timeframe. Notably, the gender, race, and financial characteristics are similar between the sample groups of stranded status (SS) and non-stranded status (NSS). The initial part of the analysis first demonstrated the group differences in the academic momentum benchmarks such as remedial courses completed, summer term enrollment, first-year GPA, second-year GPA, and cumulative GPA after the second academic year. Other momentum benchmarks were similar including the percentage of withdrawn courses and continual enrollment of less than two semesters of dropout. Of the additional explanatory variables conceptualized, initial group differences were discovered in academic probation received, changing of major, continuously low academic performance, and cumulative GPA, however, course withdrawal rates were similar. The SS and NSS differences exposed through the group descriptives illustrate the need to employ quantitative analysis to further understand the association of student characteristics and stranded status.

Academic Momentum Benchmarks

The analysis discovered that stranded students are more likely to experience roadblocks to momentum in some areas compared to non-stranded students. The significant results first revealed that stranded students are more likely to enroll in remedial courses, both in their first two terms and within their first 25 courses. Adelman (2006) refers to these remedial courses as the "remedial problem" and appeared to be a neutral factor in *The Toolbox Revisited* logistic analysis. As it relates to stranded students, the additional credits earned through remedial work are not applicable to their degree and may delay the ability to declare a major on time, increasing the odds of becoming stranded.

The findings indicate that remedial coursework can increase the likelihood of a negative student outcome (stranded status), similar to previous research findings (Jimenez et al., 2016; Martorell & McFarlin, 2011). Scott-Clayton and Rodriguez (2015) found remedial students are persisting at the same rates, and while the SS and NSS group percentages are similar for remedial courses completed in the first two terms (20.95% of SS and 14.68% NSS), the results show remedial coursework is a hindrance to persisting to an intended degree. This analysis does not definitively conclude that remedial coursework leads to more total "credits," as found by Scott-Clayton and Rodriguez (2015), however, it can be concluded by the size of the sample populations with 70 or more credits by term 8, stranded students (N = 2520) are accumulating credits at an equivalent rate or higher as non-stranded students (N = 1629). This downstream effect of remedial coursework is shown through excess credits potentially earned by SS, who are not able to declare a restrictive major. The findings build upon the previous literature by describing how remedial courses can lead to a negative student outcome of stranded status and do not appear to affect future credit accumulation.

Stranded students were also significantly more likely to take summer term courses. While Adelman (2006) describes summer term credits as reflective of continuing leverage of attainment, this finding suggests that students may also be enrolling in the summer term to retake courses, explore introductory courses in other degree fields, or catch up from remedial courses taken in their first year, among other potential reasons (p. 80). Adelman (2006) found that students who earned summer credits added 11.2% to their probability of earning a bachelor's degree (p. 72). Despite the finding suggesting that summer term enrollment has a moderate association with the likelihood of stranded status, the SS group is exhibiting an academic momentum benchmark. Previous literature has concluded that summer term enrollment is associated with a higher probability of degree completion (Adelman, 2006; Atwell et al. 2012; Davidson, 2014; Wang et al., 2015). While this study does not examine graduation rates, the findings challenge the previous research by suggesting that summer term enrollment can lead to a negative student outcome of stranded status in the third academic year. Despite finding themselves in stranded status, this positive indicator of academic momentum further suggests the need for specially designed, targeted advising for students taking summer courses to provide support in degree completion.

The results found that academic performance benchmarks were also significantly associated with stranded status and differences existed between the two groups in first-year GPA, second-year GPA, and cumulative GPA (term 4), although the difference between the group's means is small (Sullivan & Feinn, 2012). It is interesting to note that as the academic career progressed, the average mean GPA continued to diverge between SS and NSS. The impact of the difference, although subtle, confirms lower GPA benchmarks in the first two terms impact the likelihood of becoming stranded. This replicates Adelman's findings where a "rising trend in grades fits with attainment, contributing positively and significantly" (p. xxii). Much of the previous literature has concluded that decreased academic performance will decrease persistence rates and lower a student's likelihood of degree completion (Clovis & Chang, 2021; DesJardins et al., 2002; Mueller et al., 2017; Singell & Waddell, 2010). This study's findings build on the previous literature by confirming that lower academic performance across the first two years is associated with negative student outcomes (stranded status).

The lack of statistical significance between continuous enrollment (<2) and withdrawing (20% or more) and stranded status further signifies similar academic momentum rates for both SS and NSS. These findings also imply that stranded students are maintaining their academic momentum by continual enrollment in classes each term and returning to campus during the subsequent terms. While some academic momentum model benchmarks were shown to be statistically significant, the overall minimal differences in association show that stranded students *are* exhibiting similar academic momentum benchmarks compared to the non-stranded group, which is a key finding of the study. The results confirm Adelman's (2006) academic momentum model that students with a greater association with remedial courses and poor academic performance increase their time to degree completion, or in this case, declaring and moving to upper division courses within their college. The findings, which show stranded students achieving similar benchmarks to non-stranded students, underscore the importance of implementing targeted interventions to bolster academic momentum. The findings corroborate the claim by Martin et al. (2013) that for students exhibiting academic momentum, "intervention should be on time and targeted at learners earlier in their university life" and further supports a "close, continuous, semester-based monitoring system" of student GPA achievement.

Explanatory Variables

Certain academic decisions and outcomes could be a warning sign of a student's inability to declare a major, a critical milestone in their academic career. Because the GPA requirements can be difficult to reach for some students, even one poor semester of academic performance can exert an influence on the ability to declare within the expected timeframe. The impact of academic difficulties on a student's progress is first evidenced by the significant association between a student receiving academic probation and stranded status. Students facing academic challenges that result in academic probation are increasing their likelihood of becoming stranded, resulting in more time to complete a degree. This finding builds upon the previous literature findings that indicate academic probation is significantly associated with persisting to an intended degree (Dong, 2019; Bowman & Jang, 2015; Sneyers & De Witte, 2018; Wright, 2020), while also challenging the previous findings of no association (Albert & Wozny, 2019; Casey et al., 2018). The primary function of academic probation policies is to help students remain enrolled and improve the following semester. The significant findings highlight the importance of improving student interventions with the goal of improving future student outcomes and increasing retention rates.

Students changing their pre-major within the first five terms of enrollment were also more likely to become stranded. These changing student decisions mean that a student must complete a distinct set of pre-major course requirements for the new college, potentially delaying their ability to declare a major and complete a degree. When considering stranded status as a negative indicator related to degree completion, the results challenge the findings of Spight (2022) who determined that whether a student matriculated as undeclared versus declared, neither population had a significantly greater likelihood of graduating on time. The findings related to changing a major are an important contribution to the previous literature, as most studies examine the relation of changing a major to degree completion; the findings of this study provide an understanding of the impact of changing a major during the active progress of their academic career.

A student who displays consistently low academic performance is also increasing their chances of becoming stranded. This finding was expected and is demonstrated by the fact that sustained student struggles can impede a student's momentum toward degree completion, as found with previous studies related to cumulative grade point averages. The results of the analysis of academic performance over a period of six terms can build upon the previous findings that higher grades over the course of multiple semesters can lead to improved student retention (Blekic et al., 2020; Cochran et al., 2014). To counteract their early struggles, students may be forced to take courses that are not applicable to their degree to meet the major GPA requirement. This is where an early alert would be critical in ensuring that students are aware of their likelihood to declare an intended major.

An interesting finding showed that SS was more associated with continuous enrollment (<1 dropout) than NSS. Not only does this serve as an academic momentum benchmark, but it confirms that stranded students generally intend to complete their degree. This supports the study's purpose to identify potential stranded students early and facilitate a path toward degree declaration. However, the results do challenge previous literature findings that continual enrollment exhibits a positive correlation with future degree completion (Auburn University, 2008; Chen & Carroll, 2005; Offenstein et al., 2010). The rates of students withdrawing from their courses either within the first two terms or 25 courses were similar between the two groups. It can be concluded from the minimal differences between the SS and NSS groups, withdrawing from courses has little effect on a student later becoming stranded.

A closer look into the academic performance of SS and NSS shows that stranded students perform consistently lower academically than non-stranded students. The final explanatory variable of cumulative GPA following the fifth term demonstrated that enhanced academic performance over time will decrease the likelihood of stranded status. This finding follows Adelman's (2006) "trends in grades" variables, confirming that continued poor academic performance will impede degree progress. Although the associations of the explanatory variables were relatively moderate and sometimes weak, caution must be used when describing a full direct association between the student characteristic and the outcome variable. It can be said that students are more likely to be associated with stranded status group membership, given the impact of negative academic benchmarks in their early postsecondary progression.

The results of the analysis support previous research findings suggesting that reviewing the level and trend in GPA, and the student's course-taking behavior may be a way to identify possible retention risks (Singell & Waddell, 2010; DesJardins et al., 2002). The findings also build upon the previous research studies that have adapted the academic momentum model to include their own variables as benchmarks (Adelman, 1999, 2006; Attewell et al., 2012; Clovis & Chang, 2021; Davidson & Blankenship, 2016; Martin et al., 2013, Wang et al., 2015). This study adds to the literature by including academic probation, changing a major, achieving consistently low academic performance, continual enrollment (<1 dropout), withdrawal from any course, and cumulative GPA after term 5 as new benchmarks to consider.

Student Choice of Major and College

A descriptive statistics analysis of the SS group revealed that students from a wide range of majors can become stranded including education, engineering, health sciences, and business-related majors. The sample also provided a glimpse into the colleges where stranded students are most commonly found including College of Nursing, College of Engineering, College of Education, and College of Business. It is critical to use the choices of final pre-major on record and final college after term 8 as key points of time that provide an understanding of the student's major declaration goals. The colleges with the highest percentages of stranded students require higher GPA levels, whereas most of these students are trying to declare a major with a 2.75 GPA restriction or higher. This finding supports the purpose of the study by understanding the impact of GPA restrictions on students' ability to declare a major, leading to potential policy changes at the college level.

A binary logistic regression confirmed that a student's first college choice is significantly associated with future stranded status. The odds of becoming stranded were higher for the College of Sciences, while the odds of becoming stranded were lower for the student's first college choice of College of Urban Affairs, College of Business, and College of Public Health. Since the College of Science does not have any "pre-major" designation serving as a gatekeeper, the higher odds of becoming stranded with that college may be a result of students transitioning out of the College of Science due to difficult courses, lack of available courses, poor advising, etc.

The lower odds of becoming stranded for the College of Urban Affairs may be an indication of their lower GPA requirement to declare, while also providing timely advising and support along the road to degree declaration. As is the case with the College of Business and the College of Public Health, lower odds of becoming stranded after initially starting in those colleges may be a testament to their first-year programming, advising, and support structures for students. The results support the purpose of the study to provide meaningful academic advising intervention that can enhance student success (Elrich and Russ-Eft, 2013; Mu & Fosnacht, 2019; Young-Jones et al., 2013). The support from advisors should not only help students understand which courses they need to complete to graduate, but a review of the GPA admissions policies paired with current academic progress can provide students with a realistic likelihood of declaring their intended major.

While only four colleges demonstrated statistically significant results when factoring in the student's first college choice, when adjusting the analysis for the final college choice the results varied, finding odds of becoming stranded were lower for all other colleges except Nursing. These findings may be indicative of the highest GPA requirements on campus (3.00), found in the College of Nursing, wherein the higher GPA requirements levels are leading more students to become stranded, supporting previous findings that GPA requirements can negatively impact a student's ability to declare a major (Bleemer and Mehta, 2021; Bleemer et al., 2023). The analysis also provides a more description of GPA restrictions, as it relates to specific majors, colleges, and GPA levels. The results provide a nuanced look into GPA restrictions by exploring them in greater detail and taking additional student characteristics into consideration.

As some colleges have varying GPA restriction levels within their majors, the student's final pre-major was also examined as the most logical interpretation of the required GPA achievement level. Several majors predicted statistically significant higher odds of becoming stranded, including majors from the College of Business, College of Education, and College of Engineering. The study extends the previous research by identifying the types of majors that may lead to lower persistence rates (King, 2015; Spight, 2022; Whitcomb et al., 2022). The majors who predicted the highest odds of SS group membership may be requiring difficult pre-major courses or may require additional admission requirements not captured by this analysis. A wide range of pre-majors identified makes it difficult to specify if one particular college may not have accessible support structures in place to guide students in meeting program expectations. It could be that students in these fields are more committed to staying in those fields. The analysis confirms that a student's choice of college and major can significantly impact the likelihood of future stranded status group membership.

Predicting a Stranded Status Student

Building upon the associations discovered in RQ1(b), the student's demographic, academic momentum benchmarks, and explanatory variables were analyzed through binary logistic regression to determine if a combined group of characteristics can predict stranded status group membership. With 2.00 as the reference category, each level of GPA restrictions (2.50, 2.75, and 3.00) were all significant predictors of future SS group membership. Interestingly, students seeking to enter a 2.50-level major had higher odds of becoming stranded compared to students seeking a 2.75-level major, with 3.00 having the highest predictive odds. It is also important to note that when compared to a 2.00 GPA, each level created higher odds of becoming stranded, which further indicates that GPA restrictions can be a roadblock to degree completion. The findings show that as students attempt to enter majors with GPA restrictions above 2.50, they are more likely to become stranded. The results build further upon previous literature in finding that GPA restrictions are a prohibitive factor that can reduce the likelihood that a pre-major student can successfully declare their intended major (Bleemer & Mehta, 2021; Bleemer et al. 2023; Schmidt, 2021).

Demographic Characteristics

When including the student's demographic characteristics alone, the results did not reveal any significant relationship to stranded status, except for students who identified as Asian. All else equal, Asian students were more likely to be stranded. As previously described, the population samples are relatively similar with a slightly higher population of female stranded students compared to male students, as well as similar financial characteristics. The disproportionate number of Asian students who become stranded may be a result of their choice of college and major. If this group of students is more likely to major in STEM, Business, or Nursing compared to Urban Affairs, it may be the reason behind the only significant finding as it relates to the student's race identification. Like Adelman's (1999, 2006) momentum analyses, race was not significantly associated with degree completion after full controls were added for academic preparation and family socioeconomic background (Attewell et al., 2012, p. 39). This finding indicates there are other factors contributing to students becoming stranded.

When including gender, race, and financial characteristics, student loans received also emerged as a significant predictor of SS group membership. It can be difficult to ascertain why student loans specifically may be a predictor of SS, as in previous studies it was an indicator of attainment (Gilstrap, 2020). Adelman (2006) views student loans as a form of financial aid or support for the student, which could mean that without student loans, stranded students may otherwise have dropped out, or moved to a more affordable local community college (p. 51). As a practical implication for predicting students who may become stranded, student loans would need to be paired with other highly correlated variables to SS.

Academic Momentum Benchmark Variables

Including the student's academic momentum benchmarks alone, the regression results showed a significant relationship to stranded status. Students who take a remedial course in the first two terms, enroll in a summer course in the first 25 courses, demonstrate continuous enrollment (<2 dropouts), and have lower second-year GPA, are shown to be significant predictors of stranded status group membership. Both the remedial course variable and second-year GPA were the most influential in predicting stranded status ($p < .001$). The significance of remedial coursework could indicate that stranded students are entering college underprepared, leading to lower average GPAs compared to non-stranded students, thus taking additional summer classes to catch up on time lost from remedial coursework. Continuous enrollment with less than two dropouts is an expected result, as it was hypothesized that the SS group would exhibit similar academic momentum benchmarks as NSS. The continuous enrollment may be a sign of stranded student indecision, where students remain enrolled to learn about other career fields.

Related to academic performance, it can be expected that if academic struggles continue into the second year, a student is less likely to have the ability to declare. The findings related to the trends in students' grades are aligned with Adelman (2006) who found that a lowering GPA performance level can be a roadblock to achieving a degree (p. 77). Ishitani (2016) found that first-year GPA was a significant predictor of persistence, and Clovis and Chang (2021) found first-year GPA to be a predictor of degree completion. Expanding upon these findings, the results of this study found first-year GPA to also be a significant predictor where higher GPA performance is linked to more positive student outcomes.

Some academic momentum variables proved to be significant predictors of SS, but when combined with additional characteristics would provide a more reliable model of predictability. When the student's demographic characteristics were combined with academic momentum benchmarks, Asian identification remained a significant predictor along with any summer course and second-year GPA. The continued significance of remedial and summer courses as a predictor of stranded status demonstrates the unique contributions of the independent variables (Stoltzfus, 2011, p).

Explanatory Variables

Including the explanatory variables alone, the logistic regression results demonstrated a significant relationship to stranded status, where changing a major through term 5, having continuous enrollment (<1 dropout), and lower cumulative GPA through term 5 emerged as significant predictors of stranded status group membership. The significance of the changing major variable highlights the impact of student indecision as students who change their major early in their academic career are more likely to become stranded. The findings showed a slightly lower rate of students changing majors (28.95%) compared to the findings of Schudde et al., (2020) who reported 40% of the sample changed majors. Like Adelman's (2006) definition of continuous enrollment, students with less than one dropout also had higher predicted odds of becoming stranded. This finding demonstrates that stranded students remain focused on an academic goal but are facing barriers to their progress. As expected, when students struggle cumulatively over their first two academic years, it will increase their likelihood of becoming stranded.

Full Combined Characteristics Analysis

Combining the demographic characteristics along with the academic momentum benchmarks and explanatory variables, the most influential variables were summer term enrollment, second-year GPA, changing of major, and continuous enrollment with less than one semester of dropout ($p < .001$). Asian identification remained significant as well. The finding suggests that each of these significant variables can be considered a predictor of SS, where the effects of the variables on SS are independent of other variables. The methodology used in the analysis can build upon the established literature using logistic regression as a predictive framework (Del Prette et al., 2012; Gilstrap, 2020; Glynn et al., 2011; Nichols et al.,1998; Singell & Waddell, 2010; Zhang & Rangwala, 2018). The predictor variables can be emulated at other institutions and built upon the variables used in previous research studies to identify at-risk students.

Interaction of College Type

The last phase of the quantitative analysis examined if there are significant differences in variation by college, by including interaction terms with the significant variables previously identified, to conclude if certain combined characteristics are more predictive of stranded status. The most influential variables were continuous enrollment (<1 dropout), and the interaction of a Nursing student's second-year GPA ($p < .001$). These are the two most predictive variables found in the final logistic regression model. These two results are interesting as they identify a stranded student as someone unlikely to drop out of college for a term, which continues to be a positive academic momentum benchmark throughout the analysis. The significance of Nursing and second-year GPA focuses on a specific point where academic performance for Nursing students can predict the ability to declare a future degree in that college.

Comparing the results to the findings of Singell and Waddell (2010), this analysis identified similar variables that can be used to predict a student at risk of becoming stranded, including trends in grades (cumulative GPA), student loan recipient, Pell-Grant eligibility, and college type. The overall findings indicate that continuous enrollment, summer term enrollment (<1 dropout), and second-year GPA are the most significant predictors of stranded status group membership. Throughout various stages of the logistic regression analysis, additional significant predictors of SS included student loans received, identifying as an Asian student, remedial courses completed, changing of major, and cumulative GPA. The primary findings of the analysis will be further discussed.

Summary of Primary Findings

The analysis was able to categorize the stranded sample of first-time college students and provide the demographic and academic characteristics of the SS and NSS sample populations. The demographics between the two groups were relatively similar and were not able to explicitly provide a pattern of SS group membership. A statistical analysis of academic momentum model variables found that SS and NSS have similar rates of academic momentum benchmarks, oftentimes with the benchmarks showing a greater association with SS group membership. The academic performance of SS and NSS appears to diverge as academic years progress, with cumulative GPA increasing at a similar rate over time. The binary logistic regression found that a student's choice of major and college type can be a significant predictor of stranded status, with more students becoming stranded when attempting to enter a major with a 2.50 or higher GPA restriction. A student’s initial major choice, final major choice, and the final pre-major decision can also serve as significant predictors of SS group membership.

The regression analysis of the independent variables identified Asian as a potential predictor of stranded students, which was diminished as more variables were factored into the analysis. At various steps of the logistic regression, certain academic momentum and explanatory variables became significant predictors of SS. When the interaction terms (significant variables x college type) were added, several significant predictors remained including continuous enrollment, summer term enrollment, and second-year GPA. The overall implications of these main findings provide a meaningful contribution to the existing literature. Currently, much of the literature surrounding academic momentum and at-risk students is focused on outcomes such as degree completion. This analysis helps to fill a void in the literature around the steps leading to degree completion by identifying the stranded student issue, and results suggest that early intervention can help students find a path to obtaining a degree. The implications of these findings for higher education administrators are further discussed.

Implications for Higher Education Administrators

The study's purpose was to identify the stranded student through academic characteristics and determine a way to support a path to degree completion. The research demonstrates that targeted academic advising interventions can support degree completion (Aljets, 2018; Chen & Upah, 2018; Elrich & Russ-Eft, 2013; King, 2015; Mu & Fosnacht, 2013; Young-Jones et al., 2013). The findings of the study suggest that a targeted intervention by year three for undeclared students could provide students with a realistic understanding of their ability to declare their intended major and graduate. Furthermore, the study revealed several student characteristics that administrators can use to direct targeted support, including pre-major students who are seeking majors with 2.50 or higher requirements, and who are undeclared with 70 total credits. To narrow the search for stranded students, administrators can cross reference students who have taken remedial courses, remained continuously enrolled, earned summer credit, and had a lower-than-average second-year GPA.

The findings would allow for the replication of a data-driven approach, like the Automated Wellness Engine, that can provide early alerts of potentially stranded students. A predictive quantitative model could incorporate triggers of demographic, institutional, student performance, and workload variables to identify students at risk of becoming stranded (Vilano et al., 2018, p. 905). The academic momentum benchmarks achieved by stranded students highlight their commitment to degree completion and have proven to be a group that requires intentional focus from higher education administrators. The goal of any targeted intervention is to have the students declare, ideally, in their intended major, or by finding another suitable path. Meeting with an early alert team member can positively impact student success (Tampke, 2013; Zhang et al., 2014). Early detection and guidance for stranded students will also support university retention efforts.

At the college level, it was revealed that a stranded student's final major was occasionally one that did not require a pre-major to start, indicating that students are arriving at their colleges from other majors. The College of Fine Arts, College of Liberal Arts, and College of Sciences should be aware of this phenomenon and have advising structures in place when students declare a new major to understand the policies for graduation. Another way to help prevent students from becoming stranded is a more concerted effort at messaging. For higher education advisors and students, it is difficult oftentimes to locate the exact GPA requirement for each major. If a student is unaware that GPA admission policies or related policies exist, or if they find out too late, it will likely increase the likelihood of becoming stranded.

The results of the analysis highlight the need to critically examine GPA Admission restrictions and policies at the college level. Students attempting to enter highly restrictive majors are shown to have a higher likelihood of becoming stranded, supporting previous literature on the impact of GPA admission restrictions ((Bleemer & Mehta, 2021; Bleemer et al., 2023; Schmidt, 2021)) To help improve institutional retention rates and support a student's path to graduation, policy changes such as a form of "conditional" admission could allow students to begin working on upper division courses, while not wasting time, effort, and financial resources on classes that may not apply to their degree.

Limitations of the Study

The study was limited in the scope of the analysis to only include pre-major students from the 2013-2016 cohorts. Factoring in "undeclared" from additional cohorts would provide a more wide-ranging picture of the stranded student. The stranded student analysis cannot consider the impact of student interactions with their academic advisor. If a student receives inadequate advice on course planning from their advisor, it could lead to the accumulation of lost credits during their academic career and potentially becoming stranded. Additionally, some majors may have meritocratic requirements such as an entrance exam or formal interview. The study is limited in the ability to collect data on potential additional major restrictions set forth by a college.

A student may encounter roadblocks if the colleges have limited course offerings and students must maintain full-time enrollment for financial aid purposes. Also, if course offerings are limited, students may be forced to take classes outside their major requirements, leading to stranded status. This study does not include a separate review of the percentage of courses within a major that are full or at capacity during the years of the sample population's attendance. Without a complete analysis of each student's individual course history, it is impossible to definitively conclude the variety of courses students are taking or be able to measure a student's grades in introductory courses, which could further inform on the stranded student issue. Student indecision may also be a contributing factor to becoming stranded. A student may be unsure of their path despite indicating a pre-major, leading them to take diverse types of courses that may not be applicable to their future degree. The measure of major switching may inform on this indecision, but not completely. Additional qualitative analysis, course history examinations, and reviews of class enrollment rates in the stranded status group could provide further context to the issue.

Recommendations for Future Research

Future research should focus on expanding the understanding of stranded students. First, expanding on this study, the inclusion of exploring major students in a sample population could help determine if they are undeclared by term 5 without the required cumulative GPA to declare. A more robust sample for analysis would edify the general understanding of the prevalence of the issue. The current analysis can also be expanded by developing additional explanatory variables to understand why a student may become stranded. For example, including *how many* terms of poor academic performance or additional college interaction terms could more accurately predict stranded status.

Students' postsecondary academic journey can take many unexpected turns or deviations from the original plan upon entry. A qualitative analysis of students who find themselves stranded in their third academic year without the ability to declare a major can provide further illumination into the stranded student's story. While this study takes the first step to identify a pattern of stranded students, the next step of understanding the "why" will further direct the support systems and changes needed to help stranded students declare and graduate. Qualitative work can build upon the nature of advising interactions, such as identifying when students *know* they are becoming stranded. It is important to understand how students experience a stranded status and what factor this plays in their ability to complete their academic goals. These discussions can also help administrators understand why some students are more likely to stay in a stranded status.

Another step to build upon this study is to examine student outcomes and retention rates after they become stranded. For example, when a student is in their third year and undeclared, do they most often change majors, change colleges, drop out of school, or continue taking classes until they reach the GPA requirement and ultimately graduate? The concept of major GPA admissions policies should be further examined. The major questions for administrators to consider are whether the GPA restrictions are achieving their intended goal and whether are they in the best interest of the student. Building upon the limited research in this area could lead to institutional policy changes.

Conclusion

The examination of GPA restrictions stranded students and their roadblocks to momentum provided new insight into an unexplored issue facing students in postsecondary education. It was confirmed that GPA restrictions can play a significant role in the ability of students to declare a future major. Despite a student's inability to declare a major, they are often still exhibiting signs of academic momentum through taking summer classes and remaining continuously enrolled. These academic characteristics and an amalgamation of academic momentum benchmarks and explanatory variables significantly predicted a stranded student. The results confirm the need for higher education administrators to provide targeted interventions, and dedicated support systems, and consider GPA admission policy changes to provide capable students an opportunity to graduate and begin a career in the desired field without wasting time, effort, and financial resources.

Appendix A

Table 17. Last PRE-Major Found and GPA Requirement

Last PRE-Major in Record	2.00	2.50	2.75	3.00	Total
Athletic Training PRE	0	0	79	0	79
Business PRE	0	0	1086	0	1086
Civil Engineering PRE	82	0	0	0	82
Communication Studies PRE	114	0	0	0	114
Comprehensive Medical Img PRE	0	0	149	0	149
Computer Engineering PRE	85	0	0	0	85
Computer Science PRE	0	0	308	0	308
Construction Management PRE	25	0	0	0	25
Criminal Justice PRE	438	0	0	0	438
Early Childhood Education PRE	0	0	37	0	37
Electrical Engineering PRE	49	0	0	0	49
Elementary Education PRE	0	0	165	0	165
Engineering/Computer Sci PRE	0	0	11	0	11
Entertainment Engr Design PRE	38	0	0	0	38
Health Care Admin PRE	0	50	0	0	50
Human Services PRE	0	0	32	0	32
Journalism & Media Studies PRE	193	0	0	0	193
Kinesiological Science PRE	0	10	0	0	10
Mechanical Engineering PRE	0	209	0	0	209
Nuclear Medicine PRE	0	0	14	0	14
Nursing PRE	0	0	0	634	634
Nutrition PRE	0	66	0	0	66
Public Health PRE	0	6	0	0	6
Secondary Education PRE	0	0	136	0	136
Social Work PRE	98	0	0	0	98
Special Education PRE	0	0	26	0	26
Total	1123	346	2046	634	4149

Note. Health Physics PRE, Healthcare Admin PRE, Public Administration PRE, and Radio Technology PRE have less than 5 total students.

Appendix B

Table 18. Descriptive Statistics of Independent Variables

Gender		Frequency	Percent	Cumulative Percent
	Female	2397	57.77	57.77
	Male	1752	42.23	100
	Total	4149	100	

Race		Frequency	Percent	Cumulative Percent
	American Indian or Alaskan Native	5	0.12	0.12
	Asian	945	22.78	22.90
	African American or Black	246	5.93	28.83
	Hispanic	1226	29.55	58.38
	More than 1 Race/Ethnicity	449	10.82	69.20
	International	34	0.82	70.02
	Hawaiian or Other Pacific Islander	55	1.33	71.35
	Unknown	17	0.41	71.76
	White	1172	28.25	100.00
	Total	4149	100	

Pell Grant Eligible		Frequency	Percent	Cumulative Percent
	No	2646	63.77	63.77
	Yes	1503	36.23	100
	Total	4149	100	

Scholarship Recipient		Frequency	Percent	Cumulative Percent
	No	544	13.11	13.11
	Yes	3605	86.89	100
	Total	4149	100	

Student Loan Recipient		Frequency	Percent	Cumulative Percent
	No	2180	52.54	52.54
	Yes	1969	47.46	100
	Total	4149	100	

Parents No Bachelor		Frequency	Percent	Cumulative Percent
	No	2093	50.45	50.45
	Yes	2056	49.55	100
	Total	4149	100	

Parents No College		Frequency	Percent	Cumulative Percent
	No	3081	74.26	74.26
	Yes	1068	25.74	100
	Total	4149	100	

Any Remedial Course in First Two Terms		Frequency	Percent	Cumulative Percent
	No	3379	81.44	81.44
	Yes	770	18.56	100
	Total	4149	100	

Any Remedial Course in First 25 Courses		Frequency	Percent	Cumulative Percent
	No	3276	78.96	78.96
	Yes	873	21.04	100
	Total	4149	100	

Withdraw 20% or more in First 25 Courses		Frequency	Percent	Cumulative Percent
	No	4128	99.49	99.49
	Yes	21	0.51	100
	Total	4149	100	

Any Summer Course in First 25 Courses		Frequency	Percent	Cumulative Percent
	No	2177	52.47	52.47
	Yes	1972	47.53	100
	Total	4149	100	

Continuous Enrollment in First Six Terms (< 2)		Frequency	Percent	Cumulative Percent
	No	75	1.81	1.81
	Yes	4074	98.19	100
	Total	4149	100	

Academic Probation Received		Frequency	Percent	Cumulative Percent
	No	2849	68.67	68.67
	Yes	1300	31.33	100
	Total	4149	100	

Declared Intended Major by Term 5		Frequency	Percent	Cumulative Percent
	No	3264	78.67	78.67
	Yes	885	21.33	100
	Total	4149	100	

Declared Any Major by Term 5		Frequency	Percent	Cumulative Percent
	No	2520	60.74	60.74
	Yes	1629	39.26	100
	Total	4149	100	

Changed Major by Term 5		Frequency	Percent	Cumulative Percent
	No	2948	71.05	71.05
	Yes	1201	28.95	100
	Total	4149	100	

Consistently Low Academic Performance		Frequency	Percent	Cumulative Percent
	No	2817	67.9	67.9
	Yes	1332	32.1	100
	Total	4149	100	

Continuous Enrollment in First Six Terms (< 1)		Frequency	Percent	Cumulative Percent
	No	584	14.08	14.08
	Yes	3565	85.92	100
	Total	4149	100	

Any Withdraw in First Two Terms		Frequency	Percent	Cumulative Percent
	No	3277	78.98	78.98
	Yes	872	21.02	100
	Total	4149	100	

Any Withdraw in First 25 Courses		Frequency	Percent	Cumulative Percent
	No	2711	65.34	65.34
	Yes	1438	34.66	100
	Total	4149	100	

Appendix C

Table 19. Descriptive Statistics of GPA Variables

GPA Values	N	Minimum	Maximum	Mean	Std. Deviation
First-Year GPA	4149	0	4.00	3.057	0.580097
Second-Year GPA	4133	0	4.00	3.040	0.65294
Cumulative GPA through Term 4	4133	0.72	4.00	3.107	0.48822
Cumulative GPA through Term 5	4114	1.52	4.00	3.137	0.46192

Appendix D

Table 20. Stranded Status Demographic Characteristics

	Non-Stranded			Stranded			Total	
Gender	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
Female	962	40.13%	59.10%	1435	59.87%	56.90%	2397	57.77%
Male	667	38.07%	40.90%	1085	61.93%	43.10%	1752	42.23%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Race	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
American Indian or Alaskan Native	4	80.00%	0.25%	1	20.00%	0.04%	5	0.12%
Asian	345	36.51%	21.18%	600	63.49%	23.81%	945	22.78%
African American or Black	100	40.65%	6.14%	146	59.35%	5.79%	246	5.93%
Hispanic	476	38.83%	29.22%	750	61.17%	29.76%	1226	29.55%
More than 1 Race/Ethnicity	178	39.64%	10.93%	271	60.36%	10.75%	449	10.82%
International	17	50.00%	1.04%	17	50.00%	0.67%	34	0.82%
Hawaiian or other Pacific Islander	19	34.55%	1.17%	36	65.45%	1.43%	55	1.33%
Unknown	7	41.18%	0.43%	10	58.82%	0.40%	17	0.41%
White	483	41.21%	29.65%	689	58.79%	27.34%	1172	28.25%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Pell Grant Eligible	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1048	39.61%	64.33%	1598	60.39%	63.41%	2646	63.77%
Yes	581	38.66%	35.67%	922	61.34%	36.59%	1503	36.23%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Scholarship Recipient	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	207	38.05%	12.71%	337	61.95%	13.37%	544	13.11%
Yes	1422	39.45%	87.29%	2183	60.55%	86.63%	3605	86.89%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Student Loan Recipient	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	889	40.78%	54.57%	1291	59.22%	51.23%	2180	52.54%
Yes	740	37.58%	45.43%	1229	62.42%	48.77%	1969	47.46%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Parents No Bachelor	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	812	38.80%	49.85%	1281	61.20%	50.83%	2093	50.45%
Yes	817	39.74%	50.15%	1239	60.26%	49.17%	2056	49.55%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Parents No College	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1189	38.59%	72.99%	1892	61.41%	75.08%	3081	74.26%
Yes	440	41.20%	27.01%	628	58.80%	24.92%	1068	25.74%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Appendix E

Table 21. Stranded Status Academic Characteristics

	Non-Stranded			Stranded			Total	
Any Remedial in First Two Terms	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1387	41.05%	85.14%	1992	58.95%	79.05%	3379	81.44%
Yes	242	31.43%	14.86%	528	68.57%	20.95%	770	18.56%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Any Remedial in First 25 Courses	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1345	41.06%	82.57%	1931	58.94%	76.63%	3276	78.96%
Yes	284	32.53%	17.43%	589	67.47%	23.37%	873	21.04%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Withdraw 20% or more in First 25 Courses	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1621	39.27%	99.51%	2507	60.73%	99.48%	4128	99.49%
Yes	8	38.10%	0.49%	13	61.90%	0.52%	21	0.51%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Any Summer Course in First 25 Courses	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	968	44.46%	59.42%	1209	55.54%	47.98%	2177	52.47%
Yes	661	33.52%	40.58%	1311	66.48%	52.02%	1972	47.53%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Continuous Enrollment in First Six Terms (< 2)	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	35	46.67%	2.15%	40	53.33%	1.59%	75	1.81%
Yes	1594	39.13%	97.85%	2480	60.87%	98.41%	4074	98.19%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Academic Probation Received	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1203	42.23%	73.85%	1646	57.77%	65.32%	2849	68.67%
Yes	426	32.77%	26.15%	874	67.23%	34.68%	1300	31.33%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Declared Intended Major by Term 5	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	744	22.79%	45.67%	2520	77.21%	100.00%	3264	78.67%
Yes	885	100.00%	54.33%	0	0.00%	0.00%	885	21.33%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Declared Any Major by Term 5	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	0	0.00%	0.00%	2520	100.00 %	100.00%	2520	60.74%
Yes	1629	100.00%	100.00%	0	0.00%	0.00%	1629	39.26%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Changed Major by Term 5	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1228	41.66%	75.38%	1720	58.34%	68.25%	2948	71.05%
Yes	401	33.39%	24.62%	800	66.61%	31.75%	1201	28.95%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Consistently Low Academic Performance	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1220	43.31%	74.89%	1597	56.69%	63.37%	2817	67.90%
Yes	409	30.71%	25.11%	923	69.29%	36.63%	1332	32.10%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Continuous Enrollment in First Six Terms (< 1)	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	272	46.58%	16.70%	312	53.42%	12.38%	584	14.08%
Yes	1357	38.06%	83.30%	2208	61.94%	87.62%	3565	85.92%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Any Withdraw in First Two Terms	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1308	39.91%	80.29%	1969	60.09%	78.13%	3277	78.98%
Yes	321	36.81%	19.71%	551	63.19%	21.87%	872	21.02%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Any Withdraw in First 25 Courses	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
No	1096	40.43%	67.28%	1615	59.57%	64.09%	2711	65.34%
Yes	533	37.07%	32.72%	905	62.93%	35.91%	1438	34.66%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Major GPA Admission Requirement	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
2.00 GPA	503	44.79%	30.88%	620	55.21%	24.60%	1123	27.07%
2.50 GPA	122	35.26%	7.49%	224	64.74%	8.89%	346	8.34%
2.75 GPA	807	39.44%	49.54%	1239	60.56%	49.17%	2046	49.31%
3.00 GPA	197	31.07%	12.09%	437	68.93%	17.34%	634	15.28%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00 %

Appendix F

Table 22. Average GPA Scores

	Non-Stranded				Stranded				Total			
GPA Values	N	Mean	Median	SD	N	Mean	Median	SD	N	Mean	Median	SD
First-Year GPA	1629	3.13	3.21	0.601	2520	3.01	3.05	0.561	4149	3.06	3.11	0.58
Second-Year GPA	1629	3.19	3.29	0.63	2520	2.95	3.04	0.65	4149	3.04	3.14	0.65
Cumulative GPA - Term 4	1629	3.21	3.25	0.49	2520	3.04	3.05	0.47	4149	3.11	3.13	0.49
Cumulative GPA - Term 5	1629	3.23	3.27	0.46	2520	3.07	3.08	0.45	4149	3.14	3.16	0.46

Appendix G

Table 23. Student First Major Choices

	Non-Stranded			Stranded			Total	
Top 20: First Pre-Major Indicated	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
Athletic Training PRE	58	66.70%	3.60%	29	33.30%	1.20%	87	2.10%
Business PRE	426	47.10%	26.20%	479	52.90%	19.00%	905	21.80%
Civil Engineering PRE	25	27.50%	1.50%	66	72.50%	2.60%	91	2.20%
Communication Studies PRE	24	53.30%	1.50%	21	46.70%	0.80%	45	1.10%
Comprehensive Medical Img PRE	31	33.30%	1.90%	62	66.70%	2.50%	93	2.20%
Computer Engineering PRE	37	31.10%	2.30%	82	68.90%	3.30%	119	2.90%
Computer Science PRE	108	41.40%	6.60%	153	58.60%	6.10%	261	6.30%
Criminal Justice PRE	188	55.50%	11.50%	151	44.50%	6.00%	339	8.20%
Early Childhood Education PRE	14	48.30%	0.90%	15	51.70%	0.60%	29	0.70%
Electrical Engineering PRE	14	29.20%	0.90%	34	70.80%	1.30%	48	1.20%
Elementary Education PRE	42	33.60%	2.60%	83	66.40%	3.30%	125	3.00%
Engineering/Computer Sci PRE	16	30.20%	1.00%	37	69.80%	1.50%	53	1.30%
Entertainment Engr Design PRE	13	33.30%	0.80%	26	66.70%	1.00%	39	0.90%
Journalism & Media Studies PRE	97	69.30%	6.00%	43	30.70%	1.70%	140	3.40%
Mechanical Engineering PRE	70	34.80%	4.30%	131	65.20%	5.20%	201	4.80%
Nursing PRE	202	33.20%	12.40%	407	66.80%	16.20%	609	14.70%
Nutrition PRE	7	22.60%	0.40%	24	77.40%	1.00%	31	0.70%
Secondary Education PRE	33	36.70%	2.00%	57	63.30%	2.30%	90	2.20%
Social Work PRE	18	37.50%	1.10%	30	62.50%	1.20%	48	1.20%
Special Education PRE	6	35.30%	0.40%	11	64.70%	0.40%	17	0.40%
Full Sample Total	1629	39.30%	100.00%	2520	60.70%	100.00%	4149	100.00%
Top 20 Totals	1429	42.40%	87.90%	1941	57.60%	77.20%	3370	81.30%

Appendix H

Table 24. Student Final Major Choices Through Term 8

	Non-Stranded			Stranded			Total	
Top 75: Final Major Indicated	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
Computer Engineering PRE	0	0.00%	0.00%	25	100.00%	0.99%	25	0.60%
Electrical Engineering PRE	0	0.00%	0.00%	15	100.00%	0.60%	15	0.36%
Construction Management PRE	0	0.00%	0.00%	9	100.00%	0.36%	9	0.22%
Early Childhood Education PRE	0	0.00%	0.00%	9	100.00%	0.36%	9	0.22%
Mechanical Engineering PRE	2	3.03%	0.12%	64	96.97%	2.54%	66	1.59%
Nursing PRE	8	4.32%	0.49%	177	95.68%	7.02%	185	4.46%
Secondary Education PRE	2	5.00%	0.12%	38	95.00%	1.51%	40	0.96%
Comprehensive Medical Img PRE	5	5.88%	0.31%	80	94.12%	3.18%	85	2.05%
Entertainment Engr Design PRE	1	6.25%	0.06%	15	93.75%	0.60%	16	0.39%
Health Care Admin PRE	1	6.67%	0.06%	14	93.33%	0.56%	15	0.36%
Civil Engineering PRE	2	7.69%	0.12%	24	92.31%	0.95%	26	0.63%
Elementary Education PRE	3	7.89%	0.18%	35	92.11%	1.39%	38	0.92%
Business PRE	14	9.72%	0.86%	130	90.28%	5.16%	144	3.47%
Communication Studies PRE	2	10.53%	0.12%	17	89.47%	0.68%	19	0.46%
Criminal Justice PRE	6	11.54%	0.37%	46	88.46%	1.83%	52	1.25%
Nutrition PRE	2	11.76%	0.12%	15	88.24%	0.60%	17	0.41%
Computer Science PRE	10	12.35%	0.61%	71	87.65%	2.82%	81	1.95%
Nutrition Sciences BS	3	13.04%	0.18%	20	86.96%	0.79%	23	0.55%
Social Work PRE	2	13.33%	0.12%	13	86.67%	0.52%	15	0.36%
Entertainment Tech & Design BS	1	14.29%	0.06%	6	85.71%	0.24%	7	0.17%
Civil Engineering BSEG	8	20.51%	0.49%	31	79.49%	1.23%	39	0.94%

Secondary Ed-Mathematics BSED	2	22.22%	0.12%	7	77.78%	0.28%	9	0.22%
Entrepreneurship BSBA	6	24.00%	0.37%	19	76.00%	0.75%	25	0.60%
Social Work BSW	16	25.40%	0.98%	47	74.60%	1.87%	63	1.52%
Secondary Education BSED	3	27.27%	0.18%	8	72.73%	0.32%	11	0.27%
Comprehensive Med Imaging BS	7	28.00%	0.43%	18	72.00%	0.71%	25	0.60%
Computer Engineering BSEG	11	29.73%	0.68%	26	70.27%	1.03%	37	0.89%
Nursing BS	69	29.87%	4.24%	162	70.13%	6.43%	231	5.57%
Human Services PRE	3	30.00%	0.18%	7	70.00%	0.28%	10	0.24%
Elementary Education BSED	35	30.70%	2.15%	79	69.30%	3.14%	114	2.75%
Journalism & Media Studies PRE	8	30.77%	0.49%	18	69.23%	0.71%	26	0.63%
Information Management BSBA	9	31.03%	0.55%	20	68.97%	0.79%	29	0.70%
Secondary Edu-Social Stds BSED	4	33.33%	0.25%	8	66.67%	0.32%	12	0.29%
Athletic Training PRE	3	33.33%	0.18%	6	66.67%	0.24%	9	0.22%
Mechanical Engineering BSEG	35	34.65%	2.15%	66	65.35%	2.62%	101	2.43%
Construction Management BS	5	35.71%	0.31%	9	64.29%	0.36%	14	0.34%
Computer Science BA	4	36.36%	0.25%	7	63.64%	0.28%	11	0.27%
Marketing BSBA	43	36.75%	2.64%	74	63.25%	2.94%	117	2.82%
Secondary Ed-English Comp BSED	9	37.50%	0.55%	15	62.50%	0.60%	24	0.58%
Music BM	3	37.50%	0.18%	5	62.50%	0.20%	8	0.19%
Finance BSBA	56	38.36%	3.44%	90	61.64%	3.57%	146	3.52%
Electrical Engineering BSEG	13	39.39%	0.80%	20	60.61%	0.79%	33	0.80%
Management BSBA	45	39.47%	2.76%	69	60.53%	2.74%	114	2.75%
Economics BA	14	41.18%	0.86%	20	58.82%	0.79%	34	0.82%

Computer Science BS	55	41.98%	3.38%	76	58.02%	3.02%	131	3.16%
Human Services BS	8	42.11%	0.49%	11	57.90%	0.44%	19	0.46%
Biochemistry BS	3	42.86%	0.18%	4	57.14%	0.16%	7	0.17%
International Business BSBA	17	44.74%	1.04%	21	55.26%	0.83%	38	0.92%
Early Childhood Education BS	11	45.83%	0.68%	13	54.17%	0.52%	24	0.58%
Interdisc-Multidisc Studies BA	12	46.15%	0.74%	14	53.85%	0.56%	26	0.63%
Special Education BSED	12	46.15%	0.74%	14	53.85%	0.56%	26	0.63%
Accounting BSBA	95	46.57%	5.83%	109	53.43%	4.33%	204	4.92%
Biological Sciences BS	40	47.06%	2.46%	45	52.94%	1.79%	85	2.05%
English BA	19	48.72%	1.17%	20	51.28%	0.79%	39	0.94%
Health Care Administration BS	27	50.00%	1.66%	27	50.00%	1.07%	54	1.30%
Mathematics BS	7	50.00%	0.43%	7	50.00%	0.28%	14	0.34%
Communication Studies BA	44	52.38%	2.70%	40	47.62%	1.59%	84	2.02%
Criminal Justice BA	202	55.65%	12.40%	161	44.35%	6.39%	363	8.75%
Economics BSBA	19	57.58%	1.17%	14	42.42%	0.56%	33	0.80%
Public Health BS	17	58.62%	1.04%	12	41.38%	0.48%	29	0.70%
Kinesiological Sciences BS	96	59.63%	5.89%	65	40.37%	2.58%	161	3.88%
Journalism & Media Studies BA	92	61.33%	5.65%	58	38.67%	2.30%	150	3.62%
History BA	11	64.71%	0.68%	6	35.29%	0.24%	17	0.41%
Athletic Training BS	14	66.67%	0.86%	7	33.33%	0.28%	21	0.51%
Art BA	16	69.57%	0.98%	7	30.44%	0.28%	23	0.55%
Architecture BS	5	71.43%	0.31%	2	28.57%	0.08%	7	0.17%
Psychology BA	81	73.64%	4.97%	29	26.36%	1.15%	110	2.65%
Hospitality Management BS	98	77.78%	6.02%	28	22.22%	1.11%	126	3.04%
Urban Studies BS	11	78.57%	0.68%	3	21.43%	0.12%	14	0.34%
Graphic Design & Media BS	21	80.77%	1.29%	5	19.23%	0.20%	26	0.63%
Sociology BA	17	80.95%	1.04%	4	19.05%	0.16%	21	0.51%

Anthropology BA	10	83.33%	0.61%	2	16.67%	0.08%	12	0.29%
Political Science BA	23	85.19%	1.41%	4	14.82%	0.16%	27	0.65%
Public Administration BS	6	85.71%	0.37%	1	14.29%	0.04%	7	0.17%
Film BA	9	90.00%	0.55%	1	10.00%	0.04%	10	0.24%
Top 75 Total	1558	38.59%	96.55%	2464	61.04%	97.78%	4037	97.37%
Full Sample Total	1629	39.26%	100.00%	2520	60.74%	100.00 %	4149	100.00%

Note: 119 Total Final Majors identified in sample.

Appendix I

Table 25. Student First College Choice

	Non-Stranded			Stranded			Total	
First College Choice Indicated	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
College of Education	100	37.20%	6.10%	169	62.80%	6.70%	269	6.50%
College of Engineering	276	35.20%	16.90%	509	64.80%	20.20%	785	18.90%
College of Fine Arts*	43	32.60%	2.60%	89	67.40%	3.50%	132	3.20%
College of Hospitality*	16	30.20%	1.00%	37	69.80%	1.50%	53	1.30%
College of Liberal Arts*	48	31.80%	2.90%	103	68.20%	4.10%	151	3.60%
College of Sciences*	42	12.90%	2.60%	284	87.10%	11.30%	326	7.90%
College of Urban Affairs	329	57.10%	20.20%	247	42.90%	9.80%	576	13.90%
College of Health Sciences	128	40.60%	7.90%	187	59.40%	7.40%	315	7.60%
College of Business	426	47.10%	26.20%	479	52.90%	19.00%	905	21.80%
College of Nursing	202	33.20%	12.40%	407	66.80%	16.20%	609	14.70%
College of Public Health	19	67.90%	1.20%	9	32.10%	0.40%	28	0.70%
Total	1629	39.30%	100.00%	2520	60.70%	100.00%	4149	100.00%

Note: *Colleges do not contain a "PRE" major status.

Appendix J

Table 26. Student Final College Choices Through Term 8

	Non-Stranded			Stranded			Total	
Final College Choice	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
College of Education	93	27.11%	5.71%	250	72.89%	9.92%	343	8.27%
College of Engineering	148	24.79%	9.09%	449	75.21%	17.82%	597	14.39%
College of Fine Arts*	73	59.35%	4.48%	50	40.65%	1.98%	123	2.96%
College of Hospitality*	98	77.78%	6.02%	28	22.22%	1.11%	126	3.04%
College of Liberal Arts*	187	67.03%	11.48%	92	32.97%	3.65%	279	6.72%
College of Sciences*	63	50.40%	3.87%	62	49.60%	2.46%	125	3.01%
College of Urban Affairs	389	49.05%	23.88%	404	50.95%	16.03%	793	19.11%
College of Health Sciences	136	37.88%	8.35%	223	62.12%	8.85%	359	8.65%
College of Business	319	35.92%	19.58%	569	64.08%	22.58%	888	21.40%
College of Nursing	77	18.51%	4.73%	339	81.49%	13.45%	416	10.03%
College of Public Health	46	46.00%	2.82%	54	54.00%	2.14%	100	2.41%
Total	1629	39.26%	100.00%	2520	60.74%	100.00%	4149	100.00%

Note: *Colleges do not contain a "PRE" major status.

Appendix K

Table 27. Last Pre-Major in Record

	Non-Stranded			Stranded			Total	
Pre-Major	Count	Row N %	Column N %	Count	Row N %	Column N %	Count	Column N %
Athletic Training PRE	51	64.60%	3.10%	28	35.40%	1.10%	79	1.90%
Business PRE	461	42.40%	28.30%	625	57.60%	24.80%	1086	26.20%
Civil Engineering PRE	23	28.00%	1.40%	59	72.00%	2.30%	82	2.00%
Communication Studies PRE	49	43.00%	3.00%	65	57.00%	2.60%	114	2.70%
Comprehensive Medical Img PRE	37	24.80%	2.30%	112	75.20%	4.40%	149	3.60%
Computer Engineering PRE	27	31.80%	1.70%	58	68.20%	2.30%	85	2.00%
Computer Science PRE	121	39.30%	7.40%	187	60.70%	7.40%	308	7.40%
Construction Management PRE	7	28.00%	0.40%	18	72.00%	0.70%	25	0.60%
Criminal Justice PRE	231	52.70%	14.20%	207	47.30%	8.20%	438	10.60%
Early Childhood Education PRE	15	40.50%	0.90%	22	59.50%	0.90%	37	0.90%
Electrical Engineering PRE	14	28.60%	0.90%	35	71.40%	1.40%	49	1.20%
Elementary Education PRE	47	28.50%	2.90%	118	71.50%	4.70%	165	4.00%
Engineering/Computer Sci PRE	7	63.60%	0.40%	4	36.40%	0.20%	11	0.30%
Entertainment Engr Design PRE	13	34.20%	0.80%	25	65.80%	1.00%	38	0.90%
Health Care Admin PRE	22	44.00%	1.40%	28	56.00%	1.10%	50	1.20%
Health Physics PRE	1	50.00%	0.10%	1	50.00%	0.00%	2	0.00%
Healthcare Admin PRE	0	0.00%	0.00%	5	100%	0.20%	5	0.10%
Human Services PRE	12	37.50%	0.70%	20	62.50%	0.80%	32	0.80%
Journalism & Media Studies PRE	109	56.50%	6.70%	84	43.50%	3.30%	193	4.70%
Kinesiological Science PRE	2	20.00%	0.10%	8	80.00%	0.30%	10	0.20%
Mechanical Engineering PRE	72	34.40%	4.40%	137	65.60%	5.40%	209	5.00%
Nuclear Medicine PRE	7	50.00%	0.40%	7	50.00%	0.30%	14	0.30%
Nursing PRE	197	31.10%	12.10%	437	68.90%	17.30%	634	15.30%

Nutrition PRE	22	33.30%	1.40%	44	66.70%	1.70%	66	1.60%
Public Administration PRE	1	100%	0.10%	0	0.00%	0.00%	1	0.00%
Public Health PRE	4	66.70%	0.20%	2	33.30%	0.10%	6	0.10%
Radiologic Technology PRE	0	0.00%	0.00%	1	100%	0.00%	1	0.00%
Secondary Education PRE	37	27.20%	2.30%	99	72.80%	3.90%	136	3.30%
Social Work PRE	29	29.60%	1.80%	69	70.40%	2.70%	98	2.40%
Special Education PRE	11	42.30%	0.70%	15	57.70%	0.60%	26	0.60%
Total	1629	39.30%	100.00 %	2520	60.70%	100.00 %	4149	100.00 %

Appendix L

Table 28. Logistic Regression Predicting Stranded Status from Demographic Characteristics

Demographic Variables		β	SE β	Wald χ^2	*df*	*p*	Exp(B)	Confidence Interval Lower	Confidence Interval Upper
Gender (alone)	Male/Female	0.087	0.064	1.806	1	0.179	1.091	0.961	1.237
Race (alone)	American Indian or Alaskan Native	-1.742	1.12	2.419	1	0.12	0.175	0.02	1.573
	Asian	0.198	0.09	4.856	1	0.028*	1.219	1.022	1.454
	African American or Black	0.023	0.143	0.026	1	0.871	1.023	0.774	1.354
	Hispanic	0.099	0.083	1.421	1	0.233	1.105	0.938	1.301
	More than 1 Race/Ethnicity	0.065	0.113	0.33	1	0.565	1.067	0.855	1.333
	International	-0.355	0.348	1.041	1	0.307	0.701	0.354	1.387
	Hawaiian or other Pacific Islander	0.284	0.29	0.96	1	0.327	1.328	0.753	2.344
	Unknown	0.001	0.496	0	1	0.998	1.001	0.379	2.649
Financial (alone)	Pell Grant Eligibility	0.05	0.068	0.535	1	0.464	1.051	0.92	1.201
	Scholarship Received	-0.045	0.096	0.22	1	0.639	0.956	0.793	1.153
	Student Loans Received	0.124	0.064	3.727	1	0.054	1.132	0.998	1.285
	Parents No Bachelor	0.012	0.08	0.023	1	0.879	1.012	0.866	1.184
	Parents No College	-0.119	0.091	1.716	1	0.19	0.888	0.742	1.061
Gender + Race	Gender	0.086	0.065	1.742	1	0.187	1.089	0.959	1.237
	American Indian or Alaskan Native	-1.755	1.12	2.456	1	0.117	0.173	0.019	1.553
	Asian	0.199	0.09	4.873	1	0.027*	1.22	1.023	1.455
	African American or Black	0.037	0.143	0.066	1	0.797	1.038	0.784	1.374
	Hispanic	0.104	0.083	1.554	1	0.212	1.11	0.942	1.307

	More than 1 Race/Ethnicity	0.067	0.113	0.35	1	0.554	1.069	0.856	1.335
	International	-0.344	0.348	0.978	1	0.323	0.709	0.358	1.402
	Hawaiian or other Pacific Islander	0.282	0.29	0.949	1	0.33	1.326	0.751	2.34
	Unknown	0.015	0.497	0.001	1	0.976	1.015	0.384	2.686
Gender + Race + Financial	Gender	0.086	0.065	1.744	1	0.187	1.09	0.959	1.238
	American Indian or Alaskan Native	-1.767	1.121	2.486	1	0.115	0.171	0.019	1.536
	Asian	0.205	0.091	5.126	1	0.024*	1.227	1.028	1.466
	African American or Black	-0.018	0.147	0.015	1	0.902	0.982	0.736	1.31
	Hispanic	0.132	0.087	2.297	1	0.13	1.141	0.962	1.354
	More than 1 Race/Ethnicity	0.048	0.114	0.177	1	0.674	1.049	0.839	1.311
	International	-0.287	0.351	0.667	1	0.414	0.75	0.377	1.494
	Hawaiian or other Pacific Islander	0.231	0.291	0.632	1	0.427	1.26	0.712	2.23
	Unknown	0.031	0.497	0.004	1	0.951	1.031	0.389	2.732
	Pell Grant Eligibility	0.044	0.07	0.397	1	0.529	1.045	0.912	1.198
	Scholarship Received	-0.061	0.097	0.392	1	0.531	0.941	0.779	1.138
	Student Loans Received	0.132	0.066	4.046	1	0.044*	1.141	1.003	1.298
	Parents No Bachelor	0.025	0.081	0.093	1	0.761	1.025	0.875	1.2
	Parents No College	-0.14	0.093	2.271	1	0.132	0.87	0.725	1.043

Note: Variables are significant at *p<.05**p<.01 ***p<.001. White is the reference group for Race. Exp(B) = Odds Ratio.

Appendix M

Table 29. Logistic Regression Predicting Stranded Status from Academic Momentum Characteristics

								Confidence Interval	
		β	SE β	Wald χ^2	*df*	*p*	Exp(B)	Lower	Upper
Academic Momentum Variables (Alone)	Any Remedial in First Two Terms	0.413	0.222	3.455	1	0.063*	1.512	0.978	2.338
	Any Remedial in First 25 Courses	-0.135	0.211	0.41	1	0.522	0.874	0.578	1.321
	Withdraw 20% or more in First 25 Courses	-0.355	0.476	0.558	1	0.455	0.701	0.276	1.781
	Any Summer Course in First 25 Courses	0.54	0.066	66.225	1	<.001***	1.716	1.507	1.954
	Continuous Enrollment in First Six Terms (< 2)	0.573	0.25	5.245	1	0.022*	1.773	1.086	2.895
	First-Year GPA	0.062	0.124	0.251	1	0.616	1.064	0.834	1.357
	Second-Year GPA	-0.463	0.117	15.695	1	<.001***	0.629	0.5	0.791
	Cumulative GPA through Term 4	-0.305	0.232	1.727	1	0.189	0.737	0.468	1.162
Demographic + Academic Momentum	Gender	0.056	0.068	0.684	1	0.408	1.058	0.926	1.209
	American Indian or Alaskan Native	-2.297	1.152	3.978	1	0.046*	0.101	0.011	0.961
	Asian	0.237	0.093	6.434	1	0.011*	1.267	1.055	1.522
	African American or Black	-0.156	0.152	1.044	1	0.307	0.856	0.635	1.154
	Hispanic	0.075	0.09	0.682	1	0.409	1.077	0.903	1.286
	More than 1 Race/Ethnicity	0.021	0.117	0.031	1	0.861	1.021	0.811	1.285
	International	-0.106	0.363	0.085	1	0.77	0.899	0.442	1.831
	Hawaiian or other Pacific Islander	0.108	0.301	0.128	1	0.721	1.114	0.617	2.011
	Unknown	0.111	0.514	0.047	1	0.829	1.118	0.408	3.059
	Pell Grant Eligibility	0.088	0.072	1.501	1	0.221	1.092	0.948	1.258

Scholarship Received	0.187	0.103	3.285	1	0.07	1.206	0.985	1.477
Student Loans Received	0.099	0.068	2.103	1	0.147	1.104	0.966	1.263
Parents No Bachelor	-0.006	0.083	0.005	1	0.946	0.994	0.844	1.171
Parents No College	-0.127	0.096	1.755	1	0.185	0.881	0.73	1.063
Any Remedial in First Two Terms	0.414	0.224	3.416	1	0.065	1.513	0.975	2.347
Any Remedial in First 25 Courses	-0.105	0.212	0.245	1	0.621	0.9	0.594	1.365
Withdraw 20% or more in First 25 Courses	-0.38	0.481	0.625	1	0.429	0.684	0.267	1.754
Any Summer Course in First 25 Courses	0.547	0.067	66.317	1	<.001***	1.729	1.515	1.972
Continuous Enrollment in First Six Terms (< 2)	0.549	0.252	4.732	1	0.03*	1.732	1.056	2.84
First-Year GPA	0.065	0.125	0.273	1	0.601	1.067	0.836	1.363
Second-Year GPA	-0.461	0.117	15.444	1	<.001***	0.631	0.501	0.794
Cumulative GPA through Term 4	-0.347	0.234	2.205	1	0.138	0.706	0.447	1.118

Note: Variables are significant at *p<.05**p<.01 ***p<.001. White is the reference group for Race. Exp(B) = Odds Ratio.

Appendix N

Table 30. Logistic Regression Predicting Stranded Status from Student Characteristics

		β	SE β	Wald χ^2	*df*	*p*	Exp(B)	Confidence Interval Lower	Confidence Interval Upper
Explanatory Variables (Alone)	Changed Major by Term 5	0.368	0.074	24.764	1	<.001***	1.445	1.25	1.67
	Academic Probation Received	-0.015	0.098	0.023	1	0.879	0.985	0.814	1.193
	Consistently Low Academic Performance	0.117	0.109	1.17	1	0.279	1.125	0.909	1.391
	Continuous Enrollment in First Six Terms (< 1)	0.507	0.096	27.878	1	<.001***	1.661	1.376	2.005
	Any Withdraw in First Two Terms	0.034	0.115	0.089	1	0.765	1.035	0.827	1.296
	Any Withdraw in First 25 Courses	-0.062	0.099	0.386	1	0.535	0.94	0.774	1.142
	Cumulative GPA through Term 5	-0.746	0.106	49.454	1	<.001***	0.474	0.385	0.584
Demographic +Academic Momentum +Explanatory	Gender	0.069	0.069	1.015	1	0.314	1.072	0.937	1.226
	American Indian or Alaskan Native	-2.123	1.154	3.382	1	0.066	0.12	0.012	1.15
	Asian	0.242	0.095	6.528	1	0.011*	1.274	1.058	1.534
	African American or Black	-0.14	0.155	0.812	1	0.368	0.87	0.642	1.178
	Hispanic	0.104	0.091	1.281	1	0.258	1.109	0.927	1.327
	More than 1 Race/Ethnicity	0.021	0.119	0.031	1	0.86	1.021	0.809	1.289
	International	-0.066	0.366	0.033	1	0.856	0.936	0.457	1.918
	Hawaiian or other Pacific Islander	0.183	0.303	0.364	1	0.547	1.2	0.663	2.173
	Unknown	0.189	0.517	0.134	1	0.714	1.209	0.439	3.33
	Pell Grant Eligibility	0.089	0.073	1.496	1	0.221	1.093	0.948	1.26

Scholarship Received	0.184	0.105	3.093	1	0.079	1.202	0.979	1.476
Student Loans Received	0.094	0.069	1.843	1	0.175	1.099	0.959	1.258
Parents No Bachelor	-0.026	0.084	0.092	1	0.761	0.975	0.826	1.15
Parents No College	-0.122	0.097	1.604	1	0.205	0.885	0.732	1.069
Any Remedial in First Two Terms	0.424	0.225	3.527	1	0.06	1.527	0.982	2.376
Any Remedial in First 25 Courses	-0.102	0.214	0.227	1	0.634	0.903	0.594	1.373
Withdraw 20% or more in First 25 Courses	-0.311	0.504	0.382	1	0.537	0.732	0.273	1.966
Any Summer Course in First 25 Courses	0.578	0.068	72.031	1	<.001***	1.782	1.56	2.037
Continuous Enrollment in First Six Terms (< 2)	0.179	0.27	0.441	1	0.507	1.196	0.705	2.03
First-Year GPA	-0.014	0.131	0.012	1	0.914	0.986	0.763	1.275
Second-Year GPA	-0.504	0.124	16.411	1	<.001***	0.604	0.474	0.771
Cumulative GPA through Term 4	-0.07	0.325	0.047	1	0.829	0.932	0.493	1.763
Changed Major by Term 5	0.42	0.076	30.67	1	<.001***	1.522	1.312	1.766
Academic Probation Received	-0.124	0.103	1.436	1	0.231	0.884	0.722	1.082
Consistently Low Academic Performance	0.059	0.112	0.282	1	0.596	1.061	0.852	1.321
Continuous Enrollment in First Six Terms (< 1)	0.478	0.104	21.24	1	<.001***	1.613	1.316	1.977
Any Withdraw in First Two Terms	0.045	0.117	0.146	1	0.702	1.046	0.831	1.316
Any Withdraw in First 25 Courses	-0.078	0.102	0.596	1	0.44	0.925	0.757	1.128
Cumulative GPA through Term 5	-0.25	0.259	0.93	1	0.335	0.779	0.469	1.294

Note: Variables are significant at *p<.05**p<.01 ***p<.001. White is the reference group for Race. Exp(B) = Odds Ratio.

Appendix O

Table 31. Logistic Regression Predicting Stranded Status from College Interactions

								Confidence Interval	
		β	SE β	Wald χ^2	*df*	*p*	Exp(B)	Lower	Upper
Demographic + Momentum+ Explanatory Variables + College Interaction Terms	Gender	-0.021	0.079	0.067	1	0.795	0.98	0.839	1.144
	American Indian or Alaskan Native	-2.196	1.208	3.306	1	0.069	0.111	0.01	1.187
	Asian	0.81	0.544	2.217	1	0.136	2.249	0.774	6.534
	African American or Black	-0.143	0.167	0.73	1	0.393	0.867	0.625	1.203
	Hispanic	0.016	0.1	0.027	1	0.87	1.016	0.836	1.235
	More than 1 Race/Ethnicity	-0.111	0.13	0.734	1	0.392	0.895	0.694	1.154
	International	0.649	0.45	2.08	1	0.149	1.913	0.792	4.62
	Hawaiian or other Pacific Islander	-0.036	0.329	0.012	1	0.912	0.964	0.506	1.839
	Unknown	-0.236	0.545	0.187	1	0.665	0.79	0.272	2.298
	Pell Grant Eligibility	0.118	0.078	2.272	1	0.132	1.125	0.965	1.312
	Scholarship Received	0.066	0.113	0.343	1	0.558	1.069	0.856	1.335
	Student Loans Received	-0.011	0.076	0.022	1	0.883	0.989	0.853	1.147
	Parents No Bachelor	-0.033	0.091	0.131	1	0.717	0.968	0.81	1.156
	Parents No College	-0.142	0.104	1.881	1	0.17	0.867	0.708	1.063
	Any Remedial in First Two Terms	0.155	0.249	0.389	1	0.533	1.168	0.717	1.902
	Any Remedial in First 25 Courses	0.305	0.237	1.657	1	0.198	1.357	0.853	2.159
	Withdraw 20% or more in First 25 Courses	-0.369	0.546	0.457	1	0.499	0.691	0.237	2.016
	Any Summer Course in First 25 Courses	0.965	0.457	4.451	1	0.035*	2.625	1.071	6.433

Continuous Enrollment in First Six Terms (< 2)	0.356	0.286	1.543	1	0.214	1.427	0.814	2.502
First-Year GPA	-0.099	0.141	0.498	1	0.48	0.905	0.687	1.193
Second-Year GPA	-0.445	0.175	6.428	1	0.011*	0.641	0.454	0.904
Cumulative GPA through Term 4	-0.4	0.351	1.302	1	0.254	0.67	0.337	1.333
Changed Major by Term 5	0.46	0.274	2.823	1	0.093	1.585	0.926	2.712
Academic Probation Received	-0.105	0.112	0.885	1	0.347	0.9	0.722	1.121
Consistently Low Academic Performance	0.006	0.121	0.003	1	0.958	1.006	0.794	1.276
Continuous Enrollment in First Six Terms (< 1)	1.307	0.376	12.058	1	<.001***	3.695	1.767	7.726
Any Withdraw in First Two Terms	0.095	0.127	0.558	1	0.455	1.099	0.857	1.41
Any Withdraw in First 25 Courses	0.121	0.11	1.216	1	0.27	1.129	0.91	1.4
Cumulative GPA through Term 5	-0.419	0.281	2.231	1	0.135	0.657	0.379	1.14
Asian * College of Engineering	-0.918	0.583	2.478	1	0.115	0.399	0.127	1.252
Asian * College of Fine Arts	-2.366	0.82	8.324	1	0.004**	0.094	0.019	0.468
Asian * College of Hospitality	-0.046	0.785	0.003	1	0.953	0.955	0.205	4.45
Asian * College of Liberal Arts	-1.48	0.712	4.317	1	0.038*	0.228	0.056	0.92
Asian * College of Sciences	-0.214	0.692	0.095	1	0.757	0.807	0.208	3.136
Asian * College of Urban Affairs	-1.016	0.607	2.803	1	0.094	0.362	0.11	1.189
Asian * College of Health Sciences	-0.586	0.598	0.96	1	0.327	0.557	0.173	1.797
Asian * College of Business	-0.82	0.569	2.078	1	0.149	0.44	0.144	1.343
Asian * College of Nursing	-0.964	0.604	2.548	1	0.11	0.381	0.117	1.246
Asian * College of Public Health	-1.322	0.726	3.312	1	0.069	0.267	0.064	1.107
Summer * College of Engineering	0.116	0.531	0.048	1	0.827	1.123	0.397	3.176

Summer * College of Fine Arts	-0.59	0.499	1.4	1	0.237	0.554	0.209	1.473
Summer * College of Hospitality	-0.204	0.632	0.105	1	0.746	0.815	0.236	2.813
Summer * College of Liberal Arts	-0.953	0.652	2.134	1	0.144	0.386	0.107	1.385
Summer * College of Sciences	-0.368	0.536	0.472	1	0.492	0.692	0.242	1.978
Summer * College of Urban Affairs	0.03	0.625	0.002	1	0.962	1.031	0.303	3.506
Summer * College of Health Sciences	-0.68	0.484	1.975	1	0.16	0.507	0.196	1.308
Summer * College of Business	-0.887	0.514	2.98	1	0.084	0.412	0.151	1.128
Summer * College of Nursing	-0.353	0.481	0.538	1	0.463	0.703	0.274	1.804
Summer * College of Public Health	0.417	0.53	0.618	1	0.432	1.517	0.537	4.287
Second-year GPA * College of Engineering	0.168	0.15	1.251	1	0.263	1.183	0.881	1.589
Second-year GPA * College of Fine Arts	0.206	0.201	1.053	1	0.305	1.229	0.829	1.82
Second-year GPA * College of Hospitality	-0.193	0.235	0.677	1	0.411	0.824	0.52	1.307
Second-year GPA * College of Liberal Arts	-0.311	0.168	3.408	1	0.065	0.733	0.527	1.019
Second-year GPA * College of Sciences	-0.294	0.26	1.283	1	0.257	0.745	0.448	1.24
Second-year GPA * College of Urban Affairs	-0.034	0.133	0.065	1	0.799	0.967	0.745	1.255
Second-year GPA * College of Health Sciences	0.199	0.156	1.622	1	0.203	1.221	0.898	1.659
Second-year GPA * College of Business	-0.044	0.135	0.104	1	0.747	0.957	0.735	1.247
Second-year GPA * College of Nursing	0.488	0.148	10.839	1	<.001***	1.628	1.218	2.177
Second-year GPA * College of Public Health	0.164	0.226	0.525	1	0.469	1.178	0.757	1.834

Changed Major * College of Engineering	0.265	0.37	0.512	1	0.474	1.303	0.631	2.69
Changed Major * College of Fine Arts	-1.386	0.562	6.085	1	0.014*	0.25	0.083	0.752
Changed Major * College of Hospitality	-0.377	0.697	0.292	1	0.589	0.686	0.175	2.688
Changed Major * College of Liberal Arts	0.452	0.404	1.25	1	0.264	1.571	0.711	3.472
Changed Major * College of Sciences	0.659	0.601	1.203	1	0.273	1.934	0.595	6.283
Changed Major * College of Urban Affairs	0.027	0.318	0.007	1	0.932	1.027	0.551	1.915
Changed Major * College of Health Sciences	0.137	0.379	0.132	1	0.716	1.147	0.546	2.409
Changed Major * College of Business	0.06	0.324	0.035	1	0.853	1.062	0.563	2.004
Changed Major * College of Nursing	0.242	0.475	0.26	1	0.61	1.274	0.502	3.234
Changed Major * College of Public Health	-0.293	0.534	0.3	1	0.584	0.746	0.262	2.126
Cont Enroll * College of Engineering	-0.207	0.484	0.183	1	0.669	0.813	0.315	2.098
Cont Enroll * College of Fine Arts	-1.633	0.626	6.799	1	0.009**	0.195	0.057	0.667
Cont Enroll * College of Hospitality	-2.105	0.683	9.491	1	0.002**	0.122	0.032	0.465
Cont Enroll * College of Liberal Arts	-1.108	0.507	4.78	1	0.029	0.33	0.122	0.892
Cont Enroll * College of Sciences	-0.554	0.8	0.479	1	0.489	0.575	0.12	2.756
Cont Enroll * College of Urban Affairs	-0.838	0.431	3.775	1	0.052	0.432	0.186	1.007
Cont Enroll * College of Health Sciences	-0.926	0.493	3.52	1	0.061	0.396	0.151	1.042

Cont Enroll * College of Business	-0.197	0.435	0.204	1	0.651	0.822	0.35	1.927
Cont Enroll * College of Nursing	-1.07	0.497	4.632	1	0.031*	0.343	0.129	0.909
Cont Enroll * College of Public Health	-1.554	0.725	4.597	1	0.032*	0.211	0.051	0.875

Note: Variables are significant at *p<.05**p<.01 ***p<.001. White is the reference group for Race and College of Education for College type. Exp(B) = Odds Ratio.

References

Adelman, C. (1999). Answers in the toolbox: Academic intensity, attendance patterns, and bachelor's degree attainment. https://files.eric.ed.gov/fulltext/ED431363.pdf

Adelman, C. (2006). The toolbox revisited: Paths to degree completion from high school through college. *US Department of Education*.

Akoglu. (2018). User's guide to correlation coefficients. *Turkish Journal of Emergency Medicine*, *18*(3), 91–93. https://doi.org/10.1016/j.tjem.2018.08.001

Albert, A., & Wozny, N. (2018). The effect of academic probation on academic outcomes: Evidence from the US Air Force Academy. In *American Educational Research Association Conference Proceeding*.

Aljets, A. (2018, March 16). *Three reasons academic advisors should be a go-to resource for student success efforts*. Ed Surge. https://www.edsurge.com/news/2018-03-26-three-reasons-academic-advisors-should-be-a-go-to-resource-for-student-success-efforts?platform=hootsuite

Astin, A. W. (1993). *What matters in college? Four critical years revisited* (1st ed.). Jossey-Bass.

Atchley, W., Wingenbach, G., & Akers, C. (2013). Comparison of course completion and student performance through online and traditional courses. *International Review of Research in Open and Distance Learning, 14*(4), 104–116. https://doi.org/10.19173/irrodl.v14i4.1461

Attewell, P., Heil, S., & Reisel, L. (2012). What is academic momentum? And does it matter? *Educational Evaluation and Policy Analysis, 34*(1), 27–44. https://doi.org/10.3102/0162373711421958

Attewell, P., & Monaghan, D. (2016). How many credits should an undergraduate take? *Research in Higher Education, 57*(6), 682-713. https://doi.org/10.1007/s11162-015-9401-z

Auburn University. (2008) *Factors related to timely degree completion*. http://www.auburn.edu/academic/provost/pdf/Appendix_B_Factors_Related_to_Timely_Degree_Completion.pdf.

Batz, Z., Olsen, B. J., Dumont, J., Dastoor, F., & Smith, M. K. (2015). Helping struggling students in introductory biology: a peer-tutoring approach that improves performance, perception, and retention. *CBE Life Sciences Education, 14*(2), ar16. https://doi.org/10.1187/cbe.14-08-0120

Belfield C., Jenkins D., Lahr H. (2016). *Momentum: The academic and economic value of a 15-credit first-semester course load for college students in Tennessee*. Community College Research Center, Teachers College, Columbia University. https://ccrc.tc.columbia.edu/media/k2/attachments/momentumsummary.pdf

Berkner, L., He, S., Cataldi, E. F., & Knepper, P. (2003). Descriptive summary of 1995-96 beginning postsecondary students: Six years later. *Education Statistics Quarterly, 5*(1), 62-67.

Bleemer, Z., Davidson, A., & Mehta, A. (2023, July 11). *Restricted access to lucrative college majors harms underrepresented students most*. Brookings Institute. https://www.brookings.edu/articles/restricted-access-to-lucrative-college-majors-harms-underrepresented-students-most/

Bleemer, Z., & Mehta, A. (2021). *College major restrictions and student stratification.* UC Berkeley: Center for Studies in Higher Education. https://escholarship.org/uc/item/513249vg

Blekic, M., Carpenter, R., & Cao, Y. (2020). Continuing and transfer students: Exploring retention and second-year success. *Journal of College Student Retention: Research, Theory & Practice, 22*(1), 71-98. https://doi.org/10.1177/1521025117726048

Bowman, N. A., & Jang, N. (2022). What is the purpose of academic probation? Its substantial negative effects on four-year graduation. *Research in Higher Education*, *63*(8), 1285–1311. https://doi.org/10.1007/s11162-022-09676-w

Brough, P. (2019). Introduction to advanced research methods for applied psychologists. In *Advanced Research Methods for Applied Psychology* (1st ed., pp. 1–3). Routledge. https://doi.org/10.4324/9781315517971-1

Calcagno, J. C., & Bridget Terry Long. (2008). The impact of postsecondary remediation using a regression discontinuity approach: Addressing endogenous sorting and noncompliance. *NBER Working Paper Series*, 14194. https://doi.org/10.3386/w14194

Carnegie Classification of Institutions of Higher Education. (2024). *Classification Lookup*. https://carnegieclassifications.acenet.edu/institutions/

Carroll, C. D. (1989). *College persistence and degree attainment for 1980 high school graduates: Hazards for transfers, stopouts, and part-timers* (Vol. 89, No. 302). National Center for Education Statistics, US Department of Education, Office of Educational Research and Improvement. https://nces.ed.gov/pubs89/89302.pdf

Casey, M. D., Cline, J., Ost, B., & Qureshi, J. A. (2018). Academic probation, student performance, and strategic course-taking. *Economic Inquiry, 56*(3), 1646–1677. https://doi.org/10.1111/ecin.12566

Chen, Y., & Upah, S. (2020). Data analytics and STEM student success: The impact of predictive analytics-informed academic advising among undeclared first-year engineering students. *Journal of College Student Retention: Research, Theory & Practice, 22*(3), 497-521. https://doi.org/10.1177/1521025118772307

Chelberg, K. L., & Bosman, L. B. (2019). The role of faculty mentoring in improving retention and completion rates for historically underrepresented STEM students. *International Journal of Higher Education, 8*(2), 39-48. https://doi.org/10.5430/ijhe.v8n2p39

Clovis, A. & Chang, M. (2021). Effects of academic momentum on degree attainment for students beginning college at 2-year institutions. *Journal of College Student Retention: Research, Theory & Practice*, *23*(2), 322–336. https://doi.org/10.1177/1521025119826245

Cochran, J. D., Campbell, S. M., Baker, H. M., & Leeds, E. M. (2014). The role of student characteristics in predicting retention in online courses. *Research in Higher Education, 55*, 27-48. https://doi.org/10.1007/s11162-013-9305-8

Collings, R. D., & Eaton, L. (2021). The study place project: Using reciprocal determinism to improve first-year college GPA and retention. *College Student Journal, 55*(1), 89-103. https://link.gale.com/apps/doc/A668597546/AONE?u=unlv_main&sid=bookmark-AONE&xid=00aaa03f

Complete College America (2022). *15 to finish/stay on track.* https://completecollege.org/strategy/15-to-finish/

Connelly, L. M. (2013). Demographic data in research studies. *Medsurg Nursing, 22*(4), 269-271. https://link.gale.com/apps/doc/A341687270/AONE?u=unlv_main&sid=bookmark-AONE&xid=62462895

Connolly, S., Flynn, E. E., Jemmott, J., & Oestreicher, E. (2017). First year experience for at-risk college students. *College Student Journal, 51*(1), 1-6.

https://link.gale.com/apps/doc/A487602746/AONE?u=unlv_main&sid=bookmark-AONE&xid=6363f62e

Cuseo, J. (2015). The empirical case for the first-year seminar: Evidence of course impact on student retention, persistence to graduation, and academic achievement. https://www.researchgate.net/publication/284200361_The_Empirical_Case_for_the_First_Year_Seminar_Evidence_of_Course_Impact_on_Student_Retention_Persistence_to_Graduation_and_Academic_Achievement

Cuseo, J.B., Thompson, A., Campagna, M., & Sox Fecas, V. (2020). *Thriving in college and beyond: Research-based strategies for academic success and personal development* (5th ed.). Kendall Hunt Publishing Company.

Davidson, J.C. (2014). Leading indicators: Increasing statewide bachelor's degree completion rates at 4-year public institutions. *Higher Education Policy, 27*, 85-109. https://doi.org/10.1057/hep.2013.17

Davidson, J.C., & Blankenship, P. (2017). Initial academic momentum and student success: comparing 4- and 2-year students. *Community College Journal of Research and Practice, 41*(8), 467–480. https://doi.org/10.1080/10668926.2016.1202158

Del Prette, Z.A.P., Prette, A. D., De Oliveira, L. A., Gresham, F. M., & Vance, M. J. (2012). Role of social performance in predicting learning problems: Prediction of risk using logistic regression analysis. *School Psychology International, 33*(6), 615-630. https://doi.org/10.1177/0020715211430373

DeNicco, J., Harrington, P., & Fogg, N. (2015). Factors of one-year college retention in a public state college system. *Research in Higher Education Journal, 27*. https://files.eric.ed.gov/fulltext/EJ1056244.pdf

Dennehy, T.C., & Dasgupta, N. (2017). Female peer mentors early in college increase women's positive academic experiences and retention in engineering. *Proceedings of the National Academy of Sciences - PNAS, 114*(23), 5964–5969. https://doi.org/10.1073/pnas.1613117114

DesJardins, S.L., Ahlburg, D. A., & McCall, B. P. (2002). A temporal investigation of factors related to timely degree completion. *The Journal of Higher Education (Columbus), 73*(5), 555–581. https://doi.org/10.1353/jhe.2002.0042

Dong, Y. (2019). Regression discontinuity designs with sample selection. *Journal of Business & Economic Statistics, 37*(1), 171–186. https://doi.org/10.1080/07350015.2017.1302880

Ellis, J., Fosdick, B. K., & Rasmussen, C. (2016). Women 1.5 times more likely to leave STEM pipeline after calculus compared to men: Lack of mathematical confidence a potential culprit. *PloS One, 11*(7), e0157447–e0157447. https://doi.org/10.1371/journal.pone.0157447

Erlich, R. J., & Russ-Eft, D. F. (2013). Assessing student learning in academic advising using social cognitive theory. *NACADA Journal, 33*(1), 16-33. https://doi.org/10.12930/NACADA-13-135

Etikan, I., Musa, S. A., & Alkassim, R. S. (2016). Comparison of convenience sampling and purposive sampling. *American Journal of Theoretical and Applied Statistics, 5*(1), 1-4. https://doi.org/10.11648/j.ajtas.20160501.11

Eveland, T. (2020). Supporting first-generation college students: analyzing academic and social support's effects on academic performance. *Journal of Further and Higher Education*, *44*(8), 1039–1051. https://doi.org/10.1080/0309877X.2019.1646891

Faulconer, J., Geissler, J., Majewski, D., & Trifilo, J. (2013). Adoption of an early-alert system to support university student success. *Delta Kappa Gamma Bulletin, 80*(2).

Farmer, E., Hilton, A. A., & Reneau, F. H. (2016). Variables that contribute to retention and graduation of Black American females at an historically Black university. *Negro Educational Review, 67*(1-4), 133. https://www.ezproxy.library.unlv.edu/login?qurl=https%3A%2F%2Fwww.proquest.com%2Fscholarly-journals%2Fvariables-that-contribute-retention-graduation%2Fdocview%2F1926455426%2Fse-2%3Faccountid%3D3611

Flores, G., & Estudillo, A. G. (2018). Effects of a peer-to-peer mentoring program: Supporting first-year college students' academic and social integration on campus. *Journal of Human Services: Training, Research, and Practice, 3*(2), 3. 3. https://scholarworks.sfasu.edu/jhstrp/vol3/iss2/3

Gilstrap, D. (2020). Understanding persistence of at-risk students in higher education enrollment management using multiple linear regression and network analysis. *The Journal of Experimental Education, 88*(3), 470–485. https://doi.org/10.1080/00220973.2019.1659217

Glynn, J., Sauer, P., & Miller, T. (2011). A logistic regression model for the enhancement of student retention: The identification of at-risk freshmen. *The International Business & Economics Research Journal, 1*(8), 79-86. https://doi.org/10.19030/iber.v1i8.3970

Gordanier, J., Hauk, W., & Sankaran, C. (2019). Early intervention in college classes and improved student outcomes. *Economics of Education Review, 72*, 23–29. https://doi.org/10.1016/j.econedurev.2019.05.003

Grace-Martin, K. (n.d.). The difference between an odds ratio and a predicted odds. https://www.theanalysisfactor.com/odds-ratio-predicted-odds-difference/#respond

Hall, J. M., & Ponton, M. K. (2005). Mathematics self-efficacy of college freshman. *Journal of Developmental Education*, *28*(3), 26–32. https://files.eric.ed.gov/fulltext/EJ718579.pdf

Hanover Research (2014, November). *Early alert systems in higher education.* https://www.hanoverresearch.com/wp-content/uploads/2017/08/Early-Alert-Systems-in-Higher-Education.pdf

Hasan, N. (2020, August 7). *Logistic regression using SPSS*. [PowerPoint Slides, pdf]. University of Miami. https://sites.education.miami.edu/statsu/wp-content/uploads/sites/4/2020/07/Logistic-Regression-Webinar.pdf

Haq, & Nazir, A. (2016). Which statistical hypothesis test should I apply? A simple guide for beginners. *International Journal of Preventive Medicine*, *7*(1), 81–81. https://doi.org/10.4103/2008-7802.183653

Harrell, Jr., F. E., & Harrell, F. E. (2015). Binary logistic regression. *Regression modeling strategies: With applications to linear models, logistic and ordinal regression, and survival analysis*, 219-274. http://doi.org/10.1007/978-3-319-19425-7

Hockings, S. C., DeAngelis, K. J., & Frey, R. F. (2008). Peer-led team learning in general chemistry: Implementation and evaluation. *Journal of Chemical Education, 85*(7), 990. https://doi.org/10.1021/ed085p990

Horn, L. (1998). *Stopouts or stayouts?: Undergraduates who leave college in their first year*. Diane Publishing.

Howard, B. L., & Sharpe Jr., L. (2019). The summer bridge program: An effective agent in college students' retention. *Journal of Interdisciplinary Studies in Education, 7*(2), 20-30. https://doi.org/10.32674/jise.v7i2.1207

IBM. (n.d.). *IBM SPSS statistics.* https://www.ibm.com/products/spss-statistics

Ishitani, T. T. (2016). Time-varying effects of academic and social integration on student persistence for first and second years in college: National data approach. *Journal of College Student Retention: Research, Theory & Practice, 18*(3), 263–286. https://doi.org/10.1177/1521025115622781

Jenkins-Guarnieri, M. A., Horne, M. M., Wallis, A. L., Rings, J. A., & Vaughan, A. L. (2015). Quantitative evaluation of a first year seminar program. *Journal of College Student Retention: Research, Theory & Practice, 16*(4), 593–606. https://doi.org/10.2190/CS.16.4.f

Jimenez, L., Sargrad, S., Morales, J., & Thompson, M. (2016). Remedial education: The cost of catching up. *Center for American Progress*.

Kaufman, P., Bradbury, D., & Owings, J. (1992). *National education longitudinal study of 1988: Characteristics of at-risk students in NELS:88*. Washington, DC: U.S. Dept. of Education, Office of Educational Research and Improvement, National Center for Education Statistics. http://nces.ed.gov/pubs92/92042.pdf

Kent State University Library. (2023, July 20). *SPSS tutorial: Chi-square test of independence.* LibGuides. https://libguides.library.kent.edu/spss/chisquare

Kerr, E., & Wood, S. (2022, September 13). *See 20 years of tuition growth at national universities*. U.S. News & World Report. https://www.usnews.com/education/best-colleges/paying-for-college/articles/see-20-years-of-tuition-growth-at-national-universities

Kern, P. (2011). *t-Test Formula Summary Sheet*. https://www.peggykern.org/uploads/5/6/6/7/56678211/ttestformulas.pdf

Kimbark, K., Peters, M. L., & Richardson, T. (2017). Effectiveness of the student success course on persistence, retention, academic achievement, and student engagement. *Community College Journal of Research and Practice, 41*(2), 124-138. https://doi.org/10.1080/10668926.2016.1166352

King, B. (2015). Changing college majors: Does it happen more in STEM and do grades matter? *Journal of College Science Teaching*, *44*(3), 44–51. https://doi.org/10.2505/4/jcst15_044_03_44

Kiser, A. I. T., & Price, L. (2008). The persistence of college students from their freshman to sophomore year. *Journal of College Student Retention: Research, Theory & Practice, 9*(4), 421–436. https://doi.org/10.2190/CS.9.4.b

Koshland, C., & King Liu, T.-J. (2018, June 8). *Addressing capped and restricted majors at UC Berkeley: Analysis and recommendations from the undergraduate council.* Berkeley Academic Senate. https://academic-senate.berkeley.edu/sites/default/files/divco_on_capped_and_restricted_majors_recommendations_w-_encl.pdf

Krsmanovic, M. (2019). Using first-year seminar courses to improve performance funding outcomes- a case study of the state of Florida. *Voices of Reform: Educational Research to Inform and Reform, 2*(1), 24-44. http://dx.doi.org/10.32623/2.00004

Laerd Statistics. (2018). *Binomial Logistic Regression using SPSS Statistics*. https://statistics.laerd.com/spss-tutorials/binomial-logistic-regression-using-spss-statistics.php

LaMorte, W.W. (2019, March 16). *Module 7 - Comparing continuous outcomes.* Boston University School of Public Health. https://sphweb.bumc.bu.edu/otlt/MPH-Modules/PH717-QuantCore/PH717-Module7-T-tests/Module7-ttests3.html#:~:text=%22A%20P%20value%20of%200.05%20does,extreme%20as%20the%20one%20observed.

Law, D. D., Hales, K., & Busenbark, D. (2020). Student success: A literature review of faculty to student mentoring. *Journal on Empowering Teaching Excellence, 4*(1), 6. https://doi.org/10.15142/38x2-n847

Lawson, M., & Philpott, C. (2008). Reliability and validity. *Doing classroom research: A step-by-step guide for student teachers*, 70-81. https://ds.amu.edu.et/xmlui/bitstream/handle/123456789/10913/DOING%20CLASSROOM%20RESEARCH%20A%20Step-By-Step%20Guide%20For%20Student%20Teachers.pdf?sequence=1&isAllowed=y#page=83

Lisberg, A., & Woods, B. (2018). Mentorship, mindset and learning strategies: An integrative approach to increasing underrepresented minority student retention in a STEM undergraduate program. *Journal of STEM education, 19*(3). https://www.learntechlib.org/p/184625/

Malm, J., Bryngfors, L., & Fredriksson, J. (2018). Impact of supplemental instruction on dropout and graduation rates: An example from 5-year engineering programs. *Journal of Peer Learning, 11*(1), 76-88. http://ro.uow.edu.au/ajpl/vol11/iss1/6

Martin, A. J., Wilson, R., Liem, G. A. D., & Ginns, P. (2013). Academic momentum at university/college: Exploring the roles of prior learning, life experience, and ongoing performance in academic achievement across time. *The Journal of Higher Education, 84*(5), 640-674. https://doi.org/10.1353/jhe.2013.0029

Martorell, P., & McFarlin, Isaac, Jr. (2011). Help or hindrance?: The effects of college remediation on academic and labor market outcomes. *The Review of Economics and Statistics*, *93*(2), 436–454. https://doi.org/10.1162/REST_a_00098

McHugh, M. L. (2013). The chi-square test of independence. *Biochemia medica*, 23(2), 143-149. https://doi.org/10.11613/BM.2013.018

Morse, J. M. (2008). “What's your favorite color?” reporting irrelevant demographics in qualitative research. *Qualitative Health Research, 18*(3), 299-300. https://doi.org/10.1177/1049732307310995

Mu, L., & Fosnacht, K. (2019). Effective advising: How academic advising influences student learning outcomes in different institutional contexts. *The Review of Higher Education, 42*(4), 1283-1307. https://doi.org/10.1353/rhe.2019.0066

Muller, K., Feuer, E., Nyman, M., Sokolowski, K., & Rotella, L. (2017). Examining predictors of first year college student retention. *New York Journal of Student Affairs, 17*(1), 2.
https://commons.library.stonybrook.edu/nyjsa/vol17/iss1/2

Musoba, G. D., & Krichevskiy, D. (2014). Early coursework and college experience predictors of persistence at a Hispanic-serving institution. *Journal of Hispanic Higher Education, 13*(1), 48-62. https://doi.org/10.1177/1538192713513463

Nora, A., Barlow, L., & Crisp, G. (2006). Examining the tangible and psychosocial benefits of financial aid with student access, engagement, and degree attainment. *The American Behavioral Scientist (Beverly Hills), 49*(12), 1636–1651. https://doi.org/10.1177/0002764206289143

National Student Clearinghouse Research Center. (2022). *Completing college*. https://nscresearchcenter.org/wp-content/uploads/Completions_Report_2022.pdf

National University Academic Success Center (2024). *Cohen's d*. https://resources.nu.edu/statsresources/cohensd

Ngamsiriudom, W., Devkota, M. L., & Menon, M. K. (2022). Can gender and major explain college students' performance in business statistics? *American Business Review, 25*(2), 253-269. https://doi.org/10.37625/abr.25.2.253-269

Nichols, J., Orehovec, P. M., & Ingold, S. (1999). Using logistic regression to identify new "at-risk" freshmen. *Journal of Marketing for Higher Education, 9*(1), 25–37. https://doi.org/10.1300/J050v09n01_03

Offenstein, J., & Shulock, N. (2010). Taking the Next Step: The promise of intermediate measures for meeting postsecondary completion goals. *Jobs for the Future*. https://files.eric.ed.gov/fulltext/ED520014.pdf

Pedhazur, E. J., & Schmelkin, L. P. (1991). *Measurement, design, and analysis: an integrated approach*. Lawrence Erlbaum Associates.

Polit, D. F., & Beck, C. T. (2008). *Nursing research: generating and assessing evidence for nursing practice* (8th ed.). Wolters Kluwer Health/Lippincott Williams & Wilkins.

Romney, L. (2018, June 5). *9th annual how youth plan to fund college.* College Savings Foundation. https://www.collegesavingsfoundation.org/press-releases/how-youth-plan-to-fund-college/

Schmidt, S. (2021). Minimum Grade Requirements for Economics Majors: Effects on Enrollments and Student Learning. *AEA Papers and Proceedings*, *111*, 107–111. https://doi.org/10.1257/pandp.20211046

Schudde, L. T., Ryu, W., Brown, R. S. (2020). Major movement: Examining meta-major switching at community colleges. *The Review of Higher Education, 44*(2), 189-235. https://doi.org/10.1353/rhe.2020.0044

Scott-Clayton, J., & Rodriguez, O. (2015). Development, discouragement, or diversion? New evidence on the effects of college remediation policy. *Education Finance and Policy*, *10*(1), 4-45. https://doi.org/10.1162/EDFP_a_00150

Singell, L.D., & Waddell, G. R. (2010). Modeling retention at a large public university: Can at-risk students be identified early enough to treat? *Research in Higher Education, 51*(6), 546–572. https://doi.org/10.1007/s11162-010-9170-7

Skoglund, K., Wall, T. J., & Kiene, D. (2018). Impact of supplemental instruction participation on college freshman retention. *Learning Assistance Review, 23*(1), 115-135. https://files.eric.ed.gov/fulltext/EJ1170114.pdf

Slanger, W. D., Berg, E. A., Fisk, P. S., & Hanson, M. G. (2015). A longitudinal cohort study of student motivational factors related to academic success and retention using the college student inventory. *Journal of College Student Retention: Research, Theory & Practice, 17*(3), 278-302. https://doi.org/10.1177/1521025115575701

Sneyers, E., & De Witte, K. (2018). Interventions in higher education and their effect on student success: a meta-analysis. *Educational Review (Birmingham)*, *70*(2), 208–228. https://doi.org/10.1080/00131911.2017.1300874

Soria, K. M., Fransen, J., & Nackerud, S. (2013). Library use and undergraduate student outcomes: New evidence for students' retention and academic success. *portal: Libraries and the Academy, 13*(2), 147-164. https://doi.org/10.1353/pla.2013.0010

Spears School of Business. (2017, January 5). *Improve retention, improve lives: Why student retention is important to society*. Oklahoma State University. https://news.okstate.edu/articles/business/2017/improve-retention-improve-lives-why-student-retention-is-important-to-society.html

Spight, D. B. (2022). Undeclared versus declared: Who is more likely to graduate? *Journal of College Student Retention: Research, Theory & Practice, 23*(4), 945–964. https://doi.org/10.1177/1521025119879881

Statology. (2021, September 29). *Understanding the null hypothesis for logistic regression*. https://www.statology.org/null-hypothesis-of-logistic-regression/#:~:text=The%20null%20hypothesis%20states%20that%20all%20coefficients%20in%20the%20model,is%20simultaneously%20equal%20to%20zero.

Stanger-Hall, K. F., Lang, S., & Maas, M. (2010). Facilitating learning in large lecture classes: testing the “teaching team” approach to peer learning. *CBE—Life Sciences Education, 9*(4), 489-503. https://doi.org/10.1187/cbe.09-12-0093

Stolle-McAllister, K. (2011). The case for summer bridge: Building social and cultural capital for talented black STEM students. *Science Educator, 20*(2), 12. https://files.eric.ed.gov/fulltext/EJ960632.pdf

Stoltzfus, J. C. (2011). Logistic regression: A brief primer. *Academic Emergency Medicine*, *18*(10), 1099–1104. https://doi.org/10.1111/j.1553-2712.2011.01185.x

Sullivan, G. M., & Feinn, R. (2012). Using effect size-or why the p value is not enough. *Journal of Graduate Medical Education*, *4*(3), 279–282. https://doi.org/10.4300/JGME-D-12-00156.1

Swanson, N. M., Vaughan, A. L., & Wilkinson, B. D. (2017). First-year seminars. *Journal of College Student Retention: Research, Theory & Practice, 18*(4), 386–400. https://doi.org/10.1177/1521025115604811

Tampke, D. R. (2013). Developing, implementing, and assessing an early alert system. *Journal of College Student Retention: Research, Theory & Practice, 14*(4), 523-532. https://doi.org/10.2190/CS.14.4.e

TexaSoft. (2021). *Statistical comparison of two groups*. Retrieved April 15, 2023, from https://www.texasoft.com/tutorial-statistics-compare-2-groups.htm

Trovato, J. (2021, November 9). *Is Gen Z less willing to take on debt?.* encoura. https://encoura.org/is-gen-z-less-willing-to-take-on-debt/

University of Maine (2023). *Retention and student success – Best practices and successful initiatives.* Student Success and Credential Attainment. https://www.maine.edu/student-success/retention-and-student-success-best-practices-and-successful-initiatives/

Vasudev, R. (2018, June 4). *How are logistic regression & ordinary least squares regression (linear regression) related?* Toward Data Science. https://towardsdatascience.com/how-are-logistic-regression-ordinary-least-squares-regression-related-1deab32d79f5

Villano, R., Harrison, S., Lynch, G., & Chen, G. (2018). Linking early alert systems and student retention: a survival analysis approach. *Higher Education, 76*(5), 903+. https://doi.org/10.1007/s10734-018-0249-y

Walpole, M. (2003). Socioeconomic status and college: How SES affects college experiences and outcomes. *The review of higher education*, *27*(1), 45-73.

Wang, X., Chan, H. Y., Phelps, L. A., & Washbon, J. I. (2015). Fuel for success: Academic momentum as a mediator between dual enrollment and educational outcomes of two-year technical college students. *Community College Review, 43*(2), 165-190. https://doi.org/10.1177/0091552115569846

Whitcomb, K. M., Doucette, D., & Singh, C. (2022). Comparing major declaration, attrition, migration, and completion in physics with other STEM disciplines: A sign of inequitable physics culture? *Journal of Higher Education Theory and Practice, 22*(17), 63-81. https://doi.org/10.33423/jhetp.v22i17.5658

Wilms, R., Mäthner, E., Winnen, L., & Lanwehr, R. (2021). Omitted variable bias: a threat to estimating causal relationships. *Methods in Psychology, 5*, 100075. https://doi.org/10.1016/j.metip.2021.100075

Wright, N. A. (2020). Perform better, or else: Academic probation, public praise, and students decision-making. *Labour Economics*, *62*, 101773. https://doi.org/10.1016/j.labeco.2019.101773

Young-Jones, A. D., Burt, T. D., Dixon, S., & Hawthorne, M. J. (2013). Academic advising: does it really impact student success?. *Quality Assurance in Education, 21*(1), 7-19. https://doi.org/10.1108/09684881311293034

Zhang, Y., Fei, Q., Quddus, M., & Davis, C. (2014). An examination of the impact of early intervention on learning outcomes of at-risk students. *Research in Higher Education Journal, 26*. https://files.eric.ed.gov/fulltext/EJ1055303.pdf

Zhang, L., & Rangwala, H. (2018). Early identification of at-risk students using iterative logistic regression. In *Artificial Intelligence in Education: 19th International Conference, AIED 2018, London, UK, June 27–30, 2018, Proceedings, Part I 19* (pp. 613-626). Springer International Publishing. https://doi.org/10.1007/978-3-319-93843-1_45

Curriculum Vitae

Michael Hack – michael.hack@unlv.edu

EDUCATION: **University of Nevada, Las Vegas**

Candidate – Doctor of Philosophy – College of Education
Educational Psychology, Leadership, and Higher Education
Dissertation focus: *College Major GPA Restrictions and Stranded Status*

Master of Education – Higher Education
Degree Received – December 2018
Capstone: *Examining the Effectiveness of Dual Enrollment Programs*

Bachelor of Science in Business Administration Management
Degree Received – December 2009

EXPERIENCE: **UNLV Academic Success Center (ASC)** Las Vegas, NV

May 2016 – Current
- Senior Coordinator of Academic Transitions and Engagement (2019 – current)
- Academic Transitions Specialist (2016 – 2019)

Coordination of ASC Dual Enrollment Program

- Provide academic advising and support for dual enrollment students
- Established outreach efforts to high school students and counselors
- Developed Advanced Studies Program (ASP) pilot for high school students
- Created ASP admissions process and New Student Orientation
- Collect, report, and examine retention data for programs
- Complete assessment to examine the effectiveness of programming
- Supervise and train a team of Graduate Assistants and student workers

Management of ASC Graduate Assistant Professional Development Program

- Facilitate workforce readiness and career development workshops
- Oversee mock interview opportunity for Graduate Assistants

Oversee ASC Marketing and Outreach

- Responsible for development of ASC social media content and communications
- Coordinate the on and off-campus engagement efforts of the ASC
- Manage ASC participation in Welcome Weeks, Rebel Preview, etc.
- Oversee an average of 125 classroom presentations and events per year

ASC Service

- Serve on the Retention, Progression, and Completion Committee
- Developed student success initiatives to improve retention efforts
- Coordinate ASC Rebel Spirit Awards for employee recognition

First-Year Seminar

- Part-time Instructor for COLA 100E in the fall terms
- Develop engaging lessons that support students with a successful transition
- Facilitate environment for student's career and major exploration development
- Designed and provided customized FYS student survey evaluation reports
- Manage and build First-Year Seminar course schedules within MyUNLV

Hillman Family Foundations Pittsburgh, PA

July 2015 – September 2015 (Temp. Assignment)

- Grants Management Administrator

- Administered grants management database and tracked weekly activity reports
- Maintained and analyzed data on grant-making to assist program planning

State Bar of Nevada Las Vegas, NV

October 2006 – February 2015

- Admissions Manager (2013 – 2015)

- Administration of Nevada State Bar Examination
- Managed Functional Equivalency Certification for international law students
- Coordinated Nevada Supreme Court Annexed Arbitration Program
- Facilitated student practice certifications with William S. Boyd School of Law

- Admissions Investigator (2009 – 2013)

- Analysis of applicant character & fitness backgrounds
- Drafted and proposed changes to Nevada Supreme Court rules and regulations
- Facilitated the Emeritus Attorney Pro-Bono Program

- Admissions Assistant/Office Clerk (2006 – 2009)

- Coordinated accommodations for students with disabilities
- Responsible for general office duties and assisting Nevada bar candidates

ACTIVITIES: **Committees & Achievements**

- UNLV Community Engagement Council, current member
- UNLV New Student Orientation Committee, current member
- UNLV Communicators Council, current member
- ASC Retention Committee, current member
- ASC Spirit Awards Committee, current chair
- Advanced Studies Program Selection Committee, former chair
- Served as Chair for several UNLV search committees
- ASC Rebels With a Cause Award winner
- Presented at the 2021 NOSS Annual Conference
  - *The Advanced Studies Program: An Equitable Bridge for High School Students*
- Presented at the 2023 First-Year Experience Conference
  - *A Decade of Data: How to use assessment to build a better First-Year Seminar*