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Predicting Graduation and College GPA: A Multilevel Analysis Investigating the Contextual Effect of College Major

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PREDICTING GRADUATION AND COLLEGE GPA: A MULTILEVEL ANALYSIS INVESTIGATING THE CONTEXTUAL EFFECT OF COLLEGE MAJOR

by

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I dedicate this work to my family and friends. Without you, this would not be possible.

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ABSTRACT

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Despite the overwhelming evidence that higher education data are nested at various levels, single-level techniques such as regression and analysis of variance are commonly used to investigate student outcomes. This is problematic as a mismatch in methodology and research questions can lead to biased parameter estimates. The purpose of this study was to predict cumulative grade point average (GPA) and the likelihood of four-year and six-year graduation while simultaneously accounting for select pre-college characteristics, during-college experiences, and the interrelationship between student-level and major-level predictors. To achieve the desired outcomes, the study applied multilevel modeling techniques to secondary data for new undergraduate students first enrolling at one research institution in the Midwestern United States during Fall 2010 and Fall 2011. Results suggest that approximately 30% of the variation in cumulative GPA, 32% of the variation in four-year graduation, and 48% of the variation in six-year graduation can be attributed to differences in academic majors. Results also indicate that the strength of the student-level predictors of high school GPA, changing one's major, first-year GPA, and student organization involvement vary across academic majors. Collectively, the study contributes to the application of quantitative research methodology in higher education by demonstrating a more accurate predictive model of academic success for undergraduate students.

CHAPTER 1. INTRODUCTION

For students and their families, earning a bachelor's degree within four years of initial enrollment and obtaining a strong cumulative grade point average (GPA) are important to long-term return on investment. One reason graduating in four years is important to families is the average cost of tuition has increased by more than 250% during the last 30 years while family incomes have only risen by 16% (The White House, 2013). Furthermore, extending past four years may restrict funding and lead some low-income and middle-income students to dropout prior to degree completion. For example, certain scholarship programs (e.g., 21st Century Scholars) will only provide funding for four years and federal financial aid is limited to "150% of the published length of your program" (Federal Student Aid, 2016, para 1). Also, taking longer than four years to complete an undergraduate degree often means one or more years of lost income. Despite the benefits of four-year graduation, only 39.8% of students who began at a four-year college or university during 2008 graduated from the same institution within four years of initial enrollment (National Center for Education Statistics [NCES], 2015a).

Encouraging four-year graduation is also critical to institutions as the College Scorecard helps families make an educated decision on where to attend college by publically displaying graduation rates (U.S. Department of Education, 2017a). In addition, four-year and six-year graduation rates are reported on websites frequented by students during the college search process (e.g., *U.S. News and World Report*). Thus, improving four-year graduation rates will likely help recruit students and improve institutional ranking during a time when the number of high school graduates is expected to shrink through 2022 (Hussar & Bailey, 2014).

Encouraging a high college GPA is also important because college GPA is one of the best predictors of persistence to graduation for undergraduate students (Hu & St. John, 2001; Nora, Barlow, & Crisp, 2005; Nora, Cabrera, Hagedorn, & Pascarella, 1996). Earning a high GPA is also critical for students because some majors (e.g., education and nursing) require minimum GPAs in order to qualify for professional licensure. A growing number of students are also opting to pursue professional school after earning an undergraduate degree. Illustrating the need for a high GPA in order to gain entrance to professional school, the average GPA for admits to medical schools in the United States during 2016 was 3.70 (Association of American Medical Colleges, 2016).

According to Eduventures (2013), more than two-thirds of students identify getting a job as the most prominent reason they have opted to pursue postsecondary education. Furthermore, a cumulative GPA of 3.00 or higher was ranked as the third most important characteristic when hiring employees; GPA was ranked above extracurricular activities, volunteer work, foreign languages, and the school one attends (Koc, Koncz, Tsang, & Longenberger, 2015).

In order to better understand student postsecondary outcomes, including four-year gradation and cumulative college GPA, one must understand how students impact one another when clustered within academic majors, student organizations, Greek-lettered organizations, classrooms, and other environments. For instance, Tinto's (1975) theory of student departure assumes that a student's commitments and goals are shaped by a series of interactions between the academic and social systems of the institution and the student. Offering a cultural improvement to Tinto's theory, Guiffrida (2006) maintains the belief that academic and social systems shape one's college experience and development. Astin's (1970a, 1970b, 1991, 1993b) input-environment-outcome (I-E-O) model also assumes that individual college environments contribute to student outcomes; he describes environments as people, programs, policies, cultures and experiences that students encounter on or off campus. Thus, prominent higher education literature (e.g., Astin, 1970a, 1970b, 1984, 1991, 1993b; Kuh, 2008; Tinto, 1975, 1993, 2006/07) overwhelmingly supports that interrelations among students shape academic outcomes and personal development throughout the college experience.

Despite the overwhelming evidence that higher education data are nested at various levels, educational researchers and offices of enrollment management often utilize statistical techniques (e.g., multiple linear regression and analysis of variance) to investigate student outcomes, such as likelihood of four-year graduation, that fail to account for both intrapersonal and interpersonal relationships. Thus, accuracy of the results reported in the current literature may be questionable due to the employed methodological approaches addressing research questions. More specifically, the statistical conclusion validity is threatened due to the mismatch between research questions, the statistical techniques employed, and the nature of the data. For example, due to the contextual impact of college, one cannot assume independence among observations so a key assumption of parametric statistical procedures is violated. This may result in inaccurate results as the group effect will be either over or underestimated due to aggregation and disaggregation bias (Osborne, 2000). One statistical method that addresses the nature of nested educational data is multilevel linear modeling (MLM), sometimes referred to as hierarchical linear modeling (O'Connell & McCoach, 2008; Raudenbush & Bryk, 2002).

Higher education provides an obvious hierarchical structure as students are nested within majors, majors within academic colleges, academic colleges within institutions, and institutions within Carnegie classifications. However, few higher education studies (see e.g., Geiser & Santelices, 2007; Kobrin & Patterson, 2011; Patrick, 2001; Porter & Swing, 2006) have applied statistical techniques (e.g., MLM) to account for group effects influencing student outcomes during undergraduate education. For example, studies that investigated student academic success (see e.g., Bonous-Hammarth, 2000; Ethington & Wolfle, 1988; Sawyer, 2013) often fail to account for group effects by utilizing single-level analytic approaches. When MLM and multilevel generalized linear modeling (MGLM) have been used (e.g., Geiser & Santelices, 2007; Kobrin & Patterson, 2011; Patrick, 2001; Porter & Swing, 2006; Titus, 2004, 2006), institutions have commonly been used as the grouping cluster rather than academic majors. Grouping by academic major may be more important as these clusters represent "a constellation of factors that are part of students' daily experience, shaped by the peers and faculty members with whom they interact and the cultures they create" (Pascarella & Terenzini, 2005, p. 302).

In addition to the methodological issues inherent to the relevant literature, a limited number of studies (see e.g., Kobrin & Patterson, 2011; Patrick, 2001; Porter & Swing, 2006) that investigate student success after the first year of college are currently available. While persisting through the first year of college is critical, using student outcome variables that reflect only one year of college experiences fail to account for college experiences over multiple years prior to graduation. Such study will not provide the comprehensive picture of how pre-college and during-college experiences relate to academic success after four or six years of enrollment. Furthermore, institutions offering direct-admission to an academic major often do not require coursework, or a minimal amount, within one's area of study during the first year. Finally, approximately 75% of undergraduate students change their major during college (Gordon, 1995), so grouping effects of final major are often not accounted for in analyses.

Academic majors are also one environment students constantly occupy during college (Pascarella & Terenzini, 2005). Astin (1997) claims that the environment within academic majors may have more of an impact on retention than student-level characteristics. Clustering within an academic major results in taking multiple classes with other students in the same program and being influenced by faculty members within the department. Curricula also differ among majors. Illustrating the differences in the number of elective credits, students enrolled within certification programs (e.g., education, nursing, and dietetics) often have the opportunity to complete fewer elective credits than students within liberal arts programs.

Thus, this study was designed to address the gap in the literature and to demonstrate the utility of MLM in order to better predict persistence to graduation and cumulative college GPA by including select pre-college characteristics, during-college experiences, and major-level characteristics within one analysis. Serving as a base for this study, Gipson (2017) investigated the effect of pre-college characteristics and major-level characteristics on four-year graduation and cumulative college GPA after four years of enrollment with multilevel modeling approaches. Within the study, results suggested that 7.8% of variance in cumulative GPA and 20.3% of variance in four-year graduation could be attributed to initial academic majors. Also, the strength of the relationship between cumulative college GPA and the number of dual credits increased as the group average high school GPA increased among students in the same major. The strength of the relationship between both AP and dual credits and cumulative GPA was also altered by the group average ACT score. While conducting the MGLM, both the mean high school core GPA and mean ACT had a significant effect on the impact of outcomes for Pell-eligible students and the mean ACT score had a significant impact on the average four-year graduation rates of students housed within academic majors.

Gipson's (2017) study illustrates the importance of accounting for the nesting and interrelation of students grouped within academic majors as 20% of the variance in four-year graduation rates can be attributed to initial college major. In addition, the study revealed that the tailored, multilevel model may be necessary to better predict college outcomes when students are grouped within academic majors. While utilizing the initial major for grouping purposes is very impactful for the admissions process, examining the results of a model utilizing one's academic major after four years and six years will likely offer more practical implications for the development of at-risk models. Furthermore, some students cannot graduate from beginning majors (e.g., undecided and pre-majors) so individuals from these groups were eliminated during the pilot study, which resulted in reduced power due to the reduction of sample size. Lastly, during-college characteristics were not included within the analysis, yet researchers (e.g., Astin, 1997; Tinto, 1975, 1993, 2010) illustrate the importance of these experiences on academic outcomes. Thus, this investigation builds on the study by Gipson (2017) by investigating how one's major after four and six years of initial enrollment for grouping purposes impacts the academic outcomes of graduation and cumulative GPA.

Purpose of the Study

The purpose of this study was to predict cumulative grade point average (GPA) and the likelihood of four-year and six-year graduation while simultaneously accounting for select pre-college characteristics, select during-college characteristics, and the interrelationship between these student-level and major-level predictors. A secondary purpose of the study was to demonstrate how group-level variables can alter the strength of individual-level slopes. Traditionally, these characteristics have been studied individually, but in reality, they rarely occur in isolation as students are nested within academic majors. Some students also decide to move among majors during college, but research reflecting the effect of changing groups and becoming nested with new faculty members and peers is extremely limited. In addition, while researchers have investigated these outcomes, this study was one of the first to take full statistical advantage by utilizing MLM or MGLM to overcome common issues highlighted above and to increase statistical conclusion validity.

Research Questions

The primary research questions guiding this study were:

1. How much of the variation in cumulative college GPA is attributed to undergraduate majors?
2. How much of the variation in four-year and six-year graduation rates can be attributed to undergraduate majors?
3. To what extent is changing one's academic major related to cumulative college GPA, likelihood of four-year graduation, and likelihood of six-year graduation?
4. How does the interrelationship between student-level and major-level predictors influence cumulative college GPA?
5. How does the interrelationship between student-level and major-level predictors influence the likelihood of graduation after four and six years of initial enrollment?

Significance

This study offers methodological, practical, and theoretical contributions to the field of higher education. First, by utilizing MLM and MGLM in place of traditional statistical techniques (e.g., MLR and ANOVA), the study contributes to the methodology by demonstrating a more accurate predictive model of academic success for undergraduate students. Specifically, the interrelation of student-level and major-level characteristics shows how the relationship between the student-level predictors and the target outcome differ among groups. Practically, creating more-accurate at-risk models will increase the likelihood of identifying and assisting at-risk students through graduation. The outcome of the data analysis allows institutions to understand how academic grouping within majors alters the strength of the relationship of student-level predictors. The application of MLM also reveals the differential effect of majors on student characteristics, which has the ability to assist institutions, faculty, and academic advisors in best supporting the students within their majors. In turn, this has the ability to improve time to graduation and encourage a high cumulative GPA, reducing the cost of college for students and families while improving employment opportunities for graduates.

Second, the findings of this study add theoretical contributions to the literature relevant for guiding future research, as a countless number of group characteristics have the ability to influence student outcomes. Using Astin's (1970a, 1970b, 1991) I-E-O model and Tinto's (1975) theory of student departure as a base, as well as recent research, researchers can implement MLM and MGLM to investigate the intersections of environments and student characteristics in a multitude of ways. Thus, the study illustrates the endless utility of MLM in higher education research.

Finally, the results of this study are especially important as they may help admissions offices recruit and admit students who are likely to persist to graduation by illustrating the need to look past traditional admission strategies for selective institutions. Utilizing MLM will help better identify at-risk students and those in the murky middle who risk not being identified when using traditional techniques. Collectively, the results of this study might have the ability to increase four-year and six-year graduation rates as well as cumulative GPA for graduating students.

CHAPTER 2. LITERATURE REVIEW

The literature review contains seven sections. The first section of the chapter shares a brief history of higher education and academic curriculum. The second section provides a review of Astin's (1970a, 1970b, 1991) I-E-O model and Tinto's (1975) theory of student departure. The third section highlights the literature related to academic majors in higher education, while the fourth section provides an overview of the pilot study. The fifth section revolves around the cost of college, including financial aid. The sixth section details literature related to predictors of student success during college. Lastly, the final section reviews literature related to common statistical techniques utilized to predict student success during college.

Brief History of American Higher Education

Starting with Harvard in 1636, a handful of institutions were established in the 13 colonies with the goal of educating future leaders of one's church or colony (Lattuca & Stark, 2011). Such institutions followed the Oxford and Cambridge models established in Europe where faculty and the president were responsible for student conduct and moral development. Enrollments were typically less than 100 students and graduation rates were extremely low. Illustrating an early retention initiative, the governor of Maryland offered a financial incentive for students to graduate from The College of William and Mary (Thelin & Gasman, 2011). Despite limited diversity initiatives, such as offering scholarships to Native American males, the student population of the 17th and 18th centuries primarily consisted of wealthy White males (Thelin & Gasman, 2011).

Colonial higher education involved little choice in curriculum as students typically enrolled in one program of study that included Greek, Latin, Hebrew, rhetoric, logic, ethics, and natural philosophy (Lattuca & Stark, 2011). After 1652, the first two years of study at Harvard consisted of Latin, Greek, logic, Hebrew, and rhetoric (Rudolph, 1977). Year three incorporated the study of natural philosophy, moral philosophy, mental philosophy, and geography. According to Rudolph, the final year focused on a review of Latin, Greek, logic, and natural philosophy with the introduction of mathematics. Thus, early higher education looked to prepare a generalist.

The 18th century brought changes to curriculum (Rudolph, 1977; Lattuca & Stark, 2011). The inclusion of algebra and geometry at Yale was spurred by a large donation of textbooks from Europe (Rudolph, 1977). In 1754, Kings College (now known as Columbia) in New York introduced courses in husbandry and commerce (Lattuca & Stark, 2011). The first possible elective was offered at Harvard in 1755 when Hebrew was no longer required as a graduation requirement, but many students voluntarily selected to study the subject. The College of Philadelphia (University of Pennsylvania) introduced the topics of agriculture, chemistry, history, and political science (Rudolph, 1977). Despite changes in curriculum, institutions continued to prescribe curriculum to students.

Massive growth and increased access occurred during the 1800s as the number of institutions grew from 25 in 1800 to 240 by 1860 (Thelin & Gasman, 2011). Since limited funding was provided by federal and state government during the early 19th century, scholarship funds and charitable trusts were established to help expand access to low-income students (Peterson, 1963). In 1862, the Morrill Act established land-grant universities in order to expand access to higher education to all Americans (Brubacher & Rudy, 1976). Churches, state governments, charitable foundations, and the federal government, through the Freedmen's Bureau and Land-Grant Act of 1890, provided financial support for the establishment of Historically Black Colleges and Universities to further expand access to higher education (Thelin

& Gasman, 2011). As a result of these investments, enrollment grew by 278% from 1869 to 1900 (NCES, 1993). The number of bachelor's degrees conferred also rose from 9,371 in 1869-1870 to 27,410 in 1899-1900 (NCES, 1993).

Despite advances in curriculum, higher education during the early 1800s was "disorderly, lacking in standards, without coherence" (Rudolph, 1977, p. 55). A model example of such chaos was the curriculum at Harvard being structured during the first year and consisting of electives until graduation (Rudolph, 1977). However, the tide began to turn when the University of Virginia moved higher education closer to the modern curriculum by creating a departmental structure (Brubacher & Rudy, 1976). This organizational technique allowed academic specializations to emerge, which encouraged institutions to include electives and increase choice in curriculum for students (Lattuca & Stark, 2011). The concept of college major was introduced at Indiana University in 1885 as a way to provide structure for students rather than relying on complete freedom of curriculum (Lattuca & Stark, 2011).

Enrollment growth during the 1900s was spurred primarily by the passing of the Servicemen's Readjustment Act of 1944, implementation of the Higher Education Act, and the U.S. Supreme Court's decision in *Brown v. Topeka Board of Education* in 1954. According to Thelin and Gasman (2011), the Servicemen's Readjustment Act of 1944, also known as the GI Bill, provided financial support for veterans to obtain a college degree. This act was so successful at expanding access that institutions were forced to create makeshift classrooms and residence halls to accommodate a growth of nearly one million students from 1939 to 1949 (NCES, 1993). In 1954, the U.S. Supreme Court expanded access for students of color across the south by declaring segregation illegal in *Brown v. Topeka Board of Education* (Lattuca & Stark, 2011; Thelin & Gasman, 2011). Despite desegregation, it was not until the Higher

Education Act of 1965 provided federal financial aid in the form of grants and loans that attendance was boosted and students had more opportunity to select what college one would prefer to attend (Lattuca & Stark, 2011).

Policy implementations to increase access during the late 1800s resulted in vast curricular changes during the early 1900s. According to Rudolph (1977), Greek and Latin were no longer required at state institutions across the United States by 1905. By the 1920s, the utilization of college majors including general education requirements was widespread (Lattuca & Stark, 2011). The launch of Sputnik in 1957 led to increased science options and the inclusion of lab-based courses as general education requirements across the United States. The last quarter of the 20th century brought innovations to curriculum such as independent study, pass/fail grading, interdisciplinary studies, and student-centered majors (Lattuca & Stark, 2011).

The 2000s have been an era of affordability, accountability, and accessibility in higher education (Lederman & Fain, 2017). According to Lederman and Fain (2017), one method President George W. Bush used to expand access to higher education and increase affordability was more than doubling federal funding for Pell Grants. President Obama increased accountability by implementing the College Scorecard as an avenue for “easy-to-understand information on college opportunity, cost, and value” (The White House, 2015, para. 8). The College Scorecard helps families make educated decisions about where to attend college by providing information such as graduation rates, the average cost of attendance by family income, and average salary after graduation (U.S. Department of Education, 2017a). The Trump Administration has continued the push for increased affordability by expanding Pell Grants to three periods per year so students can utilize non-traditional terms to graduate faster (U.S. Department of Education, 2017b). Policy to assist in speeding time to degree is important as only 59% of first-time, full-time students who began seeking a bachelor's degree at a four-year institution in fall 2009 graduated within six years (NCES, 2017b).

While early, the 2000s have already brought some interesting changes to higher education. For example, competency-based programs have been growing in popularity (Shapiro, 2014). According to the U.S. Department of Education (2017c), competency-based learning transitions from traditional seat time to allowing students to earn credit for demonstrating mastery of a topic. Instructional delivery has also evolved during the 2000s as 20 percent of all enrollment at degree-granting institutions occurred online during 2007 (Allen & Seaman, 2007). Figure 1 displays an overview of American higher education.

Since the establishment of Harvard, American higher education has been evolving and expanding. Higher education was an elite activity for much of our history, excluding individuals based on social class, gender, religion, and race/ethnicity. However, modern higher education strives to create an environment of equal opportunity and social mobility. As we continue to expand access to higher education, we must also reform our support services to encourage student success for a rapidly changing student body.

Classical/Liberal/General	Year	Practical/Specialized/Vocational
	1650	
	1675	
European model:	1700	
classical education	1725	Parallel course in science offered
	1750	
	1775	State colleges established Normal colleges established
Growth of denominational colleges	1800	U.S. military academy founded Department system emerges
Yale Report suggests classical education	1825	
	1850	Morrill Act fosters study in agricultural and mechanical arts
Liberal education evolves from classical education	1875	Growth of state colleges Research universities emerge
	1900	Disciplinary associations arise
General education movement		Research specialization continues
Rise in nationalism	1925	Professionalism fields strengthen
		G.I. Bill veterans arrive on campuses Community colleges grow
Liberal education re-emphasized	1950	Technical development-reaction to Sputnik
Multiculturalism movement Reports call for reform	1975	Interdisciplinary encouraged
Core/coherence urged	2000	
	2017	

Figure 1. Periods of emphasis on general and specialized education (adapted from Lattuca and Stark, 2011)

Cost of Tuition and Fees

One reason graduating in four years is important to families is the average cost of tuition has increased by more than 250% during the last 30 years (The White House, 2013). Once room and board is included, the average cost to attend a 4-year public institution increased 406% from $3,682 in 1984-85 to $18,632 during 2014-2015 (National Center for Education Statistics, 2016).

Private 4-year institutions followed a similar trend as the cost of tuition, housing, and a meal plan increased 350% from $8,451 to $37,990. While inflation can account for some of this difference, wages have not kept pace with the cost of college. In fact, the average annual wage per worker increased 202% during the same period from $15,250.75 in 1984 to $46,119.78 for 2015 (Social Security Administration, 2017).

Financial aid restrictions. Federal financial aid and scholarships are often bound by time limits and credit requirements. For example, subsidized and unsubsidized loans may not be received for longer than 150 percent of the published length of an academic program (Federal Student Aid, 2016). Based on the findings by Johnson, Reidy, Droll, and Lemon (2012), students attending four-year institutions tend to receive aid until earning 180 credit hours.

Likewise, the NCAA (2017) allows student athletes in Division I to receive up to five calendar years of aid. Similarly, student-athletes in Division II and III may receive up to 10 semesters or 15 quarters of scholarship eligibility. Student-athletes must be initially enrolled full-time during a term to receive financial aid unless a limited number of courses are needed to graduate during the final semester of enrollment.

States also often place limitations on scholarships and financial aid. For example, the 21st Century Scholars program, offered by the State of Indiana, provides up to four years of tuition and fees to students from low-income families (Indiana Commission for Higher Education [ICHE], 2016a). 21st Century Scholars must also complete 30 credit hours per year and maintain satisfactory academic progress, which normally includes a GPA of 2.00 or higher (ICHE, 2016a). Another example is the Frank O'Bannon Grant. This grant provides $600 to $7,400 to middle-income families pending the completion of 30 credit hours by the end of the first year, 60 credit hours by the end of the second year, and 90 credit hours at the end of the third year (ICHE, 2016b). Collectively, financial aid restrictions illustrate the importance of four-year graduation for many low- and middle-income students.

Theoretical Framework for Student Success

Retention and academic success have been studied for decades. However, Alexander Astin and Vincent Tinto have long been considered pioneers for illustrating that a combination of pre-college characteristics, during-college experiences, and academic environments all play a role in persistence to graduation. The following section will provide an overview of Astin's (1993b) input-environment-output (I-E-O) model and Tinto's (1975, 1993, 2006/2007) theory of student departure.

Astin's I-E-O model. Astin's (1993b) I-E-O model provides a framework for examining pre-college characteristics, college experiences, and academic outcomes as students transition through higher education. Inputs include the characteristics of students at the time they enter college, such as K-12 educational background, socioeconomic status, parental education level, goals, and values. Environments include characteristics of the institution as well as student behaviors. Examples include interactions with friends, involvement in student organizations, and participation within learning communities. Outcomes involve measurable characteristics, such as retention and cumulative GPA, after exposure to the college environment.

A critical component of the I-E-O model is that academic and social outcomes are dependent upon the characteristics of students before they set foot on campus. Pre-college characteristics are important because they lead students to participate in various environments during college. Without accounting for background characteristics, it is impossible to determine the extent to which the academic and social outcomes of college can be attributed to during-college experiences.

Tinto's theory of student departure. Tinto's (1975, 1993, 2006/07, 2010) model assumes that one must become socially and academically integrated within an institution of higher education in order to persist to graduation. Key components of Tinto's theory include family background, individual attributes, pre-college schooling, goal commitment, institutional commitment, academic system integration, and social system integration. The structure of Tinto's theory has been supported by empirical research (e.g., Pascarella & Terenzini, 1983; Terenzini, Pascarella, Theophilides, & Lorang, 1985), but recent research (e.g., Palmer, Davis, & Maramba, 2011) supports the revisions suggested by Guiffrida (2006). Each of the key components are briefly described in the following paragraphs.

Attributes, precollege experiences, and family background. Tinto (1975, 1993, 2010) asserts that attributes, pre-college experiences, and family background contribute to student persistence. Race, gender, mental ability, and commitment to success are important to persistence to graduation. Tinto also argues that students whose parents possess higher levels of education, socioeconomic status, and expectations for their children are more likely to persist to graduation. While family characteristics are critical, Tinto states that individual ability is more imperative. Specifically, prior academic performance (e.g., high school GPA) is the best predictor of academic success during college.

Goal commitment. Tinto (1975) includes one's educational plan and future career aspirations as critical factors for goal commitment. He also believes that one's commitment to college completion is the second best predictor for persistence to graduation. Tinto places goal commitment directly behind attributes, family background, and prior educational experiences because goal commitments are themselves a reflection of a multidimensional process of interactions between the individual, family, and prior experiences.

Academic systems integration. According to Tinto (1975), academic integration involves both grade performance and intellectual development. He states that the most explicit form of reward one can receive during college are grades and that grade performance is the most prominent factor relating to persistence to graduation. On the other hand, intellectual development is a more intrinsic reward that shapes both academic and personal development.

For students to be academically successful, Tinto believes that faculty members must adhere to expectations established through syllabi, course materials, and conversations with students (Tinto, 2010). Clear and consistent expectations of degree completion must also be established for courses, one's major, and the broader context of the institution. If expectations remain clear and consistent, grade performance becomes a good way to measure of how students' attributes and achievements relate to the institution's values and objectives.

Social systems integration. Tinto (1975, 1993, 2006/07, 2010) social involvement and support is directly tied to student persistence. Tinto (1975) asserts that social interactions primarily occur during "informal peer group associations, semi-formal extracurricular activities, and interaction with faculty and administrative personnel within the college" (p. 107). New students often find themselves making adjustments to existing relations with family and friends from home and forming friendships with members of their new community. These new friendships are critical to one's sense of belonging and acceptance within the college environment (Tinto, 2010). Thus, a lack of social integration increases the likelihood of voluntary withdrawal from college. The theory suggests that the more students are socially and academically involved at an institution, the more likely the student will persist to graduation (Tinto, 1993).

Institutional commitment. According to Tinto (1975), one's "behaviors in the social system most directly relate to a person's institutional commitment" (p. 110). Thus, extracurricular activities and interaction with faculty are the most critical avenues of social involvement to increase student persistence. Tinto describes that if one possesses a high level of institutional commitment, one is more likely to persist through many situations. If one has low goal commitment and low institutional commitment, one is likely to permanently withdrawal from higher education. However, individuals with low institutional commitment and high goal commitment are more likely to transfer to another institution to finish one's degree.

Guiffrida's suggestions for cultural improvement. Guiffrida (2006) argues that the experiences of students of color differ from majority populations addressed in Tinto's work. He reforms Tinto's model to focus academic systems on academic performance and faculty/staff interactions. Extracurricular activities and peer group interactions are combined under university social systems. Guiffrida also believes that students must maintain connections with home social systems, including family and friends, in order to be successful during college, an aspect Tinto fails to address. Lastly, Guiffrida prefers to utilize the term *connection* in place of *integration* stating that:

> integration implies that students must become socialized into the dominant culture of the institution while abandoning their former cultures, but connection recognizes students' subjective sense of relatedness without implying the need to break ties with one's former community. This subtle yet important change allows the theory to recognize that students can become comfortable in the college environment without abandoning supportive relationships at home or rejecting the values and norms of their home communities. (p. 457)

Overall, prominent research (e.g., Astin, 1993b; Guiffrida, 2006; Tinto, 1975, 1993, 2006/07, 2010) suggests that pre-college characteristics, during-college experiences, and institutional environments influence student success. Despite this belief, "too much of the research on student retention focuses on events, often external to the institution, that are not under the immediate ability of institutions to affect" (Tinto, 2010, p. 54). Thus, this study will simultaneously investigate student-level characteristics and the contextual effect of college majors on student success.

Contextual Effect of College Majors

Merriam-Webster (2017) defines a major as "of or relating to a subject of academic study chosen as a field of specialization" (para. 1). College Board (2017) adds that approximately one-third to one-half of courses completed during college will be in your major department or in a closely related department. Serving as a practical example, Indiana University Purdue University – Indianapolis (2011) defined a major as:

> an approved area of study leading to an approved academic degree. The major may or may not be part of the conferred degree title, depending on whether the degree will be listed separately by the Indiana Commission for Higher Education in its degree inventory. A major for a baccalaureate degree usually requires 30 or more course hours of specialized study within the plan of study for the degree. In some degree programs, major requirements can make up a large portion of the requirements for the degree. (p. 1)

The National Center for Education Statistics (2017a) defines a bachelor's degree as:

> An award (baccalaureate or equivalent degree, as determined by the Secretary, U.S. Department of Education) that normally requires at least 4 but not more than 5 years of full-time equivalent college-level work. This includes all bachelor's degrees conferred in

> a 5-year cooperative (work-study) program. A cooperative plan provides for alternate class attendance and employment in business, industry, or government; thus, it allows students to combine actual work experience with their college studies. Also includes bachelor's degrees in which the normal 4 years of work are completed in 3 years. (para. 1)

The majority of four-year public institutions require 120 credit hours for most of their bachelor's degree programs (Johnson, Reidy, Droll, & Lemon, 2009; Lattuca & Stark, 2011). Thus, students must complete an average of 15 credit hours per semester, unless utilizing non-traditional terms such as summer session, in order to graduate in four years. Despite the importance of academic majors, limited research has been conducted to understand how these environments impact four-year and six-year graduation.

Instead, Holland's (1997) theory of vocational behavior/choice has commonly been used as a framework for exploring the impact of college majors on job satisfaction (Elton & Smart, 1988; Smart, Elton, & McLaughlin, 1986; Wolniak & Pascarella, 2005) and the selection of an academic major (Pike 2006a, 2006b). Holland's theory utilizes psychological and sociological factors to create a model that incorporates students and the environment of academic majors during college (Smart, Feldman, & Ethington, 2000).

Aside from job satisfaction, Holland's theory has been used to explain how students select academic majors and their satisfaction with these environments. For example, Pike (2006a, 2006b) utilized Holland's framework to show that students often rely on one's expectations about college and their personality types to select an initial major. According to Pike (2006b), "expectations act to encourage students to select academic majors that they believe are congruent with their abilities, interests, and personalities" (p. 806). In fact, one's expectations about college have the ability to reinforce characteristics of academic environments by shaping student behavior (Kuh, Gonyea, & Williams, 2005).

Astin (1997) suggests majors can influence an institution's overall graduation rate. For example, institutions enrolling large numbers of students in business, psychology, and social sciences are likely to have a higher than expected graduation rate while institutions enrolling large numbers in engineering are likely to possess a lower than expected graduation rate (Astin, 1997). This suggests that the characteristics of academic majors of the characteristics of students clustered within these environments creates a major-level effect on graduation.

Clustering within academic majors results in students taking courses with others in the same program, which Ost (2010) shows to have an impact on major-level retention. Specifically, Ost found that *weaker* students benefit academically from exposure to high-ability peers. Ost also found that science students were pulled away from the field by both higher grades in other areas and low grades in major-level courses; this effect was much stronger for women compared to men.

One key component of academic majors is the number of free electives required within a plan of study. However, the number of available elective credits within academic majors differs across, and within, institutions. One common example is that students enrolled within certification programs (e.g., education, nursing, and dietetics) often have the opportunity to complete fewer elective credits than students within liberal arts programs; yet, scarce research exists on the relationship between the number of electives and undergraduate student outcomes. Studying the impact of available elective credits is important as approximately 30 to 40 percent of students change majors during college and degree requirements widely vary (Foraker, 2012; Sklar, 2014).

Thus, this study addresses the gap in current research by determining to what extent undergraduate majors contribute to four-year and six-year graduation as well as cumulative college GPA. This study also addresses a gap in the literature by determining to what extent mean high school GPA within a major, requiring an internship or clinical experience for graduation, and the median number of elective credits influence the strength of student-level regression slopes.

Predictors of Academic Success during College

A great deal of research has been conducted to help predict college graduation and cumulative GPA. Focusing on Astin's **(**1970a, 1970b, 1991, 1993b) I-E-O model and Tinto's (1975, 2006/07) theory of student retention, this study included pre-college characteristics, during-college experiences, and major-level variables to predict cumulative GPA after four years and likelihood of graduation after four and six years. This section will review the impact of the pre- and during-college characteristics on student academic outcomes discussed in literature with empirical evidence. The characteristics reviewed here include high school GPA, standardized test scores, AP/dual credits, URM status, first-generation status, socioeconomic status, and gender. The during-college experiences of changing one's major, cumulative GPA after the first year, involvement in student organizations, and learning community participation will also be examined.

High school GPA. Relating to predictors of student success during college, researchers (e.g., Belfield & Crosta, 2012; Bonous-Hammarth, 2000; Ethington & Wolfle, 1988; Geiser & Santelices, 2007; Kobrin & Patterson, 2011; Sawyer, 2013) have frequently reported that high school GPA is positively related to college success. Kobrin and Patterson (2011) applied MLM using institutions as the grouping variable to find that every one point increase in high school

GPA results in a .424 point increase in cumulative college GPA after the first year. Geiser and Santelices (2007) employed MLM to show that high school GPA was the strongest predictor of both four-year graduation and cumulative GPA across academic disciplines. Furthermore, Belfield and Crosta (2012) found high school GPA to be the most essential predictor of college success stating that "[t]he relationship between high school GPA and college GPA is so powerful that it would seem more important for colleges to fully consider this measure in deciding on placement" (p. 39).

Grades in mathematics, science, English/language arts, social studies, and foreign languages are often utilized to calculate a core high school GPA. The NCAA (2017b) requires completion of at least 16 core courses with a minimum GPA of 2.30 in order to be eligible to participate in Division I athletics during one's first year. Recent research (e.g., Gipson, 2016) has found core high school GPA to be the type of GPA most highly correlated with cumulative college GPA.

Collectively, recent literature supports Astin's (1970a, 1970b, 1991, 1993b) and Tinto's (1975, 1993, and 2006/07) assertion that high school GPA is an important predictor of student success. However, research related to the interrelations among major-level predictors and high school GPA is lacking.

Standardized test scores. Standardized test scores, primarily the SAT and ACT, have been found to serve as significant predictors of college success (Gipson, 2016, 2017; Kobrin & Patterson, 2011; Sawyer, 2013). Not surprisingly, college admissions officers ranked standardized test scores as the third most prominent factor in admissions decisions within the United States (Clinedinst, 2014). Sawyer (2013) found that one's ACT composite score is a good predictor of GPA after the first year, and that the ACT composite is a more useful predictor regarding high levels of success compared to high school GPA. Furthermore, Kobrin and Patterson (2011) used MLM on data collected from 109 institutions to show that SAT critical reading, mathematics, and writing scores are significant predictors of cumulative GPA after the first year of college. Kobrin and Patterson also found that the high school GPA slope decreased by .054 for every 1 point increase in mean SAT score when predicting first-year GPA, illustrating the impact of contextual effect by institution when predicting student success. Despite these findings, previous studies (Kobrin & Patterson, 2011; Sawyer, 2013) employed the dependent variables of cumulative college GPA and retained/not retained after the first year of college, which often fails to account for at least three years of enrollment prior to degree completion. In addition, institutional characteristics were used as the group level for each study rather than academic majors. While utilizing institutional characteristics has the ability to shape government policy and offers implications for senior administrators, major-level data offers more practical implications for departments and faculty.

AP and dual credit courses. Participation within dual credit and AP courses during high school is increasing (Thomas, Marken, Gray, & Lewis, 2013). In fact, 82% of high schools enrolled students in dual credit courses and 69% in AP or IB courses during the 2010-2011 school year. From 2014 to 2015, enrollment in AP courses increased from 2,342,528 to 2,483,452 with a total of 4,478,936 tests completed (College Board, 2015).

Indeed, 81.5% of institutions ranked grades in college preparation courses to be of considerable importance during the admissions process during 2013 (Clinedinst, 2014). Offering some insight on college preparation coursework, Mattern, Marini, and Shaw (2013) found students who participate in AP courses are more likely to graduate within four years compared to students who do not participate in such courses. Research (see e.g., Gipson, 2016; Hargrove, Godin, & Dodd, 2008) suggests that students who take AP courses perform better academically, as measured by cumulative GPA after four years of enrollment, during college than those taking dual-credit coursework. However, Delicath (1999) found that AP and dual credits did not significantly influence time to graduation for undergraduate students. Thus, results are mixed on the impact of AP and dual credits on time to degree while consistently illustrating a positive impact on cumulative GPA.

Underrepresented minority (URM) status. Research (e.g., Astin & Oseguera, 2005; DeAngelo et al., 2011; Horn & Berger, 2004) indicates that students of color graduate, on average, at lower rates than White and Asian students, resulting in inequities in degree attainment in higher education. In a national study, Astin and Oseguera (2005) found that the disparities in degree attainment exist regardless of time to degree – four years, six years, and still enrolled after six years. This is particularly problematic as students of color are more likely to possess lower socioeconomic status (Allen, Jayakumar, Griffin, Korn, & Hurtado, 2005; Smith, 2009). Thus, students of color often require greater financial assistance, including loans, in order to pursue higher education. Additionally, students of color who obtain bachelor's degrees achieve far higher pay compared to peers without degrees (Ryan & Siebens, 2012); in fact, Pascarella and Terenzini (2005) suggest that students of color who obtain a bachelor's degree achieve a larger net average earnings premium compared to Whites.

Research also suggests that students of color face other challenges including, but not limited to, an increased likelihood of being a first-generation student (Choy, 2001), not being academically prepared (ACT, 2011), and a lack of family support (Thayer, 2000). Collectively, these findings illustrate the importance of controlling for URM status as this population is, on average, facing more complex intersections of identity than majority groups. Thus, a URM indicator serves as a proxy variable to represent the complex set of disparities that exist in the United States. It is also important to include a URM status as a predictor to explore how interrelationships between individual-level and group-level characteristics influence the likelihood of graduation and cumulative GPA for students of color.

First-generation status. The definition of what it means to be a first-generation college student has not reached consensus (Gupton, Jehangir, & Trost, 2015). Some scholars (e.g., Nuñez & Cuccaro-Alamin, 1998) define first-generation as one whose parents have obtained a high school diploma or less. However, others (e.g., Chen, 2005) consider students to be first-generation if their parents have not obtained a bachelor's degree. In this study, the studied institution utilized the second definition, which includes students whose parents have earned certificates and associate degrees as well as those who attended college for any length of time, but dropped out prior to graduation. This is critical while interpreting results as some parents have never attended higher education while some have experience and can offer additional support to their student.

The effects of first-generation status are extremely important as this characteristic spans across race, socioeconomic status, immigration status, and veteran status (Engle & Tinto, 2008). According to Pike and Kuh (2005), first-generation students are less likely to be involved or engaged on campus, which negatively influences persistence to graduation. In fact, Chen (2005) found that only 23.5% of first-generation students graduate with a bachelor's degree compared to 67.5% of students whose parent(s) had a bachelor's degree or higher. First-generation in college and socioeconomic status are often closely related as individuals who have not graduated from college, on average, earn less than individuals who possess a degree (Ryan & Siebens, 2012).

Socioeconomic status. According to Bozick and Lauff (2007), only 40% of students from low-income families attend postsecondary education after graduating from high school compared to 84% of students whose families earn greater than $100,000. Furthermore, only 14% of students from low-income families complete a bachelor's degree as compared to 29% of students from middle-income families and 60% of students from high-income families (National Center for Education Statistics, 2015b). While high-income students were five times more likely to obtain a degree compared low-income peers in 1980, the gap increased to ten times in 2009 (Mortenson, 2010). Perhaps explaining some of this gap, low-income students often work more, study less, are less involved on campus, and possess lower GPAs than peers from wealthy backgrounds (Walpole, 2003). Despite the strong evidence that socioeconomic status is related to degree completion, it is unclear if the impact of Pell-eligibility on graduation and GPA varies across academic majors.

Gender. Adebayo (2008) illustrates the existence of a gender gap between enrollment in, and successful persistence, within higher education as women not only outnumber men, but they also graduate at higher rates than their male counterparts. Women also experience a 1.5 times higher earnings premium increase compared to males after obtaining an associate degree and an advantage of 39% to 37% after earning a bachelor's degree (Pascarella & Terenzini, 2005); it is important to emphasize that earning premiums represent the earning potential for those with a high school diploma compared to a college degree. Despite these positive outcomes for females, a gender pay gap continues to persist across the United States (U.S. Department of Labor, n.d.).

While gender segregation among academic majors has been decreasing over the last 30 years (Adelman, 1999), men and women tend to be overrepresented in certain majors. For example, men tend to gravitate more toward the higher-paying majors of engineering, business, economics, statistics, and physical sciences (Pascarella & Terenzini, 2005). On the other hand, women tend to dominate enrollment within majors that traditionally result in lower earnings such as education, social sciences, humanities, and English. Research (e.g., Astin, 1997; DeAngelo et al., 2011) shows that women earn degrees at a higher rate than men. DeAngelo et al. (2011) found that 43.8% of women earned a degree within four years of initial enrollment compared to only 32.9% of men.

Change of major. When students begin college, they have often decided to pursue an academic major (Astin & Astin, 1993). However, many question their original decision and consider changing fields of study prior to graduation (Gasiewski, Eagan, Garcia, Hurtado, & Chang, 2012). Recent data (e.g., Foraker, 2012; Sklar, 2014) suggest that approximately 40% of students change their major at least once during college. Micceri (2001) found that students who changed majors were more likely to graduate. Conversely, Foraker (2012) found that only 25% of students changed majors once and another 5% of students changed more than once. Foraker also determined that changing majors after the second year had a negative impact on grades, the likelihood of graduation, and time to graduation. Sklar (2014) found that the major one switches from has an impact on the likelihood of graduation from STEM majors. Specifically, students who switched from one STEM major to another had an odds ratio of six-year graduation 139% higher than students switching from “undecided” to a STEM field. As Foraker (2012) and Sklar (2014) noted, what little research exists is conflicting in nature.

First-year GPA. Research (e.g., Adelman, 1999; Hu & St. John, 2001; Nora, Barlow, & Crisp, 2005) consistently illustrates that college GPA is directly related to student persistence. Adelman (1999) employed a national sample from the High School and Beyond study that followed students for 12 years to show that, after controlling for many other factors, first-year grades and a subsequent trend in grades was positively related to persistence to graduation. First-year GPA has also been found to be more influential on persistence than financial aid, on-campus housing, age, and income level across racial backgrounds (Hu & St. John, 2001). Tinto (1975) even goes as far as to state that grades are the most explicit type of reward one can receive during college. The relationship between persistence and cumulative GPA is not surprising as Astin (1993a) found that grades often do not reflect how much one has learned, but do provide an idea of academic performance related to one's peers.

While results of first-year GPA are consistent, information related to how the contextual effects of college majors may impact this predictor are scarce. It is also important to address one shortcoming of Hu & St. John's (2001) study by including pre-college characteristics, additional during-colleges experiences, and four-year and six-year graduation rather than one-year retention to provide practical implications for faculty, administrators, and student affairs professionals.

Involvement in student organizations. According to a myriad of researchers, (i.e., Astin, 1984; Kuh, Kinzie, Schuh, Witt, & Associates, 2010; Pascarella & Terenzini, 2005; Tinto, 1975, 2006/07) the amount of time and effort students place on co-curricular activities that encourage academic success matters during college. Involvement within student organizations has been shown to improve psychosocial development during college (Foubert & Grainger, 2006). Furthermore, Kuh (1993) found that involvement outside of the classroom positively impacts student learning and personal development. Collectively, student involvement increases persistence to graduation across demographic backgrounds (Astin, 1984; Kuh, Kinzie, Schuh, Witt, & Associates, 2010; Pascarella & Terenzini, 2005).

Learning communities. According to Pascarella and Terenzini (2005), learning communities developed from the concept of living/learning communities where students lived together and participated in academic coursework. Despite often lacking a living component, the primary goals of learning communities are to encourage learning across courses and get students involved outside of the classroom (Kuh, 2008). Within learning communities, students complete two or more courses with the same group of students (Zhao & Kuh, 2004). Evidence suggests that learning community participation may not have a direct effect on student learning, but rather participation encourages deeper student engagement throughout the college experience, which results in positive academic outcomes (Pike, Kuh, & McCormick, 2008). Examples of positive effects include greater interaction with faculty members and greater participation with collaborative learning (Zhao & Kuh, 2004). Despite the advantages of a learning community, research (i.e., Zhao & Kuh, 2004) found no difference in grades for students who participated in a learning community compared to those who did not by the senior year. Thus, additional research is needed to understand the complex relationship between pre-college characteristics, learning community involvement, and college outcomes such as cumulative GPA and timely graduation.

While evidence suggests that many of the aforementioned predictors are related, this may introduce a statistical problem known as multicollinearity, when researchers set a predictive model for student success. Even if multicollinearity were to arise, previous research (e.g., Astin, 1997; Clinedinst, 2014; Gipson, 2016; Kobrin & Patterson, 2011) illustrates the practical importance of maintaining a complex set of student-level characteristics as all are commonly used in college admissions and predictive at-risk models. Utilizing group-mean centering at the student-level will reduce multicollinearity between regression coefficients, but not for the model as a whole (Iacobucci, Schneider, Popovich, & Bakamitsos, 2016).

Contextual Influence on Student Success

Similar to mission statements, plans of study, and admissions requirements, relationships between predictors of student success and academic outcomes may vary across nested environments (e.g., institutions, academic units, and majors). Illustrating this, a meta-analysis of 3,000 SAT validity studies found that SAT coefficients predicting first-year GPA ranged from .44 to .62 across institutions (Hezlett et al., 2001). The pilot study (Gipson, 2017) using beginning major also found that 20% of the variance related to four-year graduation and nearly 8% of the variance related to college GPA could be attributed to characteristics of one's beginning major. This indicates that although individual characteristics reviewed above are helpful to predict outcome, the nature and strength of the relationship may differ with the influence of environment where individual belongs to. As reviewed earlier, the most influential, but less studied environment for students is major. This study was designed to expand current literature by examining the contextual influence of ability grouping via mean grade point average and mean ACT score as well as Kuh's (2008) high-impact practice of internships and clinical experiences on four-year graduation, six-year graduation, and cumulative college GPA.

Academic grouping. While not always overtly intentional, students are often grouped via high school GPA and standardized test scores during the admissions process. For example, a limited number of the highest achievers are admitted to honors colleges and honors programs at select institutions. Requirements for admission often vary across academic programs; a higher GPA and standardized test score is often required for engineering programs compared to the humanities. Despite common grouping practices that occur during the admissions process and a vast literature base related to grouping students by ability during K-12 education, limited research exists on the impact of grouping students by cumulative high school GPA and standardized test scores during higher education.

Existing literature related to K-12 classrooms both supports (e.g., Steenbergen-Hu, Makel, & Olszewski-Kubilius, 2016; Tiesco, 2003) and argues against (e.g., Oakes, 1985, 2008; Slavin, 1987, 1990) ability grouping. Oakes (1985) argues that students clustered within lower-ability tracks receive lower quality instruction and less material is covered. On the other hand, a lack thereof fails to properly challenge and support students at each end of the normal curve (Tiesco, 2003). However, in a meta-analysis of 100 years of research related to ability grouping, Steenbergen-Hu, Makel, and Olszewski-Kubilius (2016) found overwhelming evidence that ability grouping and acceleration “can greatly improve K–12 students’ academic achievement” (p. 893).

Relating to higher education, vast differences in mean high school GPA exist across academic majors. For example, the mean high school GPA for students grouped within computer science is typically much higher than the mean high school GPA for psychology. Does this type of grouping have an impact on persistence to graduation or cumulative GPA? One study of engineering students from New Zealand found that grade performance decreased when students were grouped into mathematics courses by academic major (Plank, James, & Hannah, 2011). Kobrin and Patterson (2011) illustrated that differences in institutional SAT score are significant predictors of cumulative GPA after the first year of college. Specifically, the researchers found that the high school GPA slope predicting first-year GPA decreased by .054 points for every one point increase in mean SAT score. This study will expand current literature by investigating how such differences in mean high school GPA impact cumulative GPA and graduation after four and six years.

Required internship/clinical experience. Internships have been identified by Kuh (2008) as a high-impact educational practice that promotes persistence to graduation. These experiences provide students with practice in a workplace setting. According to Finley and McNair (2013), students saw gains in deep learning after participating in internship experiences. The National Association of Colleges and Employers (2014) also found that participating in an internship experience improved the likelihood of earning a full-time job offer.

Results of Pilot Study on the Contextual Effect of Initial College Major

Prior to this study, I conducted a pilot study investigating the impact of initial academic major on four-year graduation and cumulative college GPA with MLM and MGLM, respectively. The sample consisted of undergraduate students from one research university who first enrolled during Fall 2011 and Fall 2012. Dependent variables included cumulative college GPA after four years of initial enrollment and four-year graduation. High school GPA, ACT score, the number of AP and dual credits, gender, first-generation status, Pell-eligibility, and underrepresented minority status were used as student-level variables. Major-levels variables included mean high school GPA, mean ACT score, and the median number of elective credits required for graduation.

The most critical finding from the pilot study was that 7.8% of the variation in cumulative college GPA and 20.3% of the variation in four-year graduation could be attributed to initial academic majors. The effects of student-level predictors were generally consistent with prior studies relating to persistence (e.g., Astin, 1997; Gipson, 2016; Kobrin & Patterson, 2011; Sawyer, 2013) as pre-college characteristics were related with cumulative college GPA and four-year graduation. However, the pilot study contributes to the literature by illustrating the importance of academic majors for predicting students' college outcomes. More specifically, Gipson (2017) found that the strength of the relationship between the average cumulative college GPA and high school core GPA significantly varied across academic majors. The study also highlighted that a greater level of variance can be attributed to academic major relating to four-year graduation when compared to cumulative GPA after four years of enrollment. Thus, utilizing multilevel modeling to account for the interrelation between student-level and major-level predictors will not only help obtain more accurate parameter estimations, but also improve at-risk models to provide suggestions for advising across academic majors.

Despite the important contribution made by the study, the pilot study was not without limitations. For example, only pre-college characteristics were included at the student-level. Including both pre-college characteristics and during-college experiences in future models would provide evidence of how institutions can better support student success by providing implications for practice. While it is important to study one's initial major, it is also critical to investigate how one's major after four and six years of initial enrollment impacts GPA and graduation. Thus, the current study was designed to extend the pilot by addressing its limitations.

Methodological Concerns in Higher Education Research

The quality of existing research in higher education is often questionable as researchers commonly employ statistical techniques that fail to account for the nesting of data. Specifically, mismatches between research questions, statistical methods, and the nature of nested data result in questionable statistical conclusion validity.

According to Moore, McCabe, and Craig (2012), an analysis of variance (ANOVA) is utilized to compare the means of several populations while multiple linear regression (MLR) is often used for predicting the influence of multiple variables on an outcome variable. Two key assumptions of ANOVA and MLR are that all groups have equal variances and all observations are independent. As reviewed earlier, individuals are often nested within a group so that independence assumption is not satisfied. In addition, when group effect exists, ANOVA and MLR also fail to account for group characteristics so they will be absorbed by the error term, which will cause correlations between disturbances (Raudenbush & Bryk, 2002). Furthermore, ANOVA is appropriate for a small number of groups, but this technique simply identifies that differences exist. Thus, solely relying on the use of ANOVA for clustered educational data may be problematic.

When utilizing MLR, researchers sometimes aggregate data to the group level, which decreases statistical power and can overestimate or underestimate parameter estimates (Osborne, 2000). Another common method is disaggregating to the individual level, but this violates the assumption of independence of observations (Osborne, 2000). Researchers also often—either knowingly or unknowingly—acknowledge the hierarchical nature of higher education data during data collection by gathering information on institutions, academic units, majors, student organizations, and individual students; sometimes, but rarely, even including these measures within single-level analysis. Consequently, a more-advanced statistical method should be used to maintain power and account for the nesting of educational data.

This study was designed to addresses gaps in the literature by utilizing MLM to account for the contextual effect of academic majors. MLM is an extension of ANOVA that allows researchers to understand why group differences exist rather than simply identifying such differences. Thus, a simple two-level model has the ability to simultaneously account for interdependencies (student-level characteristics) and intraclass correlations (group-level characteristics), as well as provide a more-accurate estimation of individual effects while maintaining statistical power. The application of MLM in higher education literature has scarcely appeared over the past two decades.

While prior MLM studies have been extremely beneficial, researchers tend to focus on outcomes collected following the first year of the college experience (see e.g., Kobrin & Patterson, 2011; Patrick, 2001; Porter & Swing, 2006). Patrick (2001) used MLM to study first-year retention for 20 majors at one university in the United Kingdom to show significantly different retention rates exist among majors. Porter and Swing (2006) employed MLM to investigate first-year retention using select individual-level characteristics and institutional-level characteristics such as acceptance rate, spending per student, institutional type, and course-study skills. The results of the study suggest that choice of content in first-year seminar courses can increase the likelihood of persistence by as much as 16 percentage points. Kobrin and Patterson (2011) used MLM to show that both high school GPA and standardized test score, specifically the SAT, are the two strongest predictors of first-year GPA. Kobrin and Patterson also found that mean institutional GPA and SAT score have contextual effects on various student-level predictors.

Utilizing outcomes after the first year is problematic when trying to predict four-year and six-year graduation as well as cumulative GPA because at least three years of college experiences are unaccounted for. In addition, using the institutional level as the sole grouping variable is problematic as this technique fails to account for major-level differences in retention, graduation, and cumulative GPA. This study aimed to address gaps in the literature by investigating how pre-college characteristics, during-college experiences, and the contextual effects of academic majors influence four-year and six-year graduation as well as cumulative GPA.

CHAPTER 3. METHODS

The primary objective of this study was to develop a predictive model of cumulative grade point average (GPA) and likelihood of four-year and six-year graduation that simultaneously accounts for select pre-college characteristics, select during-college characteristics, and the interrelationship between student-level and major-level predictors within one analysis. The questions guiding this research were:

1. How much of the variation in cumulative college GPA is attributed to undergraduate majors?
2. How much of the variation in four-year and six-year graduation rates can be attributed to undergraduate majors?
3. To what extent is changing one's academic major related to cumulative college GPA, likelihood of four-year graduation, and likelihood of six-year graduation?
4. How does the interrelationship between student-level and major-level predictors influence cumulative college GPA?
5. How does the interrelationship between student-level and major-level predictors influence the likelihood of graduation after four and six years of initial enrollment?

Hypotheses:

1. I hypothesize that a meaningful amount of variation in cumulative college GPA will be attributed to academic majors.
2. I hypothesize that a meaningful amount of the variation in the likelihood of four-year and six-year graduation will be attributed to academic majors.

3. I hypothesize that changing one's academic major negatively impacts four-year graduation, but has a positive impact on cumulative college GPA and six-year graduation.
4. I hypothesize that mean high school GPA will alter the strength of student-level cumulative GPA slopes.
5. I hypothesize that mean high school GPA will alter the strength of student-level cumulative graduation slopes.

Research Design

This study utilized a correlational research design to help answer the research questions. Furthermore, the study utilized secondary data on the experiences of undergraduate college students retrieved from one large public university located in the Midwestern United States. To increase generalizability across time, data were requested for all first-time undergraduate students who first enrolled during Fall 2010 and 2011.

Secondary Data

Data selection. Archived data were retrieved from one large public institution in the Midwestern United States by submitting a data request to the Office of the Registrar. According to Indiana University Center for Postsecondary Research's (n.d.) Carnegie Classification, the institution is classified as a large highest research doctoral granting institution. The student population represents students from all 50 states; 82% of students are domestic residents or domestic nonresidents. The institution also enrolls one of the largest numbers of international students within the United States as 18% of the undergraduate population calls another country home. All levels of socioeconomic status and parental education levels are also present on campus. Additionally, 20% of the undergraduate population is comprised of students of color. Approximately 40% of students are identified by the institution as female and approximately

60% as male. Collectively, the population of the institution is very diverse. A summary of the undergraduate population of the institution is included in Table 1.

Table 1
Summary of Institutional Characteristics

Enrollment	31,006
In-State Students	16,445 (53%)
Non-Residents	9,628 (31%)
International	4,933 (16%)
Males	17,731 (57%)
Females	13,275 (43%)
URM	2,968 (9.6%)
4-Year Graduation	58.5%
Carnegie Classification	highest research doctoral granting

Note. Population data from Fall 2017

The institution was selected purposively for the current investigation due to the following reasons. First, utilizing data from this particular institution is similar to using multiple institutions as academic majors are housed within 10 distinct colleges, many of which are the size of other institutions. Second, the university enrolls students from all 50 states and over 100 countries across the world.

Data cleaning. Data obtained for 2010 and 2011 beginners were aggregated for analyses. First, data were merged utilizing SPSS by adding cases. Second, once the merged data were created, descriptive statistics were utilized to check the accuracy of the data to ensure minimum and maximum values for each variable did not exceed expectations. Third, missing data in major-level variables were examined because MLM analysis with HLM software does not allow missing data at the group level (Raudenbush, Bryk, & Congdon, 2013).

Fourth, majors with less than five students were eliminated to ensure accurate results. A general rule of thumb is a minimum of 100 groups with about ten students in each group, but the number of individuals per group decreases as the number of groups increase (Hox, 1998). Ultimately, 199 groups remained with group sizes ranging from five students to 753 students with an average size of 50 students, a median of 22 students, and a standard deviation of 69.68. According to Maas and Hoop (2005), while applying MLM, "the estimates of regression coefficients, the variance components, and the standard errors are unbiased and accurate" (p. 86) when the numbers of groups is greater than 50. With 199 groups, the results of the MLM in this study should be unbiased and accurate. The retrieved data consisted of the following dependent variables, student-level predictors, and major-level predictors that were utilized during the study.

Dependent variables. The dependent variables for the study were cumulative college GPA after four years of initial enrollment and the success of graduation after four and six years of initial enrollment. To obtain the data for the dependent variables, post Spring 2014 and 2016 data were used for students who started during Fall 2010. Furthermore, post Spring 2015 and 2017 data were used for students who started during Fall 2011.

Successful graduation after four and six years of initial enrollment. The dependent variable of successful graduation after four and six years of initial enrollment was retrieved from official reporting at the institution. These variables are defined as completing a bachelor's degree within four and six years of first enrolling at the institution. Any student classified as enrolled, voluntarily withdrew, or dropped were classified as not graduated and coded as a 0. Students classified as "first bachelor's degree conferred" were counted as graduated and coded as a 1.

Cumulative college GPA. The dependent variable of cumulative college GPA was also retrieved from official reporting through the Office of the Registrar. GPA represents one's final standing at the time of graduation, when one left the institution without a degree (i.e., dropped out, stopped out, or dismissed), or after six years of initial enrollment, whichever occurred first. The cumulative GPA is a weighted average of all grades received as an undergraduate student.

If a same course has been taken more than once, the most recent grade received shall be included in the cumulative GPA. In the case of a course in which a conditional grade has been improved by examination, the most recent grade received shall be used.

Each grade is weighted as follows:

A+, A: 4 x semester hours = index points

A-: 3.7 x semester hours = index points

B+: 3.3 x semester hours = index points

B: 3 x semester hours = index points

B-: 2.7 x semester hours = index points

C+: 2.3 x semester hours = index points

C: 2 x semester hours = index points

C-: 1.7 x semester hours = index points

D+: 1.3 x semester hours = index points

D: 1.0 x semester hours = index points

D-: 0.7 x semester hours = index points

E, F, IF: 0.0 x semester hours = index points

Grades of pass/no pass, incomplete, not satisfactory, and withdraw are not included within one's cumulative GPA.

Sample. The sample for these analyses consisted of 9,966 students clustered within 199 academic majors. The sample consisted of 5,562 students (55.8%) who identified as male and 4,400 students (44.2%) identified as female. Furthermore, 968 students (9.7%) identified underrepresented minority status and 2,621 students (26.3%) identified as first-generation. Relating to socioeconomic status, 1,991 students (20.0%) were eligible for Pell Grants.

Student-level predictors. A total of 11 student-level predictors were utilized during the study and the descriptive statistics were summarized in Table 2. Seven variables (i.e., high school GPA, standardized test score, number of AP/dual credits, URM status, first-generation status, Pell-eligibility, and gender) represented pre-college characteristics and four variables (i.e., change of major, cumulative GPA after the first year, involvement in student organizations, and learning community involvement) represented during-college experiences.

High school GPA. The high school GPA was obtained from official high school transcripts submitted during the admissions process. GPAs reported by schools using scales other than 4.00 (e.g., 8.00, 12.00, 100.00) were converted to a 4.00 scale during the admissions process. Any GPA exceeding 4.00 is reduced to 4.00. This process was completed by Admissions and the Office of the Registrar prior to distributing the dataset to the researcher. The mean high school GPA was 3.59 and the standard deviation was .36.

Standardized test scores. Standardized test scores were reported directly to the institution by College Board and ACT. After receiving the dataset, the *Estimated Relationship between ACT Composition Score and SAT CR+M+W Score* (ACT, 2015a) was used by the researcher to convert composite SAT scores to composite ACT scores in order to increase statistical power. In cases where both SAT and ACT scores were submitted by the same student, the highest score was utilized during the analysis. In addition to increasing statistical power, converting to ACT scores makes practical sense as the test increases in 1-point increments and the range of available scores is 1-36 (ACT, 2015b). The mean ACT score was 25.88 and the standard deviation was 3.82.

AP and dual enrollment credits. AP scores were reported by College Board during the admissions process. Dual credits were also reported during the admissions process via official transcripts from high schools and institutions of higher education. The combined number of AP and dual credits was employed as one predictor because both count equally toward degree completion and there was no way for the Office of the Registrar to separate these credits prior to distributing the dataset to the researcher. The mean number of AP/dual credits earned prior to enrolling at the institution was 3.75 with a standard deviation of 6.91

URM status. Students self-identified race/ethnicity within the institution's student records system. Individuals who identified as Hispanic, American Indian or Alaska Native, Black or African American, and Native Hawaiian or Other Pacific Islander were coded as 1 and students who identified as White and Asian were coded as 0. The mean, which represents the percent of students who identified as URM, was .10 and the standard deviation was .30.

First-generation status. Students with at least one parent who had not completed a bachelor's degree were coded as 1 and students with at least one parent who has completed a bachelor's degree were coded as 0. The mean was .26 and the standard deviation was .44.

Socioeconomic status. Pell-eligibility at initial enrollment served as the income measure for this study. Pell-eligibility is a good predictor of socioeconomic status as 99.4% of students who received a Pell Grant had family incomes of less than $75,000 with 95.9% of recipients having incomes of $50,000 or less (Gobel, 2015). The Division of Financial Aid provided Pell-eligibility status based on the results of the FAFSA at time of enrollment to the Office of the Registrar. Pell-eligible students were coded as 1 and non-Pell-eligible students were coded as 0. The mean was .20 with a standard deviation of .40.

Change of major. One's initial major at the beginning of the first year and major after four and six years in schooling were included in the dataset. A new variable was added to the dataset to represent whether the student has changed academic majors. If one's initial major and final major were different, the code of 1 was added to represent a change of major. If initial major and final major were the same, the code of 0 was added. For "pre" majors, students were coded as not changing if the "pre" major linked directly to the final major; for example, a change of pre-management to management. Sixty-eight percent (68%) of students changed their major with a standard deviation of .47.

First-year GPA. First-year GPA was pulled from official transcripts using Cognos by the Office of the Registrar prior to distributing the dataset to the researcher. The GPA is based on a 4.00 scale described in the prior section. The average first-year GPA was 2.80 with a standard deviation of .83.

Student organizations. The number of student organizations that students have been involved in during their time as an undergraduate student were used to determine the level of involvement. The number of student organizations one was involved in during their undergraduate education were pulled from the institution's student organization record-keeping system and merged with the dataset prior to distribution to the researcher. Students were involved in an average of .46 student organizations with a standard deviation of .96.

Learning community participation. University Residences distributed a list of students involved in learning communities during the 2010-2011 and 2011-2012 academic years. This information was merged with the larger dataset by pairing student identification numbers by the Office of the Registrar prior to distributing the dataset to the researcher. Involvement within a learning community was coded as 1 and students not involved with a learning community were coded as 0. Twenty-six percent (26%) of students included in the sample were involved in a learning community with a standard deviation of .44.

Gender. Gender was self-identified by students within the institutional record system. Females were coded as 1 and males as 0. Forty-four percent (44%) of students in the sample identified as female with a standard deviation of .50.

Major-level predictors. Academic major after four years and six years of initial enrollment were used to represent the group-level for this study. The group-level predictors in this study were average high school GPA, required internship/clinical experience, and the median number of elective credits. Major-level predictors were placed in a separate SPSS dataset with each line representing a different major for running analyses with HLM7 software. All majors at the university were sorted alphabetically and arbitrary provided a major identification number from one thru 199. All group-level predictors were either created from the data obtained from the Office of the Registrar with further data manipulation or created by the researcher from information retrieved from archival documents.

Mean high school GPA. To calculate an average GPA for each major, individual high school GPAs were aggregated for students who were in the same major. The average GPA for students clustered within the same major was 3.57 with a standard deviation of .18. This average was merged with the major-level dataset by matching the major code.

Required internship/clinical experience. Individual plans of study were reviewed using the institution’s course catalog. The researcher coded majors with a required internship or clinical experience as 1 and those not requiring internships or clinical experiences as 0. To ensure accuracy, head advisors from each of the academic colleges confirmed the results of the review of the course catalog. In total, 50 undergraduate majors (25%) required an internship or clinical experience as a graduation requirement with a standard deviation of .43.

Median number of elective credits. The institution's course catalog was utilized to determine the median number of available elective credits in each major. The catalog is considered the source for academic and programmatic requirements for students. Each official plan of study lists the available number of electives. The median number of elective credits was calculated using this information and manually entered into the data set.

Table 2
Summary of Independent Variables

	Min	*Max*	*Range*	*Mean*	*SD*
*Student-Level**					
High school GPA	1.87	4.00	2.13	3.59	.36
ACT	13	36	23	25.88	3.82
AP/Dual Credits	0	87	87	3.75	6.91
URM Status	0	1	1	.10	.30
First-Generation	0	1	1	.26	.44
SES	0	1	1	.20	.40
Change of Major	0	1	1	.68	.47
First-Year GPA	0	4.00	4.00	2.80	.83
# Student Organizations	0	13	13	.46	.96
Learning Community	0	1	1	.26	.44
Gender	0	1	1	.44	.50
*Major-Level***					
Mean High School GPA	3.10	4.00	.90	3.57	.18
Required Internship	0	1	1	.25	.43
Median Electives	0	45.5	45.5	13.5	11.34

Note. The mean of dummy variables represents the percentage of 1s. *N = 9,966 ** N = 199

Method of Data Analysis

Two-level cross-sectional multilevel linear modeling (MLM) and two-level cross-sectional multilevel generalized linear modeling (MGLM) were employed. More specifically, MLM was used to investigate the relationship between the dependent variable of cumulative college GPA after four years of initial enrollment and the set of seven student- and three major-level predictors. MGLM was utilized to investigate the relationship between the dependent variable of graduated/not graduated after four years and six years of initial enrollment and the same set of predictors.

Preliminary Analysis

Before conducting analyses to address the research questions, the data assumptions of valid MLM analyses were checked with SPSS. According to Raudenbush and Bryk (2002), there are six data assumptions of MLM with *Q* predictors for predicting *i*th students in group *j*:

1.) Each R_{ij}, which indicates variability within group, is independent and normally distributed with a mean of 0 and variance σ^2 for every level-1 (student-level) unit *i* within each level-2 (major-level) unit;

2.) The student-level predictors, X_{qij}, are independent of R_{ij};

3.) The vectors of Q + 1 random errors at the major-level are multivariate normal, each with a mean of 0, some variance, τ_{qq}, and covariance among the random elements;

4.) The set of major-level predictors are independent every U_{qj}, representing unique group-level random effect;

5.) The errors at the student-level and major-level are also independent; and

6.) The predictors at each level are not correlated with the random effects at the other level. (p. 255)

In order to examine the assumptions, data were uploaded to the HML 7 (Scientific Software International, Inc., SSI, 2016) software. Next, dependent and independent variables were specified and the student-level and major-level residual files created by HLM7 software were saved as the SPSS file. HLM 7 was used to test homogeneity of student-level variance; the *p*-value was statistically significant due to the large sample size so a *Q-Q* plot of student-level residuals was used to check normality. To examine whether the second assumption is satisfied, the researcher examined a correlation between the residuals at student-level and the student-level predictors. Mahalanobis distance in the major-level residual file was examined to see if it follows the chi-square distribution with the degrees of freedom being eleven in order to satisfy the third assumption. To check the fourth assumption, a correlational analysis including the major-level predictors and major-level residuals was conducted. A correlational analysis of the residuals of student-level and major-level were examined to ensure independence. The results of a correlational analysis of the predictors and random effects at the other level were obtained to be sure there were no statistically-significant correlations to meet the last assumption.

The highest correlation coefficient (.568) was between the dependent variables of cumulative GPA and graduating in six years or less. The correlation between cumulative GPA and graduating in four years or less was .463. This supports the use of three different models—GPA, four-year graduation, and six-year graduation. Relating to predictors, the strongest correlation was .470 between ACT composition and high school GPA, which does not meet the definition of multicollinearity as Williams (2015) suggests caution be exercised when values are greater than .80. Furthermore, high school GPA exhibited a ceiling effect with 2,358 (23.7%) students clustered at 4.00. Involvement in student organizations and the number of AP/dual credits displayed floor effects with 7,294 students clustered at 0 for student organizations and 5,958 students clustered at 0 AP/dual credits.

Centering and Standard Errors

Since research questions 4 and 5 involve interrelations between student-level and major-level variables, centering was applied. According to Cronbach and Webb (1975), group-mean centering is used when researchers are interested in separating the between-group and within-group components from the total variation. Since I was interested in accounting for the structure of academic majors, group-mean centering was applied at the student-level. Additionally, grand-mean centering was applied at the major level. Fixed effects with robust standard errors were reported as some assumption violations were observed, which are further described in Chapter 4.

Inferential Analysis with Multilevel Analysis

To address research question 1, MLM with cumulative college GPA as an outcome was tested with the data. The ratio of the between-major variance to the sum of the between- and within-major variances is called the intraclass correlation (ICC), which generally ranges from 0 to 1. This tells us how much of the variation in cumulative GPA is attributed to differences in academic majors. If students within a major are no more similar to each other than to those in a different major, the ICC would be equal to 0 and assumption of independent observations would not violated (O'Connell & McCoach, 2008). Thus, a single-level analysis would be warranted (Muthen, 1994). In order to calculate the ICC, the following equation was used, ICC = $\frac{\tau 00}{\tau 00+ \sigma^2}$ (O'Connell, Goldstein, Rogers, & Peng, 2011), where τ_{00} represents the variance between majors and $\tau_{00} + \sigma^2$ represents the total variance. ICCs of sizable magnitude, generally above .10, justify the use of multilevel models (Hox, 2002, Snijders & Bosker, 1999).

To address research question 2, an unconditional MGLM was tested to calculate the ICC. To conduct this analysis, a Bernoulli distribution using logistic regression was employed since the values were coded as 0 (failure) and 1 (success). According to O'Connell, Goldstein, Rogers, and Peng (2011), the following equation is utilized to calculate the ICC in MGLM: ICC = $\frac{\tau 00}{\tau 00+ 3.29}$.

Next, to address research question 3 and 4, a conditional model including only student-level predictors was tested to see if the strength of predictors varies across majors. A full model including all student-level and major-level predictors was analyzed to investigate contextual influences. Let Y_{ij} = UGPA or success of graduation in four or six years, our dependent variables taken on the *i*th student associated with the *j*th major. The student-level model is given by:

$Y_{ij} = \beta_{0j} + \beta_{1j}$ * HSCOREGPA$_{ij}$ + β_{2j} * ACT$_{ij}$ + β_{3j} * APCREDITS$_{ij}$ + β_{4j} * URM$_{ij}$ + β_{5j} * FIRSTGEN$_{ij}$ + β_{6j} * SES$_{ij}$ + β_{7j} * MAJORCHANGE$_{ij}$ + β_{8j} * FIRSTYEARGPA$_{ij}$ + β_{9j} * STUDENTORGANIZATIONS$_{ij}$ + β_{10j} * LC$_{ij}$ + β_{11j} * GENDER$_{ij}$ + r_{ij} (1).

The level-2 equations for the full model were the following:

$\beta_{0j} = \gamma_{00} + \gamma_{01}$* MEANHSGPA$_j$ + γ_{02} * INTERNSHIP$_j$ + γ_{03} * MEDELECTIVES$_j$ + u_{oj} (2)

$\beta_{1j} = \gamma_{10} + \gamma_{11}$* MEANHSGPA$_j$ + γ_{12} * INTERNSHIP$_j$ + γ_{13} * MEDELECTIVES$_j$ + u_{1j} (3)

$\beta_{2j} = \gamma_{20} + \gamma_{21}$* MEANHSGPA$_j$ + γ_{22} * INTERNSHIP$_j$ + γ_{23} * MEDELECTIVES$_j$ + u_{2j} (4)

$\beta_{3j} = \gamma_{30} + \gamma_{31}$* MEANHSGPA$_j$ + γ_{32} * INTERNSHIP$_j$ + γ_{33} * MEDELECTIVES$_j$ + u_{3j} (5)

$\beta_{4j} = \gamma_{40} + \gamma_{41}$* MEANHSGPA$_j$ + γ_{42} * INTERNSHIP$_j$ + γ_{43} * MEDELECTIVES$_j$ + u_{4j} (6)

$\beta_{5j} = \gamma_{50} + \gamma_{51}$*MEANHSGPA$_j$ + γ_{52} * INTERNSHIP$_j$ + γ_{53} * MEDELECTIVES$_j$ + u_{5j} (7)

$\beta_{6j} = \gamma_{60} + \gamma_{61}$*MEANHSGPA$_j$ + γ_{62} * INTERNSHIP$_j$ + γ_{63} * MEDELECTIVES$_j$ + u_{6j} (8)

$\beta_{7j} = \gamma_{70} + \gamma_{71}$*MEANHSGPA$_j$ + γ_{72} * INTERNSHIP$_j$ + γ_{73} * MEDELECTIVES$_j$ + u_{7j} (9)

$\beta_{8j} = \gamma_{80} + \gamma_{81}$*MEANHSGPA$_j$ + γ_{82} * INTERNSHIP$_j$ + γ_{83} * MEDELECTIVES$_j$ + u_{8j} (10)

$\beta_{9j} = \gamma_{90} + \gamma_{91}$*MEANHSGPA$_j$ + γ_{92} * INTERNSHIP$_j$ + γ_{93} * MEDELECTIVES$_j$ + u_{9j} (11)

$\beta_{10j} = \gamma_{100} + \gamma_{101}$*MEANHSGPA$_j$ + γ_{102}*INTERNSHIP$_j$ + γ_{103}*MEDELECTIVES$_j$ + u_{10j} (12)

$\beta_{11j} = \gamma_{110} + \gamma_{111}$* MEANHSGPA$_j$ + γ_{112} * INTERNSHIP$_j$ + γ_{103}*MEDELECTIVES$_j$ + u_{11j} (13).

Substitution of equations (2)-(13) in equation 1 makes it possible to see the interaction of the level-2 variable with those for the student-level.

The full MLM model included all predictors at both levels. While some research (e.g., Barr, Levy, Scheepers, & Tily, 2003) suggests the use of full models with the same set of predictors at all higher level models, others (e.g., Bates, Kliegl, Vasishth, & Baayen, 2015) prefer parsimonious models as they do not over fit the data. Ideal parsimonious models capture “all of the signal and none of the noise” (Vandekerckhove, Matzke, & Wagenmakers, 2014, p.

3). Furthermore, parsimonious models are often attractive because they are easy to understand and communicate (Vandekerckhove, Matzke, & Wagenmakers, 2014). Thus, parsimonious models were developed based off the results of the student-level and full-models. Since the study is exploratory in nature, all components were considered random in the student-level models and all major-level variables were retained in the parsimonious model for components the student-level models suggest were varying across academic majors. The alpha level for all analyses was set at .05.

Threats to Validity

One threat to validity for this research is ambiguous temporal precedence, which means one does not know which variable is the cause and which is the effect (Johnson & Christensen, 2012). This threat exists because this research is observational and cross-sectional in nature as students are free to pursue their education as they choose and thus there is no control group to compare pre-college characteristics and during college experiences. Since this research used a sample including two years of students entering one major institution, population validity was not an issue for incoming first-year students. However, population validity may be an issue for transfer students, as they will not be included within the study and enter the institution during a different phase of their educational journey.

CHAPTER 4. RESULTS

This chapter presents the results corresponding to each of the research questions. The chapter begins by presenting the preliminary analyses related to underlying data assumptions for MLM and MGLM. The following sections represent the inferential analysis results for the outcome variables of cumulative GPA, four-year graduation, and six-year graduation. The chapter closes with a summary paragraph highlighting the key findings from the analyses.

Preliminary Analysis

Preliminary analyses were conducted to evaluate the assumptions of MLM and MGLM. Several of the Q-Q plots for student-level predictors did not follow a normal distribution. The correlation between all student-level predictors and the student-level residual was rounded to 0 by SPSS. The MDRSVAR in the major-level residual file indicates the natural log of the residual standard deviation from the fitted fixed effects model (Taylor, 2012). Descriptive statistic of the variable suggests that the variance is close to normally distributed with a mean of -.807 and a SD of .286 (see Appendix 1 for a histogram of the MDRSVAR). The correlation coefficient between the major-level Empirical Bayes intercept and the mean high school GPA was .557. This could bias the fixed effect parameter estimates. The correlation coefficient between student-level and major-level residuals was .028, suggesting independence.

Cumulative GPA MLM Results

The process began by estimating an unconditional model to determine the *ICC* which indicates the amount of variance in the dependent variable among groups (Hayes, 2006). The unconditional model, which does not contain any predictors at either level, is:

$$Y_{ij} = \beta_{0j} + r_{ij},$$

$$\beta_{0j} = \gamma_{00} + u_{0j}.$$

The ICC indicated that 30.0% of the variance in cumulative grade point average could be attributed to one's academic major. The obtained ICC of 30% means that significant variation can be explained by academic majors and multilevel modeling is warranted (Hox, 2002, Snijders & Bosker, 1999). Appendix 2 shows the results of the MLM analyses and a comparison of the four models that were executed—the unconditional model, the student-level model, the full model, and a parsimonious model.

Student-level model. A total of 11 student-level predictors were included in the initial analysis. Results suggest that only Pell-eligibility and involvement in a learning community were not significantly related to cumulative college GPA. After controlling for other student variables, changing one's major during college resulted in a .107 point increase in cumulative GPA, $t(198) = 7.022$, $p < .001$.

Initially, the coefficients of these student predictors (βs) in the student-level model, represented as Equation 1, were treated as randomly varying across majors. However, as shown in Table 3, the analysis indicates only the coefficients for GPA, high school GPA, change of major, first-year GPA, and involvement in student organizations vary across majors. Thus, these variables will remain random in the full and parsimonious models.

Average cumulative college GPA (β_{oj}) varies across majors, $\chi^2(75) = 6115.554$, $p < .001$. The average variation in GPA across majors was .195 units. Furthermore, the results suggest that the relationship between high school GPA (β_{1j}) and the outcome, represented as the slope of high school GPA (β_{1j}), varies across majors, $\chi^2(75) = 111.527$, $p = .004$.

The average variation in the slope of high school GPA was .008 units. The hypothesis test results also suggest that the slope for change of major (β_{7j}) varies across majors, $\chi^2(75) = 178.797$, $p < .001$.

Table 3

Summary of Variance Components for GPA Model

Variance Components	Unconditional Model	Student-Level Model	Full Model	Parsimonious Model
GPA (τ_{00})	.170*	.195*	.116*	.116*
HSGPA (τ_{11})		.008*	.008*	.008*
ACT (τ_{22})		<.001		
TRCREDITS (τ_{33})		<.001		
URM (τ_{44})		.003		
FIRSTGEN (τ_{55})		.001		
PELL (τ_{66})		.001		
MAJORCHANGE (τ_{77})		.011*	.011*	.011*
FIRSTYEARGPA (τ_{88})		.032*	.030*	.030*
STUDENTORGS (τ_{99})		.001*	.001*	.001*
LCS (τ_{1010})		.002		
GENDER (τ_{1111})		.002		

Note. *p < .05.

The slope for cumulative GPA after the first year also varied across academic majors, $\chi^2(75)$ = 675.757, $p < .001$. Lastly, the student organization slope varied across groups, $\chi^2(75) = 122.301$, $p < .001$.

Full model. The full model contains major-level predictors to help explain the variation in coefficients. For this model, the GPA intercepts, high school GPA, change of major, first-year GPA, and involvement in student organizations were treated as random based on the results of the student-level model. The analysis suggests that the GPA intercept was significant, where the overall average across the majors was 2.908, $t(195) = 117.857$, $p < .001$. Additionally, one's cumulative GPA increases by 1.474 points for every one point increase in the mean high school GPA of students grouped within an academic major, $t(195) = 9.623$, $p < .001$. Furthermore, one's cumulative GPA increased by .221 points for students enrolled in majors requiring an internship or clinical experience, $t(195) = 3.498$, $p < .001$. The GPA also increased by .009 points for each increase of one in the median number of available elective credits in a major, $t(195) = 3.453$, $p < .001$. This means that students' predicted GPA tends to be higher when students enroll in majors with a requirement for an internship or clinical experiences and studied together with students possessing higher high school GPAs.

The strength of the AP/dual credit slope was also significantly altered by the mean high school GPA of students grouped within a major, $t(8,943) = -2.356$, $p = .018$. For every one point increase in mean high school GPA, the impact of AP/dual credit on the cumulative GPA decreased by .008 units. While this relationship is statistically significant, the impact on cumulative college GPA is negligible as mean high school GPA ranged from 3.10 to 4.00 with a mean of 3.57. Mean high school GPA also significantly altered the impact of changing one's major on cumulative college GPA, $t(195) = - 2.177$, $p = .031$. For every one point increase in mean high school GPA, the impact of changing ones major is reduced by .191. With an average positive gain of .100 GPA points from changing one's major, mean high school GPA could indeed impact one's cumulative college GPA, even turning positive gains into decreases by changing from majors with the lowest average high school GPAs to majors with the highest average GPAs.

The analysis also suggests that there is a significant cross-level interaction between mean high school GPA and the student-level first-year GPA slope, $t(195) = -2.430$, $p = .016$. For every one point increase in mean high school GPA, there was a .191 point decrease in the strength of the first-year GPA-cumulative GPA correlation. This means that, in general, first-year GPA is the strongest predictor of cumulative GPA and shows a positive relationship (.638). However, the mean high school GPA moderates the relationship negatively. Thus, when a student is in a major with high average high school GPA, the predictive power of first-year GPA is weaker when compared to groups with lower average high school GPA.

After controlling for major-level variables, the student-level predictors of Pell-eligibility and involvement in learning communities continued to show no statistical relationship with cumulative college GPA. All major-level predictors had an impact on the average GPA and/or student level predictors.

Percentage of variance explained. When compared with the unconditional model, the student-level model increases the between-majors variance by 14.7%. However, the full model reduces the between-major variance by 31.8% compared to the unconditional model. Collectively, these findings suggest that additional major-level variables, which were unknown, explain a significant percentage of remaining variance.

Post-hoc analysis. A parsimonious model without the student-level variables of Pell-eligibility and learning community involvement was explored since neither variable was significantly related to cumulative college GPA. Moreover, major-level predictors were only added to the GPA intercept, mean high school GPA, change of major, first-year GPA, and involvement in student organization since the student-level and full models suggest these be considered random. The results suggest that an equivalent level of between-major variance (31.8%) was explained compared to the full model. All remaining student-level predictors were also significantly related to cumulative college GPA. The only difference was a slight change in the relationship between mean high school GPA and the first-year GPA slope. For every one point increase in mean high school GPA, there was a .185 point decrease in the strength of the first-year GPA slope compared to a .191 point decrease in the full model. The strength of remaining significant relationships were nearly equivalent between the full and parsimonious models, as shown in Appendix 2. Thus, the parsimonious model provides evidence of statistical conclusion validity for the results obtained with the full model.

Since GPAs varied across academic majors, an analysis was conducted to highlight high-performing and low-performing majors. Descriptive statistics and graphs were utilized to identify academic majors with the highest and lowest average GPAs at last enrollment or after six years, whichever came first. Not surprisingly, honors programs such as Mathematics Education Honors (3.90), Actuarial Science Honors (3.73), Economics Honors (3.73), Law and Society Honors (3.69), and History Honors (3.69) had the highest mean GPAs. Conversely, majors with the lowest mean GPAs included Social Studies – History (2.13), Theatre (2.24), and many pre-majors – CIT Core (1.26), undecided (1.39), and Computer Graphic Technology Freshmen (1.49).

Four-Year Graduation MGLM Results

The odds ratio was used as a measure of association between a predictor and graduation in presenting MGLM results as the outcome is binary. This number represents the odds that graduation in four or six years will occur given a predictor, compared to the odds of the outcome without the exposure (Szumilas, 2010). An odds ratio of 1 means the predictor makes no difference in the odds of graduation. An odds ratio greater than 1 means the predictor improves the odds of graduation while an odds ratio of less than 1 means the predictor reduces the odds of graduation.

The ICC, after fitting an unconditional model, indicated that 32.1% of the variance in four-year graduation could be attributed to academic majors. Thus, an analysis with a MGLM was appropriate to conduct in order to explain the major variance. Appendix 3 shows the results of the MGLM analyses and a comparison of the four models that were executed—the unconditional model, the student-level model, the full model, and a parsimonious model.

Student-level model. Initially, all student-level variables were considered random for this analysis. Results suggest that every one point increase in high school GPA increases the odds of graduating in four years or less by 1.329, $t(198) = 3.212$, $p = .002$. Every additional AP/transfer credit a student brings with them to college increases the odds of four-year graduation by 1.013, $t(198) = 3.649$, $p < .001$. Furthermore, every one point increase in one's GPA after the first year of college increases the odds of four-year graduation by 3.793, $t(198) = 21.632$, $p < .001$. On average, students who changed their major were .647 times as likely to graduate in four years or less compared to students who did not change their major.

Relating to one's personal background, students of color were .728 times as likely to graduate in four years compared to White and Asian counterparts, $t(198) = -3.181$, $p = .002$. Thus, the odds of graduating in four year for students of color is about ¾ of that for White and Asian students. Additionally, first-generation students were .888 times as likely to graduate in four years or less compared to students whose parents attended college, $t(198) = -2.008$, $p = .046$. Lastly, female students were 1.427 times more likely to graduate in four years or less compared to males, $t(198) = 4.252$, $p < .001$.

The likelihood of four-year graduation (β_{oj}) varied across academic majors, $\chi^2(75) = 776.777$, $p < .001$. The average variation in four-year graduation was 2.260 units. This means that the four-year graduation rates significantly vary across majors after accounting for student-level predictors. Major-level predictors may help explain this variation. The results also suggest that the impact of changing one's major (β_{7j}) on timely graduation in four years varied across groups, $\chi^2(75) = 179.328$, $p < .001$. The variation of the impact of changing one's major was .675 units. The results also suggest that the slope for cumulative GPA after the first year (β_{8j}) varied across academic majors, $\chi^2(75) = 99.352$, $p = .031$. Other slopes were not statistically significant, meaning the strength of the relationship did not vary across academic majors; these variables were considered fixed in the full model.

Full model. All of the student-level and major-level variables were included in this analysis. The intercept, change of major, and first-year GPA were treated as random based on the results of the student-level analysis, meaning that these variables showed differential impacts on the outcome variable across majors. All other variables are treated as fixed-effects, meaning that their effects are statistically equivalent across majors. Each of the major-level independent variables were used as predictors of the intercept and the slopes of the student-level independent variables. The result suggests that the odds of four-year graduation increase by 39.113 for every one point increase in average high school GPA, $t(195) = 5.499$, $p < .001$. Furthermore, every 1 point the median elective credit increases the odds of four-year graduation by 1.048, $t(195) = 4.411$, $p < .001$. Despite being fixed, the strength of the AP/dual credit slope was reduced for students clustered in majors with high average high school GPAs, $t(9,333) = -3.289$, $p = .001$. Being clustered within academic majors with higher mean high school GPAs also increased the odds of four-year graduation, $t(9,333) = 3.473$, $p < .001$. Each additional median elective credit increased the odds of four-year graduation by 1.019 for female students, $t(9,333) = 2.270$, $p = .002$.

After controlling for major-level variables, the analysis suggests that considerable variability continues to exist in four-year graduation rates for this collection of academic majors, τ_{00}, $\chi^2(112) = 937.175$, $p < .001$. A significant amount of variability also exists across the change of major slope, τ_{07}, $\chi^2(112) = 224.328$, $p < .001$. While major-level predictors were not statistically related to the first-year GPA slope, variability among majors was eliminated, τ_{08}, $\chi^2(112) = 133.392$, $p = .082$.

Percentage of variance explained. When compared with the model that includes only student-level predictors, the full model explains an additional 21.7% of the between-major variance in the four-year graduation intercepts. When the student-level model is compared to the unconditional model, the proportion of variance increases by 45.8%. These findings suggest that large variance exists among four-year graduation rates across undergraduate majors. However, the choice of major-level predictors was not ideal and additional variables could help explain the remaining variance.

Post-hoc analysis. A parsimonious model without the non-significant student-level variables of ACT score, student organizations, and learning community involvement was analyzed since these variables were not significantly related to four-year graduation. However, the parsimonious model only explained an additional 2.3% of the between-major variance compared to the full model. Major-level predictors were only added to the intercept, change of major, and first-year GPA variables since the student-level and full models suggest these be considered random. When this model was analyzed, first-generation status was no longer significantly related to four-year graduation, $t(9{,}363) = -1.305$, $p = .192$. Student-level and major-level predictors had a similar impact on four-year graduation when compared with the full model. The largest differences in the strength of the variables was .006 for mean high GPA on first-year GPA and high school GPA, which practically little impact on the interpretation. Thus, statistical conclusion validity for the inference made on the full model results is supported as the strength of parameter estimates is very similar between the two models, see Appendix 3.

One gap between the results of the parsimonious and the full models relates to the impact of mean high school GPA on the strength of the AP/dual credit slope. In the full model, there was a significant relationship between mean high school GPA and the AP/dual credits slope.

Based on an increase of .90 points between the lowest and highest mean high school GPAs, enough variation exists to flip the strength of this predictor from positive to negative. However, the student-level analysis suggests the strength of the AP/dual credit slope does not vary across groups. Therefore, only the student-level variable of AP/dual credits was included within the parsimonious model. Thus, caution should be utilized.

Since four-year graduation rates significantly varied across academic majors, post-hoc analysis was conducted to identify majors with high four-year graduation rates and low four-year graduation rates. Descriptive statistics and graphs were utilized to identify academic majors that have a strong influence on the institution's four-year graduation rate. Examples of majors with four-year graduation rates above 70% include Management (71%, 488 students), Speech, Language, and Hearing Sciences (83%, 111 students), Nursing (71%, 193 students), Agribusiness (84%, 95 students), and Biochemistry (84%, 50 students). Some majors with four-year graduation rates below 50% that had a negative impact on the institution's four-year graduation rate include Mechanical Engineering Technology (17%, 238 students), Electrical Engineering Technology (34%, 142 students), Economics (47%, 258 students), Aeronautical and Astronomical Engineering (49%, 311 students), and Building Construction Management (43%, 184 students). Illustrating the importance of the first and second years of college, a number of students left the university while enrolled in pre-major programs.

Six-Year Graduation MGLM Results

The same steps were taken to analyze data for six-year graduation using MGLM. The ICC indicated that 47.6% of the variance in six-year graduation could be attributed to academic majors. The obtained ICC of approximately 50% indicates that a significant amount of variation can be explained by academic majors and MGLM is warranted. Appendix 4 shows the results of the MGLM analyses and four comparisons of six-year GPA models.

Student-level model. The coefficients in the student-level model were treated as random. Analysis suggest the logit for high school GPA was significantly different from 0, $t(198)= 2.987$, $p = .003$; this indicates that every one point increase in high school GPA increases the odds of six-year graduation by 1.358. For every one point increase in ACT score, the estimated logit decreases by .024 units, $t(198) = -2.536$, $p = .012$. The odds of six-year graduation increase by 1.033 for every AP and dual credit one earns before college, $t(198) = 4.894$, $p < .001$. Analysis suggests that changing one's major increases the odds of six-year graduation by 2.108, $t(198) = 6.173$, $p < .001$. The odds of earning a degree within six years of initial enrollment are 2.108 times higher after changing one's major than the odds of six-year graduation for students who did not change majors. Every one point increase in one's cumulative GPA after the first year of initial enrollment increases the odds of graduating by 3.854, $t(198) = 18.071$, $p < .001$. Lastly, every additional student organization one is involved in increases the odds of six-year graduation by 1.636, $t(198) = 7.235$, $p < .001$. It is also important to note that identifying as a student of color, first-generation, or Pell-eligible were not related to six-year graduation after controlling for other student-level variables.

Considerable variability exists in the intercepts for this collection of academic majors, τ_{00}, $\chi^2(75) = 717.496$, p < .001. A significant level of variability also exists across the change of major slopes, τ_{07}, $\chi^2(75) = 106.043$, $p = .011$. Moreover, significant variability existed across the first-year cumulative GPA slopes, τ_{08}, $\chi^2(75) = 119.819$, $p = .001$.

Full model. All student-level and major-level variables were included in the full model. The intercept, change of major, and first-year GPA were considered random based on the student-level results. The data suggest the average odds of six-year graduation were 5.589 times more likely than not graduating in six years, $t(195) = 12.216$, $p < .001$. Every one point increase in the mean high school GPA of an academic major increased the odds by 94.666, $t(195) = 4.609$, $p < .001$. Furthermore, being enrolled in a major that requires an internship increases the odds of graduation by 2.148, $t(195) = 2302$, $p = .022$. Every additional median elective credit in an academic major increases the odds of graduation by 1.049, $t(195) = 3.193$, $p = .002$.

Results suggest that the odds of six-year graduation are 1.978 times more likely for students who change their major during college, $t(195) = 5.11$, $p < .001$. For every one point increase in the mean high school GPA within an academic major, the odds of six-year graduation adjust by .373, $t(9{,}333) = -2.236$, $p = .025$.

Noticeable differences exist between the four-year and six-year models. For example, ACT score was a significant predictor of six-year graduation, but it had no statistical relationship with four-year graduation. Students of color were also less likely to graduate in four years or less years compared to White and Asian peers. However, this gap was eliminated when investigating six-year graduation.

Lastly, the result suggests considerable variability in the intercepts remains for this collection of academic majors, τ_{00}, $\chi^2(112) = 1{,}030.237$, $p < .001$. Considerable variation also continues to exists across the change of major slopes, τ_{07}, $\chi^2(112) = 146.945$, $p = .015$, and across the strength of first-year GPA, τ_{08}, $\chi^2(112) = 175.788$, $p < .001$.

Percentage of variance explained. When compared with the empty model with no predictors, the model using only student-level predictors increases the between-major variance by 36.8%. Compared to the student-level model, the full model explains an additional 18.3% of the between-major variance in six-year graduation. Furthermore, the parsimonious model explains an additional 18.8% of the between-major variance when compared to the student-level model. These finding suggest that large variance exists across academic majors and student-level only models will likely result in bad estimates of six-year graduation.

Post-hoc analysis. A parsimonious model without the non-significant student-level variables of URM status, first-generation status, Pell-eligibility, and learning community involvement was analyzed since these variables were not significantly related to four-year graduation in prior analyses. Major-level predictors were only added to the intercept, change of major, and first-year GPA variables since the student-level and full models suggest these be considered random. When this model was analyzed, all remaining student-level variables were statistically related to six-year graduation. Furthermore, the strength of changing one's major was reduced by .014, first-year GPA was reduced by .009, involvement in student organizations was reduced by .061, and identifying as female increased by .019 compared to the full model, see Appendix 4. While these changes are noticeable, they are trivial and have little impact on the overall prediction.

Similar to the post-hoc analysis for four-year graduation, majors with high six-year graduation and low six-year graduation rates were of interest. Descriptive statistics and graphs were utilized to identify academic majors that have a strong influence on the institution's six-year graduation rate. Examples of majors with six-year graduation rates above 90% include Neurobiology and Physiology (100%), Agribusiness (97%), Selling and Sales Management (95%), Environmental and Ecological Engineering (96%), and Speech, Language, and Hearing Sciences (94%). Some majors that had a negative impact on the institution's six-year graduation rate include Interdisciplinary Agriculture (45%), Medical Laboratory Sciences (50%), Theatre (50%), Fine Arts (52%), and many pre majors.

Summary of Results

The results from both descriptive and inferential analyses are summarized by the research questions guiding the study. Relating to the first research question, results suggest that average cumulative college GPAs significantly vary across academic majors. Evidencing this phenomenon, the clustering effect was practically significant, suggesting that 30% of the variance in the average cumulative college GPAs could be attributed to group differences across academic majors. Thus, MLM provides more accurate parameter estimates and standard errors compared to the student-level only model.

Results related to the second research question suggest that 32.1% of the variance in four-year graduation rates can be attributed to academic majors. Furthermore, 47.6% of the variance in six-year graduation could be attributed to differences across academic majors. Both of these values are practically significant and suggest the major one selects plays a significant role in the likelihood of four-year and six-year graduation.

Regarding the third research question, changing one's major during college resulted in an average increase of approximately .10 GPA points. However, the contextual effect of mean high school GPA within the new major alters the strength of this relationship. Specifically, every one point increase in the mean high school GPA for students clustered within the major one switches to decreases the average college GPA by .191 points. Changing one's major during college increases the odds of six-year graduation by 1.978 times and four-year graduation by .660 times.

Regarding the fourth and fifth research questions, results suggest that the relationship between student predictor and cumulative GPA would change within a specific context of academic majors. For example, every one point increase in mean high school GPA increased the average college GPA by 1.474 points. Requiring an internship or clinical experience as a graduation requirement also increased predicted GPA by .221 points and every additional median elective credit increased predicted GPA by .009 points. While .009 may seem low, the median number of elective credits ranged from 0 to 45.5, meaning this variable could have a maximum impact of .41 points on predicted GPA. However, significant variation remained across the intercept (59%), high school GPA (100%), change of major (100%), first-year GPA (93.7%), and student organization involvement (100%). Thus, additional major-level predictors would help explain this variance, leading to more accurate estimates of cumulative college GPA.

Results also suggest that the interrelation between student-level and major-level variables can also improve the prediction of likelihood of graduation. Related to four-year graduation, the mean high school GPA had a significant impact on the transfer/AP credits slope and the first-generation slope while the median number of elective credits influenced the gender slope. The mean high school GPA, requiring an internship, and the median number of elective credits all influenced six-year graduation. Despite this, significant variation remained across the intercepts (78%) and variation of the strength of changing one's major increased by 3% in the full four-year graduation model; the strength of the first-year GPA slopes were no longer significantly different. For the full six-year graduation model, significant variation remained across the intercepts (81.6%), change of major slopes (97%), and first-year GPA slopes (96%). Thus, additional major-level predictors could help explain additional variation and improve parameter estimates.

CHAPTER 5. DISCUSSION

The discussion is constructed of five sections. The first section of the chapter shares a brief summary of the study. The second section discusses findings related to each of the four primary research questions. The third section highlights the limitations of the study. The fourth section provides implications for research and practice, and the final section offers concluding thoughts.

Summary of the Study

Earning a bachelor's degree in a timely manner and obtaining a strong cumulative GPA are important to long-term return on investment for students and their families. It is evident from the literature that student outcomes are shaped by pre-college characteristics, during-college experiences, and complex academic environments. Despite this, higher education researchers and offices of institutional analysis rarely apply statistical techniques to simultaneously control for student-level predictors and the contextual effects of college environments. Thus, this study was designed to address the gap in the literature and better predict persistence to graduation and cumulative GPA at the end of one's college experience.

The primary questions guiding this research were:

1. How much of the variation in cumulative college GPA is attributed to undergraduate majors?
2. How much of the variation in four-year and six-year graduation rates can be attributed to undergraduate majors?
3. To what extent is changing one's academic major related to cumulative college GPA, likelihood of four-year graduation, and likelihood of six-year graduation?

4. How does the interrelationship between student-level and major-level predictors influence cumulative college GPA?
5. How does the interrelationship between student-level and major-level predictors influence the likelihood of graduation after four and six years of initial enrollment?

In order to answer these questions, a secondary dataset was retrieved from the Office of the Registrar at one large research university in the Midwestern United States. This institution was selected purposively because the institution offers more than 200 academic majors, enrolls diverse populations representing multiple racial/ethnic groups from more than 100 countries and all 50 states, and the university is public. Thus, results are generalizable to similar four-year public institutions. Data from the entering cohorts of Fall 2010 and Fall 2011 were used to increase generalizability by avoiding a single-year focus. Following data cleaning, 9,966 students were enrolled in 199 academic majors. Remaining majors ranged in size from five students to 753 students.

Findings

Relating to the first research question, average cumulative college GPAs significantly varied across academic majors. The observed clustering effect was practically significant, suggesting that 30% of the variance in cumulative college GPAs could be attributed to group differences across academic majors. However, the pilot study suggested that 7% of the variation in GPA could be attributed to initial major. Finding that one's final major explains a large percentage of variance is not surprising as prominent research (e.g., Astin, 1993b; Tinto, 1975, 1993, 2010) suggests that academic environments play a critical role in academic outcomes. Perhaps this finding can be partially explained because faculty housed within different departments establish and adhere to expectations set in syllabi, course materials, and conversations with students at varying levels, all of which are important to academic success (Tinto, 2010). This finding could also be explained because students often struggle to find majors that are congruent with one's abilities, interests, and personalities (Pike, 2006b). Those that find the correct major early may be more likely to earn a higher GPA compared to those who take multiple semesters to find the right fit.

Academic majors also account for large proportions of variance in four-year and six-year graduation, which also aligns with Gipson's (2017) pilot study. It is also suggested that majors related to business and the social sciences tend to possess higher four-year graduation rates than the hard sciences, technology, and engineering. This aligns with Astin's (1997) finding that institutions enrolling large numbers of students in business, psychology and social sciences have higher than expected four-year graduation rates while institutions enrolling large numbers of engineering students have lower than expected rates. Interestingly, more than 50% of majors with four-year graduation rates below 50% possessed six-year graduation rates of 75-90%.

Results relating to changing one's major are not surprising as grades are likely the most explicit form of reward one can receive during college (Tinto 1975, 1993). Students often rely on pre-college expectations to select an initial major that aligns with one's abilities, interests, and personality (Pike 2006a, 2006b). It is no surprise that students would change majors to improve grade performance as GPA is a good measure of how students' attributes and achievements relate to the institution's values and objectives (Tinto, 2010). Ost (2010) found this to be true within the sciences as students were often pulled away from difficult majors as a result of receiving higher grades in another area. Another potential reason is that one's interests, abilities, and personality change as one grows socially and academically during college. Thus, changing one's major, on average, may slow time to degree completion, but finding a major that aligns with one's abilities, interests, and personality may be what it takes to persist to degree completion rather than leaving college with thousands of dollars in debt and no degree.

The effects of student-level predictors were generally consistent with prior studies (e.g., Astin, 1997; Gipson, 2016; Kobrin & Patterson, 2011; Sawyer, 2013) as pre-college characteristics were related with cumulative college GPA and four-year graduation. However, results related to prior academic performance were mixed. For example, the results of this study suggest that high school GPA is the most important pre-college predictor of cumulative college GPA, aligning with prior literature (Belfield & Costa, 2012; Geisser & Santelices, 2007; Tinto, 1975), but identifying as female was a stronger predictor of four-year graduation. Furthermore, involvement in each additional student organization increases cumulative GPA and the likelihood of graduation. While the effect size of the AP/dual credit slopes may seem low, a range of 87 credits for new beginners lends practical significance to this predictor across the three models.

Identifying as URM and first-generation significantly reduced cumulative GPA and the likelihood of four-year graduation while being low-income significantly reduced the likelihood of four-year graduation. Interestingly, these factors were not related to the likelihood of six-year graduation. Prior research (e.g., Astin & Oseguera, 2005; Chen, 2005; DeAngelo et al., 2011; Horn & Berger, 2004) suggests that students of color graduate at far lower average rates compared to White and Asian students. If one defines success as graduating in four years or less, these findings align with current research. However, if one defines success as obtaining a degree within six years, these findings contradict existing research. Regardless of one's definition of success, more should be done to eliminate disparities related to first-generation status, URM status, and Pell-eligibility in four-year graduation to increase return on investment for all students.

It has been argued that learning community involvement encourages deeper student engagement throughout the college experience, which results in positive academic outcomes (Pike, Kuh, & McCormick, 2008). However, the tested model suggests that involvement in learning communities had no impact on cumulative GPA or the likelihood of graduation in four or six years. This aligns with Zhao and Kuh's (2004) finding that involvement in learning communities has no direct impact on cumulative GPA and expands prior results to show no relation with graduation.

When all student-level predictors were added to the four-year and six-year graduation models, the percentage of within-group variance increased by 37% and 46%, respectively. Once all major-level predictors were entered into the full graduation models, 22% and 18% of this new variance is accounted for. This suggests that utilizing models containing only student-level data will create inaccurate and biased parameter estimates for students clustered within many academic majors. Inaccurate and biased estimates may result in incorrectly identifying students on the at-risk spectrum, leading to a poor use of resources as advisors, student affairs professionals, and faculty members will dedicate time and funds to students who are not truly "at-risk" while missing many students who are in need of support. Thus, institutions should employ multilevel modeling to increase accuracy and power while identifying at-risk students. Results also suggest that institutions must clearly and consistently define student success as results varied across models of cumulative GPA, four-year graduation, and six-year graduation.

In regards to explaining variation across majors, when the group-level variables of mean high school GPA, required internship/clinical experiences, and median free elective credits were introduced into the model, the strength of many student-level predictors was altered. In fact, all major-level predictors were significantly related to at least one student-level predictors and all impacted the average cumulative GPA and graduation by major. The finding that mean high school GPA altered the likelihood of graduation and earning a higher GPA aligns with Gipson's (2017) pilot study and supports the use of MLM when predicting student outcomes. Perhaps high school mean GPA has a positive effect on the major average GPA because grouping higher performing students within collaborative learning environments allows for students to acquire knowledge at faster rates than groups of lower performing students by "sharpening one's own understanding by listening seriously to the insights of others" (Kuh, 2008, p. 10).

It is also not surprising that requiring an internship or clinical experience provides positive benefits for students as Kuh (2008) found that internships promote persistence to graduation. The results of this study suggest that internships not only promote persistence, but requiring at least one internship or clinical experience for degree attainment increases the likelihood of four-year graduation, six-year graduation, and earning a higher GPA. This may be because internships allow students to apply theory to a real-world experience, increasing the congruence between one's abilities, interests, and personalities that help one identify an academic major (Pike, 2006b). Thus, when possible, faculty should consider including an internship or clinical experience as a requirement for earning a bachelor's degree.

This study also illustrates the importance of the intersection of identities within higher education. For instance, identifying as a first-generation URM student reduces cumulative GPA by an average of .06 points. Similarly, identifying as a first-generation URM student who is also Pell-eligible reduces the logit for four-year graduation by .616 units. Similar patterns were observed in the pilot study using initial college majors (Gipson, 2017). Moreover, noticeable differences exist between logit estimates for URM status and Pell-eligibility between the model solely containing student-level data and the model containing both student and major-level data. This evidences how using MLM can help institutions develop more-accurate predictive models by reducing error.

Implications for Higher Education Institutions

The present findings offer multiple suggestions for institutions of higher education. First, institutions should define what aspect of student success is most important to their student population. Institutions must make a choice to focus on cumulative GPA, four-year graduation, or six-year graduation as the outcome variable in predicted at-risk models as results differed across the three models. If the majority of students are focused on gaining admission to professional school, perhaps cumulative GPA should be the focus. If affordability and speeding time to degree completion is the focus, building a four-year graduation model may be most effective.

Second, the results of the study suggest that multilevel modeling will reduce more of the variance related to GPA, four-year graduation, and six-year graduation compared to student-level regression. Thus, institutions should utilize statistical methods that account for clustering effects, e.g., MLM, instead of student-level models like ANOVA and MLR when predicting student outcomes. If institutions cannot transition to multilevel modeling, MLR models should be differentiated by major as the strength of student-level variables varies across majors. Third, institutions should constantly monitor students to ensure graduation probabilities and predicted GPA are recalculated whenever a student transitions between academic majors as results substantially differed from the pilot study utilizing initial college majors. Specifically, one's final major explained a greater level of variation in cumulative GPA and likelihood of graduation compared to one's initial major.

Fourth, results suggest that institutions should continue to place emphasis on the pre-college characteristics of high school GPA, standardized test scores, and the number of AP and dual credits a student completes during high school. Furthermore, institutions should consider the impact of clustering students by average high school GPA within academic majors as this alters the strength of many student-level predictors. The study also provided mixed findings related to the number of free elective credits within a major, which should be considered when developing new academic curriculum.

Implications for Future Research in Higher Education and Methodology

This study provides multiple recommendations for future research. First, the study evidences the importance of utilizing advanced statistical techniques like multilevel modeling to provide more accurate parameter estimates when working with nested higher education data. These techniques allow researchers to investigate unique contextual impacts on student outcomes created by shared experiences. Second, significant variation continued to exist across the average cumulative GPAs and six-year graduation rates as well as select regression slopes. While the major level predictors utilized in the current study could explain additional variance in student outcomes compared to traditional regression models with only student-level variables, future studies should investigate other major-level predictors, such as the average number of students per advisor, rank of faculty members clustered within a major, number of students per faculty member, and the level of financial commitment from the institution as the majority of variance was not accounted for by the predictors used in this study. Based on the large percentage of variance that can be explained by academic majors, finding the right combination of student-level and major-level predictors will significantly increase the accuracy of parameter estimates commonly used to identify at-risk students.

Relating to methodology, one common problem with higher education data is the exclusion of high school GPAs and standardized test scores, especially for international students. This issue resulted in approximately 3,000 students being excluded during the data cleaning process for the current study, the effect being that the findings of this study are not generalizable for this population. As the international student population increases in higher education, future research should be conducted to uncover the best way to predict outcomes for this group. Should university average high school GPAs and test scores be added at the student-level? Would major-level GPA averages improve accuracy? If such strategies result in biased and inaccurate predictions, should a separate model be constructed for students without high school GPAs and test scores? Future research should explore this area.

The strength of some student-level predictors varied across groups while some did not. Is this unique to the studied institution or does this apply across peer institutions and institutional types? If these results are supported, what impact should this have on admissions practices? Studying why first-year GPA and changing one's major varies across groups may be a good place to focus as the strength of these predictors varied in relation to cumulative GPA, four-year graduation, and six-year graduation. Future quantitative and qualitative research should explore this phenomenon in more detail.

Future studies should explore the contextual effect of various groups (e.g., Carnegie classifications, peer institutions, colleges within an institution, fraternities/sororities, etc.) and multiple levels of MLM (e.g., three-level analysis of universities-colleges-majors) to include the hierarchical nesting of students as significantly more variation in cumulative GPA and the likelihood of graduation could be explained. This will likely improve parameter estimates and reduce error. Exploratory qualitative research should explore what major-level characteristics may increase cumulative GPA and the likelihood of graduation for URM, first-generation, and low-income students. This information would guide the creation of future multilevel models to predict academic outcomes. Finally, the current study provides interesting findings related to the intersection of identities within higher education and the relationship between pre-college, during-college, and major-level characteristics for members of such student populations. Future research should be conducted to add to this area of emerging research by investing the different clustering effects for diverse student populations (e.g., living arrangements, fraternities/sorority involvement, number of diverse faculty members per student, etc.).

Limitations

The present study is limited in generalizability, as the sample only contains students attending one institution within the Midwestern United States. However, the institution enrolls undergraduate students from all 50 states as well as one of the largest populations of international students in the country. Thus, the results likely apply to other major research institutions. Additionally, students entering during the fall semesters of 2010 and 2011 were included to increase generalizability by avoiding a single-year focus. Another limitation of the study is that dropouts sometimes transfer to another institution and complete a bachelor’s degree. Thus, interpretation of the results is limited to not graduating from one’s initial institution. Lastly, causal assumptions cannot be drawn from this research as experimental design was not employed. Given the acknowledgement of the limitations, the study is statistically solid and the consistency of the results from full and parsimonious models supports statistical conclusion validity.

Conclusion

Given the importance of graduation and cumulative college GPA, researchers and practitioners must understand the interrelationships between students and various academic environments. The results of this study illustrate academic majors are a critical environment that deserves more attention from researchers as more than 30% of the variation in cumulative GPA and four- or six- year graduation can be attributed to these environments. This study also emphasizes the importance of utilizing statistical techniques that account for clustering effects in college to provide more accurate parameter estimates and error terms to better predict college success defined GPA and timely gradation.

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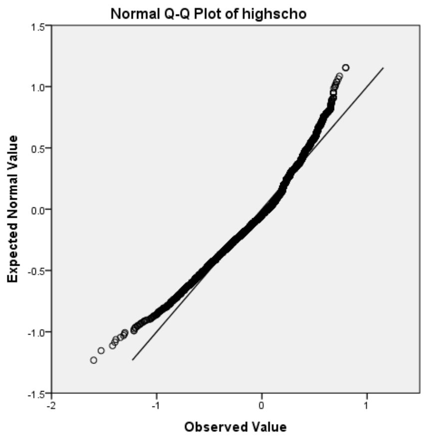
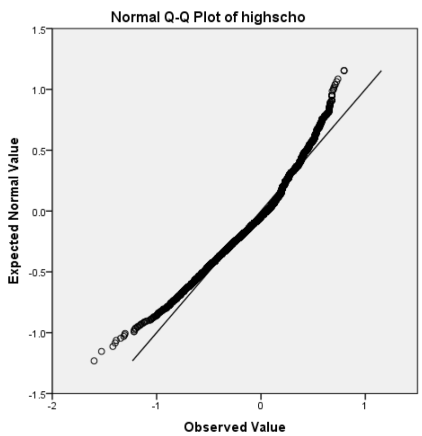
Appendix A

Residual Plots for Level-1 Predictors

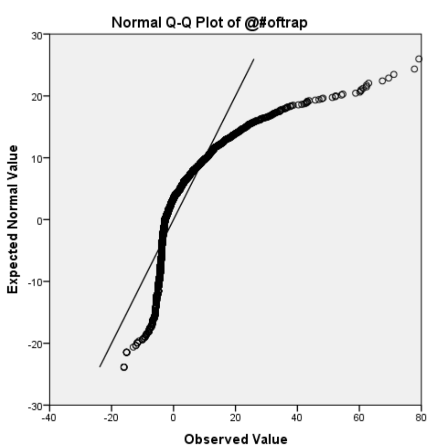
High School GPA



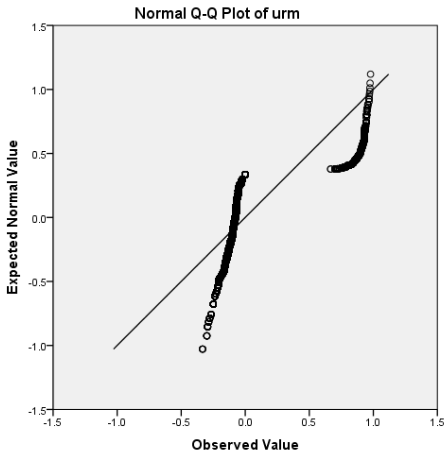
ACT Composition



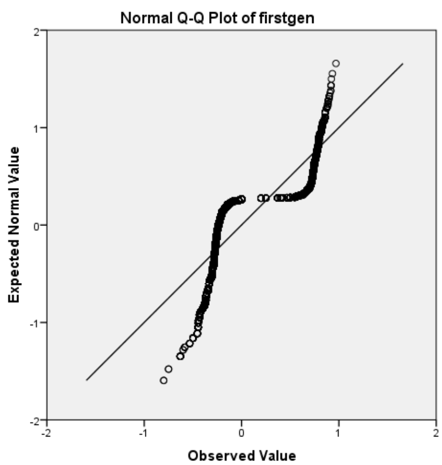
Transfer Credits



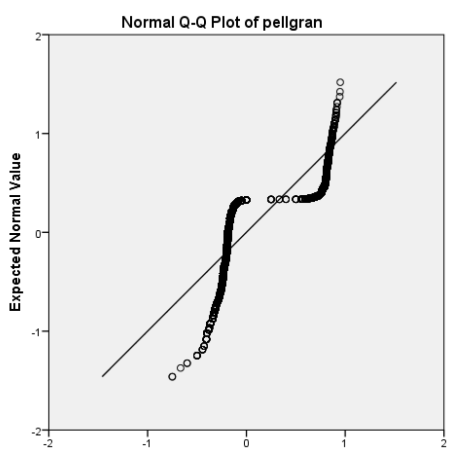
URM



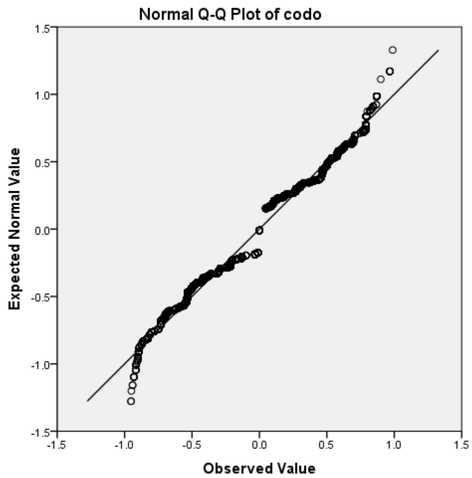
First-generation Status



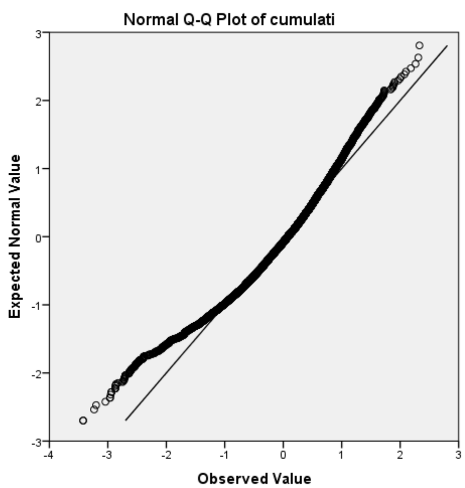
Pell-eligibility



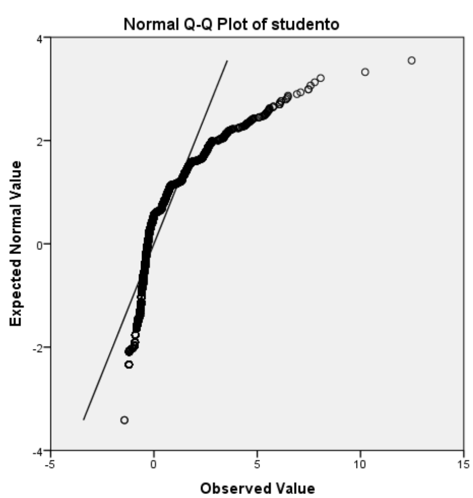
Change of Major



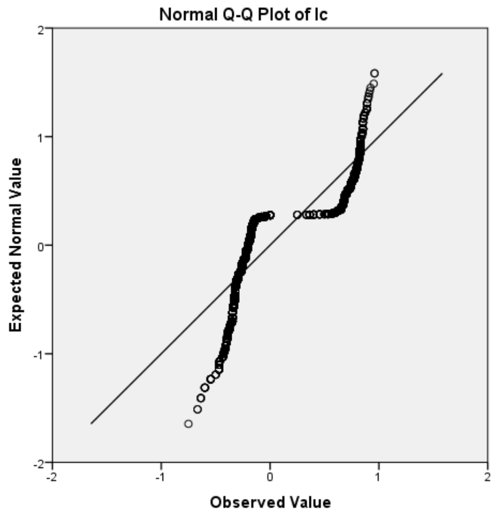
First-Year GPA



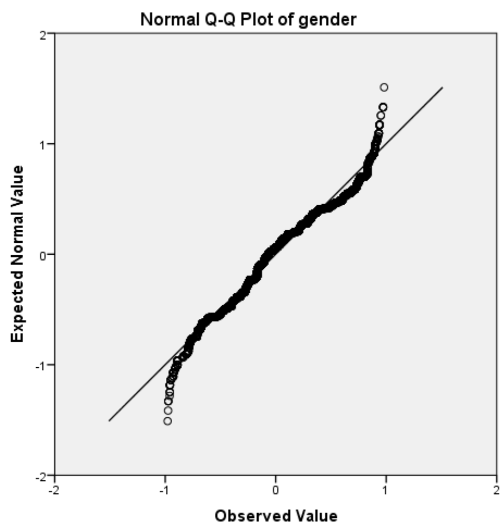
Student Organizations



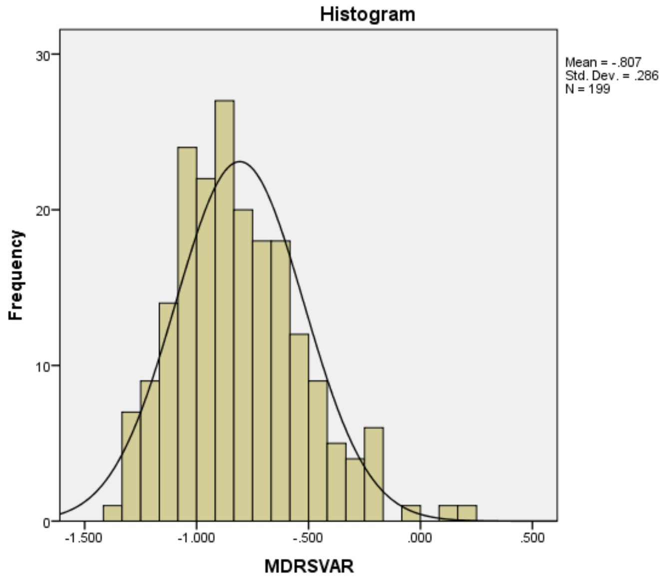
Learning Community



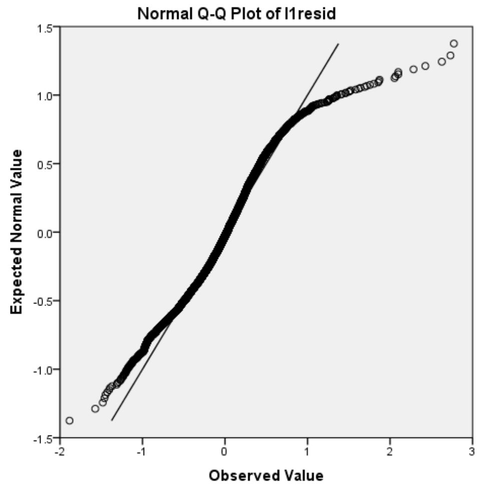
Gender

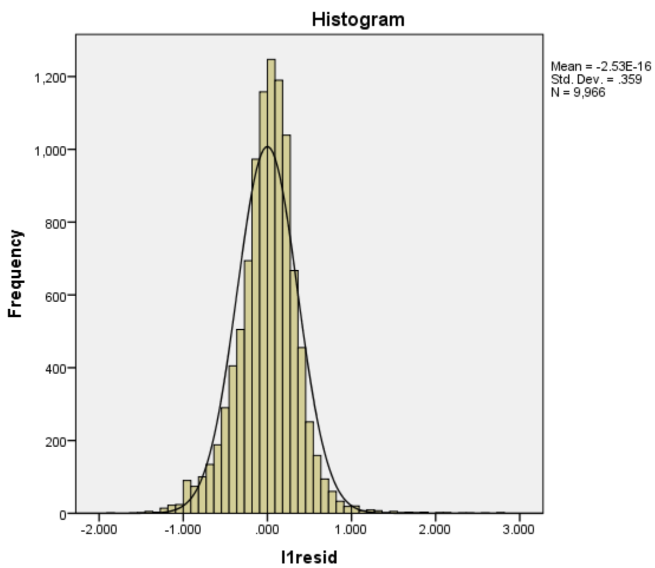


Equal Variance

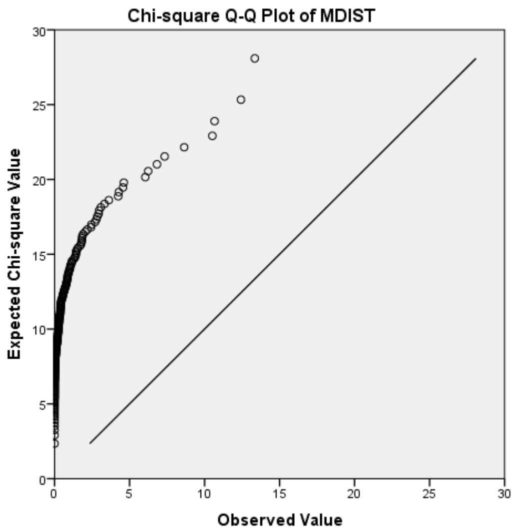


Normality of student-level residual file





Major-level Mahalanobis Distance



Appendix B

Four Models of Cumulative College GPA

	Unconditional Model	Student-level Model	Full Model	Parsimonious Model
Variable	Estimate(SE)	Estimate(SE)	Estimate(SE)	Estimate(SE)
GRAD (β_{0j})				
intercept(γ_{00})	2.907(.031)*	2.907(.032)*	2.908(.025)*	2.908(.025)*
meanhsgpa (γ_{01})			1.474(.153)*	1.474(.153)*
internship (γ_{02})			.221(.063)*	.221(.063)*
electives (γ_{03})			.009(.002)*	.009(.002)*
HSGPA (β_{1j})				
intercept(γ_{10})		.142(.015)*	.144(.015)*	.144(.015)*
meanhsgpa (γ_{11})			.158(.089)	.152(.090)
internship (γ_{12})			-.006(.035)	-.012(.035)
electives (γ_{13})			.001(.001)	.001(.001)
ACT (β_{2j})				
intercept(γ_{20})		.006(.001)*	.006(.001)*	.006(.001)*
meanhsgpa (γ_{21})			.001(.007)	
internship (γ_{22})			-.003(.004)	
electives (γ_{23})			<.001(<.001)	
TRCREDITS (β_{3j})				
intercept(γ_{30})		.003(.001)*	.003(.001)*	.003(.001)*
meanhsgpa (γ_{31})			-.008(.004)*	
internship (γ_{32})			<.001(.001)	
electives (γ_{33})			-.001(<.001)	
URM (β_{4j})				
intercept(γ_{40})		-.046(.011)*	-.046(.011)*	-.045(.011)*
meanhsgpa (γ_{41})			-.018(.076)	
internship (γ_{42})			.-.017(.024)	
electives (γ_{43})			-.002(.001)*	
FIRSTGEN (β_{5j})				
intercept(γ_{50})		-.021(.007)*	-.024(.008)*	-.023(.008)*
meanhsgpa (γ_{51})			-.019(.047)	
internship (γ_{52})			.006(.018)	
electives (γ_{53})			-.001(.001)	

Note. *$p < .05$.

Four Models of Cumulative College GPA Continued

	Unconditional Model	Student-level Model	Full Model	Parsimonious Model
Variable	Estimate(SE)	Estimate(SE)	Estimate(SE)	
PELL (β_{6j})				
intercept(γ_{60})		.005(.009)	.004(.009)	
meanhsgpa (γ_{61})			-.005(.060)	
internship (γ_{62})			.033(.022)	
electives (γ_{63})			.001(.001)	
MAJORCHANGE (β_{7j})				
intercept(γ_{70})		.107(.015)*	.100(.015)*	.101(.015)*
meanhsgpa (γ_{71})			-.193(.089)*	-.194(.089)*
internship (γ_{72})			.035(.033)	.036(.032)
electives (γ_{73})			.001(.002)	.001(.002)
FIRSTYEARGPA (β_{8j})				
intercept(γ_{80})		.639(.015)*	.638(.015)*	.639(.015)*
meanhsgpa (γ_{81})			-.191(.078)*	-.185(.078)*
internship (γ_{82})			-.034(.037)	-.032(.037)
electives (γ_{83})			-.003(.001)	-.002(.001)
STUDENTORGS (β_{9j})				
intercept(γ_{90})		.040(.005)*	.039(.005)*	.038(.005)*
meanhsgpa (γ_{91})			-.067(.034)	-.065(.034)
internship (γ_{92})			.006(.012)	.004(.012)
electives (γ_{93})			< -.001(.001)	<-.001(.001)
LCS (β_{10j})				
intercept(γ_{100})		-.012(.008)	-.014(.008)	
meanhsgpa (γ_{101})			.072(.051)	
internship (γ_{102})			-.013(.021)	
electives (γ_{103})			.001(.001)	
GENDER (β_{11j})				
intercept(γ_{110})		.031(.010)*	.034(.010)*	.032(.009)*
meanhsgpa (γ_{111})			.046(.046)	
internship (γ_{112})			.037(.028)	
electives (γ_{113})			.001(.001)	

Note. *$p < .05$.

Four Models of Cumulative College GPA Continued

Variance Components				
GPA (τ_{00})	.170*	.195*	.116*	.116*
HSGPA (τ_{11})		.008*	.008*	.008*
ACT (τ_{22})		<.001		
TRCREDITS (τ_{33})		<.001		
URM (τ_{44})		.003		
FIRSTGEN (τ_{55})		.001		
PELL (τ_{66})		.001		
MAJORCHANGE (τ_{77})		.011*	.011*	.011*
FIRSTYEARGPA (τ_{88})		.032*	.030*	.030*
STUDENTORGS (τ_{99})		.001*	.001*	.001*
LCS (τ_{1010})		.002		
GENDER (τ_{1111})		.002		

Note. *p < .05.

Appendix C

Four Models of Four-Year Graduation

	Unconditional Model		Student-level Model		Full Model		Parsimonious Model	
Variable	Estimate(SE)	OR	Estimate(SE)	OR	Estimate(SE)	OR	Estimate(SE)	OR
GRAD (β_{0j})								
intercept(γ_{00})	-.115(.097)	.891	-.150(.116)	.860	-.149(.104)	.862	-.147(.103)	.863
meanhsgpa (γ_{01})					3.666(.667)*	39.113	3.601(.657)*	36.629
internship (γ_{02})					.220(.261)	1.246	.227(.258)	1.255
electives (γ_{03})					.047(.011)*	1.048	.047(.010)*	1.048
HSGPA (β_{1j})								
intercept(γ_{10})			.285(.089)*	1.329	.350(.091)*	1.419	.382(.093)*	1.466
meanhsgpa (γ_{11})					-.053(.583)	.948		
internship (γ_{12})					-.052(.232)	.950		
electives (γ_{13})					-.015(.010)	.985		
ACT (β_{2j})								
intercept(γ_{20})			.009(.010)	1.009	.008(.008)	1.008		
meanhsgpa (γ_{21})					.227(.050)*	1.255		
internship (γ_{22})					-.037(.022)	.964		
electives (γ_{23})					<-.001(.001)	1.000		
TRCREDITS (β_{3j})								
intercept(γ_{30})			.013(.004)*	1.013	.014.003)*	1.014	.010(.004)*	1.011
meanhsgpa (γ_{31})					-.072(.022)*	.931		
internship (γ_{32})					.006(.009)	1.007		
electives (γ_{33})					-.001(<.001)	.999		
URM (β_{4j})								
intercept(γ_{40})			-.318(.010)*	.728	-.350(.103)*	.704	-.361(.100)*	.697
meanhsgpa (γ_{41})					.173(.719)	1.188		
internship (γ_{42})					-.193 (.240)	.824		
electives (γ_{43})					-.010(.009)	.990		
FIRSTGEN (β_{5j})								
intercept(γ_{50})			-.119(.060)*	.888	-.117(.058)*	.889	-.080(.061)	.923
meanhsgpa (γ_{51})					1.352(.389)*	3.864		
internship (γ_{52})					.198(.139)	1.219		
electives (γ_{53})					.014(.006)*	1.014		

Note. *p < .05.

Four Models of Four-Year Graduation Continued

	Unconditional Model		Student-level Model		Full Model		Parsimonious Model	
Variable	Estimate(SE)	OR	Estimate(SE)	OR	Estimate(SE)	OR		OR
PELL (β_{6j})								
intercept(γ_{60})			-.065(.059)	.937	-.149(.062)*	.861		
meanhsgpa (γ_{61})					-.372(.362)	.690		
internship (γ_{62})					.156(.147)	1.169		
electives (γ_{63})					-.008(.007)	.992		
MAJORCHANGE (β_{7j})								
intercept(γ_{70})			-.435 (.119)*	.647	-.416(.132)*	.660	-.403(.132)*	.668
meanhsgpa (γ_{71})					-.213(.888)	.808	-.207 (.892)	.813
internship (γ_{72})					-.370(.233)	.691	-.392(.233)	.676
electives (γ_{73})					.008(.013)	1.008	.007(.012)	1.007
FIRSTYEARGPA (β_{8j})								
intercept(γ_{80})			1.333(.062)*	3.793	1.311(.064)*	3.710	1.330(.062)*	3.780
meanhsgpa (γ_{81})					-.238(.388)	.788	.114(.373)	1.121
internship (γ_{82})					.246(.161)	1.278	-.206(.150)	1.229
electives (γ_{83})					.002(.006)	1.002	<-.001(.006)	1.000
STUDENTORGS (β_{9j})								
intercept(γ_{90})			.059(.034)	1.060	.071(.037)*	1.074		
meanhsgpa (γ_{91})					-.209(.210)	.811		
internship (γ_{92})					.097(.100)	1.102		
electives (γ_{93})					-.003(.003)	.997		
LCS (β_{10j})								
intercept(γ_{100})			-.036(.056)	.965	-.069(.064)	.934		
meanhsgpa (γ_{101})					-.066(.416)	.936		
internship (γ_{102})					-.074(.161)	.928		
electives (γ_{103})					.003(.006)	1.003		
GENDER (β_{11j})								
intercept(γ_{110})			.355(.084)*	1.427	.455(.083)*	1.576	.422(.087)*	1.524
meanhsgpa (γ_{111})					.266(.560)	1.305		
internship (γ_{112})					.254(.206)	1.289		
electives (γ_{113})					.019(.008)*	1.019		

Note. *$p < .05$.

Four Models of Four-Year Graduation Continued

Variance Components

GPA (τ_{00})	1.552*	2.260*	1.772*	1.738*
HSGPA (τ_{11})		.115		
ACT (τ_{22})		.003		
TRCREDITS (τ_{33})		<.001		
URM (τ_{44})		.262		
FIRSTGEN (τ_{55})		.069		
PELL (τ_{66})		.108		
MAJORCHANGE (τ_{77})		.675*	.696*	.652*
FIRSTYEARGPA (τ_{88})		.203*	.212	.206
STUDENTORGS (τ_{99})		.024		
LCS (τ_{1010})		.040		
GENDER (τ_{1111})		.272		

Note. *p < .05.

Appendix D

Four Models of Six-Year Graduation

	Unconditional Model		Student-level Model		Full Model		Parsimonious Model	
Variable	Estimate(SE)	OR	Estimate(SE)	OR	Estimate(SE)	OR	Estimate(SE)	OR
GRAD (β_{0j})								
intercept(γ_{00})	1.366(.134)*	3.919	1.721(.158)*	5.589	1.721(.141)*	5.589	1.711(.141)*	5.535
meanhsgpa (γ_{01})					4.550(.987)*	94.666	4.619(.980)*	101.440
internship (γ_{02})					.764(.332)*	2.148	.762(.330)*	2.142
electives (γ_{03})					.048(.015)*	1.049	.047(.015)*	1.048
HSGPA (β_{1j})								
intercept(γ_{10})			.306(.102)*	1.358	.352(.098)*	1.422	.351(.105)*	1.420
meanhsgpa (γ_{11})					.335(.601)	1.398		
internship (γ_{12})					-.409(.261)	.664		
electives (γ_{13})					.003(.012)	1.003		
ACT (β_{2j})								
intercept(γ_{20})			-.024(.010)*	.976	-.027(.011)*	.974	-.024(.009)*	.976
meanhsgpa (γ_{21})					-.037(.070)	.964		
internship (γ_{22})					.007(.026)	1.007		
electives (γ_{23})					<.001(<.001)	1.001		
TRCREDITS (β_{3j})								
intercept(γ_{30})			.032(.007)*	1.033	.029(.007)*	1.030	.028(.006)*	1.028
meanhsgpa (γ_{31})					.039(.048)	1.040		
internship (γ_{32})					.010(.013)	1.010		
electives (γ_{33})					<.001(.001)	1.000		
URM (β_{4j})								
intercept(γ_{40})			-.119(.102)	.888	-.118(.103)	.889		
meanhsgpa (γ_{41})					-.641(.764)	.527		
internship (γ_{42})					.196(.271)	1.217		
electives (γ_{43})					-.012(.010)	.987		
FIRSTGEN (β_{5j})								
intercept(γ_{50})			.051(.066)	1.052	.072(.065)	1.074		
meanhsgpa (γ_{51})					.969(.464)*	2.634		
internship (γ_{52})					.174(.140)	1.190		
electives (γ_{53})					-.002(.006)	.998		

Note. *p < .05.

Four Models of Six-Year Graduation Continued

	Unconditional Model		Student-level Model		Full Model		Parsimonious Model	
Variable	Estimate(SE)	OR	Estimate(SE)	OR	Estimate(SE)	OR		OR
PELL (β_{6j})								
intercept(γ_{60})			-.001(.085)	.999	-.007(.086)	.993		
meanhsgpa (γ_{61})					.447(.517)	1.564		
internship (γ_{62})					.374(.248)	1.453		
electives (γ_{63})					-.006(.009)	.994		
MAJORCHANGE (β_{7j})								
intercept(γ_{70})			.746(.121)*	2.108	.682(.134)*	1.978	.668(.133)*	1.950
meanhsgpa (γ_{71})					-1.047(.825)	.351	-1.113(.803)	.328
internship (γ_{72})					.140(.237)	1.151	.125(.235)	1.133
electives (γ_{73})					-.005(.012)	.995	.006(.012)	.995
FIRSTYEARGPA (β_{8j})								
intercept(γ_{80})			1.349(.075)*	3.854	1.351(.072)*	3.861	1.342(.073)*	3.827
meanhsgpa (γ_{81})					.565(.473)	1.760	.642(.476)	1.901
internship (γ_{82})					.190(.179)	1.209	.124(.170)	1.132
electives (γ_{83})					-.006(.007)	.994	-.005(.006)	.995
STUDENTORGS (β_{9j})								
intercept(γ_{90})			.492(.068)*	1.636	.439(.066)*	1.552	.378(.073)*	1.459
meanhsgpa (γ_{91})					-.985(.441)*	.373		
internship (γ_{92})					.190(.179)	1.019		
electives (γ_{93})					-.006(.007)	.998		
LCS (β_{10j})								
intercept(γ_{100})			-.060(.081)	.942	-.040(.081)	.960		
meanhsgpa (γ_{101})					.207(.485)	1.230		
internship (γ_{102})					.009(.188)	1.009		
electives (γ_{103})					-.009(.008)	.991		
GENDER (β_{11j})								
intercept(γ_{110})			.198(.105)	1.219	.245(.099)*	1.277	.264(.101)*	1.302
meanhsgpa (γ_{111})					.041(.672)	1.042		
internship (γ_{112})					-.298(.237)	.742		
electives (γ_{113})					.007(.010)	1.007		

Note. *$p < .05$.

Four Models of Six-Year Graduation Continued

Variance Components				
GPA (τ_{00})	2.995*	4.092*	3.340*	3.321*
HSGPA (τ_{11})		.215		
ACT (τ_{22})		.001		
TRCREDITS (τ_{33})		.001		
URM (τ_{44})		.136		
FIRSTGEN (τ_{55})		.034		
PELL (τ_{66})		.062		
MAJORCHANGE (τ_{77})		.492*	.477*	.447*
FIRSTYEARGPA (τ_{88})		.327*	.315*	.330*
STUDENTORGS (τ_{99})		.132		
LCS (τ_{1010})		.081		
GENDER (τ_{1111})		.283		

Note. $^*p < .05$.