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PERFORMANCE ON RETENTION AND GRADUATION OF STEM
STUDENTS**

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THE IMPACT OF MIDTERM COLLEGE MATHEMATICS PERFORMANCE ON
RETENTION AND GRADUATION OF STEM STUDENTS

A dissertation submitted in partial fulfillment
of the requirements for the degree of

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by

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ABSTRACT

THE IMPACT OF MIDTERM COLLEGE MATHEMATICS PERFORMANCE ON RETENTION AND GRADUATION OF STEM STUDENTS

Kandy Yu-Juan Ng Rich

The purpose of this study sought to examine how midterm math performance can impact a student's final math performance, STEM performance, overall performance, as well as retention and graduation with a STEM major. The sample consisted of 283 first-time full-time undergraduate students who were admitted in Fall 2014 as STEM majors within a liberal arts and sciences college at a private, not-for-profit, urban, highly diverse university located in the northeast. Academic record data from between September 2014 – May 2020 was obtained. Multiple and logistic regression analyses were performed, as well as independent samples *t*-tests. Results of the study revealed that while midterm math performance was not a direct predictor of retention and graduation when taking all college performance variables into account, it could be considered as an indirect predictor due to its positive relationship with cumulative GPA, where increasing cumulative GPA increased a student's chance of being retained and graduated as STEM. Similar results were found in relation to final math performance and STEM GPA. Furthermore, it was found that students who graduated in STEM had, on average, higher midterm and final math GPAs compared to students who leave or change their major out of STEM. This study also revealed the importance of not only looking at the retention into the second

year but also retention into the third year, where underrepresented minorities in STEM had a substantial attrition rate during this transition. The need for STEM graduates continues to be a priority and this study will add to the literature on how institutions can target formerly well-performing high school students but begin to perform poorly once matriculated as early as possible.

DEDICATION

First and foremost, this dissertation is dedicated to my husband. I know I do not say it enough, but I appreciate all that you do, and I would not have been able to complete this journey without your support and patience. Thank you for being there and never giving up on me.

To my two children, watching the two of you grow throughout my dissertation process showcases how important it is to continue learning even as an adult and I hope that I can continue to foster that love of learning in the both of you.

This dissertation is also dedicated to my po po, parents, and sister. It was certainly a long journey with many ups and downs, but I finally got there!

I cannot forget Dean Gregory Gades. Thank you for willing to take a chance on someone who never had any experience working in a college office. I would not be writing this without your flexibility and belief in me.

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CHAPTER 1 INTRODUCTION

The need to increase STEM graduates has persisted for decades. From former President Bill Clinton establishing the National Science and Technology Council through executive order in 1993 which includes the STEM education committee (The White House, n.d.), to former President George W. Bush signing into law a bill that hopes to improve math and science education (The White House, Office of the Press Secretary, 2007), to former President Barack Obama recognizing the importance of expanding STEM education to all (Handelsman & Smith, 2016), to former President Donald Trump signing a Presidential Memorandum to increase access of higher quality education in STEM for K-12 students (The White House, 2017), and President Joe Biden hoping to attract international STEM students (The White House, 2022). The need for increased STEM graduates continues to be a priority for the United States.

There is a projected growth of 10.5-percent between 2020 and 2030 for Science, Technology, Engineering, and Mathematics (STEM) occupations versus 7.5-percent of projected growth for non-STEM jobs in the same time span (Bureau of Labor Statistics [BLS], 2021). Approximately 9.3 million STEM jobs existed in May 2020 which represents 6.7 percent of all employment in the United States (BLS, 2020). Due to the need for STEM graduates to fill upcoming employment needs, retention, performance, and graduation of STEM students through college are extremely important. Scott et al. (2009) conducted a study of freshmen entering a research one university in the South who declared a STEM major. By the end of their third year, 59.5% had changed their major from STEM to a non-STEM major and the highest achieving students in STEM who changed their majors were mostly female or minorities. This was not unique to the study

conducted by Scott et al. (2009), it was found to be true in studies conducted by X. Chen (2013, 2015), Mau (2016), Moakler and Kim (2014), and Weston (2019).

This, however, does not indicate that there is a complete lack of interest in STEM. Beasley and Fischer (2012) found that while Hispanic, Asian, and White women did declare STEM majors at a significantly lesser rate compared to men, Black and Hispanic men declared STEM majors similarly at the rate of White men at the admission point. Moakler and Kim (2014) also concluded the same from their study. While many students may declare STEM at the start point, over half of students with the intention to complete a STEM degree would ultimately change from the major or leave without completing a degree (Aulck et al., 2017). About 35% of first time undergraduate students enrolled in the 2011-12 academic year who initially declared a STEM major changed out of it within three years compared to 29% of those who started as a non-STEM major (National Center for Education Statistics [NCES], 2017). Even more disconcerting, 52% of students who started out as math majors and 40% of students who were admitted in the natural sciences changed their major within three years. This showcases the important role that higher education institutions play in order to retain these STEM majors.

Mathematics plays an extremely important role as a foundational course in STEM disciplines (X. Chen, 2013). Interestingly, Chen found that of the first-year STEM admits who left without earning a degree, 40% of them did not have any math during their first year of enrollment. Of those first-year STEM admits who changed their major, 30% of these students in their first year of attendance did not have math on their transcript. For those that started in STEM and persisted within STEM, 91% took a math course in the first year they were enrolled. Not only that, 63% of these STEM persisters took either

calculus or an advanced math course within the first year. This showcases the important role that mathematics can play in a STEM major's curriculum. However, some students are not adequately prepared to handle the math that is required which can lead to attrition not only from the STEM major but from leaving college all together.

Purpose of the Study

The purpose of this study aimed to examine the role that midterm math performance can play on a student's final math performance, STEM performance, overall performance, as well as retention and graduation with a STEM major. The study also looked at whether there were differences in the midterm and final math performances between students who completed a STEM degree versus students who changed their major to a non-STEM major or left the institution.

Inadequate mathematics and science preparation in high school could greatly affect whether a student would decide to declare and retain a STEM major (Maltese, 2008). Thus, the student's performance in science and mathematics courses needs to be taken into account. Even if a student has interest in STEM, if a student is unable to keep up with their science and mathematics courses on the college level, the administration would not allow the student to continue in the major if they do not maintain the required grades.

Prior research has identified several factors which can predict enrollment, retention, persistence, and graduation of mathematics and science majors among college students, including personal demographic, environmental, and financial factors (Crisp et al., 2009; Heilbronner, 2009; Nicholls et al., 2010; Ost, 2010; Rask, 2010; Scott et al., 2009; Watkins & Mazur, 2013; Whalen & Shelley, 2010; Windsor et al., 2015).

However, in reviewing the significant amount of literature beyond the ones identified earlier, the role of math performance at the college level, especially at the midterm point, serving as a predictor of STEM retention or degree completion has barely been explored.

Theoretical Framework

Tinto (1975) analyzed the existing research on college completion and proposed a model of student persistence related to a commitment to the institution, academic goals, and career goals. He further stated that a student's grade point average (GPA) serves as the best indicator to predict whether a student would stay at an institution. This indicates that a higher GPA would lead to retention. It is important to note that if a student does not perform well, the administration may not allow them to continue. In other words, students are subject to academic dismissal if their progress toward a degree is not satisfactory. Beyond this, students may lose their financial aid when not making satisfactory academic progress toward a degree. This showcases the importance that early intervention and institutional supports can provide to improve a student's outcome.

One such example is midterm grades. Students generally have a midterm assessment that would be required allowing a student to evaluate how they are performing in their course. At this point, it would allow them to decide whether they were succeeding or should they consider withdrawing from the course. At the institution for which this study was conducted, faculty must enter the midterm grade for a first-time first-year student in the institutional system which is then entered into the institutional database. After the midterm grade deadline, a report card will be generated. It can then be accessed virtually and a copy is sent to the student's residence. This does not go on the student's permanent record. This information can allow administrators to provide

resources to the student to improve performance. However, would having the midterm grade information allow for predicting final performance, or even retention or graduation?

Tinto's (1975, 1993) Model of Institutional Departure includes pre-entry characteristics, academic integration variables, and social integration variables as reasons for why a student may decide to stay at an institution. However, Tinto's model does not address commuter students, which for the purpose of this study where majority of the students are commuters, it is important to include another theoretical model to support Tinto's theory. Bean and Metzner's (1985) Conceptual Model of Nontraditional Student Attrition has been found to be applicable to commuter students (J. Chen et al., 2020). For Bean and Metzner's model, they look at background and defined variables, academic performance, environmental variables, and intent to leave as factors.

Guided by both theories (Bean & Metzner, 1985; Tinto, 1975, 1993), demographic (gender and race/ethnicity), pre-college (high school GPA and SAT math scores), and college variables (midterm math performance, final math performance, STEM performance, and cumulative GPA) were included. The researcher also investigated how these variables have a relation to STEM student success outcomes (retention into the second year, third year, and graduation within six years as a STEM major).

Significance of the Study

The present study adds to the research on the predictive impact of math performance on academic success, retention, and graduation in STEM majors. As indicated earlier, at the institution for which this study was conducted, midterm grades

are entered in the system and at the moment, is mostly utilized by the student to assess whether they should continue their course or not. By utilizing this data, the institution can make data driven decisions that could possibly improve student outcomes. Each higher education institution obtains exorbitant amounts of information and it is important to take a look at how we can utilize existing information to assess ways to improve outcomes as most universities lack analytical abilities and may not have the means to benefit from all this data that exists (Attaran et al., 2018).

This study could aid administrators to make informed decisions on modifying course sequences to ensure timely completion of degrees, offer student support services, and provide early intervention before a student decides to attrite.

Research Questions

1. Along with demographic and pre-college variables, how does the midterm performance in gatekeeping math courses predict the gatekeeping math courses' final grade, STEM GPA, cumulative GPA, and STEM student success outcomes?
2. Along with demographic, pre-college variables, and midterm math performance, how does final performance in gatekeeping math courses predict STEM GPA, cumulative GPA, and STEM student success outcomes?
3. Along with demographic variables, pre-college variables, midterm and final math performance, how does STEM GPA predict cumulative GPA and STEM student success outcomes?
4. Along with demographic, pre-college variables, STEM performance college variables, how does cumulative GPA predict STEM student success outcomes?

5. How does the midterm performance in gatekeeping math courses for students who completed a STEM degree compare to students who changed their major to non-STEM or did not complete a degree?
6. How does final performance in gatekeeping math courses by students who completed a STEM degree compare to students who changed their major to non-STEM or did not complete a degree?

Definition of Terms

Gatekeeping courses (Weed-out courses)

Introductory and foundational courses that students will usually take during their freshman or sophomore year of college (Weston et al., 2019). These are generally prerequisite courses that students must take and usually taken in a series over a span of multiple semesters.

Graduation

Completion of a degree within six years which is 150% of the normal completion time for a bachelor's degree (Integrated Postsecondary Education Data System, n.d.) at the institution for which this study was conducted.

Midterm Performance

At the institution where the study was conducted, faculty are required to enter a midterm grade for all first-year students in their courses. The midterm grade is a grade assigned in the middle of a given semester. A midterm report card is generated, which can be accessed virtually via their student account and a physical copy will be sent to the student's residence. This information is also added into the institutional database.

Retention

There were two forms used: Retention into the second year (also known as first year retention) and retention into the third year (also known as second year retention).

STEM Completer(s)

Students who are admitted as a first-time first year undergraduate student in a STEM major and completed a STEM degree within six years.

STEM Leavers(s)

Students who are admitted as a first-time first year undergraduate student in a STEM major but changed to a non-STEM major or left the institution without completing a degree.

STEM Major(s)

The majors that were analyzed are housed in the liberal arts and sciences college of a university located in the northeast. They include biology, chemistry, environmental studies (ecology), mathematics, and physics (which includes physics, physical science, and mathematical physics).

STEM Student Success Outcomes

The majority of literature in relation to student success utilizes retention and graduation as successful outcomes. For the ease of the reader, STEM student success outcomes are defined as retention into the second year, retention into the third year, and graduation within six years while maintaining a STEM major throughout their college career.

CHAPTER 2 REVIEW OF RELATED LITERATURE

The desire to increase STEM graduates has continued for decades and studies have shown that attrition continues to be high for STEM majors (X. Chen, 2013, 2015; Mau, 2016; Scott et al., 2009; Weston, 2019). This study investigated the predictive nature of midterm math performance on various outcomes, including retention and graduation.

In this chapter, the existing literature was reviewed to describe the theoretical framework for which this study was guided by and the variables that were used in this study.

Theoretical Framework

Tinto's (1975, 1993) Model of Institutional Departure

If one mentions retention, Tinto's model quickly comes to mind. It is one of the most extensively utilized theory in regards to retention of a student in a higher education institution (Aljohani, 2016; Burke, 2019).

Tinto (1975) was one of the first theorists who explained the importance of a student's goal and institutional commitment which can lead to their decisions to stay or go. Aside from the many pre-college variables (ex., gender, high school GPA, etc.), there are academic integration (ex., grades, intellectual development, etc.) and social integration factors (ex. peer-group interactions, faculty interactions, etc.) that also play roles in whether a student would attrite. Almost two decades later, Tinto (1993) added that external commitments (ex., financial reasons, etc.) can also play a role whether a student would leave an institution. In other words, even if a student would like to stay

because they want to achieve a goal of obtaining a degree, as well as a strong tie to an institution, financial reasons can prevent a student from staying.

Tinto's theory was based upon Durkheim's theory of suicide (Tinto, 1975, 1993). Durkheim identifies four types of suicide, but Tinto mainly concentrates on egotistical suicide. Egotistical suicide happens when an individual is unable to assimilate within a community. This lack of integration can happen in the form of intellectual or social, or even both. Taking this into account, Tinto (1993) states, "*it highlights the ways in which the social and intellectual communities that make up a college come to influence the willingness of students to stay at that college*" (p. 104).

Adding to this, Tinto (1993) also cites the usage of Van Gennep and the Rites of Passage in the development of his model. There are three stages one must go through to transfer successfully into a new community, namely separation, transition, and incorporation. During the first stage of separation, one must separate themselves from their past community (ex. family, places of familiarity, etc.). Afterwards, the next stage is transition, the case of the transition from high school to college, a culture shock one could say. Finally, the stage of incorporation, where one has assimilated as part of the college community. The idea is if a student is unable to go through these rites of passage, then a student would likely leave the institution.

Since the development of the theory, it has been tested and utilized significantly which has given the model further validity and credibility of its usage (Aljohani, 2016). Multiple studies, guided by Tinto's theory, have found the importance of pre-entry attributes and academic integration (Gansemer-Topf et al., 2014; Lee & Ferrare, 2019; Xu, 2015). It is important to note that several studies have found that social integration

can only have a miniscule to no effect (Pascarella et al., 1981; Pascarella & Chapman, 1983) or even possibly have a negative impact (Pascarella et al., 1983). Even, Tinto indicated that he didn't believe that his model could really be applied to commuter institutions (Tinto, 1982). The institution that this study was conducted at has about 71% of students who live off-campus and commute. To account for this, the study was also guided by Bean and Metzner's (1985) Conceptual Model of Nontraditional Student Attrition.

Bean and Metzner's (1985) Conceptual Model of Nontraditional Student Attrition

In the case of Bean and Metzner's (1985) model, they indicate academic reasons are the most important factor for whether a non-traditional student would be retained at an institution. They defined non-traditional students as older (age 25 or older), part-time, or commuters. The authors state some of the other retention theories, including Tinto's, depend on the idea of the social aspect of college life too heavily and for the non-traditional student, they would not have the same priority. Bean and Metzner acknowledge the fact that background variables and academic variables from other theories should not be overlooked and included them in their model. They noted that environmental factors (ex. family responsibilities, finances, etc.) should be included as a factor for a non-traditional student. Thus, there are four variables within the model that are presented: background and defined variables, academic performance, environmental variables, and intent to leave. Various studies have shown the success of applying the theory to non-traditional students like commuters (J. Chen et al., 2020), veterans, (Southwell et al., 2018) and online students (Stephen et al., 2020).

Both theories have shown the importance of background variables prior to entry into college, as well as the importance of the academic factors which play a role on a student's decision of staying and persisting to graduation. Guided by both theories, the demographic and pre-college variables chosen are most applicable to the pre-entry attributes (Tinto, 1975, 1993) and background and defining variables (Bean & Metzner, 1985). The college variables fall into academic integration from Tinto's theory and academic variables from Bean and Metzner's theory.

Related Research

Demographic Variables

Gender. Lack of female representation in STEM fields is our greatest opportunity for growth. A National Center for Science and Engineering Statistics (NCSES, 2015) report indicated in 2012, 1.81 million students obtained bachelor's degrees of whom 57.4% were female. Of that 1.81 million, over 300 thousand students graduated with bachelor's degrees in STEM (16.9%), however only 38.5% of STEM graduates were female. Even though, there has been a significant increase of women obtaining bachelor's degrees in the last thirty years compared to their male counterparts (Goldin et al., 2006), the number of women graduating from STEM majors continues to remain relatively stagnant.

Sanabria and Penner (2017) found that there was no statistically significant difference between men who failed calculus and went on to complete a STEM degree and men who passed calculus and graduated with a STEM degree. However, it was a different story for women. They found there was a statistically significant difference between women who failed calculus and graduated with a STEM degree versus women who

passed calculus and completed a STEM degree. In other words, by failing calculus, it acted as a gatekeeper course in weeding out women from STEM majors.

Bloodhart et al. (2020) sought to look at a source of gender bias that many studies have not touched which was women's classmates in their STEM courses. The researchers looked at a sample of 2866 students' grades associated with 2720 students enrolled in nine STEM undergraduate courses, which were divided by life and physical sciences, at a large, western U.S. university. Of the 2720 students, they further analyzed 935 students who participated in a survey regarding how they perceived other students in their STEM courses.

The researchers believed they were one of the first studies where in their sample the women outperformed men in life and physical science courses, as well as likely earning an A or A+ at 1.5 times the rate compared to men and having higher cumulative GPAs comparatively. Even though this was the case, men were still perceived as equal or better students by both men and women. In examining of the perception of other classmates, the researchers performed four separate linear multilevel models (utilizing gender and course type as predictor variables and individual classroom as a level-2 nesting variable) to look at the proportion of which gender students were more likely to choose when it came to: who to study with, who to ask for help, believe they were most knowledgeable on the subject matter, and considered the best student in class.

Even though the women consistently outperformed the men, they found men underestimated their women classmates in both life and physical science fields more often than women did. In the physical sciences, it was consistent that women and men were more likely to choose men who they could obtain help, believed to be more

knowledgeable, and were the best performers in class. It fared a little better in the life sciences where men were equally likely to choose either gender in all four categories, while women were likely to choose either gender equally to be best in the class but would more likely choose a woman in all other categories. This indicates the continual perpetual existence of gender bias in undergraduate STEM courses, even amongst their peers.

The self-perception of one's performance in mathematics also plays a role in a woman's decision to declare a STEM major. If a woman has a low math self-concept, it lowers the chances for her to declare a major in STEM (Sax et al., 2015). Women's mathematical confidence plays a significant role as well in whether they may likely continue in calculus or STEM in general (Ellis et al., 2016). Along with gender, where women tended to leave the STEM major, we see a reflection of this in race and ethnicity as well.

Race/Ethnicity. An NCSSES (2021) report indicated in 2018, over 1.9 million students obtained bachelor's degrees. Of that 2 million, over 389,000 students graduated with bachelor's degrees in STEM (20.4%). Out of these 389,000 students, approximately 236,000 were White (60.7%), about 51,000 were Asian (13.1%), around 24,000 were Black (6.3%), roughly 49,000 were Hispanic (12.5%), about 1,500 were American Indian or an Alaskan Native (0.4%), over 700 were Hawaiian or a Pacific Islander (0.2%), about 15,000 were more than one race (3.9%), and approximately 12,000 were considered other or did not report their ethnicity (3.0%). Interestingly, while Whites continue to earn majority of STEM degrees, a previous NCSSES (2015) report stated that Asians are more likely than Whites and other underrepresented minorities to earn a college degree in STEM. In other words, Asians are part of the well-represented majority. The report also

notes that Whites and Asians are more likely to finish high school, continue into college, and complete a college degree.

Palmer et al. (2011) conducted a study to look for important factors of retention of STEM students of color in a predominantly White institution. The sample consisted of six students, one junior and five seniors, whose average GPA was 3.5. The authors utilized face-to-face in-depth interview methods to look at student's academic and social experiences, which they recorded. Follow-up telephone interviews were done as well.

The researchers used constant comparative analysis to find recurring topics. They also used open coding as well to look for themes and continued to do so until the point of redundancy. The authors made self-reflective notes when collecting and transcribing data.

There were three main themes that the authors found: (a) peer group support, (b) involvement in STEM related activities, and (c) strong high school preparation. For the first theme, the participants described peer support as giving them a positive social network and they also had support for their academic work. The participants also explained the importance of having peers who had the same goals and were supportive of each other in the STEM major. One student even indicated that he initially felt he did not fit in but was able to form a study group with the few students of color in his classes and they have come to be like his family. The second theme showcased the importance of being involved in STEM-related extracurricular activities. For this study, extracurricular STEM activities consisted of being a teaching assistant, being a part of STEM summer programs, getting involved in STEM student organizations, etc. All the participants cited these activities as being great accompaniment to their STEM courses. Though some participants indicated that they did not get involved during their first year due to the

possibility of affecting their studies, one student found that by joining a club it may actually help to ease some of the pressure he was having from classes. The third theme highlighted by the researchers were the students' indications that they had strong high school preparation. One student indicated how his Advanced Placement (AP) courses prepared him for the intensity of college level courses. Another student discussed how his mother moved him and his brother to ensure they would attend the best high school. As indicated in the previous research, having a strong high school preparation seems to be a fairly important factor for STEM persistence.

Pre-College Variables

SAT Math Scores and High School GPA. For Fall 2022 admissions, over 1700 Colleges and Universities are going SAT/ACT optional when evaluating a prospective student for admission (FairTest, 2021). Could this mean the SAT/ACT may not be adequately assessing students whether they are ready for college? Atuahene and Russel (2016) attempts to address the predictive power that the SAT-math score has on a student's successful completion of a college-level math course. Their sample consisted of 1315 freshmen admitted in Fall 2009 and Fall 2010 who completed at least one math course (developmental math, introduction to math, college algebra, algebra and trigonometry, calculus-based courses, and introduction to statistics).

In order to assess the predictor variable of SAT math scores, the researchers categorized the students into three groups: Group 1 consisted of students with SAT math scores of 470 or less, group 2 included students who scored 480-580 on the SAT math portion, and group 3 comprised of students who received a SAT math score of 590 or higher. They grouped math courses into four categories, developmental-level courses,

algebra and trigonometry, calculus-based math, and basic statistics. Grades were also separated into five categories, excellent (A, A-), above average (B+, B, B-), average (C+, C, C-), below average (D+, D, D-), failure (F, Z).

Atuahene and Russel (2016) performed a multiple regression analysis to answer whether SAT math scores would serve as a good predictor for a students' success in their college level math course. They found that for each unit increase of the SAT math score, it predicted a .01 increase in a student's score in math when controlling for gender, ethnicity, and admission group. They also found that White students performed better than underrepresented minorities (0.29 higher). In the case of gender, the results found that for each unit increase for females, it increased their math grade. This study has shown that SAT math scores and college math performance have a relationship.

It is interesting to note that one would think successful completion of a higher-level math in high school would translate to STEM persistence in college. However, X. Chen (2013) found that students who completed calculus in high school had a greater possibility of switching from a STEM to a non-STEM major compared to students who only completed up to algebra II or trigonometry in high school. Although, many studies do indicate that high school GPA serves as a predictor for success in postsecondary education (Ackerman et al., 2013; Beersingh et al., 2013; Gansemer-Topf et al., 2014; Moakler & Kim, 2014; Stewart et al., 2015; Whalen & Shelley, 2010).

After looking at the pre-college variables, once a student enters college, how do they fare?

College Variables

College Retention and GPA. Is it really the case that GPA can serve as the best way of predicting that a student will stay at an institution? If this is the case, what factors can influence GPA? Kern et al. (1998) conducted a study to find which variables could predict GPA and attrition.

For their study, they had a usable sample of 102 students, all of which were volunteer participants and undergraduate students at a southwestern state university. The researchers obtained students' academic information (ACT scores, students' GPA, enrollment status) from the registrar. They also administered three different types of instruments to look at variables which could impact students' GPA and/or attrition.

One of the instruments utilized by the researchers was the Gibb Experimental Test of Testwiseness (GIBB). It is used to measure a student's test taking ability. Another instrument used by the authors was the Learning and Study Strategies Inventory (LASSI), which measures self-reported thoughts and behaviors linked to successful learning. The items from LASSI are separated into 10 subscales: attitude, motivation, time management, anxiety, concentration, information processing, selective main ideas, study aids, self-testing, and test strategies. The researchers found that motivation, time management, and concentration were highly intercorrelated and thus were combined. This new variable was labeled as focus. The last instrument used in the study was the short form of the Intellectual Achievement Responsibility Questionnaire (IARQ) which measures students' beliefs whether their academic success or failure was within their control and responsibility.

They found five variables had direct effects on GPA: ACT scores, information processing, selecting main ideas, self-testing, and the composite variable of focus (the last four were all from LASSI). For attrition, 22 out of their 102 students dropped out of college (21.6%). They found that only GPA had a direct effect on attrition. This indicates that while ACT scores and the four out of the eight subscales from LASSI did not have a direct impact on attrition, it certainly had an indirect impact since those five variables affected GPA. Through this study, it shows how much of a role GPA can play with relation to retention. Seeing how GPA can impact retention, can a higher education institution intervene before a final grade goes on permanent record to improve a student's performance at the midterm point?

Midterm Math Performance. The study conducted by Beersingh et al. (2013) were one of the very few that addressed math midterm performance and how it can predict students final math performance. The authors conducted the study at a historically Black institution and their sample consisted of 758 students who were a part of a summer bridge program between 2007 and 2010 who enrolled in the institution as a matriculated student after. The students in the program did not meet the minimum requirements for admission into the university. This program guaranteed admission for students who successfully completed the six-week program and earned at least a grade of C in the courses they were assigned.

The researchers conducted a logistic regression analysis to identify factors that predicted successful math performance. Guided by Astin's I-E-O model, Beersingh et al. (2013) utilized SAT scores (both verbal and math), high school GPA, gender, socioeconomic status, academic major (STEM, other major, undecided major), and

midterm grades as predictor variables. For the midterm grade, the researchers obtained the midterm grades (A-F) from students' midterm math examination performance. Students who received a C or higher were considered successful, while a student who received a D or failed was considered unsuccessful. The outcome variable was based on the performance in a gateway math course in their first year. Similar to the midterm math grade, the researchers coded students who received a C or higher as successful and those who received a D or F were coded as unsuccessful.

The researchers found that high school GPA, gender, and the midterm math grade were three significant predictors of whether a student would be successful in their first-year math course. For each point of increase in high school GPA, students were 1.33 times more likely to succeed in their first-year math course. In the case of gender, females were 1.65 times more likely to succeed in their first-year math course compared to males. The midterm grade had the greatest odds, for each point of increase, students were 82.74 times more likely to succeed in the math course.

The study conducted by Beersingh et al. (2013) highlights the importance of utilizing the midterm grade as a factor to provide resources for students to succeed before the final grade is a part of their permanent record. However, once it does become permanent record, how does their overall STEM performance play a role?

STEM Performance. Chen (2013) conducted one of the most comprehensive longitudinal studies on STEM admission and attrition. The author looked at data from 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09) along with the 2009 Postsecondary Education Transcript Study (PETS:09). The sample included roughly 7,800 first-time bachelor's degree students and about 5,600 first-time associate's

degree students. In reviewing this literature, the following information will focus on bachelor's degree students.

The researcher conducted a bivariate analysis and found more females compared to males tend to leave STEM by switching to a non-STEM field. Interestingly, the opposite held true, more males as opposed to females left STEM by leaving college all together. In relation to race and ethnicity, Asians tended to be able to persist in STEM and dropped out at a lower rate compared to the other race and ethnic groups in the study. Furthermore, more Black students switched out of a STEM major to a non-STEM major compared to Asians and Whites.

STEM performance can be an important factor for why a student may stay or withdraw from STEM. Chen's research also delves into this and found that first-year STEM admits who withdraw from their institution had a STEM GPA of 2.3 in their first year, first-year STEM admits who change their major had a STEM GPA of 2.6 during the same time, while STEM persisters average a STEM GPA of 3.0 within their first year of enrollment.

The author conducted a multinomial probit analysis to look at various factors at the same time and how each can be related to STEM attrition. The independent variables included in the model were demographic (sex, race/ethnicity, parental education, and income), pre-college academic (high school GPA and highest level of math course taken), institutional context (how selective and the level and control of the institution the student first attended), first-year STEM related (percentage of STEM credits earned out of all credits, highest level of mathematics completed, and students' STEM GPA compared to their non-STEM GPA), and other factors through 2009 (percentage of STEM courses out

of all STEM courses attempted where students' have failed or withdrawn, STEM GPA compared with their non-STEM GPA, and cumulative GPA). The dependent variables included were whether a student changed out of a STEM major to a non-STEM major or left the institution without completion of a degree.

From the multinomial probit model, the author found that the amount of STEM courses and the level of math courses completed during the first year, along with overall STEM performance and the percentage of withdrawn or failed STEM courses out of all attempted STEM courses were the most important elements in relation to whether students switch out of STEM to non-STEM. First-time STEM students with a lower amount of STEM credits in their first year had a higher probability of switching out of a STEM major when compared to students with a higher amount of STEM credits in their first year. Students who completed introductory math courses had a higher chance of switching to non-STEM versus students who took calculus or advanced math courses in the first year. Another thing to note was those whose non-STEM grades were higher than their STEM grades had a higher probability of switching from STEM to non-STEM compared to those who had equal or higher STEM grades versus their non-STEM grades.

Interestingly, the researcher found that none of the demographic variables were significantly related with the non-STEM switch compared to what was found when a bivariate analysis was conducted. Cumulative GPA was a surprising factor where students with a 3.5 or higher had a higher probability of changing to a non-STEM major compared to those who had less than 3.0.

For those who left an institution all together, one was likely to be male, from lower social economic status, or attended a selective higher education institution. Other

factors that contributed to a higher probability of a student leaving an institution without completing a degree included having a lower cumulative GPA and withdrawing or failing from STEM courses.

Chen's research touches on the role that math courses and the students' performance in these courses can play in relation to STEM to non-STEM major changes and withdrawal from institutions. Is math a part of the so-called "gatekeeping" courses that prevent students from persisting in STEM?

Gatekeeping/Weed-Out Courses and Math Performance. The term gatekeeping or weed-out courses have existed for years, if not decades, in relation to STEM curriculum. The belief that STEM is so difficult that only the best of the best can make it through has likely had an impact on students not being able to persist considering most drop out or change their major within their first year after underperforming in these gatekeeping courses (Rask, 2010).

Weston et al. (2019) interviewed students about what makes a course a "weed-out" course. Seven categories emerged: assessments that consist of material that are not in alignment with the content, curved grading, quicker pace and heavy load, course material too hard or abstract for an introductory course, lecture style that consists of memorization of material and dry content, teaching the material to one-self, and the competitiveness within the weed-out courses. The interviewees indicated these seven categories created detrimental consequences of STEM attrition. Unsurprisingly, the same result was found from a similar study conducted twenty years ago (Seymour & Hewitt, 1997).

Weston et al. (2019) discusses about courses that "weed-out" student from the STEM major. They identified that calculus and chemistry courses had the highest instances of students receiving a D, F, or incomplete/withdrawal grades at an average of 20%. Of the 85 students who responded about their weed-out experiences, 50 (59%) of the students decided to change their major due to these experiences.

Weston et al. (2019) conducted a study on the patterns of STEM attrition by analyzing institutional records from six institutions. The sample consisted of 14,573 students and of those students, 13.8% (2020) switched to a different major from their original STEM major. The authors conducted a logistic regression analysis utilizing first semester cumulative GPA, number of incompletes or withdrawals in weed-out courses and non-weed-out courses, number of D's or F's in weed-out courses and non-weed-out courses, SAT/ACT math score, number of courses that have been repeated, gender, underrepresented minorities, average course difficulty, discipline, and institution as predictor variables. Number of semesters and class level were used as covariates. The criterion variable was whether a student switched out of their STEM major.

The researchers found that STEM switchers take more weed-out courses than persisters, 2.09 vs. 1.34, respectively. They also found for those who did not receive a D, F, withdrawal, or incomplete (DFWI) in a weed-out course, 12% of the students switched. Compared to those who received one DFWI in a weed-out course, 23% switched and those who received two DFWI, 33% of students switched out of their STEM major.

The researchers also noted that students with lower standardized math scores were more likely to switch out of their major compared to those with higher standardized math

scores, but that gap closes as the students receive one or two DFWI in weed-out courses. In the case of gender, the rates of switching increased proportionally when they received at least one DFWI in a weed-out course.

Weston et al. (2019) conducted a logistic regression analysis whether receiving a DFWI in a weed-out course predicted switching. They also sought to find out if it was a better predictor than obtaining a DFWI in a non-gatekeeping course. They found there was a significantly higher rate of switching when receiving at least one DFWI in a weed-out course compared to a non-weed-out course. Students who received a D or an F in a gatekeeping course had a 5% increased risk of switching and students who received an incomplete or withdrawal had a 4% increased risk of switching. While for students who received a DFWI in a non-gatekeeping course, they had a 2% increased risk of switching. Considering the fact that math houses quite a number of these weed-out courses, being successful in math could possibly mean whether a student would change their major or possibly leave an institution.

By performing well in math, could that lead to the retention and graduation of STEM majors?

STEM Retention and Graduation

STEM Retention. Ackerman et al. (2013) conducted a study based on the Trait-Complex approach which present the use of rather narrow individual traits to predict academic performance. They also wanted to look at traditional measures (ex. high school GPA) and domain knowledge (ex. AP scores) as variables to see if these variables could also predict academic performance. Their sample included 589 first-time freshmen enrolled in a transitional course (a course which helps to situate students into college).

The authors utilized the seven different measures. For motivational traits, two approach-oriented scales (desire to learn and mastery) and two avoidance-oriented scales (worry and emotionality in achievement contexts) were utilized from the Motivational Trait Questionnaire short form (MTQ). For personality, three scales of extroversion, openness to experience, and conscientiousness from the NEO-Five-Factor Inventory (NEO-FFI) and two scales of social potency and social closeness from the Multidimensional Personality Questionnaire (MPQ) were used. The authors used nine scales from the Motivated Strategies for Learning Questionnaire (MSLQ). These included test anxiety, intrinsic goal orientation, peer learning, metacognitive self-regulation, time and study environmental management, effort regulation, critical thinking, organization, and rehearsal. For self-concept, four scales from different domains of academic self-concept were given, which included verbal, math, spatial, and science. For self-estimates of abilities and skills, four scales of self-estimates were administered, which consisted of organizational skills, spatial and science abilities, verbal abilities, and math abilities. For numerical preferences, a shortened version of the Viswanathan's Preference for Numerical Information scale was administered. For life goals, the authors used two scales from a measure created by Roberts and Robins.

From the measures used, the authors created five trait complexes which encompasses the answers from the various measures: science/math self-concept, mastery/approach-achievement motivation, verbal/intellectual self-concept, avoidance in achievement contexts, and social/extroversion. The authors also obtained students' academic records, high school GPA, SAT scores, AP scores, college GPA, major, and enrollment status from the Office of Institutional Research and Planning at Georgia Tech.

The researchers found that high school GPA, SAT math scores, average AP scores, first year GPA, math/science self-concept, and mastery/organization were significant predictors whether a student would persist in STEM. While gender itself was not a significant predictor, when it interacted with two trait complexes (math/science self-concept and mastery/organization), it was found to be significant. This study shows that many factors play a role to increase the possibility a student would be retained, but would they be able to complete a degree in STEM?

STEM Degree Completion. Wolniak's (2016) study looks at factors which can influence STEM major selection, academic success, and degree completion in STEM fields. The author's sample consisted of about 7330 students obtained from the 2004/09 Beginning Postsecondary Students Longitudinal Study (BPS:04/09) data which includes first-time college students during 2003-2004 academic year. BPS:04/09 participants were surveyed at the end of their first year of college (2004), and after three (2006) and six years (2009) from when they first started college. The author recorded STEM degree completion as dichotomous, students who completed a STEM bachelor's degree in six years or the combination of students who did not complete a bachelor's degree in six years and students who completed a non-STEM bachelor's degree in six years. Other variables included were whether a student had a STEM major in their first year of college, level and type of financial aid received during first year of college, college academics and integration. Academic integration consisted of four 2004 and four 2006 survey items. Social integration consisted of three 2004 and three 2006 survey items. Students' college GPA, demographic, socioeconomic, high school performance measures, and various institutional measures (like level of school selectivity) were also included.

Similar to the study conducted by Moakler and Kim (2014), females were found to be less likely to declare a STEM major early. Another similarity was that African American students were more likely to declare a STEM major early. All high school performance measures were found to be a significant predictor of a student declaring a STEM major.

The author divided the sample into five groups of students' possibility of declaring a STEM major, from low to high propensity toward a STEM major when initially entering college. It was found that students who declare a STEM major in their first year of college would likely complete a STEM degree in six years. Cumulative GPA was another strong predictor of STEM degree completion. The author discovered that social integration had a significant negative impact on STEM degree completion among the students in the middle-low propensity group but a positive impact on the middle propensity group. Academic integration had a significant positive impact on the middle-low propensity group. This further indicates how much of a role GPA can play in a role of retention, which ultimately leads to graduation.

Importance of Early Intervention

As mentioned earlier, there is a significant lack of literature on the importance of how midterm grades may have an impact on final grades, as well as retention and graduation. It is important to note that early intervention can play a big role in a student's success (Coley et al., 2016). While many studies discuss ways to improve performance and retention through courses or programs prior to matriculation (Beersingh et al., 2013; Ghazzawi et al., 2021; Windsor et al., 2015), are there ways institutions can help students persist in STEM where they have started, possibly even before receiving a final grade?

Thiry (2019) conducted interviews of STEM persisters in their senior year. The sample consisted of 161 students who were further divided between those who had low and high math readiness. There were multiple factors the author grouped in relation to why students remained in STEM: individual characteristics, adjustments to behavior or identities, instrumental moves, and institutional and social supports.

In interviews with STEM persisters, the author noted that while only 25% of high math ready students indicated that seeking help when they did not perform well initially in their STEM courses contributed to their decision to stay in a STEM major, 61% of the low math ready students who sought help boosted their decision to stay in STEM (Thiry, 2019). In other words, students who received help especially when not performing well likely can increase the chances of them persisting in STEM.

The study further notes majority of students who were high-achieving high schoolers were shocked when they failed at the midterm point or received a C in a STEM gatekeeping course (Thiry, 2019). Students who switch out of STEM tended to be greatly affected by this due to the inability to overcome this feeling of failure and the women in this study were particularly susceptible to this. For the students who persisted in STEM, they saw this as an opportunity to adjust their methods in relation to their studying habits and learning and the men in the study tended to fall in this category. The interviews also revealed that STEM persisters were able to recognize that after a weak grade or performance in a course meant that they should seek out academic assistance to improve their performance. This highlights the importance of targeting those students who may not be performing well, even at the midterm point, and showcases that it could possibly have a relation to retention and graduation.

Conclusion

Aside from the studies mentioned, there are still many that touch on various factors which can predict enrollment, retention, persistence, and graduation of mathematics and science majors (Crisp, Nora, & Taggart, 2009; Heilbronner, 2009; Nicholls, Wolfe, Besterfield-Sacre, & Shuman, 2010; Ost, 2010; Rask, 2010; Scott, Tolson, & Huang, 2009; Watkins & Mazur, 2013; Whalen & Shelley, 2010; Windsor et al., 2015). The variables used in the multitude of studies do not look at math midterm performance on the college level as an indicator to link to STEM retention or degree completion. It has been noted that early intervention could possibly be an important factor in looking at a student who persists in STEM or switches and by utilizing math midterm performance, it can serve as another indicator to predict their final performance, retention, and graduation. Thus, this study focused on the hypothesis that a student's math midterm performance will be significantly correlated with their final math performance, STEM GPA, cumulative GPA, retention, and graduation.

CHAPTER 3 METHODOLOGY

The current literature showcases that there is a high amount of attrition from STEM majors, either through changing to a non-STEM major or leaving an institution all together. There is also literature on how math performance can relate to students leaving STEM majors. While there is a lack of existing studies based upon midterm math performance and how it relates to overall academic performance, retention, and graduation, prior studies have shown the importance of early intervention. As the midterm performance may serve as an important data point in improving a student's final and overall performance, this study aimed to explore how midterm grades in math courses can relate to academic achievement.

Tinto's (1975, 1993) Theory of Institutional Departure guided this study. Through his theory, utilizing pre-college variables and academic integration variables for this study seems to be most applicable, especially considering that several studies have shown that social integration can have little to no effect (Pascarella et al., 1981; Pascarella & Chapman, 1983) or even a negative effect (Pascarella et al., 1983). This study is further guided by Bean and Metzner's (1985) Conceptual Model of Nontraditional Student Attrition due to its applicability to commuter students since the institution from which this study was conducted have a majority of students who commute or live off campus.

The results of this study hope to aid administrators and faculty to create or modify policies and curriculum which will allow students the ability to remain and complete their degree timely in STEM. These results may also allow administrators to allocate resources to provide early intervention which can improve a student's academic integration at an institution.

Methods and Procedures

In this study, the researcher has employed a non-experimental correlational quantitative research design since the variables was not manipulated (Fraenkel et al., 2015). Further, a quantitative study is the most appropriate approach due to the variables being used to predict an outcome (Creswell & Guetterman, 2019).

Research Questions and Hypotheses

Research Question 1. Along with demographic and pre-college variables, how does the midterm performance in gatekeeping math courses predict the gatekeeping math courses' final grade, STEM GPA, cumulative GPA, and STEM student success outcomes?

Hypothesis 1. Null hypothesis: Demographic factors, pre-college variables, and midterm performance in gatekeeping math courses does not predict the gatekeeping math courses' final grade, STEM GPA, cumulative GPA, or STEM student success outcomes.

Alternate hypothesis: Demographic factors, pre-college variables, and midterm performance in gatekeeping math courses does predict the gatekeeping math courses' final grade, STEM GPA, cumulative GPA, or STEM student success outcomes.

Research Question 2. Along with demographic, pre-college variables, and midterm math performance, how does final performance in gatekeeping math courses predict STEM GPA, cumulative GPA, and STEM student success outcomes?

Hypothesis 2. Null hypothesis: Demographic factors, pre-college variables, midterm math performance and final performance in gatekeeping math courses does not predict STEM GPA, cumulative GPA, or STEM student success outcomes.

Alternate hypothesis: Demographic factors, pre-college variables, midterm math performance and final performance in gatekeeping math courses does predict STEM GPA, cumulative GPA, or STEM student success outcomes.

Research Question 3. Along with demographic variables, pre-college variables, midterm and final math performance, how does STEM GPA predict cumulative GPA and STEM student success outcomes?

Hypothesis 3. Null hypothesis: Demographic factors, pre-college variables, midterm and final math performance, and STEM GPA does not predict cumulative GPA or STEM student success outcomes.

Alternate hypothesis: Demographic factors, pre-college variables, midterm and final math performance, and STEM GPA does predict cumulative GPA or STEM student success outcomes.

Research Question 4. Along with demographic, pre-college variables, STEM performance college variables, how does cumulative GPA predict STEM student success outcomes?

Hypothesis 4. Null hypothesis: Demographic factors, pre-college variables, midterm and final math performance, STEM GPA, and cumulative GPA does not predict STEM student success outcomes.

Alternate hypothesis: Demographic factors, pre-college variables, midterm and final math performance, STEM GPA, and cumulative GPA does predict STEM student success outcomes.

Research Question 5. How does the midterm performance in gatekeeping math courses for students who completed a STEM degree compare to students who changed their major to non-STEM or did not complete a degree?

Hypothesis 5. Null hypothesis: The means of the midterm performance in gatekeeping math courses for students who completed a STEM degree and students who changed their major to a non-STEM major or did not complete a degree are equal.

Alternative hypothesis: The means of the midterm performance in gatekeeping math courses for students who completed a STEM degree and students who changed their major to a non-STEM major or did not complete a degree are not equal.

Research Question 6. How does final performance in gatekeeping math courses by students who completed a STEM degree compare to students who changed their major to non-STEM or did not complete a degree?

Hypothesis 6. Null hypothesis: The means of the final performance in gatekeeping math courses for students who completed a STEM degree and students who changed their major to a non-STEM major or did not complete a degree are equal.

Alternative hypothesis: The means of the final performance in gatekeeping math courses for students who completed a STEM degree and students who changed their major to a non-STEM major or did not complete a degree are not equal.

Research Design

As indicated earlier, the researcher has utilized a non-experimental correlational quantitative research design. This study distinguished various variables which predicted an outcome (Creswell & Guetterman, 2019). A non-random purposive sample has been used. It is most appropriate since the sample chosen was predetermined by the researcher

as representative of the population of the study (Fraenkel et al., 2015), observing only students who were first-time undergraduate STEM majors in a liberal arts and sciences college within a university located in the northeast. For the purpose of this study and to ensure confidentiality, the college and university will be assigned pseudonyms: Caldeum College and Tristram University.

Descriptive statistics have been provided prior to analyzing the research questions. For the first four research questions, multiple and logistic regression has been used. For the latter three research questions, independent-samples *t*-tests were utilized.

Predictor and Outcome Variables for Research Questions 1-4. As shown in Table 1, the predictor and outcome variables are listed and were used to analyze research questions 1-4.

Table 1*Predictor and Outcome Variables for Research Questions 1-4*

Variables	Type of variable
Predictor variables	
Demographic variables	
Gender	Categorical (Male/Female)
Race/ethnicity	Categorical (7 Levels)
Pre-College variables	
SAT math scores/ACT math equivalent	Continuous (200-800)
High school GPA	Continuous (0 – 100)
College variables	
Midterm math performance	Continuous (0.0 – 4.0)
Final math performance	Continuous (0.0 – 4.0)
STEM GPA	Continuous (0.00 – 4.00)
Cumulative GPA	Continuous (0.00 – 4.00)
Outcome variables	
Final math performance	Continuous (0.0 – 4.0)
STEM GPA	Continuous (0.00 – 4.00)
Cumulative GPA	Continuous (0.00 – 4.00)
STEM Student Success Outcomes	
Retention into the second year	Categorical (Yes/No)
Retention into the third year	Categorical (Yes/No)
Graduation within six years	Categorical (Yes/No)

In order to accurately conduct multiple and logistic regressions, the race/ethnicity variable was a categorical variable with seven levels. Due to this, it was dummy coded into six binary (0, 1) dummy variables utilizing White as the comparison group as shown in Table 2.

Table 2*Dummy Coding of Race/Ethnicity Variable*

	<i>n</i>	Parameter coding					
		(1)	(2)	(3)	(4)	(5)	(6)
2 or more races	18	1	0	0	0	0	0
Asian	84	0	1	0	0	0	0
Black	56	0	0	1	0	0	0
Hispanic	31	0	0	0	1	0	0
Non-resident	10	0	0	0	0	1	0
Unknown	16	0	0	0	0	0	1
White	68	0	0	0	0	0	0

The midterm and final math performance included grades from the following courses: Calculus I, Calculus II, University Calculus I, University Calculus II, Calculus with Biological Applications, Calculus with Business Applications, Calculus Applications for Pharmacy and Allied Health, Pre-Calculus with Business Applications, College Algebra and Trigonometry (Pre-Calculus), College Algebra, Introduction to College Mathematics I, Introduction to College Mathematics II, Bio-Statistics, Statistical Applications for Pharmacy and Allied Health, Applied Statistics I, Introduction to Statistics, Probability and Statistics I, Probability and Statistics II, Mathematics for the Elementary School Teacher, Fundamentals of Mathematics I, and Mathematics for Liberal Arts. The STEM GPA consisted of all science and math courses taken by a student. The cumulative GPA included all grades from a student's college career.

Independent and Dependent Variables for Research Questions 5 and 6. As shown in Table 3, the independent and dependent variables are provided to answer research questions 5 and 6.

Table 3*Independent and Dependent Variables for Research Questions 5 and 6*

Variables	Type of variable
Independent variables	
Completion of a STEM degree	Categorical
Graduated with a STEM major	
Left the institution or changed major	
Dependent variables	
Midterm math performance	Continuous (0.0 – 4.0)
Final math performance	Continuous (0.0 – 4.0)

Data Analysis

Data has been collected from the Office of Institutional Research (OIR) and a codebook of the variables was developed to ensure there will be consistency throughout the study (Creswell & Guetterman, 2019). This also allowed for easy reference when the data was inputted into SPSS software for analysis. For example, in the case of the gender variable, it has been coded as 0 = Female and 1 = Male.

The data was ran through SPSS and has been cleaned and assessed to ensure the integrity of the data and taken into account inaccuracies and missing data (Creswell & Guetterman, 2019). For example, it is important to differentiate between a failure or a withdrawal from a course when a student may have a 0.00 grade point average. A failure is factored into one's GPA while a withdrawal, either officially or unofficially, would not impact one's GPA at the institution for which this study was conducted.

In the case of missing data, several students were missing SAT math scores. Per Tristram University's undergraduate bulletin, new freshman applicants must submit SAT or ACT scores to the institution for evaluation (Redacted, 2013). For the Fall 2014 STEM

cohort, those that were missing SAT math scores submitted ACT scores which included ACT math. To ensure there was consistency, the admissions office at Tristram University utilized concordance tables to generate an equivalent SAT math score for ACT math scores. The researcher was able to obtain the concordance table from that time period and updated the equivalent SAT math scores accordingly.

Prior to answering the research questions, descriptive statistics have been provided. It is essential due to the exorbitant amount of data that has been utilized in the study to summarize each variable, otherwise it would have become unmanageable (Fraenkel et al., 2015). Frequency information was provided for the categorical predictor variables from research questions 1-4 and the independent variables from questions 5 and 6. The means and standard deviation information has been provided for continuous predictor variables.

For the first three research questions, multiple regression is the most appropriate method due to the use of several variables to predict a continuous or discrete variable (Grimm & Yarnold, 2010; Meyers et al., 2013). In the case of research questions 1-4, binary logistic regression is also applicable to the analysis since the predictor variables can be quantitative or categorical in nature while the outcome variable must be dichotomous which will be used for the first four research questions. Multiple and logistic regression has allowed the researcher to look at the predictive nature of midterm mathematics performance and academic attrition and achievement.

For the last two research questions, independent samples *t*-test was performed. This statistical test is appropriate since there will be a comparison of the means (a

continuous dependent variable) for two groups within the independent variable (Creswell & Guetterman, 2019; Gall et al., 2014).

Multiple Regression. There are considerations and assumptions that must be made in relation to multiple regression and must be tested to ensure the reliability of the models. Multicollinearity must be addressed to ensure there does not exist a high correlation amongst the predictor variables (Grimm & Yarnold, 2010). The researcher has created a correlation matrix reviewing the Pearson product-moment correlation coefficients for each pair of predictor variables listed in Table 1, which is the most commonly utilized technique to check for correlations. (Gall et al., 2014). It is recommended that most researchers would consider correlations of predictor variables where $r > .80$ to be highly intercorrelated and may jeopardize the results of the multiple regression model (Grimm & Yarnold, 2010). Even more stringent, Meyers et al. (2013) indicates that when two predictor variables are highly correlated where $r > .70$, one should consider only using one of the two predictor variables. Meyers et al. (2013) also suggest evaluating the tolerance and variance inflation factor (VIF) when testing for multicollinearity.

There are assumptions that Grimm and Yarnold (2010) discusses that falls into three categories which must be true in order to use multiple regression. The first category is in relation to residual scores. To ensure the integrity of the analysis, residual scores should have homoscedasticity, be normally distributed, and must be independent of each other, including the predictor variables. Outliers must be verified to be accurate, and the researcher has completed analyses to ensure if there were any substantial differences between the models produced. To test for homoscedasticity, Levene's test has been

conducted (Meyers et al., 2013). For normal distribution, a Q-Q Plot was produced. In the case of independence of errors, Durbin-Watson statistic has been computed. Lewis-Beck (1980) notes that a moderate level of violations of these assumptions in relation to residual scores may not necessarily cause problems.

The second category are specification errors (Grimm & Yarnold, 2010). To prevent specification errors, one must ensure there is a linear relationship between the criterion variable and the predictor variable individually and collectively, that all related predictor variables are included in the model, and unrelated predictor variables should be omitted. The researcher has performed a scatterplot as recommended by Meyers et al. (2013) to ensure a linear relation between the outcome variables and predictor variables. For the latter two criteria, guided by Tinto's (1975, 1993) Model of Institutional Departure and Bean and Metzner's (1985) Conceptual Model for Nontraditional Student Attrition should help to minimize specification errors. For example, utilizing GPA as a variable would be appropriate and related to academic integration (Tinto) and academic performance (Bean and Metzner).

The third category are measurement errors (Grimm & Yarnold, 2010) which is not applicable to this study since measures were not utilized.

Once lack of multicollinearity and all other assumptions have been met, the researcher analyzed the raw and standardized beta coefficients of each predictor variable. Additionally, R^2 has been evaluated to examine the strength of the relationships between the predictor and outcome variables. F ratios were reviewed to see whether the percentage of the variance of the criterion variable were statistically significant. The level of statistical significance was set at $p < .05$ as recommended and widely used by

researchers (Creswell & Guetterman, 2019; Fraenkel et al., 2015; Gall et al., 2014; Grimm & Yarnold, 2010; Meyers et al., 2013).

For this study, bivariate correlations were computed and then separate multiple regression analyses have been conducted to address the first three research questions. The race/ethnicity variable was a categorical variable with seven levels and was dummy coded into six binary (0, 1) dummy variables as shown in Table 2.

First, final math performance was regressed on demographic variables (gender and race/ethnicity), pre-college variables (SAT math scores and high school GPA), and midterm math performance.

Second, a multiple regression analysis was performed by regressing STEM GPA on demographic, pre-college, midterm and final math performance.

Finally, cumulative GPA was regressed on demographic, pre-college, midterm and final math performance, and STEM GPA.

Logistic Regression. There are seven assumptions that must be met to utilize logistic regression (Meyers et al., 2013). First, the dependent variable must be dichotomous. The categorical outcome variables utilized in this study to answer research questions 1-4 are dichotomous which met the first assumption. Next, the outcome variable in the model needs to be statistically independent. The data has been cleaned and verified to ensure the second assumption was met.

Third, the model must contain all related predictors and no irrelevant predictors, also known as specificity assumption. Similar to the multiple regression assumption on specification errors, the predictor variables were chosen with Tinto's (1975, 1993) Model

of Institutional Departure and Bean and Metzner's (1985) Conceptual Model of Nontraditional Student Attrition in mind.

Fourth, the criterion variables and all categorical predictor variables must be mutually exclusive and exhaustive. All categorical predictors and outcome variables have been evaluated to be mutually exclusive and exhaustive. For example, in the case of graduation, one can be graduated or not graduated. Fifth, multicollinearity was addressed and the VIF statistic and tolerance was assessed not to be higher than 10 and .1, respectively.

Sixth, continuous independent variables must be linearly related to the log odds of the dependent variable. The Box-Tidwell test (1962) was performed to confirm this.

Lastly, a sufficiently large sample size should be used. Hosmer et al. (2013) states 10 cases per predictor variables is enough. The sample size for this study certainly meets this criterion.

After all assumptions were met, Nagelkerke R^2 has been assessed for the variance between the outcome variables and the predictor variables (Meyers et al., 2013). The statistical significance of the model (χ^2) was reviewed and was also set as $p < .05$. Each predictor has been evaluated with the Wald coefficient. To assess a predicted probability of an event happening, an examination of $\text{Exp}(B)$ (odds ratio) was completed. For statistically significant predictor variables greater than one, this signifies that for each unit (X) of the odds ratio in the predictor variable, the outcome variable will be X times more likely to fall into the group coded as 1. For significant predictors less than one, it will be recomputed to $1/\text{Exp}(B)$ and for each unit (X) of the odds ratio, the criterion variable will be X times more likely to be in the group coded as 0.

In this study, logistic regression analyses have been performed to answer research questions 1-4.

To answer the first research question, logistic regression analyses regressing STEM student success outcomes (retention into the second year, retention into the third year, and graduation within six years as STEM majors) on demographic variables, pre-college variables, and midterm math performance were performed.

For the second research question, STEM student success outcomes were regressed on demographic variables, pre-college variables, midterm and final math performance.

In the case of the third research question, three binary logistic regression analyses have been performed by regressing STEM student success outcomes on demographic variables, pre-college variables, midterm and final math performance, and STEM GPA.

Finally, to answer the fourth research question, STEM student success outcomes were regressed on demographic variables, pre-college variables, midterm and final math performance, and STEM and cumulative GPA.

Independent samples *t*-test. For the latter two research questions, independent samples *t*-tests have been utilized and is considered to be suitable due to the comparison of two mean scores between independent groups (Fraenkel et al., 2015). This showcases the importance of faculty entering a midterm grade into the institutional system by comparing the means of STEM completers and STEM leavers.

For independent samples *t*-test, two assumptions, normality and homogeneity of variance, must be met (Meyers et al., 2013). A visual assessment of normality was conducted via a Normal Q-Q Plot. Levene's test for equality of variances was conducted to check for homogeneity of variance. If assumptions are met, the *t*-test performed was

two tailed with an alpha level set as $p < .05$ (Creswell & Guetterman, 2019; Gall et al., 2014; Meyers et al., 2013). If the assumption of normality has been met but the homogeneity of variance has been violated, a Welch's t -test will be performed instead with the same alpha level set to $p < .05$ (Howell, 2010).

To answer the fifth research question, an independent samples t -test has been performed by comparing the midterm performance in gatekeeping math courses between students who completed a STEM degree (STEM completers) and students who either did not complete a degree or changed to a non-STEM major (STEM leavers).

For the sixth research question, a t -test for independent means was conducted to compare STEM completers and STEM leavers in their final performance in gatekeeping math courses.

Reliability and Validity of the Research Design

For a correlational study, internal and external threats to validity can occur (Fraenkel et al., 2015). Selection bias may be an internal threat to validity. Similarly, due to the usage of purposive sampling, biasness is likely to occur. To minimize this, all STEM majors have been included in the study and subjects did not have contact with the researcher. Mortality is a possible threat to external validity which was minimized in this study by maximizing the sample and ensuring data from all STEM students were obtained. Additionally, considering the utilization of a purposive sample, generalization to a population may not be possible which may influence the external validity. To minimize this, thorough detail about the sample has been provided by the researcher.

Note that for a correlational study, it is recommended that a minimum sample size of 30 is acceptable by majority of researchers and will deliver a better approximation of

how the variables are related (Creswell & Guetterman, 2019; Fraenkel et al., 2015). In the case of logistic regression models, a minimum sample size of 10 for each predictor variable is adequate (Hosmer et al., 2013). The final sample size for this study was 283 which meets this minimum threshold.

To ensure the reliability of the data considering the usage of multiple regression, multicollinearity has been addressed. If there exist intercorrelation between the predictor variables, the multiple regression models may be affected (Grimm & Yarnold, 2010). In other words, bivariate correlations of the various pairs of predictor variables were conducted to ensure there were no highly correlated pairs.

Sample

The sample that was used in this study consisted of first-time undergraduate students who enrolled within a liberal arts and sciences college at a private, not-for-profit, urban, highly diverse university located in the northeast in Fall 2014. The institution is Carnegie classified as a Doctoral/Professional University and has a student population of 20,143 as of Fall 2020. The cohort consist of over 300 students accepted into STEM majors (Redacted, 2014). These majors include biology, chemistry, environmental studies (ecology), mathematics, and physics (which includes physics, mathematical physics, and physical science). The student sample is made up of traditional college age students between the ages of 18 and 24. All data utilized in this study has been obtained via the institutional research database. Descriptive statistics of the sample are provided in Chapter 4, see Tables 4-8.

Instruments

Instruments were not used in this study.

Treatment/Intervention

Treatments or interventions have not been utilized in this study.

Procedures for Collecting Data

The Office of Institutional Research (OIR) was contacted to obtain the data required for this study. The data obtained for the study were from past student records during the Fall 2014 to Spring 2020 semesters (six academic years). Data included first-time undergraduate students of traditional college age (between the ages of 18 and 24) who were declared a STEM major upon admission.

Upon approval of the dissertation proposal, a St. John's University Institutional Review Board (IRB) exempt application was submitted. It is most appropriate to submit an IRB exempt application since the study was completed in an established educational setting and encompassed the research of existing data and records which had non-identifiable information that cannot be linked back to the subjects. A modification of the original IRB approval was submitted to St. John's University IRB upon inspection of the data and Math ACT scores needed to be requested.

Due to administrative delays from lack of administrative staff, the study was unable to be completed in the Fall 2022 semester as planned and was deferred to the Spring 2023 semester.

Research Ethics

Data for the study has been obtained from the OIR. To ensure data integrity and confidentiality, the researcher has verified the data acquired did not have subject identifiers. Furthermore, the raw data has only been viewed by the researcher and their mentor and was stored and encrypted. Secondary data has been utilized so that there is no

link to the original student, faculty, or course information to maintain confidentiality and minimize any undue assumptions that could have arisen.

Conclusion

This chapter highlighted the usage of a non-experimental correlational research design for this study. The purposeful sample of a cohort of STEM majors has been analyzed utilizing multiple and logistic regression and independent samples *t*-tests in the following chapter, which will also include the limitations of the study.

CHAPTER 4 RESULTS

The purpose of this study investigated the impact of midterm mathematics performance on academic performance, retention, and graduation outcomes at a private, not-for-profit, urban, highly diverse university located in the northeast. As mentioned in Chapter 3, the sample consists of students who were declared as a STEM major within a liberal arts and sciences college and entered as a first-time undergraduate student in Fall 2014. For the purpose of this study, academic performance consisted of a student's midterm math GPA, final math GPA, STEM GPA, and cumulative GPA. Further, retention into the second and third year, and finally graduation in a STEM major within six years were utilized as successful outcomes.

Research questions introduced in Chapters 1 and 3 have been analyzed and findings were presented in this chapter.

Descriptive Statistics

Tables 4-6 shows descriptive statistics of the cohort of students who were admitted as STEM majors in Fall 2014 and their academic performance indicators from six academic years (September 2014 – May 2020). The final sample consisted of 283 students. Of the sample, 60.8% were female and 39.2% were male. Females, on average, outperformed males with regards to their high school GPA, midterm math GPA, final math GPA, STEM GPA, and cumulative GPA. SAT math score was the only performance indicator where males performed better on average compared to females.

In relation to admitted majors, the majority were biology majors making up 75.6% of the sample, 13.1% were chemistry majors, 0.7% were environmental studies majors, 2.8% were mathematics majors, and 7.8% were physics majors. While

environmental studies majors outperformed other majors on all performance indicators, there were only two students in the sample which may not be accurate to be used for comparison. Considering the other majors without environmental studies, mathematics majors had, on average, outperformed others in high school GPA, SAT math score, final math GPA, STEM GPA, and cumulative GPA. However, in relation to the midterm math GPA, biology majors on average performed better compared to the others. This is interesting because math majors were able to then perform better than biology majors at the final point even though biology majors did better at the midterm point.

For race/ethnicity, 6.4% of students identified as 2 or more races, 29.7% identified as Asian, 19.8% identified as Black, 11% identified as Hispanic, 3.5% were non-residents, 5.6% were unknown, and 24% identified as White. Non-resident students outperformed all other students in performance indicators with the exception of high school GPA. Examining the other races/ethnicities without non-residents, White students had a better high school GPA, midterm math GPA, final math GPA, STEM GPA, and cumulative GPA on average compared to the others. Only in the case of the SAT math scores did students who identified as Asians outperformed White students, when not taking non-resident students into account.

Tables 7-8 shows descriptive statistics of the same cohort and their STEM student success outcomes. Females compared to males had a higher percentage of being retained into the second year, third year, and graduate as a STEM major within six years.

In relation to initial major, the two environmental studies majors were able to be retained and graduated as STEM. Looking at other majors, physics had the highest percentage of being retained into the second year at 72.7%. By the third year, biology and

physics majors had a similar percentage retained as the highest at 50%. Biology majors had the largest percentage who were able to graduate as STEM majors in six years when not taking environmental studies into account at 43%.

An analysis of race/ethnicity, 2 or more races had the highest percentage of students being retained in the second year, third year, and graduation as STEM majors. Interestingly, Black students had a fairly high percentage of being retained into the second year as a STEM major at 69.6% but by the third year it dropped to only 41.1%. Hispanic students also had a fairly big drop from retention into the second year at 51.6% being retained to only 25.8% retained into the third year. When looking at underrepresented minorities (URM) in STEM consisting of Black and Hispanic students compared to the non-underrepresented minorities (non-URM) of Whites and Asians (NCSES, 2015), both URM and non-URM were retained into the second year at the same percentage of 63.2%. However by the third year, URM students retained was only 35.6% compared to non-URM students at 50.7%. By graduation, URM dropped down to 31% versus non-URM of 42.1%

Looking at the total sample, 63.6% were retained into the second year as STEM but by the third year, it dropped to 46.6%, which then led to a final drop to 40.3% of students graduating as STEM majors.

Table 4*Descriptive Statistics of First-time Full-time Undergraduate STEM Students:**Pre-College Academic Performance Outcomes*

	<i>n</i>	High School GPA		SAT Math Score	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Gender					
Female	172	91.22	5.08	579.71	66.65
Male	111	88.84	5.52	604.86	75.23
Major					
Biology	214	90.23	5.29	580.47	66.80
Chemistry	37	90.35	5.93	620.54	79.41
Env. Studies	2	95.00	—	690.00	14.14
Mathematics	8	94.00	6.19	633.75	64.79
Physics	22	88.91	4.70	600.91	77.45
Race/Ethnicity					
2 or more races	18	91.11	5.26	579.44	56.41
Asian	84	91.42	5.40	613.33	76.12
Black	56	86.71	4.67	550.36	49.21
Hispanic	31	89.39	4.77	561.29	51.17
Non-resident	10	90.80	6.80	658.00	86.51
Unknown	16	90.19	4.39	600.00	77.97
White	68	91.97	4.91	595.59	67.85
Total	283	90.29	5.38	589.58	71.08

Table 5*Descriptive Statistics of First-time Full-time Undergraduate STEM Students:**Math Performance Outcomes*

	<i>n</i>	Midterm Math GPA		Final Math GPA	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Gender					
Female	172	2.96	1.11	3.17	1.05
Male	111	2.58	1.20	2.84	1.08
Major					
Biology	214	2.94	1.07	3.12	1.02
Chemistry	37	2.37	1.33	2.66	1.21
Env. Studies	2	3.65	.49	4.00	—
Mathematics	8	2.83	1.20	3.77	.20
Physics	22	2.18	1.32	2.56	1.25
Race/Ethnicity					
2 or more races	18	2.61	1.42	2.69	1.43
Asian	84	2.92	1.12	3.15	1.03
Black	56	2.52	1.07	2.73	1.06
Hispanic	31	2.32	1.34	2.59	1.07
Non-resident	10	3.85	.33	3.71	.53
Unknown	16	2.69	1.08	2.96	1.14
White	68	3.07	1.06	3.38	.93
Total	283	2.81	1.16	3.04	1.08

Table 6*Descriptive Statistics of First-time Full-time Undergraduate STEM Students:**STEM and Overall Performance Outcomes*

	<i>n</i>	STEM GPA		Cumulative GPA	
		<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>
Gender					
Female	172	2.72	.93	3.18	.66
Male	111	2.71	.96	3.02	.69
Major					
Biology	214	2.67	.93	3.11	.68
Chemistry	37	2.68	.95	3.06	.70
Env. Studies	2	3.64	.08	3.75	.03
Mathematics	8	3.15	1.01	3.35	.64
Physics	22	3.00	.96	3.08	.71
Race/Ethnicity					
2 or more races	18	2.63	1.00	2.98	.88
Asian	84	2.71	1.00	3.14	.69
Black	56	2.30	.87	2.81	.58
Hispanic	31	2.49	.90	2.89	.68
Non-resident	10	3.39	.59	3.45	.58
Unknown	16	2.93	.90	3.14	.69
White	68	3.05	.79	3.41	.55
Total	283	2.72	.94	3.11	.68

Table 7*Descriptive Statistics of First-time Full-time Undergraduate STEM Students:**STEM Retention Into the Second and Third Year*

	<i>n</i>	STEM retention into the second year				STEM retention into the third year			
		<i>No</i>	%	<i>Yes</i>	%	<i>No</i>	%	<i>Yes</i>	%
Gender									
Female	172	59	34.3	113	65.7	89	51.7	83	48.3
Male	111	44	39.6	67	60.4	62	55.9	49	44.1
Major									
Biology	214	72	33.6	142	66.4	107	50.0	107	50.0
Chemistry	37	20	54.1	17	45.9	28	75.7	9	24.3
Env. Studies	2	—	—	2	100.0	—	—	2	100.0
Mathematics	8	5	62.5	3	37.5	5	62.5	3	37.5
Physics	22	6	27.3	16	72.7	11	50.0	11	50.0
Race/Ethnicity									
2 or more races	18	5	27.8	13	72.2	5	27.8	13	72.2
Asian	84	29	34.5	55	65.5	42	50.0	42	50.0
Black	56	17	30.4	39	69.6	33	58.9	23	41.1
Hispanic	31	15	48.4	16	51.6	23	74.2	8	25.8
Non-resident	10	4	40.0	6	60.0	5	50.0	5	50.0
Unknown	16	6	37.5	10	62.5	10	62.5	6	37.5
White	68	27	39.7	41	60.3	33	48.5	35	51.5
Total	283	103	36.4	180	63.6	151	53.4	132	46.6

Table 8*Descriptive Statistics of First-time Full-time Undergraduate STEM Students:**Graduation in STEM Within Six Years*

	<i>n</i>	Graduation in STEM within six years			
		<i>No</i>	<i>%</i>	<i>Yes</i>	<i>%</i>
Gender					
Female	172	99	57.6	73	42.4
Male	111	70	63.1	41	36.9
Major					
Biology	214	122	57.0	92	43.0
Chemistry	37	29	78.4	8	21.6
Env. Studies	2	—	—	2	100.0
Mathematics	8	5	62.5	3	37.5
Physics	22	13	59.1	9	40.9
Race/Ethnicity					
2 or more races	18	5	27.8	13	72.2
Asian	84	51	60.7	33	39.3
Black	56	36	64.3	20	35.7
Hispanic	31	24	77.4	7	22.6
Non-resident	10	5	50.0	5	50.0
Unknown	16	11	68.8	5	31.3
White	68	37	54.4	31	45.6
Total	283	169	59.7	114	40.3

Bivariate Correlations of Continuous Variables

When conducting multiple regression analyses, it is important to verify that the predictors are not highly correlated with one another, $r > .70$ (Meyers et al., 2013).

Bivariate correlation analyses were conducted to assess this, and the results are presented in Table 9.

Table 9

Bivariate Correlations for Continuous Variables

	HS GPA	SAT M Score	Midterm Math	Final Math	STEM GPA	A. STEM GPA
High School GPA	—					
SAT Math Score	.376***	—				
Midterm Math Perf.	.297***	.245***	—			
Final Math Perf.	.348***	.253***	.695***	—		
STEM GPA	.477***	.349***	.518***	.734***	—	
Adj. STEM GPA	.441***	.316***	.358***	.546***	—	—
Cumulative GPA	.434***	.251***	.476***	.683***	.893***	.837***

Note. *** $p < .001$

All variables were found to be statistically significant with each other. All were not highly correlated as predictors except for final math performance and STEM GPA in relation to research question 3. In this case, an adjusted STEM GPA was conducted.

Grades from the gatekeeping math courses that formed the final math performance were removed from the STEM GPA. Another bivariate correlation was conducted with the adjusted STEM GPA and other continuous variables except for STEM GPA. While still statistically significant at $p < .001$, final math performance and adjusted STEM GPA was no longer highly correlated.

Research Question 1

Along with demographic and pre-college variables, how does the midterm performance in gatekeeping math courses predict the gatekeeping math courses' final grade, STEM GPA, cumulative GPA, and STEM student success outcomes?

Hypothesis 1

Null hypothesis: Demographic factors, pre-college variables, and midterm performance in gatekeeping math courses does not predict the gatekeeping math courses' final grade, STEM GPA, cumulative GPA, or STEM student success outcomes.

Alternate hypothesis: Demographic factors, pre-college variables, and midterm performance in gatekeeping math courses does predict the gatekeeping math courses' final grade, STEM GPA, cumulative GPA, or STEM student success outcomes.

Multiple Regression Analyses

Three separate multiple regression analyses were conducted to assess the predictive nature of demographic variables (gender and race/ethnicity), pre-college variables (high school GPA and SAT math scores), and midterm math performance on final math performance, STEM GPA, and cumulative GPA.

Final Math Performance. A multiple regression was performed to predict final math performance from demographic and pre-college variables, and midterm math performance.

There was linearity as assessed by partial regression plots and a plot of studentized residuals against the predicted values. There was independence of residuals, as assessed by a Durbin-Watson statistic of 1.972. There was homoscedasticity, as assessed by visual inspection of a plot of studentized residuals versus unstandardized

predicted values. There was no evidence of multicollinearity, as assessed by tolerance values greater than 0.1. There were four cases where the studentized deleted residuals were greater than ± 3 standard deviations. After assessing the original data, the four cases were verified to be correct. Since there did not exist an appreciable difference between including or excluding the data, the researcher decided to include the four cases. No leverage values were greater than 0.2 and no values for Cook's distance were above 1. The assumption of normality was met, as assessed by a Q-Q Plot.

The multiple regression model statistically significantly predicted final math performance, $F(10, 272) = 28.968, p < .001, \text{adj. } R^2 = .498$. Only two variables added statistical significance to the prediction: high school average, $p = .013$, and midterm math performance, $p < .001$. Regression coefficients and standard errors can be found in Table 10.

Table 10*Multiple Regression Results: Final Math Performance (RQ 1)*

Final Math Perf.	<i>B</i>	95% CI for <i>B</i>		<i>SE B</i>	β	R^2	ΔR^2
		<i>LL</i>	<i>UL</i>				
Model						.516	.498***
Constant	-1.107	-2.826	.612	.873			
Gender	-.070	-.271	.131	.102	-.032		
2 or more races	-.401	-.801	.000	.203	-.091		
Asian	-.140	-.387	.107	.126	-.060		
Black	-.164	-.453	.125	.147	-.061		
Hispanic	-.254	-.588	.080	.170	-.074		
Non-Resident	-.132	-.654	.389	.265	-.023		
Unknown	-.131	-.553	.292	.215	-.028		
HS GPA	.025*	.005	.045	.010	.125*		
SAT Math	.001	-.001	.002	.001	.046		
Mid. Math Perf.	.581***	.497	.666	.043	.625***		

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

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

STEM GPA. For the following multiple regression analysis, STEM GPA was regressed on demographic and pre-college variables, and midterm math performance.

Linearity was found as assessed by a plot of studentized residuals against the predicted values and partial regression plots. An independence of residuals was found, as assessed by a Durbin-Watson statistic of 1.813. There was homoscedasticity upon visual inspection of a plot of studentized residuals versus unstandardized predicted values.

There was no evidence of multicollinearity, as assessed by tolerance values greater than 0.1 and VIF scores below 10. Three cases were found to have studentized deleted residuals greater than ± 3 standard deviations. Upon assessment of the original data, the

three cases were found to be accurate. A substantial difference was not found between entering or removing the three outliers; thus, the researcher determined it was appropriate to include the outliers. Cook's distance values were not found to be above 1 and leverage values found in the data set were not greater than 0.2. The assumption of normality was met upon assessment of a Q-Q Plot of the inputted data.

The multiple regression model statistically significantly predicted STEM GPA, $F(10, 272) = 20.064, p < .001, \text{adj. } R^2 = .403$. Six variables were found to be statistically significant in the prediction of the model. Three were from the race/ethnicity variable: Asian ($p = .009$), Black ($p = .014$), and Hispanics ($p = .044$) and the other three were high school average ($p < .001$), SAT math score ($p = .044$), and midterm math GPA ($p < .001$). Regression coefficients and standard errors are shown in Table 11.

Table 11*Multiple Regression Results: STEM GPA (RQ 1)*

STEM GPA	<i>B</i>	95% CI for <i>B</i>		<i>SE B</i>	β	R^2	ΔR^2
		<i>LL</i>	<i>UL</i>				
Model						.425	.403***
Constant	-3.042	-4.565	-1.518	.774			
Gender	.058	-.120	.237	.090	.033		
2 or more races	-.331	-.686	.024	.180	-.092		
Asian	-.292**	-.511	-.073	.111	-.153**		
Black	-.321*	-.578	-.065	.130	-.147*		
Hispanic	-.304*	-.600	-.008	.150	-.109*		
Non-Resident	.067	-.395	.530	.235	.014		
Unknown	-.103	-.478	.272	.190	-.027		
HS GPA	.049***	.031	.066	.009	.300***		
SAT Math	.001*	.000	.003	.001	.112*		
Mid. Math Perf.	.283***	.208	.358	.038	.374***		

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

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

Cumulative GPA. A multiple regression analysis was performed by regressing cumulative GPA on demographic, pre-college, and final math performance.

An assessment of partial regression plots and a plot of studentized residuals against the predicted values was conducted and values were found to be linear. The Durbin-Watson statistic obtained was 1.76 which is indicative of an independence of residuals since the value is close to 2. Homoscedasticity was found via a visual inspection of a plot of studentized residuals against unstandardized predicted values.

Multicollinearity was not found due to a lack of tolerance values greater than 0.1. Four cases were found to be outliers due to their studentized deleted residuals being greater

than ± 3 standard deviations. Review of the original data confirms that the four cases were correct. The researcher made the decision to include the four cases due to the lack of considerable difference to the model between including or excluding the cases. Cook's distance values were not found to be above 1 and leverage values were not found to be greater than 0.2. The assumption of normality was found by assessing a Q-Q Plot of the data.

The multiple regression model was found to statistically significantly predict cumulative GPA, $F(10, 272) = 14.569, p < .001, \text{adj. } R^2 = .325$. Six variables added statistical significance to the model, four within the race/ethnicity variable: 2 or more races ($p = .042$), Asian ($p = .013$), Black ($p = .007$), and Hispanic ($p = .03$), and the other two variables included high school average ($p < .001$) and midterm math performance ($p < .001$). Regression coefficients and standard errors are presented in Table 12.

Table 12*Multiple Regression Results: Cumulative GPA (RQ 1)*

Cumulative GPA	<i>B</i>	95% CI for <i>B</i>		<i>SE B</i>	β	R^2	ΔR^2
		<i>LL</i>	<i>UL</i>				
Model						.349	.325***
Constant	-.644	-1.902	.615	.639			
Gender	.001	-.146	.148	.075	.001		
2 or more races	-.305*	-.598	-.012	.149	-.110*		
Asian	-.230*	-.411	-.049	.092	-.155*		
Black	-.293**	-.505	-.082	.108	-.172**		
Hispanic	-.271*	-.516	-.026	.124	-.125*		
Non-Resident	-.103	-.485	.278	.194	-.028		
Unknown	-.132	-.441	.178	.157	-.045		
HS GPA	.035***	.021	.050	.007	.280***		
SAT Math	.000	-.001	.001	.001	.030		
Mid. Math Perf.	.207***	.146	.269	.031	.353***		

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

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

Binary Logistic Regression Analyses

Three separate binary logistic regression analyses were performed to assess the fit of the model to the data. STEM student success outcomes (retention into the second year, retention into the third year, and graduation within six years as STEM majors) were regressed on demographic and pre-college variables, and midterm math performance.

Retention into the second year. A binomial logistic regression was conducted to determine the effects of demographic and pre-college variables, and midterm math performance on the likelihood that a student is retained into the second year.

The logistic regression model was found not to be statistically significant, $\chi^2(10) = 11.066, p = .352$ which indicates the model could not differentiate between students who were retained or not retained as a STEM student into the second year. Regression results are not presented due to lack of statistical significance. In reviewing the model summary, the Cox and Snell R^2 was .038 and the Nagelkerke R^2 was .052 which indicates that the model only explains between 3.8% to 5.2% of the variance.

Retention into the third year. A binomial logistic regression was conducted to determine the effects of demographic and pre-college variables, and midterm math performance on the likelihood that a student is retained into the third year as a STEM major.

All continuous independent variables were found to be linearly related to the logit of the dependent variable and no outliers were found. The logistic regression model was statistically significant, $\chi^2(10) = 23.991, p = .008$. The Nagelkerke R^2 model was able to explain 10.9% (Nagelkerke R^2) of the variance in the retention of STEM students into the third year and correctly classified 60.8% of cases. The sensitivity was 53.8%, specificity was 66.9%, positive predictive value was 58.7%, and negative predictive value was 62.3%.

Of all the predictor variables, only midterm math performance was found to be statistically significant ($p = .02$) which is shown in Table 13.

Table 13*Logistic Regression Results: Retention into the Third Year as STEM (RQ 1)*

	<i>B</i>	SE	Wald	<i>df</i>	<i>p</i>	Odds Ratio	95% CI for O.R.	
							Lower	Upper
Gender	.048	.280	.030	1	.863	1.050	.607	1.816
2 or more races	1.135	.600	3.573	1	.059	3.111	.959	10.090
Asian	-.044	.337	.017	1	.897	.957	.495	1.852
Black	-.058	.395	.022	1	.883	.944	.435	2.046
Hispanic	-.823	.493	2.788	1	.095	.439	.167	1.154
Non-resident	-.383	.704	.296	1	.586	.682	.172	2.709
Unknown	-.466	.590	.623	1	.430	.628	.198	1.994
HS GPA	.025	.028	.792	1	.374	1.025	.971	1.082
SAT Math	.002	.002	.982	1	.322	1.002	.998	1.006
Mid. Math Perf.	.282	.121	5.440	1	.020	1.325	1.046	1.679
Constant	-4.330	2.394	3.272	1	.070	.013		

For each unit of increase in midterm math performance, there was a 1.33 times greater chances that a student would be retained into a STEM major in the third year.

Graduation within six years as a STEM major. A binomial logistic regression was performed to determine whether demographic variables and pre-college variables, along with midterm math performance had an impact on if students graduate within six years as STEM majors or not.

All continuous independent variables were found to be linearly related to the logit of the dependent variable and no outliers were found. The logistic regression model was statistically significant, $\chi^2(10) = 33.871, p < .001$. The logistic regression model explained 15.2% (Nagelkerke R^2) of the variance in the graduation of STEM students within six years. The model correctly classified 64.0% of cases. Sensitivity was found to be 39.5%, specificity was 80.5%, positive predictive value was 57.7%, and negative predictive value was 66.3%.

Two predictor variables were found to be statistically significant: midterm math performance ($p = .003$) and 2 or more races when compared to White students ($p = .015$).

The results are displayed in Table 14.

Table 14

Logistic Regression Results: Graduation Within Six Years as STEM (RQ 1)

	<i>B</i>	SE	Wald	<i>df</i>	<i>p</i>	Odds Ratio	95% CI for O.R.	
							Lower	Upper
Gender	.002	.290	.000	1	.996	1.002	.568	1.767
2 or more races	1.501	.618	5.905	1	.015	4.486	1.337	15.053
Asian	-.263	.347	.577	1	.447	.768	.389	1.516
Black	.098	.407	.058	1	.810	1.103	.496	2.451
Hispanic	-.656	.516	1.614	1	.204	.519	.189	1.427
Non-resident	-.262	.711	.136	1	.713	.770	.191	3.100
Unknown	-.460	.621	.549	1	.459	.631	.187	2.132
HS GPA	.033	.029	1.330	1	.249	1.034	.977	1.094
SAT Math	.003	.002	2.025	1	.155	1.003	.999	1.007
Mid. Math Perf.	.387	.130	8.859	1	.003	1.473	1.141	1.900
Constant	-6.295	2.502	6.329	1	.012	.002		

A student who indicated they were 2 or more races were 4.49 times more likely to graduate as a STEM major in six years compared to a student who identified as White. A unit increase in midterm math GPA was indicative of 1.47 times increase in the possibility of a student graduating as a STEM major within six years.

Research Question 2

Along with demographic, pre-college variables, and midterm math performance, how does final performance in gatekeeping math courses predict STEM GPA, cumulative GPA, and STEM student success outcomes?

Hypothesis 2

Null hypothesis: Demographic factors, pre-college variables, midterm math performance and final performance in gatekeeping math courses does not predict STEM GPA, cumulative GPA, or STEM student success outcomes.

Alternate hypothesis: Demographic factors, pre-college variables, midterm math performance and final performance in gatekeeping math courses does predict STEM GPA, cumulative GPA, or STEM student success outcomes.

Multiple Regression Analyses

Two separate multiple regression analyses were performed to assess the predictive nature of demographic variables, pre-college variables, midterm and final math performance on STEM GPA and cumulative GPA.

STEM GPA. A multiple regression analysis was conducted where STEM GPA was regressed on demographic and pre-college variables, midterm math performance and final math performance.

Linearity was found as assessed by a plot of studentized residuals against the predicted values and partial regression plots. An independence of residuals was found by assessment of the Durbin-Watson statistic, which was 1.832. Homoscedasticity was found upon visual inspection of a plot of studentized residuals compared to unstandardized predicted values. No evidence of multicollinearity was found, as assessed by tolerance values greater than 0.1 and VIF scores below 10. In relation to unusual points in the data, there were no studentized deleted residuals greater than ± 3 standard deviations, values for Cook's distance were not above 1, and leverage values were not

greater than 0.2. Assessment of a Q-Q plot was done and found that the assumption of normality has been met.

The model produced was able to statistically significantly predict STEM GPA, $F(11, 271) = 40.500, p < .001, \text{adj. } R^2 = .606$. Four variables had statistical significance in the prediction of STEM GPA. These were high school average ($p < .001$), final math performance ($p < .001$) and the others were from the race/ethnicity variable: Asian ($p = .016$) and Black ($p = .026$). Regression coefficients and standard errors can be seen in Table 15.

Table 15*Multiple Regression Results: STEM GPA (RQ 2)*

STEM GPA	<i>B</i>	95% CI for <i>B</i>		<i>SE B</i>	β	R^2	ΔR^2
		<i>LL</i>	<i>UL</i>				
Model						.622	.606***
Constant	-2.467	-3.708	-1.226	.630			
Gender	.095	-.050	.240	.074	.053		
2 or more races	-.123	-.413	.168	.147	-.034		
Asian	-.219*	-.397	-.040	.091	-.114*		
Black	-.236*	-.445	-.028	.106	-.108*		
Hispanic	-.172	-.414	.069	.123	-.062		
Non-Resident	.136	-.239	.512	.191	.029		
Unknown	-.035	-.340	.269	.155	-.009		
HS GPA	.036***	.021	.050	.007	.220***		
SAT Math	.001	.000	.002	.001	.082		
Mid. Math Perf.	-.019	-.098	.060	.040	-.025		
Final Math Perf.	.519***	.433	.605	.044	.638***		

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

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

Cumulative GPA. A multiple regression was performed to predict cumulative GPA from demographic and pre-college variables, midterm math performance and final math performance.

Linearity was found by a plot of studentized residuals versus predicted values and partial regression plots. Independence of residuals was found via the Durbin-Watson statistic produced which was 1.782. Upon visual inspection of a plot of studentized residuals compared to unstandardized predicted values, homoscedasticity was found. Tolerance values were greater than 0.1 and VIF values were less than 10 which is indicative of a lack of multicollinearity. When assessing for outliers, four cases were

found to have studentized deleted residuals to be greater than ± 3 standard deviations. Verification of the data was conducted and found these cases were accurate. Generating a new model without the outliers did not present a considerable difference and thus the researcher included the four cases in the final model. Other unusual points were not found upon assessment of leverage values, where none were greater than 0.2, and Cook's distance values, where none were greater than 1. Normality was found via assessment of a generated Q-Q plot of the model.

The multiple regression model was found to be statistically significant in predicting a student's cumulative GPA, $F(11, 271) = 27.321, p < .001, \text{adj. } R^2 = .507$. Two race/ethnicity variables, Asian ($p = .026$) and Black ($p = .013$) were found to be statistically significant, along with high school average and final math performance, both $p < .001$. Regression coefficients and standard errors are presented in Table 16.

Table 16*Multiple Regression Results: Cumulative GPA (RQ 2)*

Cumulative GPA	<i>B</i>	95% CI for <i>B</i>		<i>SE B</i>	β	R^2	ΔR^2
		<i>LL</i>	<i>UL</i>				
Model						.526	.507***
Constant	-.221	-1.300	.858	.548			
Gender	.028	-.098	.154	.064	.020		
2 or more races	-.152	-.405	.100	.128	-.055		
Asian	-.176*	-.331	-.021	.079	-.119*		
Black	-.231*	-.412	-.049	.092	-.136*		
Hispanic	-.174	-.384	.036	.107	-.080		
Non-Resident	-.053	-.379	.273	.166	-.014		
Unknown	-.082	-.347	.183	.134	-.028		
HS GPA	.026***	.013	.038	.006	.204***		
SAT Math	.000	-.001	.001	.000	.002		
Mid. Math Perf.	-.014	-.083	.054	.035	-.025		
Final Math Perf.	.382***	.307	.456	.038	.605***		

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

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

Binary Logistic Regression Analyses

Three separate binary logistic regression analyses were performed where STEM student success outcomes were regressed on demographic and pre-college variables, and midterm and final math performance.

Retention into the second year. A binomial logistic regression was performed to determine the impact of demographic and pre-college variables, and midterm and final math performance on the possibility that a student returns as a STEM major in their second year at the institution.

The logistic regression model was found not to be statistically significant, $\chi^2(11) = 15.867, p = .146$. The model was not able to accurately tell the difference between students who remained as a STEM major into the second year or those who changed their major or left. Since there was a lack of statistical significance, regression results were not shown. Upon review of the model summary, the Cox and Snell R^2 was .055 and the Nagelkerke R^2 was .075 which indicates the variance explained by the model was between 5.5% to 7.5%.

Retention into the third year. A binominal logistic regression was conducted to ascertain the effects of demographic and pre-college variables, along with midterm and final math performance on the chances of students being retained as a STEM major into the third year.

The continuous independent variables in the model were confirmed to be linearly related to the logit of the dependent variable. In assessing for outliers, there were five cases with standardized residuals greater than ± 2.5 standard deviations. Verification of the data was conducted and there was no appreciable difference between including or excluding the cases. Thus, the researcher decided to include the outliers.

The logistic regression model was statistically significant, $\chi^2(11) = 49.571, p < .001$. The model explained 21.5% (Nagelkerke R^2) of the variance in the retention of STEM students into the third year and correctly classified 68.2% of cases. For this model, sensitivity was 74.2%, specificity was 62.9%, positive predictive value was 63.6%, and negative predictive value was 73.6%.

Two predictor variables were found to be statistically significant: final math performance ($p < .001$) and students who identified as 2 or more races when compared to White students ($p = .01$). The results are displayed in Table 17.

Table 17

Logistic Regression Results: Retention into the Third Year as STEM (RQ 2)

	<i>B</i>	SE	Wald	<i>df</i>	<i>p</i>	Odds Ratio	95% CI for O.R.	
							Lower	Upper
Gender	.143	.292	.240	1	.624	1.154	.651	2.043
2 or more races	1.762	.683	6.646	1	.010	5.823	1.525	22.227
Asian	.096	.351	.074	1	.785	1.100	.553	2.188
Black	.109	.415	.069	1	.794	1.115	.495	2.512
Hispanic	-.597	.512	1.359	1	.244	.550	.202	1.502
Non-resident	-.283	.723	.154	1	.695	.753	.183	3.106
Unknown	-.413	.622	.441	1	.507	.662	.196	2.237
HS GPA	-.001	.030	.003	1	.960	.999	.942	1.058
SAT Math	.002	.002	.549	1	.459	1.002	.997	1.006
Mid. Math Perf.	-.233	.171	1.857	1	.173	.792	.566	1.108
Final Math Perf.	.980	.220	19.879	1	.000	2.666	1.732	4.102
Constant	-3.483	2.518	1.914	1	.167	.031		

A student who indicated they were 2 or more races was 5.82 times more likely to be retained into the third year as a STEM major. For each single-point increase in final math GPA, there was 2.67 times increased possibility of a student remaining as a STEM major into their third year.

Graduation within six years as a STEM major. A binomial logistic regression was conducted to assess whether demographic variables, pre-college variables, midterm math performance, and final math performance influenced the possibility of students graduating as STEM majors within six years.

All continuous independent variables were verified to be linearly related to the logit of the dependent variable. Five outliers were found where their standardized residuals were greater than ± 2.5 standard deviations. The data was confirmed to be correct and a substantial difference was not found between adding or removing the outliers. The researcher decided to include these cases in the final model.

The model generated was found to be statistically significant, $\chi^2(11) = 58.771, p < .001$. The Nagelkerke pseudo R^2 indicated that the model accounted for approximately 25.3% of the total variance. The model correctly classified 70.0% of the cases. Sensitivity was 57.0%, specificity was found to be 78.7%, positive predictive value was 64.4%, and negative predictive value was 73.1%.

Two predictor variables were found to statistically significantly added to the model: final math performance ($p < .001$) and 2 or more races when compared to White students ($p = .002$) as displayed in Table 18.

Table 18*Logistic Regression Results: Graduation Within Six Years as STEM (RQ 2)*

	<i>B</i>	<i>SE</i>	<i>Wald</i>	<i>df</i>	<i>p</i>	<i>Odds Ratio</i>	<i>95% CI for O.R.</i>	
							<i>Lower</i>	<i>Upper</i>
Gender	.101	.300	.114	1	.736	1.107	.614	1.994
2 or more races	2.286	.738	9.591	1	.002	9.838	2.315	41.809
Asian	-.141	.358	.154	1	.695	.869	.430	1.754
Black	.300	.427	.492	1	.483	1.349	.584	3.118
Hispanic	-.385	.536	.516	1	.473	.681	.238	1.946
Non-resident	-.169	.732	.053	1	.818	.845	.201	3.550
Unknown	-.415	.650	.408	1	.523	.660	.185	2.359
HS GPA	.008	.031	.064	1	.801	1.008	.949	1.071
SAT Math	.003	.002	1.354	1	.245	1.003	.998	1.007
Mid. Math Perf.	-.123	.173	.504	1	.478	.884	.630	1.242
Final Math Perf.	1.053	.242	18.975	1	.000	2.867	1.785	4.605
Constant	-5.811	2.638	4.850	1	.028	.003		

A student who identified as 2 or more races were 9.84 times more likely to graduate within six years as a STEM major compared to a student who indicated they were White. In the case of final math performance, for each unit of increase, there was a 2.87 times greater likelihood a student graduated as a STEM major in six years after controlling for demographic variables, high school average, SAT math scores, and midterm math performance.

Research Question 3

Along with demographic variables, pre-college variables, midterm and final math performance, how does STEM GPA predict cumulative GPA and STEM student success outcomes?

Hypothesis 3

Null hypothesis: Demographic factors, pre-college variables, midterm and final math performance, and STEM GPA does not predict cumulative GPA or STEM student success outcomes.

Alternate hypothesis: Demographic factors, pre-college variables, midterm and final math performance, and STEM GPA does predict cumulative GPA or STEM student success outcomes.

Multiple Regression Analysis

A multiple regression analysis was conducted to assess the predictive nature of demographic variables, pre-college variables, midterm and final math performance, and STEM GPA on cumulative GPA. When assessing the bivariate correlations, it was found that final math GPA was highly correlated to STEM GPA ($r = .734$). Adjustment of the STEM GPA was conducted by removing grades from gatekeeping math courses that formed the final math performance from the STEM GPA and was renamed as adjusted STEM GPA. Upon adjustment, the sample size was reduced to 276 and there was no substantial intercorrelation between the predictors ($r > 0.7$) as seen in Table 9.

Cumulative GPA. A multiple regression was carried out to predict cumulative GPA from demographic and pre-college variables, midterm math performance, final math performance, and adjusted STEM GPA.

Linearity was found upon visual inspection of a plot of studentized residuals versus the predicted values and partial regression plots. The Durbin-Watson statistic found for the model was 1.853 which is indicative of an independence of residuals. Homoscedasticity was found via visual assessment of a plot of studentized residuals

compared to unstandardized predicted values. Multicollinearity was not found since tolerance values were found to be greater than 0.1.

The studentized deleted residuals of four cases were greater than ± 3 standard deviations. A review of the initial data was done and the four cases were confirmed to be accurate. Since there was not a substantial difference between adding or removing the four outliers, they were included in the final data set. Leverage and Cook's distance values were reviewed for unusual points and was not found to be greater than .02 or 1, respectively. Assumption of normality was met after visually scrutinizing a Q-Q Plot by the researcher.

The multiple regression model was statistically significant in predicting cumulative GPA, $F(12, 263) = 77.490, p < .001, \text{adj. } R^2 = .769$. Three variables were found to statistically significantly added to the prediction: SAT math scores ($p = .028$), final math performance ($p < .001$), and STEM GPA ($p < .001$). Regression coefficients and standard errors are displayed in Table 19.

Table 19*Multiple Regression Results: Cumulative GPA (RQ 3)*

Cumulative GPA	<i>B</i>	95% CI for <i>B</i>		<i>SE B</i>	β	R^2	ΔR^2
		<i>LL</i>	<i>UL</i>				
Model						.780	.769***
Constant	1.392	.640	2.144	.382			
Gender	-.051	-.137	.035	.044	-.037		
2 or more races	-.107	-.278	.064	.087	-.039		
Asian	-.046	-.152	.060	.054	-.032		
Black	-.094	-.218	.030	.063	-.056		
Hispanic	-.104	-.246	.039	.072	-.049		
Non-Resident	-.127	-.349	.094	.112	-.036		
Unknown	-.039	-.227	.149	.095	-.013		
HS GPA	.004	-.005	.013	.005	.032		
SAT Math	-.001*	-.001	.000	.000	-.077*		
Mid. Math Perf.	.005	-.041	.052	.024	.009		
Final Math Perf.	.182***	.127	.237	.028	.292***		
STEM GPA	.480***	.427	.534	.027	.673***		

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

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

Binary Logistic Regression Analyses

Three separate binary logistic regression analyses were performed. STEM student success outcomes were regressed on demographic and pre-college variables, midterm and final math performance, and STEM GPA.

Retention into the second year. A binomial logistic regression was conducted to ascertain the effects of demographic and pre-college variables, midterm and final math performance, and STEM GPA on whether a student is likely to be retained into the second year as a STEM major.

The logistic regression model was not statistically significant, $\chi^2(17) = 20.072$, $p = .271$. The model could not discern students who were retained as STEM majors into the second year versus those who either change their major or leave the institution. Due to lack of statistical significance, regression results are not provided. The model summary indicated the Cox and Snell R^2 was .072 and the Nagelkerke R^2 was .100. In other words, the model was only able to explain between 7.2% to 10% of the variance.

Retention into the third year. A binomial logistic regression was performed to determine the impact of demographic variables, pre-college variables, midterm math performance, final math performance, and STEM GPA on whether students were retained as STEM majors into their third year.

All continuous independent variables in the model were verified to be linearly related to the logit of the dependent variable. There were five outliers where their standardized residuals were greater than ± 2.5 standard deviations. The data was confirmed to be accurate and comparing the models of included and excluded outliers did not offer a substantial difference. It was decided that the final model will include the outliers.

The logistic regression model was statistically significant, $\chi^2(12) = 52.919$, $p < .001$. The model explained 22.8% (Nagelkerke R^2) of the variance in the retention of STEM students into the third year and correctly classified 69.3% of cases. For this model, sensitivity was 73.5%, specificity was 65.6%, positive predictive value was 65.1%, and negative predictive value was 73.9%.

Two predictor variables were found to be statistically significant: final math performance ($p = .003$) and students who identified as 2 or more races when compared to White students ($p = .008$) as shown in Table 20.

Table 20

Logistic Regression Results: Retention into the Third Year as STEM (RQ 3)

	<i>B</i>	SE	Wald	<i>df</i>	<i>p</i>	Odds Ratio	95% CI for O.R.	
							Lower	Upper
Gender	.081	.295	.075	1	.785	1.084	.608	1.932
2 or more races	1.829	.689	7.039	1	.008	6.229	1.613	24.060
Asian	.192	.358	.287	1	.592	1.211	.601	2.443
Black	.241	.423	.326	1	.568	1.273	.556	2.915
Hispanic	-.537	.517	1.081	1	.299	.584	.212	1.609
Non-resident	-.357	.725	.243	1	.622	.700	.169	2.896
Unknown	-.440	.632	.484	1	.486	.644	.186	2.224
HS GPA	-.018	.031	.333	1	.564	.982	.924	1.044
SAT Math	.001	.002	.346	1	.556	1.001	.997	1.006
Mid. Math Perf.	-.230	.173	1.775	1	.183	.794	.566	1.115
Final Math Perf.	.783	.251	8.618	1	.003	2.091	1.278	3.422
STEM GPA	.470	.259	3.302	1	.069	1.601	.964	2.659
Constant	-2.420	2.589	.874	1	.350	.089		

A student who indicated they were 2 or more races were 6.23 times more likely to remain as a STEM major into the third year. For a unit increase in final math GPA, there was 2.09 times increased likelihood of a student being retained as a STEM major into their third year.

Graduation within six years as a STEM major. A binomial logistic regression was performed to determine if demographic variables, pre-college variables, midterm math performance, final math performance, and STEM GPA had effects on the likelihood of students graduating within six years as STEM majors.

Linearity of the continuous variables in relation to the logit of the dependent variable was conducted. A Bonferroni correction was applied utilizing all eighteen terms in the model resulting in statistical significance being accepted when $p < .00278$ (Tabachnick & Fidell, 2014). Based on this assessment, all continuous independent variables were confirmed to be linearly related to the logit of the dependent variable in the model. Standardized residuals greater than ± 2.5 standard deviations were found in four cases. A review of the outliers was conducted and the data was accurate. The researcher included the four cases after reviewing the models of included and excluded outliers and could not find any considerable difference.

The model was statistically significant, $\chi^2(12) = 76.803, p < .001$. The Nagelkerke pseudo R^2 indicated that the model accounted for approximately 32.1% of the total variance. The model correctly classified 72.1% of the cases. Sensitivity was 63.2%, specificity was found to be 78.1%, positive predictive value was 66.1%, and negative predictive value was 75.9%.

Two predictor variables were found to statistically significantly added to the model: STEM GPA ($p < .001$) and 2 or more races when compared to White students ($p = .001$). The results are displayed in Table 21.

Table 21*Logistic Regression Results: Graduation Within Six Years as STEM (RQ 3)*

	<i>B</i>	<i>SE</i>	<i>Wald</i>	<i>df</i>	<i>p</i>	<i>Odds Ratio</i>	<i>95% CI for O.R.</i>	
							<i>Lower</i>	<i>Upper</i>
Gender	-.066	.314	.045	1	.833	.936	.506	1.731
2 or more races	2.612	.785	11.063	1	.001	13.628	2.924	63.518
Asian	.076	.376	.041	1	.840	1.079	.516	2.254
Black	.686	.450	2.319	1	.128	1.985	.821	4.799
Hispanic	-.215	.553	.151	1	.698	.807	.273	2.383
Non-resident	-.363	.744	.238	1	.626	.696	.162	2.993
Unknown	-.542	.680	.635	1	.426	.582	.153	2.206
HS GPA	-.037	.034	1.202	1	.273	.963	.901	1.030
SAT Math	.002	.002	.788	1	.375	1.002	.997	1.007
Mid. Math Perf.	-.120	.178	.452	1	.502	.887	.626	1.258
Final Math Perf.	.483	.267	3.274	1	.070	1.621	.961	2.736
STEM GPA	1.221	.305	16.049	1	.000	3.390	1.866	6.161
Constant	-3.238	2.774	1.362	1	.243	.039		

In the case where a student who identified as 2 or more races, they were 13.62 times more likely to graduate as a STEM major in six years versus a student who identified as White. For each unit of increase in STEM GPA, there was a 3.39 times greater possibility a student graduated as a STEM major in six years.

Research Question 4

Along with demographic, pre-college variables, STEM performance college variables, how does cumulative GPA predict STEM student success outcomes?

Hypothesis 4

Null hypothesis: Demographic factors, pre-college variables, midterm and final math performance, STEM GPA, and cumulative GPA does not predict STEM student success outcomes.

Alternate hypothesis: Demographic factors, pre-college variables, midterm and final math performance, STEM GPA, and cumulative GPA does predict STEM student success outcomes.

Binary Logistic Regression Analyses

Three separate binary logistic regression analyses were conducted to analyze the fit of the model. STEM student success outcomes were regressed on demographic and pre-college variables, midterm and final math performance, and STEM and cumulative GPA.

Retention into the second year. A binomial logistic regression was conducted to determine the effects that demographic variables and pre-college variables, midterm math performance, final math performance, STEM GPA, and cumulative GPA had on the likelihood of a student being retained into the second year as a STEM major.

All continuous independent variables were found to be linearly related to the logit of the dependent variable and no outliers were found. The logistic regression model was statistically significant, $\chi^2(13) = 25.241, p = .021$. The Nagelkerke R^2 explained 11.7% of the variance in the model and was able to correctly classify 68.2% of the cases.

Sensitivity was assessed to be 91.1%, specificity was found to be 28.2%, positive predictive value was 68.9% and negative predictive value was 64.4%.

Two predictor variables were found to be statistically significant: cumulative GPA ($p = .004$) and Black students when compared to White students ($p = .042$). The results are presented in Table 22.

Table 22*Logistic Regression Results: Retention into the Second Year as STEM (RQ 4)*

	<i>B</i>	<i>SE</i>	<i>Wald</i>	<i>df</i>	<i>p</i>	<i>Odds Ratio</i>	<i>95% CI for O.R.</i>	
							<i>Lower</i>	<i>Upper</i>
Gender	-.094	.292	.103	1	.748	.911	.514	1.613
2 or more races	1.022	.650	2.474	1	.116	2.779	.778	9.935
Asian	.389	.358	1.180	1	.277	1.475	.732	2.973
Black	.880	.433	4.140	1	.042	2.412	1.033	5.632
Hispanic	.096	.469	.042	1	.838	1.101	.439	2.758
Non-resident	-.081	.741	.012	1	.913	.922	.216	3.944
Unknown	.408	.607	.452	1	.501	1.504	.458	4.943
HS GPA	-.014	.030	.207	1	.649	.986	.930	1.046
SAT Math	.002	.002	.638	1	.425	1.002	.997	1.006
Mid. Math Perf.	.052	.157	.110	1	.741	1.053	.775	1.431
Final Math Perf.	.263	.209	1.573	1	.210	1.300	.863	1.961
STEM GPA	-.738	.390	3.584	1	.058	.478	.223	1.026
Cumulative GPA	1.300	.454	8.208	1	.004	3.671	1.508	8.935
Constant	-2.504	2.616	.916	1	.338	.082		

A student who identified as Black were 2.41 times more likely to be retained into the second year as a STEM major compared to a White student. Increasing cumulative GPA was associated with an increased possibility of 3.67 times for a student being retained as a STEM major in the second year.

Retention into the third year. A binomial logistic regression was performed to ascertain the effects of demographic variables, pre-college variables, midterm math performance, final math performance, STEM GPA, and cumulative GPA on whether students were retained into their third year as STEM majors in the institution.

All continuous independent variables in the model were verified to be linearly related to the logit of the dependent variable. In the evaluation for outliers, five cases had standardized residuals greater than ± 2.5 standard deviations. Upon review of the cases, it

was verified to be correct and included in the final model since there was not an appreciable difference between removing or adding the outliers.

The logistic regression model was found to be statistically significant, $\chi^2(13) = 60.946, p < .001$. The model explained 25.9% (Nagelkerke R^2) of the variance in the retention of STEM students into the third year and correctly classified 70.0% of cases. The sensitivity was 75.8%, specificity was 64.9%, positive predictive value was 65.4%, and negative predictive value was 75.4%.

Three predictor variables were found to be statistically significant: final math performance ($p = .004$), cumulative GPA ($p = .007$), and students who identified as 2 or more races when compared to White students ($p = .007$) as displayed in Table 23.

Table 23

Logistic Regression Results: Retention into the Third Year as STEM (RQ 4)

	<i>B</i>	SE	Wald	<i>df</i>	<i>p</i>	Odds Ratio	95% CI for O.R.	
							Lower	Upper
Gender	.147	.300	.241	1	.623	1.159	.644	2.086
2 or more races	2.005	.739	7.353	1	.007	7.423	1.743	31.610
Asian	.239	.361	.436	1	.509	1.269	.625	2.577
Black	.343	.431	.635	1	.425	1.410	.606	3.280
Hispanic	-.457	.522	.769	1	.381	.633	.228	1.759
Non-resident	-.183	.739	.061	1	.805	.833	.196	3.545
Unknown	-.396	.639	.383	1	.536	.673	.192	2.355
HS GPA	-.024	.032	.549	1	.459	.976	.917	1.040
SAT Math	.002	.002	.988	1	.320	1.002	.998	1.007
Mid. Math Perf.	-.253	.176	2.062	1	.151	.777	.550	1.096
Final Math Perf.	.749	.260	8.277	1	.004	2.114	1.270	3.521
STEM GPA	-.389	.405	.921	1	.337	.678	.306	1.500
Cumulative GPA	1.351	.500	7.292	1	.007	3.860	1.448	10.288
Constant	-4.372	2.735	2.556	1	.110	.013		

A student who indicated they were 2 or more races were 7.42 times more likely to be retained into their third year as a STEM major. For each single-point increase in a student's final math GPA, they were 2.11 times more likely to be retained into their third year. In the case of cumulative GPA, each unit increase meant there was a 3.86 times greater likelihood of the student remaining as a STEM major into their third year.

Graduation within six years as a STEM major. A binomial logistic regression was performed to determine if demographic variables, pre-college variables, midterm math performance, final math performance, STEM GPA, and cumulative GPA had effects on the likelihood of students graduating within six years as STEM majors.

Linearity of the continuous variables in relation to the logit of the dependent variable was conducted. A Bonferroni correction was applied utilizing all twenty terms in the model resulting in statistical significance being accepted when $p < .0025$ (Tabachnick & Fidell, 2014). All continuous independent variables were then assessed and confirmed to be linearly related to the logit of the dependent variable. Four outliers had standardized residuals greater than ± 2.5 standard deviations. Review of the data confirmed they were accurate. No substantial difference was assessed between models including and excluding the outliers; therefore, all four cases were included in the final model.

The model was statistically significant, $\chi^2(13) = 88.198, p < .001$. The Nagelkerke pseudo R^2 indicated that the model accounted for approximately 36.2% of the total variance. The model correctly classified 74.9% of the cases. Sensitivity was 64.9%, specificity was found to be 81.7%, positive predictive value was 70.5%, and negative predictive value was 77.5%.

Two predictor variables were found to statistically significantly added to the model: cumulative GPA ($p = .002$) and 2 or more races when compared to White students ($p < .001$). The results are shown in Table 24.

Table 24

Logistic Regression Results: Graduation Within Six Years as STEM (RQ 4)

	<i>B</i>	SE	Wald	<i>df</i>	<i>p</i>	Odds Ratio	95% CI for O.R.	
							Lower	Upper
Gender	.013	.321	.002	1	.968	1.013	.540	1.900
2 or more races	2.899	.873	11.020	1	.001	18.147	3.278	100.469
Asian	.157	.381	.169	1	.681	1.170	.554	2.471
Black	.870	.464	3.519	1	.061	2.386	.962	5.918
Hispanic	-.066	.563	.014	1	.907	.936	.311	2.822
Non-resident	-.150	.777	.037	1	.847	.861	.188	3.949
Unknown	-.478	.686	.487	1	.485	.620	.162	2.376
HS GPA	-.048	.036	1.789	1	.181	.953	.889	1.022
SAT Math	.004	.002	2.123	1	.145	1.004	.999	1.009
Mid. Math Perf.	-.136	.184	.547	1	.459	.873	.609	1.251
Final Math Perf.	.476	.282	2.847	1	.092	1.610	.926	2.800
STEM GPA	.072	.459	.025	1	.875	1.075	.437	2.645
Cumulative GPA	1.930	.622	9.622	1	.002	6.893	2.035	23.340
Constant	-6.157	3.007	4.192	1	.041	.002		

If a student identified as 2 or more races, they were 18.15 times more likely to graduate as a STEM major in six years compared to a student who identified that they were White. For each unit of increase in cumulative GPA, there was a 6.89 times increased likelihood a student graduated within six years as a STEM major.

Research Question 5

How does the midterm performance in gatekeeping math courses for students who completed a STEM degree compare to students who changed their major to non-STEM or did not complete a degree?

Hypothesis 5

Null hypothesis: The means of the midterm performance in gatekeeping math courses for students who completed a STEM degree and students who changed their major to a non-STEM major or did not complete a degree are equal.

Alternative hypothesis: The means of the midterm performance in gatekeeping math courses for students who completed a STEM degree and students who changed their major to a non-STEM major or did not complete a degree are not equal.

Independent-samples *t*-test

An independent-samples *t*-test was conducted comparing the means of the midterm performance in gatekeeping math courses for STEM completers (students who graduated with a STEM degree) and STEM leavers (students who graduated with a non-STEM degree or left the institution altogether).

Prior to performing the *t*-test, normality and homogeneity of variance was assessed. Upon visual inspection of the Normal Q-Q Plots, midterm math performance was found to be normally distributed for STEM leavers but not for STEM completers. The data was negatively skewed due to the likelihood of higher GPA performance since these students successfully completed their degree in STEM. Since the sample was sufficiently large, the central limit theorem can apply which indicates that the sampling mean is normally distributed as the sample increases (Howell, 2010). The assumption of the homogeneity of variances was violated when assessed by the Levene's test for equality of variances ($p < .001$). Due to this violation, Welch's *t*-test will be utilized (Welch, 1947).

There were two outliers in the data upon inspection of a boxplot. It was verified that it was not an error. The researcher included the outliers due to a lack of considerable difference when conducting the *t*-test with or without the outliers.

There were 169 STEM leavers and 117 STEM completers. STEM leavers' midterm math performance ($M = 2.54, SD = 1.23$) was lower than STEM completers' midterm math performance ($M = 3.11, SD = 1.02$), which was a statistically significant difference, $M = -0.57, 95\% \text{ CI } [-0.83, -0.30], t(275.191) = -4.242, p < .001$. Thus, rejecting the null hypothesis.

Research Question 6

How does final performance in gatekeeping math courses by students who completed a STEM degree compare to students who changed their major to non-STEM or did not complete a degree?

Hypothesis 6

Null hypothesis: The means of the final performance in gatekeeping math courses for students who completed a STEM degree and students who changed their major to a non-STEM major or did not complete a degree are equal.

Alternative hypothesis: The means of the final performance in gatekeeping math courses for students who completed a STEM degree and students who changed their major to a non-STEM major or did not complete a degree are not equal.

Independent-samples t-test

An independent-samples *t*-test was performed comparing the means of the final performance in gatekeeping math courses for STEM leavers and STEM completers.

Assessment of normality via graphic inspection of Normal Q-Q plots was conducted and similarly to research question 5, STEM leavers were found to be normally distributed, but STEM completers were found to be skewed negatively. Once again, the central limit theorem can be applied here due to the large sample size and normality was confirmed. Levene's test for equality of variances was used to assess homogeneity of variances. It was found to be violated ($p < .001$). Welch's t -test will be used because of the violation (Welch, 1947).

The boxplot produced indicated there were eight outliers. The data was checked for input errors and was confirmed to be accurate. Upon removal of the eight outliers, a new boxplot generated had four outliers. The researcher made the decision to include all outliers since there was not a substantial difference when the t -test performed included or excluded the outliers.

There were 168 STEM leavers and 117 STEM completers. STEM leavers' final math performance ($M = 2.76$, $SD = 1.08$) was lower than STEM completers' final math performance ($M = 3.52$, $SD = 0.60$), which was a statistically significant difference, $M = -0.75$, 95% CI [-0.95, -0.55], $t(270.879) = -7.550$, $p < .001$. Consequently, the null hypothesis was rejected.

Conclusion

Multiple and logistic regression analyses performed while controlling for demographic variables and pre-college variables, midterm math performance stood out as statistically significant in predicting final math performance, STEM GPA, cumulative GPA, retention into the third year, and graduation within six years as a STEM major. Adding on final math performance as a predictor, it was a statistically significant

predictor for STEM GPA, cumulative GPA, retention into the third year, and graduation as a STEM major in six years.

Prior to including STEM GPA as a predictor in the multiple regression model, adjusted STEM GPA was used. It was a statistically significant predictor for cumulative GPA. For the logistic regression, STEM GPA was a statistically significant predictor for graduation as a STEM major in six years. In the case of cumulative GPA, it was statistically significant in predicting retention into the second year, third year, and graduation of a STEM major in six years.

Results from *t*-tests found that students who leave STEM, either by changing to a different major or leaving an institution altogether, performed much more poorly in math at the midterm and final point compared to students who graduate with a STEM degree.

Discussion of the major findings and its implications, relationship to prior research, limitations, further research, and practical recommendations are presented in Chapter 5.

CHAPTER 5 DISCUSSION

The purpose of this study assessed the role of midterm performance in gatekeeping math courses in predicting final math performance, STEM performance, cumulative GPA, along with retention and graduation as a STEM major. While there did not exist an abundant amount of research in the utilization of the midterm grades as a factor for retention and graduation of STEM students, this study will serve as one of the few that present the importance of using this performance point to improve STEM outcomes.

Earlier, multiple regression and logistic regression analyses were conducted by controlling for demographic variables and pre-college variables and then cumulatively including midterm and final math performance, STEM GPA, and cumulative GPA to assess the relationship of these predictors to the criterion variables of final math performance, STEM GPA, cumulative GPA, and STEM success outcomes. Afterwards, *t*-tests were performed on STEM leavers and completers to compare their midterm and final math performance.

In this chapter, a highlight of the implication of the findings will be conducted along with a link to prior research, limitations of this study, and recommendations for practice and future research.

Implications of Findings

Midterm Math Performance

The first research question aimed to look at how midterm math performance was related to various GPA and STEM success outcomes. In looking at the predictability of

midterm math performance while controlling for demographic and pre-college variables, three multiple regression and three logistic regression analyses were performed.

Midterm math performance was found to have a positive relationship to all the dependent variables except for retention into the second year. This suggests that an increase in the midterm math performance could lead to increased final math performance, STEM GPA, cumulative GPA, retention into the third year as a STEM major, and graduation as a STEM major within six years.

Most notably, it served as the sole statistically significant predictor for retention into the third year, whereby a student, for each unit increase of their midterm math GPA, improved their chances by 1.33 times of remaining as a STEM major into their third year. While not the only statistically significant predictor, there was an increased odds of 1.47 times per unit increase in a student's midterm math performance to graduate as a STEM student within six years.

While midterm math performance did not serve as a direct predictor when all college academic variables were taken into account, it does serve as an indirect predictor since it has positive association with cumulative GPA which was a statistically significant predictor when all variables were included in the model.

A *t*-test was also conducted to address research question 5 and it was found that students who leave STEM by either changing their major or leaving an institution altogether likely had lower midterm math GPA compared to those who graduated as STEM majors. Thus, it is reasonable to consider that students who have lower midterm math GPA would likely not be retained or graduate as a STEM major.

Final Math Performance

To look at the further relationship of how midterm math could play a role, the second research question added final math performance as a predictor along with midterm math performance, demographic and pre-college variables. Two multiple regression and three logistic regression models were generated and analyzed.

Final math performance was found to positively predict STEM GPA, cumulative GPA, STEM retention into the third year, and graduation within six years as a STEM major. This could imply that when a student's final math GPA increases, there would likely be an increase in their STEM GPA and cumulative GPA. Furthermore, an increase in final math performance could also increase the chances of a student being retained as a STEM major into the third year, as well as graduate in six years' time as a STEM major.

More specifically, for each unit increase of a student's final math GPA, there was 2.67 times increase of a student to be retained to the third year as a STEM major. In the case of graduation as a STEM major in six years, there was 2.87 times increased odds of a student completing their degree per unit increase of their final math performance.

Interestingly, final math performance came up as statistically significant, serving as a positive predictor in research question 3 even when adding STEM GPA as a predictor which was not statistically significant in that model. Final math performance also came up as a positive predictor along with cumulative GPA in research question 4 for retention into the third year. This showcases the importance of including final math performance as a predictor for success in STEM. Furthermore, while it did not directly predict retention into the second year and graduation as a STEM major when all variables were included in the model, it did directly predict cumulative GPA in the other models.

This indicates that there could likely be an indirect effect to cumulative GPA which leads to retention and graduation of STEM majors.

A comparison of means through a *t*-test was done to answer the final research question. Similar to midterm math performance, it was found that STEM leavers were likely to have lower final math GPAs compared to STEM completers. Thus, further solidifying that a student would likely leave STEM if they were to perform poorly compared to their peers who completed a STEM degree.

STEM GPA

The third research question included STEM GPA as a predictor, adding on to the previous predictors. To evaluate this question, a multiple regression and three logistic regression analyses were conducted.

A positive relationship was found for STEM GPA in relation to cumulative GPA and graduation as a STEM major within six years, suggesting that an increase in STEM GPA would result in an increase in cumulative GPA along with the chances of graduating as a STEM major in six years. Furthermore, for each unit increase in a student's STEM GPA, they had a 3.39 times increased chance of graduating as a STEM major within six years. STEM GPA could also serve as another indirect predictor of retention and graduation of STEM majors in the case of predicting cumulative GPA.

Cumulative GPA

Cumulative GPA was included to answer the fourth research question, along with the previous college academic related variables. Three logistic regression analyses were performed to address the question.

Unsurprisingly, cumulative GPA played positive roles in all three criterion variables. Implying that a student would probably be retained into the second year, third year, and graduation in six years a STEM major as cumulative GPA increases.

For each unit increase of cumulative GPA, a student has a 2.67 times increased chance of being retained into the second year. For retention into the third year, each unit increase of cumulative GPA saw 3.86 times increased likelihood for a student to remain. Lastly, a student was 6.89 times more likely to graduate as a STEM major in six years per unit increase in the cumulative GPA.

Demographic Variables

Interestingly, gender was not found to be a statistically significant predictor for any of the regression analyses conducted. Based on this study, this specific sample could imply that being either gender did not seem to matter in the case of performance and their further retention or graduation in STEM.

In relation to the race/ethnicity variable, students who identified as 2 or more races stood out the most when compared to White students. They had increased likelihood of being retained into the third year and graduation in six years as a STEM major across all the research questions, except for research question 1 where they had increased likelihood only in graduation. While they had the increased chances of being retained into their third year and graduate, they served as statistically significant negative predictor in relation to the cumulative GPA in research question 1.

Students who identified as Asian and Black were negatively related to STEM GPA and cumulative GPA when compared to students who identified as White in both research question 1 and 2. This could indicate that a student who identifies as either

Asian or Black would have a decrease in STEM GPA and cumulative GPA when controlling for gender, pre-college variables, midterm math GPA, and then the addition of final math GPA. For Hispanic students, it was similar only in the case of research question 1 where they would have a lower STEM GPA and cumulative GPA when controlling for gender, pre-college variables, and midterm math performance.

However, in research question 4, intriguingly, a student who identified as Black was 2.41 times likely to be retained as a STEM major into the second year along with cumulative GPA. This was the only logistic regression model that was found to be statistically significant in relation to retention into the second year. This indicates that while being Black had a negative relationship as a statistically significant predictor when controlling for other variables in relation to STEM GPA and cumulative GPA, it was shown that Black students were more likely to be retained into their second year compared to their White counterparts.

Many studies highlight retention into the second year and then graduation, but not really what happens in between. The descriptive statistics in this study really highlighted the big drop off of URM students into the third year, indicating that there may be something that is happening during a student's transition into the third year. This highlights the importance of targeting these students to improve their outcomes and help them through to graduation.

Pre-College Variables

High school GPA played a positive role in predicting final math performance in research question 1 and then in predicting STEM GPA and cumulative GPA in both research questions 1 and 2. This highlights the importance of preparation at the high

school level before matriculating into an institution as an increase in high school GPA was indicative of an increase in the dependent variables mentioned earlier. It should be noted that while high school GPA did not serve as a direct predictor of retention or graduation, it may indirectly affect it due to its positive predictive nature in relation to final math performance and cumulative GPA.

The SAT math scores as a predictor was the only one with opposite results. It was found to be statistically significant in two models, being a positive predictor for STEM GPA in research question 1 but being a negative predictor for cumulative GPA in research question 3. This could be the case that the STEM GPA was adjusted for research question 3, which is why it yielded the opposite result.

Relationship to Prior Research

The theoretical framework presented in Chapter 2 certainly supports this study whereby the researcher found that academic performance was a positive indicator of whether students were likely to attrite or graduate as STEM majors which is in line with academic integration from Tinto's (1975, 1993) model and academic performance from Bean and Metzner's (1985) model. Additionally, guided by the theories, the usage of demographic and pre-college variables served as significant predictors in relation to whether a student would decide to stay as a STEM major within the institution.

Previous studies found that females tend to perform better than males in math and STEM courses (Beersingh et al., 2013; Bloodhart et al., 2020) and it was found to be the case for the female students in this sample as well. Prior research highlights that women tended to leave from STEM at much higher rates compared to their male counterparts (Bloodhart et al., 2020; Ellis et al., 2016; Sanabria & Penner, 2017; Sax et al., 2015;

Thiry, 2019). Conversely in this study, gender was never revealed as a statistically significant predictor in retention or graduation.

This study was in alignment with many of the studies in relation to race/ethnicity where underrepresented minorities tended to perform poorly compared to well-represented students (Atuahene & Russel, 2016; X. Chen, 2013). Further, Chen (2013) indicated that Black students were more likely to leave compared to White students. However as mentioned earlier, interestingly, Black students were more likely to be retained into the second year in this study. Nonetheless, by the third year, there were more Black students who left STEM compared to White students.

While various studies found that increasing SAT math scores or standardized math test scores seem to increase students' math or overall GPA (Ackerman et al., 2013; Atuahene & Russel, 2016; Kern et al., 1998; Weston et al., 2019), this study found conflicting results. SAT math was a positive predictor in the case of predicting STEM GPA within research question 1 but was a negative predictor in the case of predicting cumulative GPA in research question 3. Many institutions are currently going SAT/ACT optional (FairTest, 2021) and this includes Tristram University and serving as an inconsistent predictor in this study may possibly be a reason why institutions may have decided to do so.

This study was in line with many other studies that found high school GPA as a positive predictor of math performance, STEM GPA, and cumulative GPA (Ackerman et al., 2013; Beersingh et al., 2013; Gansemer-Topf et al., 2014; Moakler & Kim, 2014; Stewart et al., 2015; Whalen & Shelley, 2010; Wolniak, 2016).

This study was in alignment with the sole study found in relation to midterm grades and final math performance (Beersingh et al., 2013). Another similarity to prior research, lower math performance also predicted lower chances of being retained (Weston et al., 2019). Similar results were found where STEM leavers had lower STEM GPA compared to those who completed a STEM degree within six years (X. Chen, 2013). It was also in line with other studies that indicated cumulative GPA serving as one of the best indicators of predicting a student's likelihood of being retained and graduating (Kern et al., 1998; Wolniak, 2016).

Limitations of the Study

This study only accounted for one university and one cohort of students. In other words, it may not be easily generalizable across subjects nor can it be applied to a different setting. Threats to statistical conclusion validity includes random heterogeneity of respondents, since each individual student has other characteristics that may play a role that can affect the validity of the study.

Another limitation was due to the usage of pre-existing data for this study, the researcher did not have prior knowledge of existing environmental factors (physical or social) that may have impacted students' academic performance, retention, and/or graduation. Additionally, at the institution for which this study was conducted, once the midterm grade has been entered it cannot be modified, thus any error on the professor's part or if a student made up midterm work have not been taken into account.

Recommendations for Future Practice

This study confirmed the importance of midterm math performance in relation to the cumulative GPA which is a driver for retention and graduation for STEM majors. The

data from this study can surely be utilized to make data-driven decisions about STEM programs. However, it is extremely important to utilize this data to improve programs and not to use it only for accountability. For any institution, the ultimate goal is the success of the student and completion of a degree or certificate regardless of whether it is in STEM. As administrators and faculty, it is important to recognize each students' strengths and weaknesses and facilitate their learning, but many may not understand or recognize the pattern that this data can offer. Having an expert in data analysis in relation to academic performance would allow for better evaluation of STEM programs and improving academic advisement processes. Additionally, this data can be a driver in forming a holistic approach of fostering a student's success, where knowing the midterm grade can lead to a discussion with their academic advisor, faculty, peers, and/or family members. This data and future data would surely be useful in predictive analytics in the form of recommending courses or majors to students and allow advisors to help provide students with various options to drive their success, whether they decide to stay in STEM or not.

A faculty member or advisor who specializes in math or STEM education should also be considered. This person can evaluate existing practices in gatekeeping math courses and assist with improving pedagogical practices that specifically target these courses. Furthermore, they can monitor drop, withdrawal, failure, and incomplete rates to assess improvements and identify gaps that may exist in gatekeeping courses. Considering students of all academic backgrounds sit in the same classroom, bridging that gap should be a high priority.

Midterm grades are another tool in the toolbox for administrators and faculty to allow them to reevaluate how resources can be provided to students to increase retention and graduation within STEM. By being able to target students as early as possible and having the ability to provide additional resources to struggling students may lead to their success. Consideration to require STEM midterm grades for all STEM students regardless of year may allow advisors to be able to advise appropriately and further target those who may be struggling especially toward the end of their college career. In this study, it was found that there was a substantial drop off of students going from their second year into their third year as STEM, especially those who were underrepresented in STEM. For example, students who received an unsatisfactory midterm grade should be required to meet with an advisor to discuss their academic performance and possibly facilitate a meeting with faculty on how the student can improve their grade.

In this study, high school average and midterm math performance both served as positive predictors in relation to final math performance, STEM and cumulative GPA. This highlights the importance of ensuring that students are adequately prepared prior to entering their math courses, as well as while they are in their courses. Creation of preparatory pre-college math workshops during the summer before admission into an institution prior to the fall semester after students have taken placement tests will ensure they are in the adequate level. This will allow the ability for students to get caught up so they will be on track for graduation rather than need to take remedial courses that may ultimately not count toward their degree, as well as allow for retaining the knowledge to likely perform better in their math courses when officially enrolled in the fall. It may also help to minimize summer melt which generally affect low-income minority students who

initially made the commitment to attend college but never did (U.S. Department of Education, 2013). Furthermore, the initial “shell shock” students experience at the midterm point that would happen in their first semester from underperforming in gatekeeping courses (Thiry, 2019), instead would happen at the midterm point of their preparatory summer course where it could leverage the change needed to improve their performance in STEM courses as they matriculate.

Increasing interventions may help students to successfully complete their degree in a timely manner and offer more options to allow them to succeed. An example of an intervention may come in the form of referral to a dedicated mathematics or STEM center if financial resources allow. It allows students to have the independence and ability to seek help once they have viewed their midterm grades, which may help improve their performance in math. As found by Thiry (2019), students who sought help when they were underperforming tended to perform better and were more likely to pass their course. By having a math center, students would be able to find other peers who may be in a similar situation and foster a way to allow them to do better in their courses. In addition, having content specific advisors and tutors may give them the targeted advisement and tutoring needed to improve their performance.

Recommendations for Future Research

Looking at other cohorts within the same university will allow for comparison and may yield results and variables that may further help predict performance and graduation. Including professor pedagogical abilities, socioeconomic status, and/or online versus in person courses may also be useful variables. It may also be useful to study cohorts in other universities utilizing similar methodology as this study.

A study on an academic year to year performance in STEM as a comparison may offer more answers as to why there was a considerable number of students leaving STEM after the second year. In this study, there was not as much of a change from the third year to graduation. Thus, looking at factors quantitatively and qualitatively may provide some insight.

A longitudinal study can also be conducted to look at the employment rate of students who have graduated in STEM majors and whether their performance in college had an impact on their chances of being hired in STEM-related fields.

Further statistical analyses on students who started as STEM majors but completed non-STEM degrees compared to those who started and finished as a STEM major. This may help to break down the results further and may allow administrators in higher education institutions to see what may be important factors which can increase retention and graduation of students in STEM.

Further study may need to be conducted to look at how much prior math performance may impact future science and math performance. While this study only looked at higher education courses, it may be important to look further into high school math performance and see if that may have an impact on STEM performance in college.

A qualitative study looking at characteristics of students who are in the midst of underperforming in their science and math courses may provide further insight of how to engage these kinds of students and present more variables that may have an effect on STEM retention and graduation.

This study looked at a cohort of students prior to the COVID-19 pandemic. The Center for Research on Education Outcomes (2020) estimated that due to the majority of

schools going into lockdown during the pandemic, online education led to declines in reading and mathematics achievement in students which would likely take years to recover. How would this impact the students who were already likely at-risk? A longitudinal study conducted based on these factors along with their midterm performance may help to predict STEM performance and graduation with a STEM major. As higher education institutions have adapted to these changes due to the pandemic, analyses from these studies may help to supplement and improve STEM education.

Conclusion

Mathematics will certainly continue to serve as a foundation for most if not all STEM majors. This study highlighted the importance of not only the midterm math performance, but also the final math performance, as they have positive indirect relationships to retention and graduation through the cumulative GPA. As a higher education administrator and someone who graduated as a STEM major, this really showcases the vital role that midterm grades have played and how it could be another jumping point to catch STEM students earlier before they become at-risk.

As an academic advisor, this study has also highlighted that while it is important to look at the retention into the second year as well as graduation, it is so important not to forget what happens in between and guiding students to persist. In this case, a large part of the sample was made up of biology majors where most students are considered pre-med. It could be a possible reason for the considerable drop from the second year to the third year as students may have become disillusioned from the idea of pursuing medical school or realizing the lack of needing to be a biology major to pursue medical school.

Thus, the more information we can gather and aggregate can certainly increase our understanding on how to advise students.

When one considers at-risk or students who are targeted due to performing poorly, there may be a negative viewpoint of this status that may impact students and could lead to attrition. However, we must recognize and view it as a form of growth as students who may have initially underperformed, at the midterm point for example, but was able to persist and do well in the end, for example the final point. This could serve as a way to jumpstart a student's lifelong learning process and a skill that can be transitional to beyond graduation.

In conclusion, the need for STEM graduates over the decades has not waned and this study showcases the importance of midterm performance in gatekeeping math courses and how it plays a role in predicting the final math performance, STEM GPA, cumulative GPA, as well as retention and graduation. In addition, it supports the need to understand the data that could be used as a driver to improve. Furthermore, it is important for administrators to take into account the possible consequence of the midterm math GPA and ensure that institutions are able to adequately address and provide assistance to their students so that they may be retained, persist, and graduate within STEM.

APPENDIX A INSTITUTIONAL REVIEW BOARD APPROVALS



Federal Wide Assurance: FWA00009066

Nov 10, 2022 8:30:44 AM EST

PI: Kandy Rich
CO-PI: Ceceilia Parnter
The School of Education, Ed Admin & Instruc Leadership

Re: Expedited Review - Initial - **IRB-FY2023-19** *The Impact of Midterm College Mathematics Performance on Retention and Graduation of STEM Students*

Dear Kandy Rich:

The St John's University Institutional Review Board has rendered the decision below for *The Impact of Midterm College Mathematics Performance on Retention and Graduation of STEM Students*. The approval is effective from November 8, 2022 through --.

Decision: Approved

PLEASE NOTE: If you have collected any data prior to this approval date, the data must be discarded.

Selected Category:

Sincerely,

Raymond DiGiuseppe, PhD, ABPP
Chair, Institutional Review Board
Professor of Psychology



Federal Wide Assurance: FWA00009066

Feb 16, 2023 2:39:55 PM EST

PI: Kandy Rich

Dept: The School of Education, Ed Admin & Instruc Leadership

Re: Modification - IRB-FY2023-19 *The Impact of Midterm College Mathematics Performance on Retention and Graduation of STEM Students*

Dear Kandy Rich:

The St John's University Institutional Review Board has rendered the decision below for *The Impact of Midterm College Mathematics Performance on Retention and Graduation of STEM Students*.

Decision: Approved

Sincerely,

Raymond DiGiuseppe, PhD, ABPP
Chair, Institutional Review Board

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