2018

Texas Success Initiative Test Scores as a Predictor of College Mathematics Success

Brooke Lee
Walden University

Walden University

College of Education

This is to certify that the doctoral study by

Brooke Lee

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Stacy Wahl, Committee Chairperson, Education Faculty
Dr. Richard Hammett, Committee Member, Education Faculty
Dr. Nicolae Nistor, University Reviewer, Education Faculty

Chief Academic Officer
Eric Riedel, Ph.D.

Walden University
2018

Abstract

Texas Success Initiative Test Scores as a Predictor of College Mathematics Success

by

Brooke Lee

MS, University of Texas, 2003

MA, Webster University, 2000

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Education

Walden University

November 2018

Abstract

Advisors use placement test scores as a means of predicting students' proficiency in mathematics; however, there is a debate about how accurately these scores predict students' success. This nonexperimental quantitative study focused on one test, the Texas Success Initiative (TSI). The purpose of the study was to determine whether the test is an accurate predictor of students' success in college algebra for students in science, technology, engineering, and mathematics (STEM) majors, and whether students who took the test continued pursuing a STEM major. The theoretical framework for this study was Tinto's theory of retention. Statistical Package for the Social Sciences software was used to generate 500 random cases from 2,339 students ranging from 18 to 50 years of age who enrolled in Math 1414 during the Spring 2015 to Spring 2017 semesters at the Texas community college setting. Hierarchical multiple and logistic regression were performed to test whether the TSI scores significantly predicted students' math grade and retention. The hierarchical multiple regression revealed that the TSI score explained only 13% of the variance in math grades (R^2 = .13). The logistic regression showed that the TSI score explained a variance of only 7% (Nagelkerke R^2 = .07) and yielded a higher number of false positives in predicting retention in a STEM mathematics track after controlling for high school GPA, gender, ethnicity, and age. Findings revealed no significant relationship between TSI scores and students' academic success and retention. The results from this study may contribute to positive social change by providing academic advisors with additional knowledge of the best practice for placing students to achieve success in college math courses.

Texas Success Initiative Test Scores as a Predictor of College Mathematics Success

by

Brooke Lee

MS, University of Texas, 2003

MA, Webster University, 2000

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Education

Walden University

November 2018

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

Colleges and universities in Texas use the Texas Success Initiative (TSI) as a predictor of students' proficiency in mathematics (Fields & Parsad, 2012; Hughes & Scott-Clayton, 2011; Melguizo, Kosiewicz, Prather, & Bos, 2014; Ngo & Melguizo, 2016). Researchers have suggested that reliance on this placement test results in an inappropriate math assignment course for about 25% of students (Ngo & Melguizo, 2016; Scott-Clayton, 2012; Scott-Clayton, Crosta, & Belfield, 2014). Very few researchers, overall, have examined the accuracy of placement exams, and most of the completed studies were sponsored by the test developers (Scott-Clayton, 2012), calling the accuracy of the findings into question. Therefore, examining placement tests are pertinent to understand their impact on students.

The purpose of my independent academic research was to analyze the accuracy of these tests to address the gap in the literature in this area. Specifically, I examined the TSI as a predictor of academic success for students in science, technology, engineering, and math (STEM) tracks and its use by one community college in the southwestern United States. As part of my analysis, I included essential control variables (covariates) such as high school grade point average (GPA), gender, age, and ethnicity to determine what percentage of the variation was explained in TSI as a predictor of math score. I did so because scholars have found that several of these variables have a relationship to academic success in general (Wladis, Conway, & Hachey, 2015).

In this chapter, I review the background, problem statement, and purpose of the study. In addition, I present the research questions and hypotheses, the theoretical framework, the nature of the study, and definitions of several key terms used throughout the study. The chapter concludes with a discussion of the study's assumptions, limitations, delimitations, and significance.

Background

Educators rely on the results of placement tests to place students in math courses, even though there is evidence that test results sometimes result in incorrect placement. Authors of predictive placement accuracy studies typically evaluate students' scores on these tests to predict their performance in a course (Camara, 2013; Kumazawa, Shizuka, Mochizuki, & Mizumoto, 2016; Lane, 2014; McClarty, Way, Porter, Beimers, & Miles, 2013; Melguizo et al., 2014; Patterson & Ewing, 2013; Schmit & Saif, 2015; Scott-Clayton et al., 2014; Slomp, Corrigan, & Sugimoto, 2014). Yet, several researchers (e.g., Ngo & Melguizo, 2016; Scott-Clayton, 2012; Scott-Clayton et al., 2014) suggested that placement tests such as the Scholastic Aptitude Test (SAT), SAT Subject Tests, and Accurate Placement (ACCUPLACER) test result in the placement of about 25% of students in incorrect math class levels. There is also a gap in the literature.

In this study, I addressed the gap in the literature related to the predictive power of the placement of STEM students in college math classes by TSI test scores. By examining the criterion-related (accuracy) evidence for this placement test, I provided those who use the test for students' math course placement with information about whether it meets the accuracy criteria (Caines, Bridglall, & Chatterji, 2014) required to accurately predict students' success. The positive social change resulting from this study lies in the proper placement of college students into math courses. Improper placement could result in students failing in their courses (Ngo & Melguizo, 2016), which could negatively affect student retention and the percentage of STEM graduates (Ricks, Richardson, Stern, Taylor, & Taylor, 2014)

Problem Statement

The problem that I addressed in this study is the inaccurate math course assignments that occur when advisors use the TSI test scores to make placement decisions. When determining appropriate math course placement, reliance on placement tests alone has been shown to result in inaccurate course assignment for about 25% of students (Ngo & Melguizo, 2016; Scott-Clayton, 2012; Scott-Clayton et al., 2014). Such incorrect placements can often lead to student failure or attrition (Ngo & Melguizo, 2016). At the XYZ community college in the southwestern U.S. in this study, the attrition level is as high as 32%, and the mathematics failure rate is as high as 54%. I gathered the background data in Table 1 from the college's Office of Institutional Research, Planning, and Effectiveness after obtaining Institutional Review Board (IRB) approval from the community college to review the background data (see Appendix). Table 1 details the success and retention rates from Spring 2015 through Spring 2017 academic years. This information supports the rationale for the study.

Table 1

Percentage of Success and Retention in a Southwestern U.S. Community College

Term	Subject	Course name	Success rate (%)	Retention rate (%)
Spring 2015	Math	College Algebra for STEM majors	46.42	68.10
Fall 2015	Math	College Algebra for STEM majors	56.74	80.56
Spring 2016	Math	College Algebra for STEM majors	50.40	69.88
Fall 2016	Math	College Algebra for STEM majors	52.10	79.76
Spring 2017	Math	College Algebra for STEM majors	52.61	77.71

Saxon and Morante (2014) stated that accurate student placement is a challenge for higher education staff. Questions about the accuracy of placement test scores have led educators at many colleges in the United States to re-evaluate their reliance on these test scores in course placement decisions (Ngo & Kwon, 2015) due to the lack of evidence as to which tests, if any, best predict academic success. This problem is compounded by the fact that few researchers have examined the validity of placement exams (Scott-Clayton, 2012). In addition, many of the existing studies were sponsored by the test authors themselves (Scott-Clayton, 2012). Thus compromising the impartiality of the research. By analyzing the accuracy of these tests through independent academic research, I sought to narrow the gap in the literature in this area. My contribution involved analysis of the use of TSI by educators at one community college in Texas as a predictor of academic success for students in STEM tracks.

Purpose of the Study

The purpose of this nonexperimental quantitative study was to explore the TSI placement test to determine to what extent it predicts students' success in college algebra for STEM majors and students' continued pursuit of a STEM major. The placement test that I investigated was personal motivation to better understand the relationship between students' TSI scores and their success in math courses. The dependent variable was the grade that the student received in the college algebra course for STEM majors. Another measure of success was the retention of students who took this course in the academic years spanning Spring 2015 to Spring 2017.

Research Questions and Hypotheses

The independent variable was the TSI score. The control variables were the students' high school GPA, gender, ethnicity, and age. These control variables were not the focal point of the research study given that they are constants, but their presence had some impact on the dependent variable that must be taken into consideration. Thus, I included them in the research model and tested them together with the independent variables. Through this study, I addressed the following research questions and hypotheses:

RQ1: Does the TSI score predict college math grades while controlling for high school GPA, gender, ethnicity, and age?

$H_0$1: TSI score does not predict college math grades while controlling for high school GPA, gender, ethnicity, and age.

$H_1$1: TSI score predicts college math grades while controlling for high school GPA, gender, ethnicity, and age.

RQ2: Does the TSI score predict retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age?

H_0 2: TSI score does not predict retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age.

H_1 2: TSI score predicts retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age.

Theoretical Framework for the Study

In this study I examined the practice of using scores from the TSI to place students into mathematics courses (Fields & Parsad, 2012; Hughes & Scott-Clayton, 2011; Melguizo et al., 2014; Ngo & Melguizo, 2016). This study fits within a broader theoretical framework of attrition; therefore, I framed this study using Tinto's (1975, 1991) theory of retention to examine the ramifications of using the TSI test scores to place students into math courses and how this affects student academic success and student attrition. Attrition refers to students who did not remain in the college algebra course.

According to Tinto (1975), students' decisions to drop out are based on both student characteristics and the extent of their academic, environmental, and social integration in an institution. In his original model (Tinto, 1975), Tinto described five categories that potentially impact a student's dropout decision. The three main principles of Tinto's model describe processes whereby administrators of higher education institutions indicated their commitment to the students they serve, to the education of all of their students, and to the development of support in both social and educational communities integrating all students as members. Figure 1 depicts a conceptual diagram representing Tinto's model. In the current study, I attempted to build upon the model to show the effect of inaccurate placement into STEM courses on students' decision to dropout.

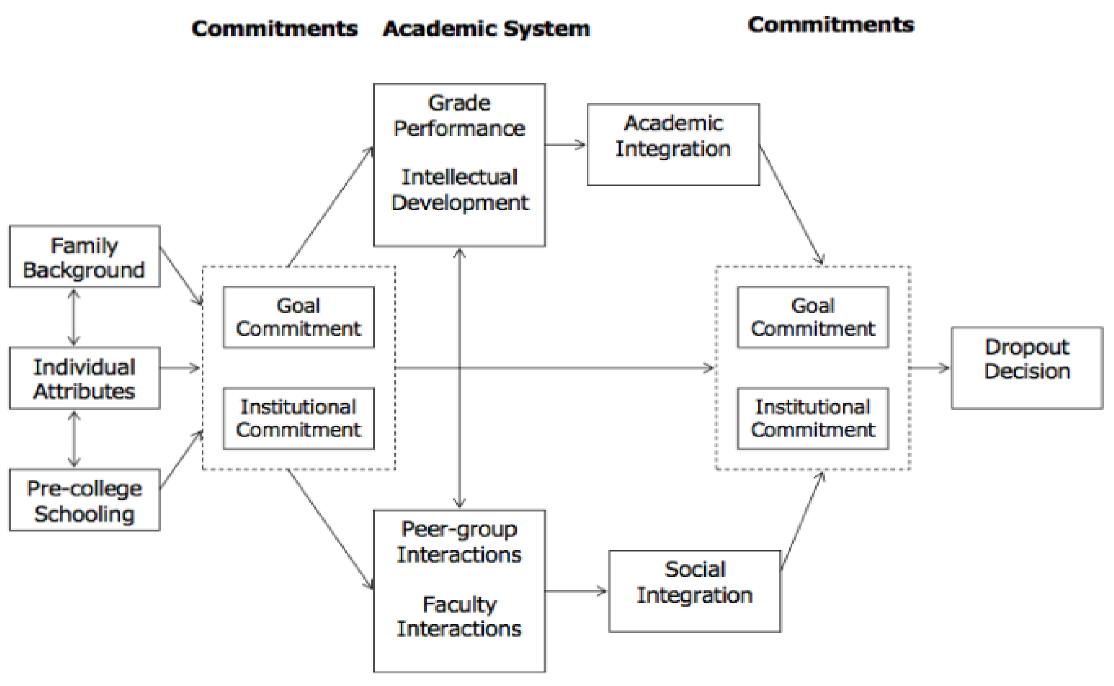

Figure 1. A conceptual schema for dropout from college. From "Dropout from Higher Education: A Theoretical Synthesis of Recent Research," by V. Tinto, 1975, *Review of Educational Research, 45,* p. 95.

Nature of the Study

I used quantitative methodology with a nonexperimental design. The quantitative study design was appropriate in accomplishing the goal of the study, which was to ascertain whether there is a relationship between the dependent variables of retention and grades and the independent variable TSI score while controlling for the covariates high school GPA, gender, ethnicity, and age. According to Creswell (2013), researchers using quantitative data stress unbiased measurements or counts and apply computational techniques to perform the statistical, mathematical, or numerical analysis of data that were collected via questionnaires, interviews, or surveys or by manipulating the statistical data that already exist. A qualitative approach was not appropriate, as qualitative researchers focus on establishing a theory, model, or definition, or improving the understanding of a phenomenon (Creswell, 2013).

I used a nonexperimental design because there was no manipulation of variables involved and because it would have been difficult—if not impossible—to randomly assign participants to control and treatment groups. Furthermore, using a nonexperimental design required less time than an experimental study. In addition, I viewed a nonexperimental study as appropriate because the focus of the study was not to identify causal relationships between variables, but to examine potential linear relationships between the independent and the dependent variables (Bryman, 2012). This approach aligns with the problem statement because the focus of all the research questions was to determine the predictive power of the TSI test scores with respect to the success of STEM students, as measured by student retention and student math grades. The dependent variables that I investigated in this study were the math grade earned in the college course (continuous variable) and retention in the STEM track (a dichotomous categorical variable). The independent variable was TSI score (continuous) while covariates were high school GPA (continuous), gender (dichotomous), age (continuous), and ethnicity (categorical).

The primary procedures that I used to analyze study data were multiple hierarchical regression and a logistic (logit) regression. Due to the nature of the research questions, I concluded that multiple regression analysis was the best means of statistically analyzing study data. Performing this type of analysis allowed me to determine to what extent the independent variable TSI score predicted the dependent variables of retention and grades while controlling for the covariates high school GPA, gender, ethnicity, and age. To better understand the observed data, I also constructed a series of logistic regression models to address each hypothesis. In this research, the primary procedures that I used are multiple hierarchical regression and a logistic regression. According to Peng, Lee, and Ingersoll (2002), each of these regression methods is suitable for estimating the relationships between variables, and each is theoretically and statistically sound and a valid means to examine the research questions and hypotheses. I provide further details regarding my multiple hierarchical regression and logit regression analyses in Chapter 3.

Definitions

Following are definitions of terms I used to guide this study:

Retention: The act of staying in class until completion of the course (Hagedorn, 2005).

Retention rate: The percentage of a college or university's first-year students who persist in their studies and register in a program the following year (Wyman, 1997).

Texas Success Initiative (TSI): A Texas state-mandated program designed to help staff of colleges and universities to assess students' readiness in the areas of reading, writing, and mathematics for their college-level coursework (Texas Higher Education Coordinating Board, 2017).

Assumptions

In the case of this research, several assumptions are acceptable if they categorized as methodological, theoretical, topic-specific, or a combination of these. Certain assumptions accepted without proof, and other assumptions required testing of specific assumptions of the data. For this study, I assumed that the data collected from the Office of Institutional Research, Planning, and Effectiveness Department, as well as the college registrar, were accurate and an unbiased assessment of students' academic performance. Furthermore, I assumed that the students performed to the best of their abilities while taking the placement test.

I also had assumptions about my data, which I tested prior to the analysis. These included assumptions of normality, homoscedasticity, and absence of multicollinearity. The assumption of normality was that the regression residuals would be normally distributed (Fields, 2014; Pallant, 2016). I tested this assumption through an examination of a normal probability plot. Skewness and kurtosis values indicated that none of the variables were outside of the ±2 range, which is considered the standard for normality (Fields, 2014; Pallant, 2016). The assumption of homoscedasticity means that the variance around the regression line is the same across all values of the independent (predictor) variables; it is tested by examining a scatterplot of residuals versus the predicted values (Hair, Anderson, Tatham, & Black, 1995). Finally, the absence of multicollinearity means that the independent variables are not too highly correlated with each other (Hair, Anderson, Tatham, & Black, 1995). I tested this assumption using Variance Inflation Factors (VIF). VIF measures how much the variance of the predictor variable is influenced by the other predictor variables and values over 10 suggest the presence of multicollinearity (Hair, Anderson, Tatham, & Black, 1995). Therefore, the VIF values higher than 10 indicates correlation between the independent variables such as age, ethnicity, gender, high school GPA, and TSI scores.

Scope and Delimitations

Delimitations are factors that a researcher deliberately imposes on the study to narrow the scope and create the research boundaries. Leedy and Ormrod (2010) posited that delimitations describe what the researcher is not going to do in the study. The first delimitation of this study is the demographic data that I restricted to one community college in the southwestern region of the United States. Furthermore, I only focused on students who enrolled in MATH 1414 College Algebra for STEM majors between the Spring 2015 and Spring 2017 semesters. I also delimited the study to an exploration of the relationship between college algebra scores and TSI scores while controlling for age, gender, HS GPA, and ethnicity. I did not study other potentially confounding factors, such as socioeconomic status.

Limitations

The convenience sample of participants that I gathered for this study may not be representative of the target population. This purposeful sample came from the participating college's Office of Institutional Research, Planning, and Effectiveness. I used these data to focus on students who enrolled in MATH 1414 College Algebra for STEM majors between the Spring 2015 and Spring 2017 semesters. I added the data such as TSI scores and high school grades from the college registrar's database, and I included the demographic measures in the overall dataset. This sample may not be generalized to the larger population of colleges because this is only one community college from the southwestern United States.

Significance

The only existing studies testing the predictive power of test scores have been sponsored by the test makers themselves. I addressed the gap in the literature through a nonexperimental quantitative study of the predictive power of the practice of placement of STEM students in college math classes by TSI test scores at one community college in the southwestern United States. These findings are an important contribution to the college, district, and the state of Texas because of the prevalence of the use of these tests in placement in math courses. In recent years, scholars have questioned the validity of the use of the TSI and other tests (Belfield & Crosta, 2012; Fuller & Deshler, 2013; Medhanie, Dupuis, LeBeau, Harwell, & Post, 2012; Scott-Clayton, 2012); therefore, it was necessary to investigate the efficacy of the TSI placement test scores and student success in college algebra course. The findings of this study provide stakeholders with critical information to make well-informed decisions about criteria used to evaluate the placement of students in college algebra courses for STEM majors. An examination of the criterion-related (predictive validity) evidence for this placement test fosters positive social change by providing the test users with information about whether it contains the "validity, fairness, and equity" (Caines, Bridglall, & Chatterji, 2014, p. 7) to accurately predict students' success in math classes and their retention in STEM courses and majors.

In terms of educational policy, this study fits within a broader context. Addressing whether placement tests are an effective way to identify students' math skills for community college math placement for STEM majors is important because many colleges and universities in the United States do not produce sufficient numbers of STEM graduates to meet the demands of America's technology and industry labor market (Moakler & Kim, 2014). These results will promote positive social change through fostering the success of STEM majors by placing them at the correct starting point in their educational careers. The success of STEM majors begins by properly placing students in the math course that will best equip them to gain the math skills necessary to pursue a STEM major. As students' preparation for higher-level math courses improves, this success could lead to higher levels of retention, degree completion, and transfers to 4-year institutions as a STEM major (see Table 1). This is especially important because scholars have noted that the United States faces a challenge in producing enough college graduates in STEM fields (Moakler & Kim, 2014) to be a top competitor in the globalized world.

Summary

Accurate student placement is a challenge within higher education. Colleges use placement test scores from ACCUPLACER, COMPASS Education Group, and the TSI as predictors of students' proficiency in mathematics. Scholars have suggested, however, that reliance on these placement tests results in the misplacement of a significant percentage of students to inappropriate math courses (Ngo & Melguizo, 2016; Scott-Clayton, 2012; Scott-Clayton et al., 2014). By analyzing the validity of these tests through independent academic research, the gap in the literature in this area was narrowed. The focus of this study was the TSI and its use by one community college in Texas as a predictor of academic success for students in STEM tracks.

What now follows is Chapter 2, which includes a review of current research as it pertains to the research questions, including the history of the theoretical foundation of the study.

Chapter 2: Literature Review

The problem that I addressed in this study is the inaccurate math course assignment that occurs when advisors use the TSI test scores to make placement decisions for community college students. There is a lack of empirical data on the predictive validity of placement exams, and those studies that do exist may be biased as they have been predominantly sponsored by the test makers themselves (Scott-Clayton, 2012). In conducting this nonexperimental quantitative study, I sought to determine whether the TSI test can accurately predict students' success in college algebra for STEM majors, as well as to ascertain whether these students continue pursuing a STEM major.

There is a lack of consensus in the academic community regarding college and university placement policies and the processes employed for this purpose, as well as the instruments (Couturier & Cullinane, 2015). According to Couturier and Cullinane (2015), this lack of consensus undermines retention and degree progress of college students in STEM disciplines. This is particularly true for STEM students with an emphasis in mathematics, as many students are hindered by placement tests and policies in obtaining college algebra qualifications (Couturier & Cullinane, 2015; Scott-Clayton, 2012). One of the specific locations that Couturier and Cullinane (2015) cited is Texas, where some schools are striving to improve their placement test policies, but other institutions are now requiring a significant shift away from placement tests and into new means of ensuring that STEM students are correctly placed.

In this chapter, I discuss and synthesize literature pertaining to the problem and the purpose of this study. The first section includes an overview of the search strategy I used to find relevant literature for this chapter's review. The subsequent literature review portion of the chapter includes sections on STEM students, predicting success in college, and placement tests. Topics in the section on STEM students include retention rates; mathematics students; graduation rates; and gender, ethnicity, and age. Topics in the placement tests section include mathematics, validity, high school GPA, and noncognitive indicators. The chapter concludes with a summary of key points.

Literature Search Strategy

I obtained the literature included in this chapter through a strategic search of the recently published literature on educational testing. My process consisted of a multidatabase review, with sources identified via the Walden University Library and local university and college libraries. Most sources identified in this review were published in 2014 or afterwards. I input the following key search terms and phrases into the Walden University Library search engine: *STEM students*, *STEM mathematics*, *STEM students Texas*, *STEM Tinto's theory*, *STEM retention rates*, *STEM graduation rates*, *improving STEM retention*, *improving STEM graduation*, *demographics STEM students*, *demographics STEM Tinto's theory*, *placement tests*, *examples of placement tests*, *placement policy*, *placement policies higher education*, *validity of placement tests*, *placement STEM tests*, *placement tests STEM*, *high school GPA*, *predicting graduation rates*, *non-cognitive indicators graduation*, *non-cognitive indicators STEM success*, *non-cognitive placement higher education*, and *predicting success in college*.

Theoretical Foundation

I chose Tinto's (1987) theory of student retention and attrition in education as the framework for this study because it reflects the discourse of this research. The purpose of this section is to discuss literature pertaining to Tinto's theory. Tinto (2000) argued that the one experience that most college students share is being in the classroom, and student retention rates plummet when college classrooms are not engaging enough during the first year of study. To address this problem, Tinto developed the first-year learning community, wherein groups of students are brought together by instructors for further engagement in their chosen field of study. Such a community bridges the social-academic divide and has been successfully implemented across universities throughout the Western education system (Priest, Saucier, & Eiselein, 2016; Tinto, 1999, 2000).

Tinto (2000) sought to further understand the reasons that so many students choose to leave their professional academic experience. This discussion built off his work from 1987. Tinto sought to pattern student departures with underlying frameworks taken from Durkheim and Gennep (Tinto, 2000). Overarching findings pointed more toward the policies, practices, and features of curricula employed by colleges and universities than cultural, financial, or external reasons for low student retention (Tinto, 2000).

Some authors have criticized Tinto's (1987) theory for not being as culturally inclusive in delineating students' choices to leave college (Guiffrida, 2006). Instead of dismissing the theory, however, other authors have continued to develop the foundational aspects of the theory to apply it to a contemporary educational environment (Guiffrida, 2006). For example, Kommers and Pham (2016) employed Tinto's (1987) theory to build a logistic regression model for Asian and non-Asian students and explore how these demographics differed in their persistence in academic achievement. The results of the study illustrated that cultural differences do exist within both academic integration and the retention rates of demographically diverse students (Kommers & Pham, 2016).

Further advancements in Tinto's (1987) theory have focused on the complexities of retention, and how some schools have had to develop their own methodologies for recruitment, the implementation of academic advising, and the development of curricula, to meet the needs of diverse student populations (Mooring, 2016). Chrysikos, Ahmed, and Ward (2017) argued that retention is an ore, if not the paradigm, of key performance indicators of a college or university's education and assurance processes. Thus, using Tinto's theory to understand the unique nature under which retention rates rise or fall is beneficial for qualitative and quantitative researchers (Chrysikos, Ahmed, & Ward, 2017). Tinto (1975) formulated a model for dropout and has been extended by Kember (1989), Rovai (2003), and Nistor and Neubauer (2010).

Moreover, Xu (2018) used an online survey, constructed on the basis of Tinto's theory, to collect data from a broad sample of college students in STEM courses. The purpose of the research was to ascertain the factors that influence retention rates (Xu, 2018). The investigator found that both the college experience (academic and social) influenced the participants' choice on whether to continue with their degree (Xu, 2018). More specifically, Xu found that STEM students emphasize the importance of faculty teaching quality and accessibility of the teaching staff. In addition, integration with peers and faculty were important (Xu, 2018), a similar finding to studies completed over 20 years ago (Mutter, 1992), suggesting that though academic researchers have found better means of improving retention, they have not developed concrete models yet.

Literature Review Related to Key Variables

I designed the following review of the literature to shed light on the previously published literature on various themes and elements that were combined to realize this study. To accurately develop a full understanding of the problem, as well as to identify patterns and discrepancies in the literature, I practiced the strategic search depicted above. I chose each of the subsections discussed due to both its relevance to the study and the data contained within the recently published literature.

STEM Students

The acronym STEM is the term given to describe students in science, technology, engineering, and mathematics disciplines (Brown, Concannon, Marx, Donaldson, & Black, 2016). According to Brown et al. (2016), recent calls for widespread educational reforms have been supported through the United States due to the lack of graduating students in STEM fields, creating a depletion in the human capital associated with these fields. This decline occurred over the last 30 years and has been steady in the decline of STEM students, and STEM graduates (Brown et al., 2016).

Some authors have argued that with the flattening of the new globalized economy, the educational practice of STEM subjects has recently taken on an entirely revolutionized importance due to economic competition (Kennedy & Odell, 2014). Kennedy and Odell discussed that STEM education is a meta-discipline, embodying a fully integrated effort while removing barriers between STEM subjects. As a result, STEM students now require a basic to advanced understanding of each element of the subjects in order to be comprehensive in one field (Brown et al., 2016; Kennedy & Odell, 2014). In addition to the inherent requirement for STEM students and graduates, as well as new curricula-based endeavors within the study of STEM, recent evolutions in the understanding of students in STEM studies has shed light on the fact that STEM subjects are the most likely subject matters to keep students with disabilities, such as those on the autism spectrum in higher education (Wei et al., 2014). Wei et al. also noted that pathways for potential STEM students to enroll in STEM courses become far more complex and irrelevant in terms of the data. Colleges and universities take on a student to ascertain whether he/she should be accepted, which is an inherent limitation of current practices that does not translate into graduation or other success rates of STEM students.

These pathways usually attempt to predict performance. According to Castro-Alonso, Ayres, and Paas (2017), performance in STEM disciplines depends on the spatial ability and visuospatial working memory of the individual, which is inherently difficult to map and predict. Certain abilities may be more important than others, such as creativity, in predicting achievement, according to Castro-Alonso et al. (2017). Similarly, some individual characteristics (e.g., gender, ethnicity, and other demographic variables) have been found to moderate some of these sub-abilities (Castro-Alonso et al., 2017; Wei et al., 2014). For example, females have a lower average mental rotation spatial ability than males, while no gender effects on spatial working memory were noted. This suggests that variables exist within each demographic but testing services do not cater to each demographic (Castro-Alonso et al., 2017; Wei et al., 2014). Just as an introductory section to STEM, the data contained in the introduction further validates the significance of this study because in terms of educational policy, this study fits within a broader context of addressing whether placement tests are an effective way to identify students' math skills for community college math placement for STEM majors. This exploration is critical because many colleges and universities in the United States do not produce sufficient numbers of graduates in STEM fields to meet the demands of America's technology and industry labor market (Moakler & Kim, 2014). In the following section, I will continue this discussion by looking at the retention rates of STEM students.

Retention rates. The retention rates of STEM students have been the subject of research for decades (Amarnani, Garcia, Restubog, Bordia, & Bordia, 2016). STEM studies, in general, are inherently competitive; therefore, such programs can place an increasing amount of strain and stress on students (Perez, Cromley, & Kaplan, 2014). The stress placed on STEM students is just one of the significant reasons put forth by scholars and scientists as to why retention rates in these disciplines are so low (Perez et al., 2014). Cromley, Perez, and Kaplan (2016) found that other factors, such as student cognition, motivation, and institutional policies, can determine the degree of student retention in STEM. The authors argued that regarding course grades and study skills, the rates of each are directly proportional to the rates of retention (Cromley et al., 2016).

Cromley et al. (2016) also argued that many characteristics attributed to motivation have been linked to both grades and retention in STEM fields, such as self-efficacy, continued interest in learning more about the subject, and effort control. Cromley et al. furthered that these assumptions would make cognition and motivation interdependent, while playing into the context of various institutional policies and guidelines, such as academic support, financial aid, career counseling, forced curving of course grades, course timing, and course registration. Together, these factors combine to have an impact on retention rates within universities and STEM courses. Cromley et al. were not the only researchers to dive into the subject of retention rates of STEM students. Ricks, Richardson, Stern, Taylor, and Taylor (2014) chose to look specifically into the various sub-disciplines within STEM study to identify niche reasons as to why their retention rates are so much lower than other academic disciplines. Ricks et al. investigated retention and graduation rates for engineering because these are far lower nationally than desired. One means of impacting this issue put forth by Ricks et al. is to create learning communities within the campus to foster relationships between students and the faculty of a school that can lead to a mitigation of the stress and negative experiences associated with high-pressure degree courses. Ricks et al. also noted the negative stressors of financial issues, mathematics deficiencies, and a distinct lack of a supportive culture within the engineering discipline as being at the core of many students' apprehension in continuing with engineering studies.

Over a decade ago, in 2006, the national average retention rate for engineering students was less than 55% (Ricks et al., 2014). After regularly undertaking engineering learning community group sessions, both qualitative and quantitative data collected by Ricks et al. showed an increase in both retention rates, and self-efficacy for engineering students, suggesting that mitigating the issues associated with STEM students—in this case, those in engineering—may be easier than anticipated by many institutions. Other authors have researched means of increasing retention rates of STEM students by instituting entire programs that span cities, states, and entire nations, operated mainly by governments or non-profit groups (Windsor et al., 2015). These include mathematics boot camps, networking, and research events to introduce students to the sorts of incomes and lifestyles one can attain after graduating with a STEM degree, faculty relationships, as well as other intervention programs aimed at increasing rates of retention and subsequent graduation (Windsor et al., 2015).

Furthermore, Dagley, Georgiopoulos, Reece, and Young (2016) found that using the EXCEL program, which is not the Microsoft Excel, could increase the rates of retention for most STEM students. The National Science Foundation (NSF) founded the EXCEL Program from 2006 to 2012 as a STEM Talent Expansion Program (Dagley et al., 2016). In addition, A. Davila who is a staff for the EXCEL Program at the University of Central Florida explained that EXCEL is not an acronym and the intention of EXCEL program was to help students excel in their STEM field (personal communication, February 8, 2018). The EXCEL program has become a significantly impactful program on the retention of STEM students, subsequently making it an institutionalized program throughout the campus at the University of Central Florida (Dagley et al., 2016). On the Florida campus, approximately 200 first-year STEM students are recruited into a learning community with residential, social, and curricular components (Dagley et al., 2016). First-year retention, long-term retention, and graduation rates were all higher for the EXCEL cohorts than the comparison groups when studied by Dagley et al. (2016). Overall, these researchers found that the retention of students in a STEM major is 43%

greater for the EXCEL program than the comparison group, especially for women, African Americans, and Hispanics.

Those in the EXCEL program consistently demonstrated rates of high retention and graduation rates. The large cohort size and the all-inclusive nature of the EXCEL program are why Dagley et al. (2016) believed it to be a unique model for addressing the current need for STEM graduates. To conclude this section, it could be argued that even the retention and graduation rates for those STEM students with higher retention rates are not adequate on a national level (Amarnani et al., 2016). This inadequacy further validates the need for this study, as many of the students who were denied entry to the mathematics courses, as noted by Windsor et al. (2015), might be more likely to stay in their other STEM classes due to the increase in understanding of their subject matter. The topic of mathematics students will continue the discussion.

Mathematics students. Mathematics is a core area of study and understanding for all STEM students (Carver et al., 2017). As a topic, it is one of the few subjects that transcends almost all disciplines; however, it is essential to STEM students because science, technology, and engineering are three notoriously mathematically-based subjects (Carver et al., 2017). Similar to the work of Cromley et al. (2016), Larson et al. (2015) found that self-efficacy in mathematics is essential for the success of STEM students. These authors argued that mathematics attainment is a key indicator of long-term retention rates of STEM students, as well as a predictor of whether students will press on to reaching core milestones in education, like graduating with a bachelor’s degree (Larson et al., 2015). Larson et al. undertook a longitudinal study to determine whether math or science-based self-efficacy could predict the status of graduation 4 to 8 years later after controlling for high school academic achievement, as well as mathematics aptitude test, throughout a university sample of foundational science class students. Larson et al. aimed to understand whether mathematics and science self-efficacy could significantly predict the graduation status over the same 4- to 8-year period following semester grade point averages that was controlled for in previous performance and aptitude.

In addition, Larson et al. (2015) used a participant sample of 211 university students, all of whom graduated with a bachelor's degree, and 69 who did not graduate but had previously enrolled in a university course in mathematics and science. Overall, the researchers found that graduation rates were correlated with previous performance and aptitude. This finding signifies that the success of mathematics students may be able to be predicted by prior performance and aptitude within the discipline (Larson et al., 2015). Combined with self-efficacy in these subjects, Larson et al. also identified which students would drop out before graduation with exceptional accuracy. These findings shed light on how much of an issue retention rates for the STEM, particularly mathematics students, is identifiable. With such low reported rates of retention, Miles, van Tryon, and Mensah (2015) argued that this could lead to a depletion in innovation within the United States, which could have drastic long-term economic impacts on the entirety of the nation.

The fastest growing employment projections are in computer science, technology, healthcare, and engineering; however, without improved retention rates, or more acceptance rates to mathematics courses in the first place, these fields of employment will shrink. The impacts of such shrinkage would spread across the United States, and potentially the rest of the world that depend on subsidiary employment structures that feed into STEM-orientated fields (Miles et al., 2015). Miles et al. argued that it should be the high school and middle school settings where teachers, leaders, and other necessary stakeholders start to inspire students into undertaking careers in STEM fields. Groen et al. (2015) furthered this argument by pointing out that mastery learning courses have had to be developed throughout Western education, citing several institutions have found that high schools and colleges do not amply educate their students in STEM subjects. As a result, the first year of most bachelor's programs now entails a year of catching up on understanding and implementing a homogeneous degree of preparedness within student cohorts in STEM classes. Many of the mastery learning classes have been efficient in getting students up-to-date, particularly in mathematics, but limitations continue to point toward a lack of confidence in these subjects, perpetuated through insufficient levels of understanding during a commencement of mathematics degree courses (Groen et al., 2015).

Moreover, Groen et al. (2015) found that mastery was related to academic success, confidence, a feeling of independence, time management, retention of content, attitudes towards learning mathematics, and decreased stress and anxiety, but students felt they were merely being educated in order to pass a test. Groen et al. also found that students that had a sense that they were taught to pass a test felt a lack of confidence throughout their mathematics classes, and this was found to be associated with drop-out rates, presenting yet another limitation in the subject. Roberts and Baugher (2015) found similar results with active STEM students, noting the negative psychological impacts of current educational structures in mathematics, with those students who do get into mathematics STEM courses struggling due to the inherent limitations of their middle and high school experience and curriculum in mathematics. This is a significant finding thus far in this review, as it proves that there is a degree of consistency within research that points to both the physical and psychological stressors placed on STEM and mathematics students (Anthony, Robinson, & Wilson, 2017).

Increased retention and graduation rates of STEM students is fundamentally vital to the future economy of any nation (Maltby, Brooks, Horton, & Morgan, 2016), but first, students must become involved in the course. The purpose of this nonexperimental quantitative study is to focus on the TSI to determine whether the test can accurately predict students' success in college algebra for STEM majors; therefore, it is inherently valuable to ascertain what factors play into the favorable graduation rates of these students, as these elements may be used to reformat existing tests that continue to present as limited within literature.

Graduation rates. Both practical and psychological reasons for heightened and lowered graduation rates in STEM courses exist. Wilson et al. (2015) examined links among levels of belonging, forms of behavioral engagement, emotional engagement, and types of emotional engagement among STEM undergraduates in a set of five culturally and geographically diverse institutions in the United States. Wilson et al. collected data from a survey designed to capture the associations between these critical elements of the undergraduate experience. Through this form of data collection, Wilson et al. obtained results from more than 1,500 student participants. These outcomes, measured in the context of the classroom, supported the importance of belonging to behavioral and emotional engagement in STEM courses (Wilson et al., 2015).

Of these findings, the most significant and consistent links were among the models of the five participating institutions, which occurred between a sense of belonging at the classroom level, as well as positive emotional engagement (Wilson et al., 2015). Patterns of association to engagement were also identified as being similar for self-efficacy and belonging (Wilson et al., 2015). In general, the findings of this study confirmed the importance of belonging in STEM in a classroom context, as well as providing additional insight into the importance of self-efficacy as a factor in supporting student engagement. The results found by Wilson et al. demonstrated that belonging is a well-defined attribute associated with engagement and is not merely reducible to feelings of self-efficacy. This is a significant finding because it further sheds light on the complex processes that go into perpetuating high rates of retention by STEM students.

A significant number of researchers have shifted in the opposite direction to the likes of Wilson et al. (2015) by noting the importance of intervention programs for increasing success in the STEM program. For example, Stieff and Uttal (2015) argued that spatial training would help raise graduation rates of STEM students, whereas Freeman et al. (2014) argued in favor of active learning, both of which are somewhat positive in their application. Stieff and Uttal found that there is evidence that supports spatial training for STEM students, as the process involved in spatial training was positively associated with increased test scores by STEM students. This is an evolving field of research, however, which has only produced mildly positive evidence in the improved graduation rates of STEM students. Freeman et al. found similar results with active learning, arguing that the traditional lecture setting, and subsequent size of the student cohort in many of these classes, make it increasingly difficult for STEM students to engage as efficiently with the learning process. Though active learning was found to increase test scores for STEM students when compared to a lecture-only cohort, these results were varied and could not adequately be used to predict long-term trends in retention and graduation rates (Freeman et al., 2014).

Furthermore, Rodenbusch, Hernandez, Simmons, and Dolan (2016) took the concepts first introduced in this review by Freeman et al. (2014) and Stieff and Uttal (2015) one step further, by arguing in favor of a course-based undergraduate research experience (CURE), wherein students are given a degree of autonomy in their learning process by developing their own curricula. Few researchers have studied the long-term effects of CURE on participating student outcomes; therefore, Rodenbusch et al. tested the impact of taking part in the Freshman Research Initiative (FRI) on students' prospects of graduating with a STEM degree, their prospects of graduating within six years, and GPA at time of graduation using the FRI, a program that engages students in CURE processes. The results revealed that students who completed each of the three semesters of FRI, compared to a control group, were considerably more than their non-FRI cohorts to earn a STEM degree and graduate within six years (Rodenbusch et al., 2016). FRI was found to have not had a meaningful impact on students' GPAs at graduation, and the outcomes were similar for diverse students, suggesting that this course does not face the same limitations as others regarding demographic diversity (Rodenbusch et al., 2016). The results identified by Rodenbusch et al. provided some of the most vigorous and best-controlled evidence to support the need for early involvement of undergraduates in research. These results may be translated into earlier educational curricula to improve test scores in STEM studies.

To conclude this section, it is reasonably apparent that the two streams of thought: practical versus psychological factors, continue to limit how researchers identify core trends in graduation rates of STEM students. Wolniak (2016) conducted one of the very few studies that have identified means of improving interest in STEM and was inherently qualitative in its means, but still employed a mixed methodology wherein students with relatively average STEM scores in high school were given positive reinforcement for undertaking higher education STEM courses during college, resulting in a positive outcome for those students, both in terms of graduation from any degree course, but also in undertaking and graduating from STEM courses. Though this could be a significant finding, Wolniak noted that an inherent limitation placed on students and STEM courses is the fact that high school graduating GPAs and test scores for STEM courses do not consider the psychological triggers that can compound to increase STEM retention. Wolniak argued that these may differ by demographic differences and recommended that future researchers should seek to identify means of evolving these tests and creating cultures of inclusions and support for STEM students in college courses.

Gender, ethnicity, and age. Due to the gradual depletion of students taking on STEM courses, the lowering of retention rates, and the substantially failing graduation rates, researchers have sought to identify patterns within student cohorts of STEM students (Tomasko, Ridgway, Waller, & Olesik, 2016). The predominant limitation within STEM demographics pertains to racial minorities and women (Tomasko et al., 2016). Authors have posited that the lack of racial minorities and women in STEM studies may be due to the lack of professional identities many of these demographics fail to develop before choosing their post-secondary education (McGuire et al., 2017). These professional identities are based mainly on social constructs and cultural and social capital, which may lead many individuals to believe that a STEM course is not an acceptable choice for them from a social perspective, rather than from an intellectual level (McGuire et al., 2017).

Starobin, Smith, and Santos Laanan (2016) also studied these traits using a qualitative methodology. These researchers went in depth to identify female transfer students' experiences who majored in STEM areas at a Midwestern university by highlighting their academic and social adjustment (Starobin et al., 2016). Starobin et al. further examined female STEM experiences by looking at how cultural and social capital intersects through the early background, as well as the pre- and post-transfer experiences of female community college transfer students in STEM disciplines. Overall, the researchers found that female STEM students benefit most from a positive student-faculty interaction, and from positive and supportive classroom environments, which helps to increase their self-efficacy within their discipline (Starobin et al., 2016). This finding may explain why Wladis, Conway, and Hachey (2015) found that women perform poorly in online STEM courses far more than any other demographic.

Moreover, Wladis, Conway, and Hachey (2015) analyzed how ethnicity, gender, and various other non-traditional student characteristics related to the difference between online versus face-to-face outcomes in STEM courses at community colleges. Wladis, Conway, and Hachey chose a quantitative methodology, contrasting the qualitative methodology of Starobin et al. (2016). The researchers used a grade of C or higher to measure the outcomes of successful course completion (Wladis, Conway, & Hachey, 2015).

In terms of course completion, older students performed significantly better with online courses, and women performed significantly worse with online educational courses than face-to-face courses (Wladis, Hachey, & Conway, 2015). Wladis, Hachey, and Conway found that there was no meaningful interaction between online courses and ethnicity. Although Black and Hispanic students may underperform in STEM courses compared to their White and Asian peers on average, whether in online and face-to-face courses, this gap was not increased by the online environment (Wladis, Hachey, & Conway, 2015). The same authors studied the same type of cohort in the same year, using data from more than 2,000 community college STEM majors, obtained via the National Postsecondary Student Aid Study. The purpose of the research was to investigate how ethnicity, gender, and other factors contribute to risk factors such as academic preparation, socio-economic status, citizenship status, and English as a second language related to online STEM enrollment patterns (Wladis, Hachey, & Conway, 2015).

Wladis, Conway, and Hachey (2015) further found that African American and Hispanic demographics were significantly underrepresented in online STEM courses, even after controlling for other factors. Women were particularly overrepresented. In addition to this, the researchers found that even though ethnicity, gender, and non-traditional factors were all critical predictors for STEM majors at community colleges, in the case of online matriculation, gender and ethnicity were more meaningful predictors than non-traditional attributes, which is the opposite pattern observed at 4-year colleges/universities (Wladis, Conway, & Hachey, 2015). These findings identified significant trends and indicated that demographic differences perpetuate throughout enrollment in STEM courses, suggesting that these differences are present and developed prior to application to college and university STEM courses.

Although many authors and researchers put these inherent demographic differences down to cultural and social capital differences regarding the upbringing of women and minorities, Smith, Cech, Metz, Huntoon, and Moyer (2014) also noted that common goals may have an influence over choice in whether to maintain STEM education or not. Using the case study example of Native American students, Smith et al. found that these demographics also need the same support and programs that aim to foster a sense of belonging observed by Starobin et al. (2016). Primé, Bernstein, Wilkins, and Bekki (2015) identified the same trends as the other researchers cited in this subsection, and argued that faculty advisors, who have consistently been found to play an important role in the development of STEM students, should take on more responsibility in maintaining their student cohort. These researchers cited that follow-up studies were needed to confirm whether this was the case (Primé et al., 2015).

To conclude this section, STEM students face several significant challenges. Their numbers are depleting across the country, and their contribution to the economy is essential for national prosperity. Despite these issues, STEM students are not an under-studied demographic. There is a wealth of data that points to the problem, as well as possible solutions. My research will help fill the only gap identified in this section: how relying on a test, such as the Texas Success Initiative, to make placement decisions ensures the proper placement of students. In the following section, I will discuss the literature on predicting success in college from various sources.

Predicting Success in College

Almost one half of all undergraduate STEM students end up leaving their fields by dropping out of college, or through changing disciplines (Belser, Prescod, Daire, Dagley, & Young, 2017). Although several researchers have sought out means of understanding what factors contribute to retention and burnout of STEM students, a majority of these have been in the vein of individual traits and have not necessarily found a specific means of predicting success for STEM students in college (Belser et al., 2017). A high number of researchers have argued that the initial major choice of students, as well as career readiness scores, and participation in a STEM-focused career advice and planning class, may be effective in predicting the success of STEM students in college, and this was most recently studied by Belser et al. (2017). Furthermore, all participants in the program who scored a minimum SAT math score of 550 expressed interest in STEM disciplines (Belser et al., 2017). Institutional data were additionally provided to the researcher by the university-run Institutional Knowledge Management office and included students' first majors and retention rate data (Belser et al., 2017). Measurements were made using the Career Thoughts Inventory (CTI), which assesses participants' level of career readiness and negative career thoughts by way of a 48-point Likert scale (Belser et al., 2017).

The findings of the study suggested that participation in career advising and planning is associated with higher student retention in STEM majors, but also indicated that participation in a STEM-focused career planning class barely predicted which students were prone to leave a STEM major (Belser et al., 2017). In addition to this, the researchers found that by adding the CTI total score and students' initial majors, the change did begin to predict non-retained students, but these variables were not sufficient in discriminating amongst the non-retained students (Belser et al., 2017). These variables represented individual participant characteristics and demographic details, suggesting that incorporating additional distinguished variables may strengthen the ability to predict non-retained students (Belser et al., 2017). In summary, the results identified by Belser et al. suggested that second-year STEM retention can be accurately predicted to a certain degree for students who participate in a STEM-focused career planning course and for students who see reductions in their career apprehensions as measured by the CTI. Similar results were identified by Simon, Aulls, Dedic, Hubbard, and Hall (2015) while exploring student persistence in STEM programs, but Simon et al. also noted the importance of involving students in STEM research before attending college.

Strayhorn (2015) also suggested that engagement in STEM before college enrollment is a key variable for predicting success and/or retention of STEM students. Nugent et al. (2015) sought to identify these factors within middle school youth. The purpose of their research was to develop and test a designed model of factors that contributed to STEM learning and career orientation, by examining the multifaceted paths and relationships between social, motivational, and instructional elements underlying these outcomes for middle school students (Nugent et al., 2015). The authors used a theoretical framework of social cognitive career theory due to its emphasis on explaining the mechanisms that influence both academic performance and career orientations (Nugent et al., 2015).

The critical constructs investigated by Nugent et al. (2015) were youth STEM interest levels, degree of self-efficacy, as well as career outcome expectancy as based on the consequences of various but particular actions. The researchers also chose to investigate the effects of prior knowledge within the cohort, their use of a range of problem-solving strategies, and the support and guidance of informal educators and mentors, family members, and peers (Nugent et al., 2015). Therefore, a structural equation model was developed by Nugent et al., and structural equation modeling processes were used to test the proposed hypothetical relationships between these constructs. The results showed that educators and mentors, individual peers, and family had a strict influence on youth STEM interest, which, in turn, predicted their STEM self-efficacy as well as career outcome expectancy (Nugent et al., 2015). Youth-expected outcomes fostered STEM career orientation for such careers. These results suggest that students are more likely to engage long-term in STEM careers when influenced by a confluence of factors. Of these factors, it was the human factors related to social capital that were most likely to inspire young people's engagement (Nugent et al., 2015).

Mau (2016) concurred with the findings of Nugent et al. (2015), arguing that men and Asian Americans were the most likely to stay in STEM programs as compared to all other demographics and their variables. This is a major limitation of the STEM field and is mostly based on dated and archaic societal norms (Pinheiro, Melkers, & Youtie, 2014). It presents the need to encourage and inspire "future generations of students in the pursuit of scientific research has been viewed as a cornerstone" of U.S. research and development efforts, and innovative thinking (Pinheiro et al., 2014, p. 56). Pinheiro et al. noted that a majority of research into predicting student success in STEM is based on quantitative models, which is actually inherently limiting when the authors have the desired outcome of promoting retention and success. This is because students are more likely to enter, remain, and succeed in STEM studies if they were raised and/or exposed to a great deal of STEM-based activity; therefore, quantitative models that do not include gathering data on this variable are particularly limited (Pinheiro et al., 2014).

Pinheiro et al. (2014) also argued that quantitative research into these fields is to blame for inconsistencies in findings. Le, Robbins, and Westrick (2014) found that women were more likely to persist in STEM studies, a finding that does not support the rest of the research so far cited in this paper. Le et al. (2014) used an expanded person-environment fit (PE fit) model in two studies, to test the combined effects of ability-demand fit, as well as interest-vocation fit, in predicting college students' choice of

STEM and persistence within the STEM fields. Analysis of the results came from 207,093 students who were entering 51 postsecondary institutions. The results supported the hypothesis that academic ability and interest fit are involved in the choice of the STEM field and persistence within the STEM field (Le et al., 2014). The results showed that ability-demand more significantly impacted behavioral outcomes than interest-vocation fit, thus expanding the P-E fit framework (Le et al., 2014). Le et al. also found that gender moderated the effects of these difference predictors in which females are weaker than males.

The opposite effect was found for STEM persistence, in that the relationship between ability and persistence was found to be stronger for female students than it was for male students. As such, the findings of Le et al. (2014) contributed to the academic attention that individualized difference factors play a significant role in organizational and educational research. Findings such as these prompted Fisher (2015) to specifically look at math persistence in STEM, finding that high school math course selection contributed significantly to acceptance into STEM courses, and persistence throughout college and university-level STEM degrees (Fisher, 2015).

To conclude this section, there is a distinct lack of consistency in the discussion of the best means of predicting whether an individual or an entire demographic will be successful in STEM studies. In addition to this, there is also a lack of specific literature into the math section of STEM research, except for the paper published by Fisher (2015), which argued that high school math involvement was positively associated to long-term completion of STEM studies. Overall, the only consistency within the findings of research in this section is that the earlier students begins their interest in STEM studies, the more likely they are to remain in the field.

Placement Tests

There are a wealth of different math and other STEM placement tests across the United States that universities use to determine whether a prospective student has ample knowledge to complete his/her college or university education (Melguizo et al., 2014). Some scholars, however, have found that it is the faculty and administration of many institutions that do not possess adequate knowledge in how to assess and place students into math programs (Melguizo et al., 2014). Melguizo et al. found that in a Los Angeles Unified School District, most faculty members and administrators within the school system did not know how to place students into math development programs designed to promote STEM research in higher education. This finding supports those of Zientek, Schneider, and Onwuegbuzie (2014), who found that students are not necessarily either refused entry or wrongly placed as a result of their wrongdoing or incapability in their subject matter but rather, this is a result of the failings of the institution and its adult workforce (Melguizo et al., 2014; Zientek et al., 2014).

The negative critiques of mathematics placement tests by scholars are plentiful. Saxon and Morante (2014) summed up these critiques succinctly by stating that the most commonly used assessment tools are inaccurate, misused, and lack predictive validity. The authors also noted that 42% of all students entering community college, university, and other higher education institutions are underprepared for the academic workload and quality demanded by these institutions (Saxon & Morante, 2014). These placement issues can occur in one of two ways. The first of these problems is that a student is refused entry to a course based on a placement test that does not adequately assess the student's current understanding and potential long-term growth in the field (Saxon & Morante, 2014). The other is that many students are accepted into courses based on placement assessments that do not adequately ascertain the same information, and these students are able to undertake the course despite not being prepared or academically savvy enough to realize positive long-term results in the field (Saxon & Morante, 2014).

As many institutions base their entire acceptance process on placement tests exclusively, and not specific prior experience in the respective STEM fields, the inaccuracy of the placement tests has the potential to ensure that generations of Americans are not properly educated (Saxon & Morante, 2014), which would have long-term economic impacts on the United States as a whole. These placements tests and their consistent failure to the youth of the United States is the overarching theme of the current research study, as it has been in a plethora of others. An increasing number of underprepared students are admitted to colleges and universities on a yearly basis, with just as many capable and prepared students being refused entry at the same time (Rodgers, Blunt, & Trible, 2014). Transitioning to college is notoriously more complex for STEM students (Rodgers et al., 2014); therefore, this problem must be addressed.

In addition, Avery, Gurantz, Hurwitz, and Smith (2017) found that students are more likely to choose their college majors based on Advanced Placement (AP) integer scores; when these students begin their college education, their behavioral response to negative and positive feedback will eventually determine whether they remain in their discipline. These authors posited that if students receive a favorable placement test score before college, they may drop out if they do not receive the same favorable test scores throughout their first year (Avery et al., 2017). In addition to this, tests score for placements will gradually decrease over time; therefore, fewer students will be accepted to a course, which reduces the amount of funding made available to that course (Rodríguez, 2014). To conclude, placement tests have consistently failed both the students and the universities and colleges that they are intended to help (Callahan & Garzolini, 2015).

Mathematics. As previously discussed in this review of relevant literature, assessment and placement policies that are used to assign students to developmental math and other STEM courses fall short of delivering the results they are intended for (Melguizo et al., 2014). Melguizo et al. evaluated the effectiveness of a set of math placement policies used for enrolling community college students based on the students' academic success in math. Using a discrete-time survival model within a regression discontinuity framework, Melguizo et al. estimated that the actual impact of various placement decisions is minimal to long-term success. The primary conclusion that emerged was that the initial placement of students in a lower-level course extended the time until a student completed the higher-level course they were not assigned to by an average of 1 year (Melguizo, Bos, Ngo, Mills, & Prather, 2016). In most cases, however, after this period, the penalty was not statistically significant (Melguizo et al., 2016). The authors found minor differences in the degree of applicability and the degree of transferable credit accumulation between students initially placed in the lower level course (Melguizo et al., 2016).

The study that Melguizo et al. (2016) conducted was developed after the publication of a research paper by Ngo and Kwon (2015). Ngo and Kwon found that community colleges can result in improved placement accuracy in remedial math and increase the access to higher-level courses using multiple measures of student readiness in their placement procedures. This finding was identified after Ngo and Kwon were made aware of the concerns about the accuracy of placements, which have recently forced states and colleges throughout the country to consider using different measures to determine placement decisions. The researchers provided evidence from California, a state with some of the worst educational levels in the country, where community colleges are required by law to use multiple sources and measures. Ngo and Kwon examined whether this practice improves access and success in college-level courses using data from the Greater Los Angeles Community College District. The scholars found that students placed into higher-level math because of multiple measures performed the same as their higher-scoring peers regarding passing rates and long-term credit completion. Similarly, Madison et al. (2015) found that placement tests were not effective in predicting success in math. The authors concluded this after administering 25 basic algebra items and 15 calculus readiness items to 1572 high school seniors, suggesting that either students are not ready to undertake college mathematics courses, or that the tests were not effectively examining capabilities of students (Madison et al., 2015). This presents a major limitation to this field of research.

Ngo and Melguizo (2016) also argued that changing placement policy may help to increase remedial education student results in community colleges, but there is little to no understanding of the impacts of these reforms. This is an area of research that this study aims to fill. Ngo and Melguizo further stated that in states such as California, many colleges and universities are now switching to computer-adaptive placement tests, which have been found to exacerbate the penalty of remediation for marginal students and result in more placement errors in math courses. This is a fair niche area of research, however, and there are still limitations in understanding the full scope of American placement tests, particularly those in states such as Texas.

Validity. The validity of placement tests is the core area of discussion in most of recent investigations. In this section, I will use specific case study examples to highlight the depth of this systemic problem. Authors such as Gerlach, Trate, Blecking, Geissinger, and Murphy (2014) called for valid and reliable assessment to measure the scale of literacy of a student long before entering college. Westrick and Allen (2014) examined the validity of using Compass® tests scores, and high school GPA, for placing students into their first-year college courses, as well as for the identification of students at risk of failing when they did enter college. Consistent with other researchers, Westrick and Allen argued that the combination of high school GPA and Compass® scores performed better than each measured alone. The results also indicated that, relative to Compass® scores, the predictive strength of high school GPA decays with student age. The authors, therefore, recommended using multiple measures as a means of making course placement decisions, as well as for identifying students for intervention.

A year later, Westrick, Le, Robbins, Radunzel, and Schmidt (2015) added the variable of student economic status (SES) in an examination of the strength of the relationship of ACT® Composite scores and high school grades, with academic performance and persistence into the second and third years at 4-year colleges and universities across the United States (Westrick et al., 2015). Based upon a sample of 189,612 students studying in 50 institutions, ACT composite scores and high school grade point average continued to be highly correlated with first-year academic performance (Westrick et al., 2015). First-year academic performance emerged as the best predictor of the second- and third-year retention, while SES proved to be an ineffective predictor of both academic achievement and retention (Westrick et al., 2015). Fields (2014) concurred with these findings, noting the importance of utilizing alternative measures to increase the validity of the findings.

In addition to this, one of the other significant findings that sheds light on the lack of validity of placement tests is the consistency in minorities receiving lower test scores. Berry, Cullen, and Meyer (2014) argued that recent meta-analyses showed that Black and Hispanic subgroups had lower outcomes in the observed correlation between forms of cognitive ability test scores and performance when compared to White and Asian subgroups in college admissions, military employment, and civilian employment. Berry et al. were unable to determine why this was the case, and they suggested that further research is needed in this field to ascertain why these findings exist. Mozgalina and Ryshina-Pankova (2015) argued that to increase the validity of test scores, the development of assessment procedures to assign students into courses that enable successful fostering of their abilities is necessary.

Finally, to conclude this discussion, it is important to note that authors such as Zilberberg, Finney, Marsh, and Anderson (2014) believed that the validity of test scores for college and university admittance for STEM students is questionable on a global level. These authors argued that the nonconsequential nature of the low-stakes tests can and will undermine students' test-taking motivation, lowering performance and therefore risking the validity of test-based assumptions, whether they pertain to programs, institutions, or nations (Zilberberg et al., 2014). Furthermore, students in countries such as the United States, where academic progress throughout Kindergarten to Grade 12 (K-12) is assessed systematically, are likely to develop antagonistic and negative attitudes toward low-stakes testing by the time these students enter college (Zilberberg et al., 2014). Alternative measures, therefore, should either be combined with or developed instead of current placement tests—which are, by and large, invalid. The following section investigates how high school GPA may be used in this way.

High school GPA. In the case of high school grade point average, authors such as Ybarra (2016) have noted the discrepancies between various demographics but have also discussed how GPA can also be used to predict STEM success into college and university. Although researchers have shown the statistical significance of high school GPAs in predicting future academic outcomes is attainable, the systems with which these scores are calculated vary drastically across schools, presenting another limitation of the use of these metrics alone for college placement (Warne, Nagaishi, Slade, Hermesmeyer,

& Peck, 2014). Some schools choose to employ unweighted grades as a pass/fail measure, which carries the same point value but does not differ on the course in which they earned the grade; other schools use weighting systems that assign a higher value to grades earned in honors courses (Warne et al., 2014).

Due to these inconsistencies, comparing high school GPAs from different schools is difficult, and some authors have argued that it may be impossible; therefore, GPAs cannot be used exclusively when placing students in STEM courses (Warne et al., 2014). Despite this, academic performance is consistently used as a primary predictor of college graduation, and placement tests are used to admit them (Gershenfeld, Ward Hood, & Zhan, 2016). Islam and Al-Ghassani (2015) furthered that high school performance and gender can be used to positively predict calculus scores for students in college on an international level. The researchers based this argument on a finding of the same nature in a cohort of students in the Science of Sultan Qaboos University in Oman; they also argued that if individuals outperform their peers during high school, they are significantly more likely to continue to outperform their peers during university (Islam & Al-Ghassani, 2015). Chew, Knutson, and Martini (2014) explained that issues persist using high school GPA as a predictive measure of student success in the STEM. This lack of consistency, even when based on a variety of factors, cannot be used independently or exclusively instead of placement tests (Chew et al., 2014).

Noncognitive indicators. Non-cognitive indicators or skills have also been described as soft skills, or social and emotional learning skills (Martorell, McFarlin, & Xue, 2014). These are the skills that cannot be captured via high school GPA or placement tests and are mostly left out of all decision making, despite their inherent relation to positive outcomes (Martorell et al., 2014). Non-cognitive indicators revolve around behavioral skills, such as self-regulation. For example, if a student presents with a high level of self-regulation, then this data can be used in conjunction with other behavioral skills to predict future success (Martorell et al., 2014). Additional skills include social fluidity, self-confidence, optimism, curiosity, grit, and conscientiousness (Martorell et al., 2014).

Furthermore, Beattie, Laliberté, and Oreopoulos (2016) collected a comprehensive set of non-academic indicators, such as non-cognitive skills, from a representative sample of incoming freshman to an American university to explore the measures that best predicted the large variance in first-year college performance that was unaccounted for by past grades. The authors uncovered consistency in their findings of student anomalies (students who had far lower behavioral test results scores than predicted) regarding behavioral skills (Beattie et al., 2016). These consistencies included: waiting longer to start assignments, a higher propensity for procrastination, significantly less conscientious attitudes than peers, expression of superficial goals concerning careers, and cramming before exams (Beattie et al., 2016).

In contrast to these findings, those students who exceeded expectations expressed far more purpose-driven, philanthropic goals and were willing to study for more hours every week to meet and exceed their predicted GPA (Beattie et al., 2016). These findings were identified after using a seven-variable average test of critical non-cognitive indicators and led Beattie et al. to argue that these indicators are far more successful in predicting future academic attainment. Pipere and Mieriņa (2017) concluded the same findings as Beattie et al. but used the prediction within a student cohort of 9th graders. These researchers explored the role of non-cognitive indicators concerning mathematics and mainly looked at self-belief, personality traits, social attitudes, and welfare of students (Pipere & Mieriņa, 2017).

The findings from the Pipere and Mieriņa's (2017) study showed that personality, social attitudes, and well-being (welfare) variables matter more to mathematics academic achievement than sociodemographic variables, suggesting that non-cognitive indicators are the paradigm over such variables as socioeconomic status (Pipere & Mieriņa, 2017). Furthermore, Pipere and Mieriņa identified that self-belief is even more of a positive indicator for success in math; when combined with openness, conscientiousness, and social attitudes of domination and contentment, as well as values such as universalism and stimulation, the likelihood of success in math rises exponentially.

Moreover, Stankov, Morony, and Lee (2014) cited that even within the research into non-cognitive indicators, the specific areas of this field that increase the validity of prediction can be further honed. These scholars argued that contemporary efforts to distinguish non-cognitive predictors of academic performance and school success have primarily focused on self-constructs like self-efficacy, anxiety, and self-concepts, which are measured for a specific domain, such as mathematics (Stankov et al., 2014). As a result, the authors extended the measurement of the non-cognitive realm in education so that it incorporated both the social and the psychological adjustment variables, as well as including ratings of confidence in addition to these self-constructs (Stankov et al., 2014).

The findings of Stankov et al. (2014) showed that confidence explained a majority of the variance in accomplishment acquired by various self-related constructs combined, and that psychological modification variables added a minimal amount to the equation. Moreover, in contrast to some cognitive and non-cognitive variables, confidence is responsible for 46.3% of total variance in accomplishment, while measures of previous cognitive performance in combination with other non-cognitive variables are responsible for 40.5% of the total variance. This is a significant growth in predictive ability, suggesting that Stankov et al. (2014) identified a more successful means of predicting success in STEM.

Stankov (2014) also argued the same findings. This researcher cited non-cognitive indicators as being far more successful in predicting the future success of STEM students during college, although further research is needed to assess whether these tests need to be done consistently in order to account for trends in human emotion (Stankov, 2014). To conclude this section, non-cognitive indicators are consistently identified as being positively associated with higher predictive validity. In the following section, the researcher will summarize and conclude the literature review.

Summary and Conclusions

Tests such as the Texas Success Initiative may not be predictively valid in ascertaining whether a student will be successful in STEM studies. While scholars have conducted varied investigations to evaluate placement tests; predictive validity is often not at the core of the purpose of their research. Regarding the findings of this chapter, several key points can be derived from the data. Firstly, the literature pertaining to STEM students was found to be homogenous in the consistent plea for better means of inspiring students into undertaking STEM studies, both for the innovative abilities of the United States, and for the fact that STEM students are largely responsible for key inputs into the U.S. economy (Brown et al., 2016; Castro-Alonso et al., 2017; Kennedy & Odell, 2014; Wei et al., 2014). In addition to this, scholars have found consistency in the need to increase retention rates for STEM students (Cromley et al., 2016; Perez et al., 2014; Ricks et al., 2014).

Belser et al. (2017) highlighted the importance of finding a means of accurately developing placement tests that are both accurate and beneficial in the long-term for retaining STEM students. In this chapter, I verified the problem being addressed in this study and shed light on the gaps in literature pertaining to the purpose of this paper. This summary concludes Chapter 2. Chapter 3 details the research design and rationale of the study, important details concerning the population and sample, and instruments to obtain the needed information to understand academic success and retention regarding the TSI placement test.

Chapter 3: Research Method

The purpose of this nonexperimental quantitative study was to determine whether the TSI test is a predictor of students' success in college algebra for STEM majors and whether these students continue pursuing a STEM major. The question that I investigated is whether the TSI is an accurate predictor of success in the gateway math course, MATH 1414 (College Algebra for STEM Majors), and in entering a STEM degree track overall. Colleges use TSI as predictors of students' proficiency in mathematics (Fields & Parsad, 2012; Hughes & Scott-Clayton, 2011; Melguizo et al., 2014; Ngo & Melguizo, 2016). Scholars have suggested, however, that reliance on these placement tests results in the assignment of about 25% of students to inappropriate math courses (Ngo & Melguizo, 2016; Scott-Clayton, 2012; Scott-Clayton et al., 2014). Several researchers have empirically examined the predictive validity of placement exams; however, it is important to note that test makers sponsored most of these studies (Scott-Clayton, 2012). Thus, analyzing the validity of these tests in independent academic research adds to the literature in this area. The focus of this study was the TSI and its use by one community college in Texas as a predictor of academic success for students in STEM tracks.

In the following sections, I discuss the purpose of the study. The purpose statement is followed by the research questions and an overview of the research method and design. Next, I describe the participants and the procedures for their selection, along with the materials and instruments I used in conducting the study. Following these topics is a delineation of the operational definition of variables and information on the data collection and analysis processes. After discussing the assumptions, limitations, and delimitations, I conclude Chapter 3 with a description of ethical assurances and a summary of the chapter.

Research Design and Rationale

The two dependent variables that I investigated in this study were students' math grades and the decision to continue with a STEM program. The independent variable was TSI score. There are four covariates that were controlled for in the analysis: age, gender, HS GPA, and ethnicity.

I examined the research questions through a quantitative method using multiple regression analysis. A quantitative research method with a correlational design was appropriate for this study because the results are based on secondary data using an established source. A quantitative research involves the use of computational, mathematical, numerical, or statistical tools to drive the results (Creswell, 2013). Due to the nature of the research questions, multiple regression analysis was the best fit for this study because I sought to determine how far the TSI score predicted the college algebra course grades and retention while controlling for the covariates of age, gender, HS GPA, and ethnicity. Multiple regression analysis is one of the broadly used statistical procedures to examine the relationship between a single dependent variable and two or more independent variables (Mason & Perreault, 1991).

The nature of the research design was a quantitative nonexperimental design. Although other designs such as causal-comparative, quasi-experimental, and experimental for a quantitative methodology exist, the selection of a nonexperimental design using regression analysis was most applicable to this study.

Methodology

Population

The chosen target population in this study consisted of 2,394 students who were enrolled at a community college in the southwestern region of the United States and who were registered to take college algebra course for STEM majors from Spring 2015 to Spring 2017 academic years. All students were required to take a placement test such as the TSI unless they were exempt. The community college in this study was a Hispanic-serving institution (Hispanic Association of Colleges & Universities, 2017). The U.S. Department of Education (2016) defined a Hispanic-serving institution as a not-for-profit institution of higher learning with at least 25% of the student enrollment identified as Hispanic.

Sampling and Sampling Procedures

The sample that I used to conduct this study included 180 students between 18 and 50 years of age from a select community college in the southwestern region of the United States who entered a STEM field. The selection of participants was through a probability sampling method from readily available data, also known as random or chance sampling (Kothari, 2004). I used IBM SPSS Statistics (version 24) to generate 180 random cases from the 2,394 students who enrolled in Math 1414 during the Spring 2015 to Spring 2017 semesters.

To determine the minimum sample size, I used G*Power 3.1.9.2 for this study. I determined that, when performing a hierarchical multiple linear regression that would detect a medium effect size of $f^2 = 0.15$ at a 5% level of significance with 80% power, the study would require a minimum sample size of 55. The calculation of a minimum sample size for logistic regression requires previous knowledge such as the expected odds ratio (effect size), a proportion of observations in either group of the dependent variable (retention in a STEM program), and the distribution of each independent variable (Hosmer, Lemeshow, and Sturdivant, 2013). Hosmer, Lemeshow, and Sturdivant suggested a minimum sample of 10 observations per independent variable in the model but cautioned that researchers should seek 20 observations per variable if possible. LeBlanc, and Fitzgerald (2000) suggested a minimum of 30 observations per independent variable. Using the calculation suggested by Leblanc and Fitzgerald, I calculated a minimum sample size as 30 x the number of independent and control variables calculated as 30 x 6 = 180 participants.

Archival Data

The office of the Institutional Research, Planning, and Effectiveness provided the deidentified student data that included details on who enrolled in MATH 1414 College Algebra for STEM majors between the Spring 2015 and Spring 2017 semesters, as well as TSI scores, high school GPA, age, gender, and ethnicity. After receiving written permission from Walden University's IRB, I acquired the dataset and saved it as an Excel file to be imported to IBM SPSS for statistical analysis.

Instrumentation and Operationalization of Constructs

The information used in this section came from a southwestern U.S. community college's Office of Institutional Research, Planning and Effectiveness. The operationalization of the dependent and independent variables was, as follows:

Dependent variables. There were two dependent variables.

College math grade. This variable is the grade received by the students in the math course to which they were assigned based on TSI placement. This is an interval variable that I coded between 0 (F) to 4 (A).

Retention in STEM track. This is a binary variable coded as 1 if the student remained in the STEM track from Spring 2015 to Spring 2017 and 0 otherwise.

Independent variables. There were five independent variables.

TSI. The TSI test is a Texas state-mandated assessment designed to place students in a specific math course commensurate with their math ability (Texas Higher Education Coordinating Board [THECB], 2017). Effective the fall of 2013, all students who attend Texas public institutions of higher education must comply with the TSI unless they are exempt (THECB, 2017). The TSI assessment scores range from 310 to 390, and the minimum score for placement in college algebra for STEM majors is 350 (THECB, 2016). The score of 350 is associated with the probability of successful completion of a college math course, which is defined as receiving a grade of C or higher (THECB, 2017). The predictive placement validity and reliability of the TSI assessment were investigated by the College Board as part of the contractual obligation to the THECB (College Board, 2015; THECB, 2016). This is an interval variable.

HS GPA. This variable is the student's high school grade point average on a continuous scale of 0 to 4.

Gender. I coded this variable as 1 for female and 0 for male (categorical). This data will come with the student record.

Ethnicity. I coded this binary variable as 1 for Hispanic and 0 otherwise (categorical).

Age. This is a theoretically continuous variable correlating to the student's age in years.

Data Analysis Plan

I used hierarchical multiple regression and logistic regression to answer the research questions and hypotheses. The research study sought to determine if TSI scores predict college math grades and retention while controlling for high school GPA, gender, ethnicity, and age.

I used IBM SPSS Statistics (version 24) software to calculate descriptive statistics of the data for the variables. To describe the sample quantitatively, I obtained frequency and percentage summaries for the categorical variables. Also, I calculated the measure of central tendencies of means, standard deviations, and minimum and maximum values for the continuous variables because running basic descriptive is important to get an idea of how representative the sample is to the population.

Before regression is performed, certain assumptions must be considered to run multiple regression. There needs to be a linear relationship between the variables; this includes no significant outliers and the presence of normality. I assessed the linearity assumption through scatter plots generated by SPSS. These scatter plots also serve as a visual aid in detecting unusual values (outliers), and outliers were removed. I assessed the normality assumption through kurtosis and skewness statistics. I obtained and investigated the skewness and kurtosis statistics of the data of the study variables to test whether the data are normally distributed or not. Skewness statistics greater than 3 indicate strong non-normality. Kurtosis statistics between 10 and 20 also indicate non-normality (Kline, 2005). If there is a violation of the normality assumption, transformations need to be applied to the variables to correct this.

I used hierarchical multiple regression to answer the first research question. Hierarchical multiple regression enabled me to enter the independent variables into the regression equation in the order of my choosing, which allowed me to control the effects of covariates on the results. Researchers use multiple linear regression to identify the degree of strength of effect that the independent variables may have on the dependent variable and to forecast the effects of change (Creswell, 2013; Tabachnick & Fidell, 2012).

I tested the following multiple regression model:

College Math Grade = $\beta_0 + \beta_1$ **TSI** + β_2 **HS GPA** + β_3 **Gender** + β_4 **Ethnicity** + β_5 **Age** + ε

I reported a corresponding *p*-value of each model and determined the variance explained by the model using the R^2 (Klugh, 2013). Individual predictors were reported by the predictor's standardized beta weights (β) and corresponding *p*-values (Klugh, 2013). I indicated statistical significance when there were *p*-values less than or equal to 0.05.

I answered the second research question and hypothesis by conducting multiple logistic regression. There are a few assumptions that need to be tested before running multiple logistic regression. One assumption is that there must be a linear relationship between the continuous independent variables and the logit transformation of the dependent variable. I used the Box-Tidwell (Fox, 2015) approach, which adds interaction terms between the continuous independent variables and their natural logs to the regression equation, to test this. The other assumption is that there must not be any multicollinearity (Hilbe, 2009) meaning that there should not be any strong relationships between the independent variables. To test for this, the variance inflation factors were assessed. Any VIF larger than 9 will be deemed problematic (Fox, 2016). I tested the logistic (logit) regression model by estimating the log-odds (logit) of the probability of the dependent variable.

Retention in STEM Track $= \beta_0 + \beta_1$**TSI** $+ \beta_2$ **HS GPA** $+ \beta_3$ **Gender** $+ \beta_4$ **Ethnicity** $+ \beta_5$ **Age** $+ \varepsilon$

Any *p*-value less than or equal to 0.05 indicates significance, and I reject the respective null hypotheses and support the alternative hypotheses.

Threats to Validity

The external validity threats of this study may be the population sample of students that attend other colleges. Generalizability may be a problem because the survey does not represent the entire population of college students; rather, it focused only on college students in one community college. Other issues that can be a threat to validity include random sampling error and unintentional over- or under-representation due to the sampling process. Sampling procedures may create another threat to validity. An internal validity threat may be based on the design. In this logistic regression study, I sought to determine whether there is a correlation between a criterion variable and the best combination of two or more predictors. To compare the experimental design with the correlation design, an experimental design requires a stronger internal validity.

Ethical Procedures

I omitted the name of the college in this study, and no mention of other information that could lead to the identification of the school has been made. The course number is a Texas Common Course Number; many colleges use this to refer to college algebra. The use of archival data precluded the need to protect the sample of students' data as it did not include any identifying information from the students. I did not gather identifying information such as name or addresses from the archival data to protect the privacy of the sample. I did not obtain the participants' informed consent for data collection because the data were obtained from secondary data sources, and there were no actual data collection conducted in the study.

I followed the required retention period of the documents set by the Institutional Review Boards. As a precautionary measure, I removed any identifying information, such as names, and replace this information with a numerical code to ensure confidentiality. No unauthorized persons can access the data because I keep the data in a strong password-protected file in my computer that only I have access to. After 5 years, I will destroy the hard copies of the data via shredding and permanently deleting the electronic files, as per Walden University's protocol.

Summary

Through this quantitative nonexperimental study using regression analysis, I answered the research questions and hypotheses. I used SPSS to analyze the data collected from one community college in the southwestern region of the United States. During data analysis, I performed descriptive statistics analysis, multiple regression, and logistic regression analysis to address the research hypotheses of the study. The data came from a sample of students who were enrolled in MATH 1414 College Algebra for STEM majors between the Spring 2015 and Spring 2017 semesters. I added data such as TSI scores and high school grades from the Office of Institutional Research, Planning, and Effectiveness, and included the demographic measures in the overall dataset. In Chapter 4, I presented the findings of the data analysis and discuss the results' implications for practice, research, and theory.

Chapter 4: Results

The purpose of this nonexperimental quantitative study was to explore how accurately the TSI placement test predicts both students' success in college algebra for STEM majors and the retention of those same students. The two dependent variables in this study were students' math grades and the decision to continue with a STEM program. The independent variable was students' TSI scores. There were four controlled covariates in the analysis: age, gender, ethnicity, and high school GPA. I conducted descriptive statistics analysis, hierarchical multiple regression analysis, and hierarchical logistic regression analysis to determine the objectives of the study. I used SPSS to perform the different statistical analyses. Results were used to answer and test the following research questions and hypotheses:

RQ1: Does the TSI score predict college math grades while controlling for high school GPA, gender, ethnicity, and age?

$H_0$1: TSI score does not predict college math grades while controlling for high school GPA, gender, ethnicity, and age.

$H_1$1: TSI score predicts college math grades while controlling for high school GPA, gender, ethnicity, and age.

RQ2: Does the TSI score predict retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age?

H_0 2: TSI score does not predict retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age.

$H_1 2$: TSI score predicts retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age.

This chapter begins with a discussion of the collected data about the baseline demographic and basic univariate analyses to justify the inclusion of covariates in the model. The results of testing of the required assumptions for the use of the parametric statistical analysis of multiple regression analysis follows. The results of the hierarchical multiple regression analysis and the hierarchical logistic regression analysis are presented to address Research Question 1 and 2, respectively. A summary concludes this chapter.

Data Collection

Deidentified student data used in this study were archival and came from the Office of Institutional Research, Planning, and Effectiveness at a community college in the southwestern region of the United States. I obtained these data after receiving IRB approval from Walden University (# 05-15-18-0156489). The chosen target population for this study consisted of 2,394 students who were registered to take a college algebra course for STEM majors between the Spring 2015 and Spring 2017 academic years. The final population of the study consisted of 2,339 students. There was an approximate 2.3% discrepancy in the actual number of the population collected compared to the planned number of population to be collected. For this study, the minimum required number of samples was 180. Any students with missing values were excluded from the dataset. Of the 2,339 students in the final population, 698 (29.8%) had no missing data. SPSS was used to generate 500 random cases from the 698 students. Therefore, the samples consisted of 500 (21.4%) students, which was a representative of the 2,339 students. The final sample of 500 provided more reliable results than the 180 minimum requirements because larger samples tend to decrease the probability of errors, increase the accuracy of population estimates, and augment the generalizability of the results to more representative of the population ((LeBlanc & Fitzgerald, 2000; Osborne & Costello, 2004).

Baseline Descriptive and Demographic Characteristics

The sample of 500 students exhibited the demographic characteristics illustrated in Table 2. There were more male (295; 59%) than female (205; 41%) students, and more than half of the 500 students were Hispanic (359; 71.8%). The most frequent math grade was an F (183; 36.6%); however, the majority (378; 75.6%) of the 500 students remained in the STEM track from Spring 2015 to Spring 2017.

Table 2

Baseline Descriptive and Demographic Characteristics

Variable	Frequency	%
Term		
Fall 2015	151	30.2
Fall 2016	149	29.8
Spring 2015	26	5.2
Spring 2016	117	23.4
Spring 2017	57	11.4
Gender		
Male	295	59.0
Female	205	41.0
Ethnicity		
Others	141	28.2
Hispanic	359	71.8
College math grade		
F	183	36.6
D	54	10.8
C	91	18.2
B	96	19.2
A	76	15.2
Retention in STEM track		
No	122	24.4
Remained	378	75.6

Basic Univariate Analyses

I performed univariate analyses to justify the inclusion of covariates in the model. The ANOVA test of difference was conducted to determine whether the covariates of high school GPA, gender, ethnicity, and age were significantly related with the dependent variable of college math grades. ANOVA was used because the dependent variable was continuously measured. A level of significance of .05 was used in the ANOVA. Based on the ANOVA test, Table 3 shows that the dependent variable of college math grades was only significantly related with the covariate of high school GPA ($F(4, 495) = 11.30$, $p < .001$).

Table 3

ANOVA Results of Relationship of College Math Grades With High School GPA, Gender, Ethnicity, and Age

		df	*SS*	*MS*	*F*	*p*
Age	Between groups	4	12.25	3.06	0.58	0.68
	Within groups	495	2613.55	5.28		
	Total	499	2625.80			
Gender	Between groups	4	2.13	0.53	2.22	0.07
	Within groups	495	118.82	0.24		
	Total	499	120.95			
Ethnicity	Between groups	4	1.00	0.25	1.23	0.30
	Within groups	495	100.24	0.20		
	Total	499	101.24			
HS GPA	Between groups	4	5.65	1.41	11.30	0.00*
	Within groups	495	61.91	0.13		
	Total	499	67.56			

Then, I conducted a nonparametric test of difference to determine whether the covariates of high school GPA, gender, ethnicity, and age were significantly related with the dependent variable of retention in a STEM mathematics track. I applied a nonparametric test because the dependent variable was dichotomously measured. First, a Kruskal-Wallis test was employed to determine whether there was a relationship between the dichotomously measured dependent variable of retention in a STEM mathematics track and the categorically measured covariates of gender and ethnicity. A level of significance of 0.05 was used in the Kruskal-Wallis test. Table 4, which present the results of the Kruskal-Wallis test, shows that the dependent variable of retention in a STEM mathematics track was not significantly related with the covariates gender (χ^2(1, *N* = 500) = 2.20, *p* = .14) and ethnicity (χ^2(1, *N* = 500) = .31, *p* = .58). Next, a Spearman Rho correlation analysis was conducted to determine whether there is a relationship between the dichotomously measured dependent variable of retention in a STEM mathematics track with the continuously measured covariates of age and high school GPA. A level of significance of .05 was used in the Spearman Rho correlation analysis.

Table 4

Results of Kruskal-Wallis Test of Relationship of Retention in STEM Track With Gender and Ethnicity

Dependent variable	Independent variable	χ^2	*df*	*p*
Retention in STEM track	Gender	2.20	1	0.14
	Ethnicity	0.31	1	0.58

From the results of the Spearman Rho correlation analysis, as shown in Table 5, I determined that the dependent variable of retention in a STEM mathematics track was significantly negatively correlated with the covariates of age (r_s(498) = -.13, *p* = .003) and significantly positively correlated with high school GPA (r_s(498) = .20, *p* < .001). The impacts of these covariates should be controlled when investigating the relationships both between TSI scores and college math grades and between TSI scores and retention in a STEM mathematics track because there were significant relationships between the dependent variables and the covariates.

Table 5

Results of Spearman Rho Correlation Analysis of Relationship of Retention in STEM Track With High School GPA and Age

			Retention in STEM track
Spearman Rho	Age	Correlation Coefficient	-0.13*
		p (2-tailed)	0.003
		N	500
	HS GPA	Correlation Coefficient	0.20*
		p (2-tailed)	0.00
		N	500

* Correlation is significant at the 0.01 level (2-tailed).

Results

Table 6 summarizes the descriptive statistics summaries of the said samples. The sample used in this study was 500 students between 18 and 50 years of age, with a mean age of 19.18 years old. The oldest student was 36 years old, and the youngest was 18 years old. The mean high school GPA among the 500 students was 3.31 (*SD* = .37). The mean TSI score among the 500 students was 350.29 (*SD* = 10.73).

Table 6

Descriptive Statistics Summaries

Variable	*N*	*Min*	*Max*	*M*	*SD*
Age	500	18	36	19.18	2.29
HS GPA	500	1.59	4.72	3.31	0.37
TSI Math	500	310	390	350.29	10.73

Statistical Assumptions

This current study involved the use of the parametric statistical analysis of multiple regression analysis to address the different objectives of the study. The different required assumptions of these statistical analyses included linearity, no outlier, and normality. Each of these assumptions was tested.

Linearity. The first assumption tested was that the multiple linear regression needs the relationship between the independent variables and dependent variable to be linear. The linearity assumption can best be tested with scatterplots of the independent variable versus the dependent variable. The multiple linear regression used TSI scores as the independent variable and math grades as the dependent variable. Figure 2 shows the linear relationship between these two variables. There was a clear positive linear relationship observed between TSI scores and math grades in Figure 2. The graph pattern showed an increasing straight-line trend. The increasing line pattern suggested that a higher TSI score resulted in a higher math grade. Thus, the assumption of linearity was not violated.

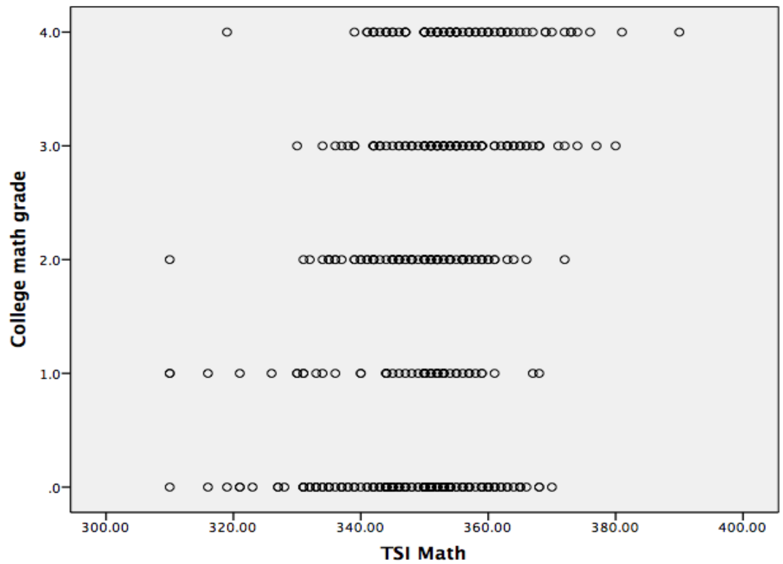

Figure 2. Linear Plot of TSI Score Versus College Math Grades.

Outlier. The second assumption was tested to check for outliers since multiple linear regression is sensitive to outlier effects. The scatterplot investigation for the outlier is only appropriate for continuously measured variables. The continuous variable involved in the multiple linear regression included the dependent variable of college math grades (Figure 3), independent variable of TSI scores (Figure 4), control variables of high school GPA (Figure 5), and age (Figure 6). The scatterplot showed that there was no presence of outliers in the data of college math grades, TSI score, high school GPA, and age. Furthermore, the scatterplots did not show any anomalies in the dataset of the stated study variables.

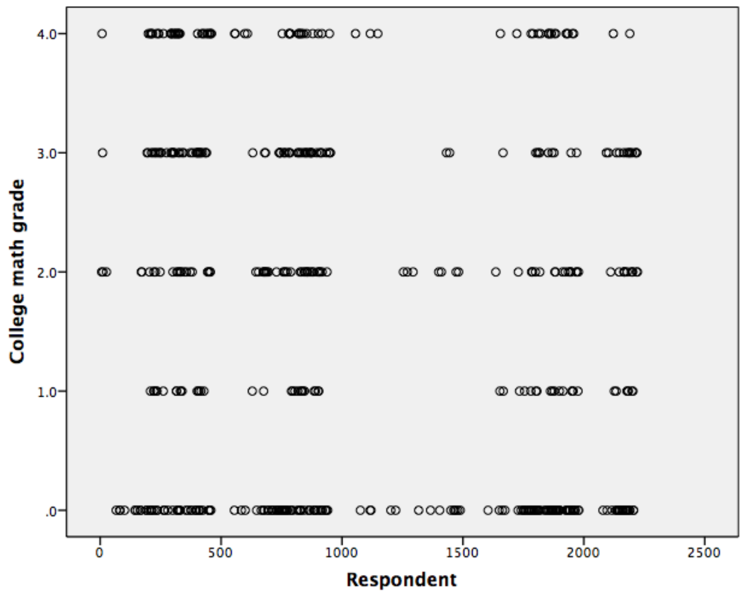

Figure 3. Scatterplot of College Math Grades.

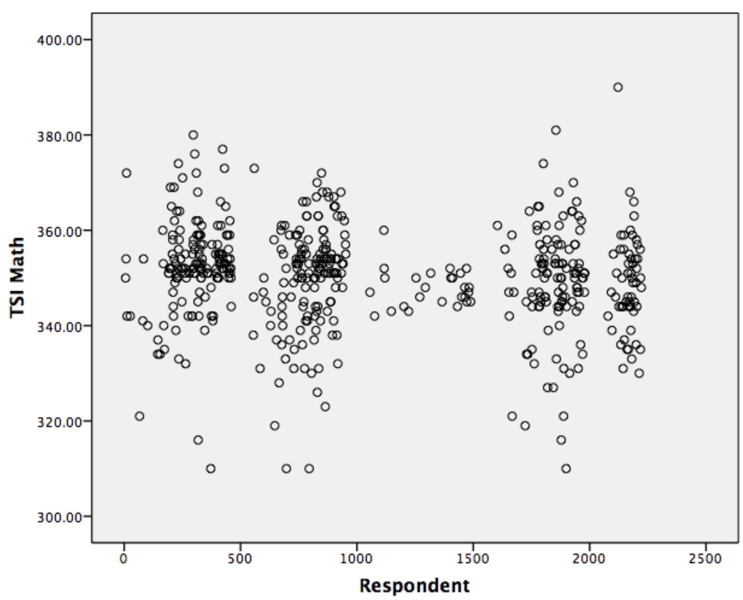

Figure 4. Scatterplot of TSI Score.

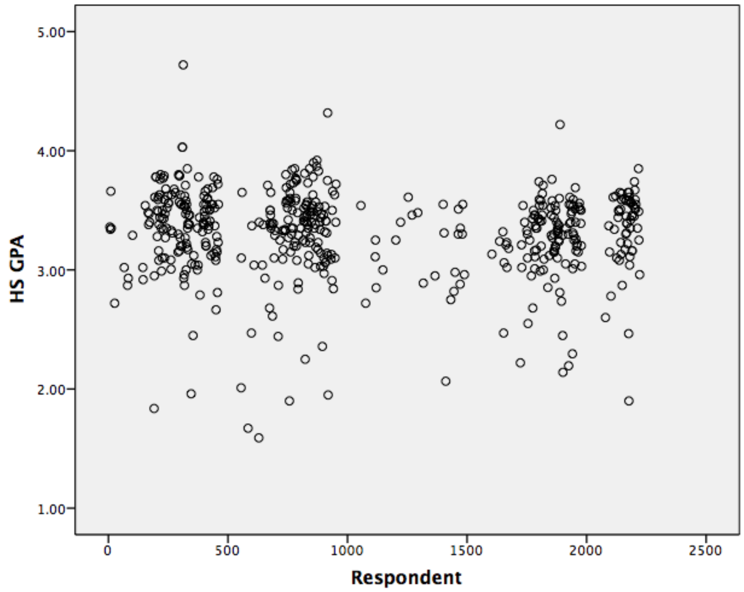

Figure 5. Scatterplot of High School GPA.

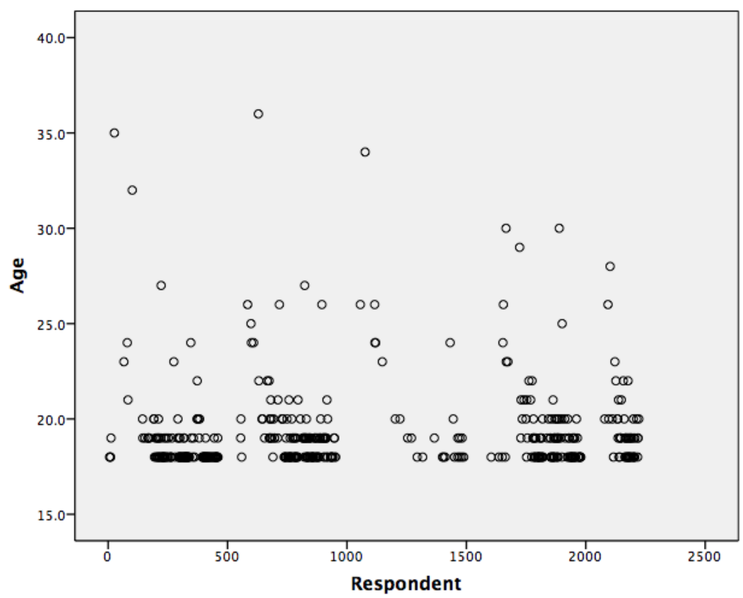

Figure 6. Scatterplot of Age.

Normality. The third assumption tested for the normality of the data of the different dependent variables. Normality means that the data of the dependent variable exhibits a normal distribution. The dependent variables included college math grades and retention. Normality was tested through an examination of the skewness and kurtosis statistics to check the distribution of the different dependent variable data.

To determine whether the data follows a normal distribution, skewness statistics greater than three indicate strong non-normality and kurtosis statistics between 10 and 20 also indicate non-normality (Kline, 2005). As can be seen in Table 7, the skewness (.22 and -1.20) and kurtosis (-1.43 and -.57) statistic values of the dependent variables of college math grades and retention in STEM track were in the acceptable range enumerated by Kline (2005). Thus, all the data of the dependent variables exhibited normal distribution and did not violate the normality assumption.

Table 7

Skewness and Kurtosis Statistics of College Math Grades and Retention in STEM Track

	N	Skewness		Kurtosis	
	Statistic	Statistic	Std. Error	Statistic	Std. Error
College math grade	500	0.22	0.11	-1.43	0.22
Retention in STEM track	500	-1.20	0.11	-0.57	0.22

Research Question 1

I conducted a hierarchical multiple regression analysis to examine how far the independent variable of TSI score predicted the dependent variable of math grade while controlling for the covariates of high school GPA, gender, ethnicity, and age. The hierarchical multiple regression analysis determines if the TSI scores significantly predicted math grades while controlling for high school GPA, gender, ethnicity, and age. A level of significance of .001 was used in the hierarchical multiple regression analysis. I used only two models. Model 1 included high school GPA, gender, ethnicity, and age. The TSI score was added to Model 2, and Model 2 was used to determine the significance of the predictive relationship of TSI scores and math grades while controlling for high school GPA, gender, ethnicity, and age. There is a significant predictive relationship if the *p*-value is less than the level of the significance value. Results of the hierarchical multiple regression are shown in Tables 8 and 9.

The hierarchical multiple regression revealed in Model 1, high school GPA, age, ethnicity, and gender contributed significantly to the regression model, ($F(4, 495) = 11.82$, $p < .001$, $R^2 = .09$) and accounted for 9% of the variance in college math grade. The individual predictor variables were also investigated in this study. High school GPA ($\beta = .30$, $p < .001$) was a significant predictor in the model. With each increment of a standard deviation of high school GPA, the college math grade increased by .30 standard deviation on average. Age, ethnicity, and gender were not significant predictors of the college math grade.

In addition, Model 2 was statistically significant, ($F(5, 494) = 15.05$, $p < .001$, $R^2 = .13$) and the predictors of high school GPA, age, ethnicity, gender, and TSI scores accounted for 13% of the variance in the college math grade. The results of the R^2 value increased by 5% when the TSI score was added as the predictor of math grades in Model 2. Additionally, the change in R^2 was highly significant ($F(1, 494) = 25.64$, $p < .001$).

Therefore, adding TSI scores to the regression model increased the model's predictive capacity significantly and increased the percentage of variance accounted for by 5%.

Table 8

Model Summary and ANOVA Results of Hierarchical Multiple Regression

Model	Model Summary					ANOVA		
	R^2	ΔR^2	ΔF	$df_{(1,2)}$	p	F	$df_{(1,2)}$	p
1	.09		11.82	4, 495	.000[a]	11.82	4, 495	.000[a]
2	.13	.05[b]	25.64	1, 494	.000[b]	15.05	5, 494	.000[b]

a. Predictors: (Constant), Age, Ethnicity, Gender, HS GPA
b. Predictors: (Constant), Age, Ethnicity, Gender, HS GPA, TSI
c. Dependent Variable: College math grade

The individual predictor variables were further investigated, and high school GPA ($\beta = .24$, $p <.001$) was a significant predictor in the regression Model 2. The model showed that with an increase of one standard deviation in high school GPA, the college math grade rose by .24 standard deviation on average. The TSI score ($\beta = .23$, $p < .001$) was a significant predictor in the model. For a one standard deviation increment on a TSI score, college math grade increased by .23 standard deviation; however, the high school GPA had a stronger relationship with the dependent variable than the TSI scores. Demographic factors such as age, ethnicity, and gender were nonsignificant predictors of college math grade in the regression Model 2 due to the *p*-values being greater than .001. Since the TSI score was a significant predictor using *p*-value, the null hypothesis for Research Question 1, "TSI score does not predict college math grades while controlling for high school GPA, gender, ethnicity, and age," was rejected. Instead, the results supported the alternative hypothesis that "TSI score predicts retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age." Although the results showed statistical significance, the practical significance of this result must be interpreted with caution because of the low effect size.

Table 9

Hierarchical Multiple Regression Results for Individual Predictor Variables

Model		β	*p*
1	HS GPA	0.30	0.00***
	Gender	0.06	0.19
	Ethnicity	-0.02	0.72
	Age	0.07	0.16
2	HS GPA	0.24	0.00***
	Gender	0.09	0.05
	Ethnicity	0.00	0.95
	Age	0.11	0.02
	TSI Math	0.23	0.00***

Note. N = 499; ****p* < .001

Research Question 2

I performed a hierarchical logistic regression analysis to test whether the independent variable of TSI score predicted the dependent variable of retention in a STEM mathematics track while controlling for the covariates of high school GPA, gender, ethnicity, and age. The hierarchical logistic regression analysis determines whether TSI scores have a significant predictive relationship with retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age. A level of significance of .05 was used in the hierarchical logistic regression analysis. There is a significant predictive relationship if the *p*-value of the χ^2 test is less than the level of significance value. The results of the hierarchical logistic regression are shown in Tables 10, 11, and 12.

The results of the logistic regression analysis, ($\chi^2(5, N = 500) = 25.23, p < .001$), were significant, which indicated that the regression model for predicting retention in a STEM mathematics track had an acceptable model fit. As shown in Table 10, the Cox and Snell R^2 (measure of effect size) of the logistic regression Model 2 was only .05, which means the predictor of TSI scores explained a variance of only 5% in predicting retention in a STEM mathematics track after controlling for high school GPA, gender, ethnicity, and age. The Cox and Snell R^2 increased by 2% when the TSI scores were added as a predictor of retention in Model 2. The Nagelkerke R^2 of the logistic regression Model 2 was only .07, which also indicated a very low effect size, meaning that the predictor of TSI scores explained a variance of only 7% in predicting retention in a STEM mathematics track after controlling for high school GPA, gender, ethnicity, and age. The Nagelkerke R^2 increased by 2% when TSI score was added as a predictor of retention in Model 2.

Table 10

Model Summary of Hierarchical Logistic Regression

Model	Cox & Snell R^2	Δ Cox & Snell R^2	Nagelkerke R^2	Δ Nagelkerke R^2
1	.03		.05	
2	.05	.02[b]	.07	.02[b]

a. Predictors: (Constant), Age, Ethnicity, Gender, HS GPA
b. Predictors: (Constant), Age, Ethnicity, Gender, HS GPA, TSI Math
c. Dependent Variable: Retention in a STEM mathematics track

As illustrated in Table 11, the columns specify the two predicted values while the rows specify two observed (actual) values. Two out of the four cells indicate correct classifications, while the other two cells indicate incorrect classifications, which refers to a false positive error (Type I) or a false negative error (Type II). The table shows the comparison between the students who remained in the STEM field and those who did not. The model correctly classified 370 students who remained in the STEM track but misclassified 8 others (it correctly classified 97.9% of cases). The model also correctly classified 6 students who did not remain in the STEM track but misclassified 116 others (it correctly classified 4.9% of cases). Thus, approximately 23.9% (116) of students who were predicted to remain in the STEM track (486) failed to do so, while 57.1% (8) of those predicted not to persist in the STEM track (14) actually endured. The total number of misclassified students was 124, which resulted in an error equal to 24.8%. The interpretation of the findings in this study must be approached with caution to avoid misleading generalizations even though the overall accuracy of the classification was 75.2%.

Table 11

The Observed and the Predicted Frequencies for Retention in a STEM Mathematics Track by Logistic Regression With the Cutoff of 0.50

Observed		Predicted		
		Retention in STEM track		Percentage Correct
		No	Remained	
Retention in STEM track	No	6	116	4.9
	Remained	8	370	97.9
Overall Percentage				75.2

In Table 12, the investigation of the individual independent variables of the logistic regression model showed that TSI scores (Exp(β) = 1.03, $p < .001$) were statistically significant predictors for retention in a STEM mathematics track after controlling for the impact of high school GPA, gender, ethnicity, and age. The odds ratio of TSI scores was 1.03, which implied that a one-unit increase in TSI scores increased the odds of remaining in the STEM track from Spring 2015 to Spring 2017 by .03 or 3% on average. Given the results of the hierarchical logistic regression analysis, the null hypothesis for Research Question 2, "TSI score does not predict retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age," was rejected. Instead, the results supported the alternative hypothesis that "TSI score predicts retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age." Even though the result showed statistical significance, the practical significance of this result is very low because the effect size was very low wherein TSI score explained a maximum of 7% in predicting retention in a STEM mathematics track after controlling for high school GPA, gender, ethnicity, and age.

Table 12

Hierarchical Logistic Regression Results for Individual Predictor Variables

Model		*p*	*Exp(β)*
1	HS GPA	0.00***	2.95
	Gender	0.35	1.23
	Ethnicity	0.72	0.92
	Age	0.75	1.02
2	HS GPA	0.01	2.46
	Gender	0.20	1.34
	Ethnicity	0.83	0.95
	Age	0.40	1.04
	TSI Math	0.00***	1.03

Note. $\chi^2(5, N = 500) = 25.23$, ***$p < .001$

Summary

The purpose of this quantitative non-experimental study was to examine how accurately the TSI placement test predicted both students' success in college algebra for STEM majors and the retention of said students in STEM majors. Descriptive statistics analysis, hierarchical multiple regression analysis, and hierarchical logistic regression analysis were conducted to test the research questions and hypotheses posed in this study. For Research Question 1, the results of the hierarchical multiple regression analysis showed that TSI scores were a weak predictor of college math grades while controlling for high school GPA, gender, ethnicity, and age due to the low effect size. For Research Question 2, the results of the hierarchical logistic regression analysis showed that TSI scores were also a weak predictor of retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age because of the higher number of false positives. Chapter 5 contains the findings from the study, explains how they relate to the literature on this topic, suggests implications for action, and provides recommendations for future research.

Chapter 5: Discussion, Conclusions, and Recommendations

In this nonexperimental quantitative study, I explored how accurately TSI placement predicts the success of college students in STEM majors. The dependent variable was the grade that each student received in a college algebra course offered to students majoring in a STEM field. Another measure of the success of the TSI placement test pertained to the retention of the students who took the course during the academic years spanning from Spring 2015 to Spring 2017. I undertook this study because, except for studies performed by the test creators, I could find no research on the relationship between TSI performance and academic success and retention. An understanding of the effects of the placement test, specifically TSI, on student performance was needed to support student success. The research questions I sought to answer in this study were

RQ1: Does the TSI score predict college math grades while controlling for high school GPA, gender, ethnicity, and age?

RQ2: Does the TSI score predict retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age?

The hierarchical multiple regression analysis for Research Question 1 showed that the TSI test was a weak predictor for college math grades while controlling for high school GPA, gender, ethnicity, and age. Therefore, the TSI placement test may not be a useful measure of performance in STEM classes due to the low R^2 values. For the hierarchical logistic regression analysis for Research Question 2, the TSI test showed a low predictability for retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age. Thus, the TSI test scores may not be an effective way to place students in math courses.

Interpretation of the Findings

There has been little scholarly attention given to the relationship between placement tests and academic success, based on my review of the literature. In recent years, scholars have questioned the validity of the use of the TSI and other tests (Belfield & Crosta, 2012; Fuller & Deshler, 2013; Medhanie et al., 2012; Scott-Clayton, 2012); however, the only existing studies testing the predictive power of test scores have been sponsored by the test creators themselves. Therefore, research is needed to fill the gap in the literature.

In this quantitative nonexperimental study, I posed two research questions, which I examined via hierarchical multiple and logistic regression analyses. Research Question 1 focused on the relationship between TSI scores and math grades while controlling for high school GPA, gender, ethnicity, and age. Investigation of the standardized beta coefficient (β) showed that TSI scores ($\beta = .23$, $p < .001$) significantly predicted math grade after controlling for high school GPA, gender, ethnicity, and age. This outcome implied that a higher score on the TSI math placement test would result in a higher score in college math grades after controlling for high school GPA, gender, ethnicity, and age. Therefore, the findings of the hierarchical multiple regression analysis support the alternative hypothesis. However, this conclusion can be misleading and may fail to accurately predict students' college math grade despite the statistical significance because of the low effect size, which was 13%. Therefore, the TSI test scores were not significantly related to the college math grade because they only accounted for approximately 13% of the variance in college math grade.

The Nagelkerke R^2 of the logistic regression was only .07, which indicates a very low effect size, meaning that the predictor of TSI score explained the variance of only 7% in predicting retention in a STEM mathematics track after controlling for high school GPA, gender, ethnicity, and age. Although the overall fit of the model yielded a 75.2% correct classification, a Type I error (a false positive) occurred, meaning that the test results incorrectly predicted the number of students who remained in the STEM track. Thus, the TSI math test is a weak predictor of student success and retention, and the practical consequence of this result must be cautiously considered.

The interpretation mentioned above is critical because mathematics is a core area of study and understanding for all STEM students (Carver et al., 2017). Mathematics is also one of the few subjects that transcend almost all disciplines; however, it is essential to STEM students because science, technology, and engineering are three heavily mathematically-based subjects (Carver et al., 2017). As a result, STEM students now require a basic to advanced understanding of each element of the subjects to be comprehensive in one field (Brown et al., 2016; Kennedy & Odell, 2014).

There are several studies whose authors have linked the relationship between the placement test scores as predictors of students' academic success and retention (e.g., Amarnani et al., 2016; Armstrong, 2000; Callahan & Garzolini, 2015; Cromley et al., 2016; Ricks et al., 2014; Saxon & Morante, 2014). According to Saxon and Morante (2014), the commonly used placement assessment tools are inaccurate and misused, and lack predictive validity. The authors articulated that the inaccuracy of the placement tests has the potential to ensure that generations of Americans are not adequately educated. Furthermore, Callahan and Garzolini (2015) stated that placement tests have consistently failed both the students and the universities and colleges that they are intended to help, an assertion which the findings from this study also support.

In addition, Amarnani et al. (2016) explained that it is critical that students remain in STEM fields because there is a positive correlation between retention and overall academic performance. Hence, the second research question explored how accurately TSI scores predicted retention in STEM mathematics while controlling for high school GPA, gender, ethnicity, and age. The hierarchical logistic regression results indicated that the predictor of TSI score explained the variance of only 7% in predicting retention in a STEM mathematics track after controlling for high school GPA, gender, ethnicity, and age. Furthermore, the higher number of false positives predicted that students remained in the STEM track, when, in fact, they did not.

The study also revealed that students' performance and retention might not be dependent on their TSI test placement scores because of its weak predictability. To accurately predict students' success in both college math grade and retention, there are other factors relevant to a STEM field, such as student cognition, motivation, and institutional policies (Cromley et al., 2016). Cromley et al. (2016) argued that course grades and study skills are directly proportional to the rates of retention. The authors further added that these assumptions would make cognition and motivation interdependent, while playing into the context of various institutional policies and guidelines, such as academic support, financial aid, career counseling, forced curving of course grades, course timing, and course registration.

Cromley et al. (2016) were not the only researchers to study the retention rates of STEM students. Ricks et al. (2014) investigated retention and graduation rates for engineering students because these are far lower nationally than desired (Moakler & Kim, 2014). Ricks et al. noted the negative stressors of financial issues, mathematics deficiencies, and a distinct lack of a supportive culture within the engineering discipline underpin many students' apprehension in continuing with engineering studies. Furthermore, Armstrong (2000) investigated the predictive validity of placement test scores with math course grade and retention and concluded that there is a weak relationship between placement test scores and course grades or retention in general. My study supports the literature that the placement test alone cannot predict student performance in STEM courses because of the low effect size.

Limitations of the Study

The main limitation of the study was the use of a convenience sample. The sourcing of data from this one community college in the southwest region of the United States may limit the generalizability of these results. The second limitation was that the data used in this study focused only on the students who enrolled in MATH 1414 College Algebra for STEM majors in the time period spanning the Spring 2015 and Spring 2017 semester. The third limitation was that this sample may not be generalized to the larger population of colleges because it represents only one community college from the southwestern region of the United States. The fourth limitation was that many TSI scores or high school GPAs were missing because students were not required to submit their high school GPA due to the study college's open-door policy. Furthermore, students were exempt from taking the TSI if they had already met the minimum college readiness standard on other placements tests such as SAT, ACCUPLACER, or statewide high school test; had successfully completed a college math course; or had been or currently were in the military (THECB, 2017). The last limitation was that I used a small sample size due to many missing values; therefore, replicating my study may require a larger sample size in order to minimize errors.

Recommendations

Future studies may explore the research questions using a different method, such as a mixed-method or qualitative approach. In this manner, the experiences and perspectives of the participants will be more deeply explored. Additional studies may also focus on the same topic but use different research questions. For example, future research may explore the experiences of the participants who took the TSI placement exam a few years after graduation. Additionally, other studies might explore the participants' perspectives on the impact that the TSI placement exam had on their choice to continue in their academic studies. Finally, research may be able to explore the effects and impacts of the TSI placement exam in terms of the specific fields of science, technology, engineering, and mathematics.

Implications

This study examined the predictive power of the placement of STEM students in college math classes by TSI test scores at one community college in the southwestern region of the United States. The findings of this study may have a positive social impact because they help to fill the gap in the literature related to the effectiveness of TSI placement testing. Even though the findings of this study significantly predicted the TSI placement test for mathematics, the practical consequences of the results must be cautiously considered due to the low effect sizes and the higher number of false positives. According to Banerjee, Chitnis, Jadhav, Bhawalkar, and Chaudhury (2009), errors (false positive or false negative) cannot be avoided completely, but researchers can minimize errors by increasing the sample size.

Because all students who attend Texas public institutions of higher education must comply with the TSI mandate unless they are exempt, the findings of this study inform the state of Texas by providing further knowledge of the predictive power of the TSI assessments (THECB, 2017). The efficacy of the TSI placement test was found to be a weak predictor of student success, and therefore, placing students at the correct starting point in the local setting based only on the TSI score should be questioned. Furthermore, Cromley et al. (2016) argued that many characteristics were attributed to motivation that are linked to both grades and retention in STEM fields, such as self-efficacy, continued interest in learning more about the subject, and effort control. Therefore, higher institutions in Texas should consider multiple measures in their placement decision rather than using the TSI scores as a single basis, because no placement test itself provides an exact measure of mathematics skills (Saxon & Morante, 2014).

It bears noting that educational policy will benefit from the results of this study in the broader context. Addressing the concerns on the effectiveness of placement testing will enable administrators to not only focus on students' placement scores, but also to determine ways to identify the specific skills needed for success in the math course. An accurate determination of students' skills is necessary because it allows the colleges and universities to focus on the strengths and weaknesses of the students. Positive social change will result as STEM majors who are placed in appropriate courses with a well-defined curriculum may persist to graduation in greater numbers.

Conclusion

The purpose of this quantitative nonexperimental study was to explore the accuracy of the TSI placement test in predicting the academic success and retention of students pursuing a STEM path. Descriptive statistics analysis, hierarchical multiple regression analysis, and hierarchical logistic regression analysis were conducted to test the research questions and hypotheses posed in this study. The data was collected and analyzed to answer the two research questions. The results of the study supported the conclusions of available literature about the need for a better method to predict students' success in one college math course.

For Research Question 1, the results of the hierarchical multiple regression analysis showed that TSI scores had a low predictability for college math grades while controlling for high school GPA, gender, ethnicity, and age. For research question 2, the results of the hierarchical logistic regression analysis showed that TSI scores had a low predictability for predicting retention in a STEM mathematics track while controlling for high school GPA, gender, ethnicity, and age. Therefore, the TSI test score is a weak predictor of student success in Math 1414. Furthermore, higher institutions should attempt to align students' math proficiencies measured by placement tests with other considerations such as cognitive and noncognitive factors to place students in math courses because combining both cognitive and noncognitive variables appears to play a vital role in students' performance and retention (Saxon & Morante, 2014).

References

Amarnani, R. K., Garcia, P. R. J. M., Restubog, S. L. D., Bordia, P., & Bordia, S. (2016). Do you think I'm worth it? The self-verifying role of parental engagement in career adaptability and career persistence among STEM students. *Journal of Career Assessment, 26*(1), 77-94. doi:10.1069072716679925

Anthony, H. G., Robinson, S. J., & Wilson, C. D. (2017). *Math success for STEM majors: Active learning strategies and engineering contexts.* Paper presented at the 2017 ASEE Zone II Conference: Engineering Everywhere for Everyone, San Juan, PR.

Armstrong, W. B. (2000). The association among student in courses, placement test scores, student background data, and instructor grading practices. *Community College Journal of Research and Practice*. *24*(8), 681-695. doi:10.1080/10668920050140837

Avery, C., Gurantz, O., Hurwitz, M., & Smith, J. (2017). Shifting college majors in response to advanced placement exam scores. *Journal of Human Resources*, *52*(4), 1-53. doi:10.3368/jhr.53.4.1016-8293R

Banerjee, A., Chitnis, U. B., Jadhav, S. L., Bhawalkar, J. S., & Chaudhury, S. (2009). Hypothesis testing, Type I and Type II errors. *Industrial Psychiatry Journal*, *18*(2), 127-131. doi:10.4103/0972-6748.62274

Beattie, G., Laliberté, J. W. P., & Oreopoulos, P. (2016). Thrivers and divers: Using non-academic measures to predict college success and failure (NBER Working Paper No. w22629). *National Bureau of Economic Research*. doi:10.3386/w22629

Belfield, C. R., & Crosta, P. M. (2012). *Predicting success in college: The importance of placement tests and high school transcripts* (CCRC Working Paper No. 42). New York, NY: Community College Research Center, Columbia University.

Belser, C. T., Prescod, D. J., Daire, A. P., Dagley, M. A., & Young, C. Y. (2017). Predicting undergraduate student retention in STEM majors based on career development factors. *Career Development Quarterly*, *65*(1), 88-93. doi:10.1002/cdq.12082

Berry, C. M., Cullen, M. J., & Meyer, J. M. (2014). Racial/ethnic subgroup differences in cognitive ability test range restriction: Implications for differential validity. *Journal of Applied Psychology*, *99*(1), 21-37. doi:10.1037/a0034376

Brown, P. L., Concannon, J. P., Marx, D., Donaldson, C. W., & Black, A. (2016). An examination of middle school students' STEM self-efficacy with relation to interest and perceptions of STEM. *Journal of STEM Education: Innovations and Research*, *17*(3), 27-38. Retrieved from https://www.jstem.org/

Bryman, A. (2012). *Social research methods*. New York, NY: Oxford University Press.

Caines, J., Bridglall, B. L., & Chatterji, M. (2014). Understanding validity and fairness issues in high-stakes individual testing situations. *Quality Assurance in Education*, *22*(1), 5-18. doi:10.1108/QAE-12-2013-0054

Callahan, J., & Garzolini, M. J. A. (2015). *An elective mathematics readiness initiative for STEM students.* Paper presented at the 2015 ASEE Annual Conference and Exposition, Seattle, WA. Retrieved from http://peer.asee.org/23520

Camara, W. (2013). Defining and measuring college and career readiness: A validation framework. *Educational Measurement: Issues and Practice*, *32*(4), 16-27. doi:10.1111/emip.12016

Carver, S. D., Van Sickle, J., Holcomb, J. P., Jackson, D. K., Resnick, A., Duffy, S. F., ... & Quinn, C. M. (2017). Operation STEM: Increasing success and improving retention among mathematically underprepared students in STEM. *Journal of STEM Education: Innovations and Research*, *18*(3), 20-29. Retrieved from https://www.jstem.org/

Castro-Alonso, J. C., Ayres, P., & Paas, F. (2017). Computerized and adaptable tests to measure visuospatial abilities in STEM students. In T. Andre (Ed.) *Advances in human factors in training, education, and learning sciences* (pp. 337-349). Los Angeles, CA: Springer. doi:10.1007/978-3-319-60018-5_33

Chew, J., Knutson, K., & Martini, E. A. (2014). *Instituting a proactive risk assessment model: The promise and peril of predictive approaches to student success.* Paper presented at Assessment in Action Conference: Assessment, Kalamazoo, MI. Kalamazoo MI: Western Michigan University.

Chrysikos, A., Ahmed, E., & Ward, R. (2017). Analysis of Tinto's student integration theory in first-year undergraduate computing students of a UK higher education institution. *International Journal of Comparative Education and Development*, *19*(2/3), 97-121. doi:10.1108/IJCED-10-2016-0019

College Board. (2015). *Texas success initiative: Technical manual*. New York, NY: The College Board.

Couturier, L. K., & Cullinane, J. (2015). A call to action to improve math placement policies and processes: Six policy recommendations to increase STEM student aspirations and success while decreasing racial and income gaps. *Jobs for the Future*. Retrieved from https://eric.ed.gov/?id=ED559677

Creswell, J. (2013). *Research design: Qualitative, quantitative, and mixed methods approaches.* Los Angeles, CA: Sage.

Cromley, J. G., Perez, T., & Kaplan, A. (2016). Undergraduate STEM achievement and retention: Cognitive, motivational, and institutional factors and solutions. *Policy Insights from the Behavioral and Brain Sciences, 3*(1), 4-11. doi:10.1177/2372732215622648

Dagley, M., Georgiopoulos, M., Reece, A., & Young, C. (2016). Increasing retention and graduation rates through a STEM learning community. *Journal of College Student Retention: Research, Theory & Practice, 18*(2), 167-182. doi:10.1177/1521025115584746

Department of Education. (2016). Definition of Hispanic serving institutions. Retrieved from https://www2.ed.gov/programs/idueshsi/definition.html

Fields, R. (2014). *Towards the National Assessment of Educational Progress (NAEP) as an indicator of academic preparedness for college and job training*. Washington, DC: National Assessment Governing Board.

Fields, R., & Parsad, B. (2012). *Tests and cut scores used for student placement in postsecondary education: Fall 2011.* Washington, DC: National Assessment Governing Board.

Fisher, L. A. (2015). *Relationship between high school math course selection and retention rates at Otterbein University* (Doctoral dissertation, Otterbein University). Retrieved from http://digitalcommons.otterbein.edu/stu_honor/3

Fox, J. (2015). *Applied regression analysis and generalized linear models.* Thousand Oaks, CA: Sage.

Freeman, S., Eddy, S. L., McDonough, M., Smith, M. K., Okoroafor, N., Jordt, H., & Wenderoth, M. P. (2014). Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, *111*(23), 8410-8415. doi:10.1073/pnas.1319030111

Fuller, E. J., & Deshler, J. M. (2013). The effect of a new placement process on student success in first semester calculus. *Creative Education*, *4*(9), 18-21. doi:10.4236/ce.2013.49B0

Gerlach, K., Trate, J., Blecking, A., Geissinger, P., & Murphy, K. (2014). Valid and reliable assessments to measure scale literacy of students in introductory college chemistry courses. *Journal of Chemical Education*, *91*(10), 1538-1545. doi:10.1021/ed400471a

Gershenfeld, S., Ward Hood, D., & Zhan, M. (2016). The role of first-semester GPA in predicting graduation rates of underrepresented students. *Journal of College Student Retention: Research, Theory & Practice*, *17*(4), 469-488. doi:10.1177/1521025115579251

Groen, L., Coupland, M., Langtry, T., Memar, J., Moore, B., & Stanley, J. (2015). The mathematics problem and mastery learning for first-year, undergraduate STEM students. *International Journal of Learning, Teaching and Educational Research, 11*(1), 141-160. Retrieved from http://ijlter.org/index.php/ijlter/article/view/303/136

Guiffrida, D. A. (2006). Toward a cultural advancement of Tinto's theory. *Review of Higher Education, 29*(4), 451-472. doi:10.1353/rhe.2006.0031

Hagedorn, L. S. (2005). How to define retention. A new look at an old problem. In A. Seidman (Ed.), *College student retention: Formula for student success* (pp. 89-105). Westport, CT: Praeger.

Hair, J. F., Jr., Anderson, R. E., Tatham, R. L. & Black, W. C. (1995). *Multivariate Data Analysis* (3rd ed). New York, NY: Macmillan.

Hilbe, J. M. (2009). *Logistic regression models.* Boca Raton, FL: CRC Press.

Hispanic Association of Colleges & Universities. (2017). HACU 2017 legislative agenda background information. Retrieved from https://www.hacu.net/hacu/2017_Data_on_Hispanics.asp

Hosmer, D. W., Jr., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression* (3rd ed.). Hoboken, NJ: Wiley.

Hughes, K. L., & Scott-Clayton, J. (2011). Assessing developmental assessment in community colleges. *Community College Review*, *39*(4), 327-351. doi:10.1177/0091552111426898

Islam, M. M., & Al-Ghassani, A. (2015). Predicting college math success: Do high school performance and gender matter? Evidence from Sultan Qaboos University in Oman. *International Journal of Higher Education*, *4*(2), 67-80. doi:10.5430/ijhe.v4n2p67

Kember, D. (1989). A longitudinal-process model of drop-out from distance education. *Journal of higher education*, *60*(3), 278-301. doi:10.1080/00221546.1989.11775036

Kennedy, T. J., & Odell, M. R. L. (2014). Engaging students in STEM education. *Science Education International*, *25*(3), 246-258. Retrieved from http://www.icaseonline.net/

Kline, R. B. (2005), *Principles and practice of structural equation modeling*. New York, NY: The Guilford Press.

Klugh, H. (2013). *Statistics: The essentials for research*. New York, NY: Psychology Press.

Kommers, S., & Pham, D. (2016). How Tinto's theory differs for Asian and non-Asian international students: A quantitative study. *Journal of International Students*, *6*(4), 999-1014. Retrieved from https://jistudents.org/

Kothari, C. R. (2004). *Research methodology: Methods and techniques*. Daryaganj, New Delhi: New Age International.

Kumazawa, T., Shizuka, T., Mochizuki, M., & Mizumoto, A. (2016). Validity argument for the VELC Test® score interpretations and uses. *Language Testing in Asia*, *6*(1), 1-18. doi:10.1186/s40468-015-0023-3

Lane, S. (2014). Validity evidence based on testing consequences. *Psicothema*, *26*(1), 127-135. doi:10.7334/psicothema2013.258

Larson, L. M., Pesch, K. M., Surapaneni, S., Bonitz, V. S., Wu, T. F., & Werbel, J. D. (2015). Predicting graduation: The role of mathematics/science self-efficacy. *Journal of Career Assessment*, *23*(3), 399-409. doi:10.1177/1069072714547322

Le, H., Robbins, S. B., & Westrick, P. (2014). Predicting student enrollment and persistence in college STEM fields using an expanded PE fit framework: A large-scale multilevel study. *Journal of Applied Psychology*, *99*(5), 915-949. doi:10.1037/a0035998

LeBlanc, M., & Fitzgerald, S. (2000). Logistic regression for school psychologists. *School Psychology Quarterly*, *5*(3), 344-358. doi:10.1037/h0088791

Leedy, P. D., & Ormrod, J. E. (2010). *Practical research: Planning and design*. Upper Saddle River, NJ: Merrill.

Madison, B. L., Linde, C. S., Decker, B. R., Rigsby, E. M., Dingman, S. W., & Stegman, C. E. (2015). A study of placement and grade prediction in first college mathematics courses. *Primus*, *25*(2), 131-157. doi:10.1080/10511970.2014.921653

Maltby, J. L., Brooks, C., Horton, M., & Morgan, H. (2016). Long term benefits for women in a science, technology, engineering, and mathematics living-learning community. *Learning Communities: Research & Practice*, *4*(1), 1-19. Retrieved from https://washingtoncenter.evergreen.edu/lcrpjournal/

Martorell, P., McFarlin, I., Jr., & Xue, Y. (2014). Does failing a placement exam discourage underprepared students from going to college? *Education Finance and Policy*. doi:10.1162/EDFP_a_00151

Mason, C. H., & Perreault Jr, W. D. (1991). Collinearity, power, and interpretation of multiple regression analysis. *Journal of Marketing Research, 28*(3), 268-280. doi:10.2307/3172863

Mau, W. C. J. (2016). Characteristics of US students that pursued a STEM major and factors that predicted their persistence in degree completion. *Universal Journal of Educational Research*, *4*(6), 1495-1500. doi:10.13189/ujer.2016.040630

McClarty, K. L., Way, W. D., Porter, A. C., Beimers, J. N., & Miles, J. A. (2013). Evidence-based standard setting establishing a validity framework for cut scores. *Educational Researcher, 42*(2), 78-88. doi:10.3102/0013189X12470855

McGuire, S. P., Davis, K. A., Farid, A., Hardy, K. K., Hsu, Y. C., Kaiser, U., ... & Wang, S. (2017). Am I a STEM professional? Documenting STEM student professional identity development. *Studies in Higher Education*. *42*(4), 701-720. doi:10.1080/03075079.2015.1070819

Medhanie, A. G., Dupuis, D. N., LeBeau, B., Harwell, M. R., & Post, T. R. (2012). The role of the ACCUPLACER mathematics placement test on a student's first college mathematics course. *Educational and Psychological Measurement*, *72*(2), 332-350. doi:10.1177/0013164411417620

Melguizo, T., Bos, J. M., Ngo, F., Mills, N., & Prather, G. (2016). Using a regression discontinuity design to estimate the impact of placement decisions in developmental math. *Research in Higher Education*, *57*(2), 123-151. doi:10.1007/s11162-015-9382-y

Melguizo, T., Kosiewicz, H., Prather, G., & Bos, J. (2014). How are community college students assessed and placed in developmental math? Grounding our understanding in reality. *Journal of Higher Education*, *85*(5), 691-722. doi:10.1080/00221546.2014.11777345

Miles, R., van Tryon, P. J. S., & Mensah, F. M. (2015). Mathematics and science teachers' professional development with local businesses to introduce middle and high school students to opportunities in STEM careers. *Science Educator*, *24*(1), 1-11. Retrieved from https://www.nsela.org/science-educator-journal-

Moakler, M. W., & Kim, M. M. (2014). College major choice in STEM: Revisiting confidence and demographic factors. *Career Development Quarterly*, *62*(2), 128-142. doi:10.1002/j.2161-0045.2014.00075.x

Mooring, Q. E. (2016). Recruitment, advising, and retention programs: Challenges and solutions to the international problem of poor nursing student retention: A narrative literature review. *Nurse Education Today*, *40*(2016), 204-208. doi:10.1016/j.nedt.2016.03.003

Mozgalina, A., & Ryshina-Pankova, M. (2015). Meeting the challenges of curriculum construction and change: Revision and validity evaluation of a placement test. *Modern Language Journal*, *99*(2), 346-370. doi:10.1111/modl.12217

Mutter, P. (1992). Tinto's theory of departure and community college student persistence. *Journal of College Student Development*, *33*(4), 310-318. Retrieved from http://www.myacpa.org/JCSD

Ngo, F., & Kwon, W. W. (2015). Using multiple measures to make math placement decisions: Implications for access and success in community colleges. *Research in Higher Education*, *56*(5), 442-470. doi:10.1007/s11162-014-9352-9

Ngo, F., & Melguizo, T. (2016). How can placement policy improve math remediation outcomes? Evidence from experimentation in community colleges. *Educational Evaluation and Policy Analysis*, *38*(1), 171-196. doi:10.3102/0162373715603504

Nistor, N., & Neubauer, K. (2010). From participation to dropout: Quantitative participation patterns in online university courses. *Computers & Education*, *55*(2), 663-672. doi:10.1016/j.compedu.2010.02.026

Nugent, G., Barker, B., Welch, G., Grandgenett, N., Wu, C., & Nelson, C. (2015). A model of factors contributing to STEM learning and career orientation. *International Journal of Science Education*, *37*(7), 1067-1088. doi:10.1080/09500693.2015.1017863

Osborne, J. W., & Costello, A. B. (2004). Sample size and subject to item ratio in principal components analysis. *Practical assessment, research & evaluation*, *9*(11), 1-9. Retrieved from https://pareonline.net/

Pallant, J. (2016). *SPSS survival manual: A step by step guide to data analysis using SPSS* (6th ed.). Maidenhead: Open University Press/McGraw-Hill.

Patterson, B. F., & Ewing, M. (2013). *Validating the use of AP® exam scores for college course placement* (Research Report 2013-2). New York, NY: The College Board.

Peng, C. Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *The journal of educational research*, *96*(1), 3-14. doi:10.1080/00220670209598786

Perez, T., Cromley, J. G., & Kaplan, A. (2014). The role of identity development, values, and costs in college STEM retention. *Journal of Educational Psychology, 106*(1),315-329. doi:10.1037/a0034027

Pinheiro, D., Melkers, J., & Youtie, J. (2014). Learning to play the game: Student publishing as an indicator of future scholarly success. *Technological Forecasting and Social Change, 81*(2014), 56-66. doi:10.1016/j.techfore.2012.09.008

Pipere, A., & Mieriņa, I. (2017). Exploring non-cognitive predictors of mathematics achievement among 9th grade students. *Learning and Individual Differences, 59*(2017), 65-77. doi:10.1016/j.lindif.2017.09.005

Priest, K. L., Saucier, D. A., & Eiselein, G. (2016). Exploring students' experiences in first-year learning communities from a situated learning perspective. *International Journal of Teaching and Learning in Higher Education*, *28*(3), 361-371. Retrieved from http://www.isetl.org/ijtlhe/

Primé, D. R., Bernstein, B. L., Wilkins, K. G., & Bekki, J. M. (2015). Measuring the advising alliance for female graduate students in science and engineering: An emerging structure. *Journal of Career Assessment*, *23*(1), 64-78. doi:10.1177/1069072714523086

Ricks, K. G., Richardson, J. A., Stern, H. P., Taylor, R. P., & Taylor, R. A. (2014). An engineering learning community to promote retention and graduation of at-risk engineering students. *American Journal of Engineering Education*, *5*(2), 73-90. doi:10.19030/ajee.v5i2.8953

Roberts, C. H., & Baugher, G. A. (2015). Academic enhancement and retention efforts in mathematics designed to support and promote enhanced STEM education for adult learners at Mercer University. *Interdisciplinary STEM Teaching & Learning Conference*. Retrieved from https://digitalcommons.georgiasouthern.edu/stem/

Rodenbusch, S. E., Hernandez, P. R., Simmons, S. L., & Dolan, E. L. (2016). Early engagement in course-based research increases graduation rates and completion of science, engineering, and mathematics degrees. *CBE-Life Sciences Education*, *15*(2), 1-10. doi:10.1187/cbe.16-03-0117

Rodgers, K., Blunt, S., & Trible, L. (2014). A real PLUSS: An intrusive advising program for underprepared STEM students. *NACADA Journal*, *34*(1), 35-42. doi:10.12930/NACADA-13-002

Rodríguez, O. (2014). *Increasing access to college-level math: Early outcomes using the Virginia Placement Test*. (CCTC Brief No. 58). New York, NY: Columbia University, Teacher College, Community College Research Center. doi:10.7916/D8HQ3X1P

Rovai, A. P. (2003). In search of higher persistence rates in distance education online programs. *Internet and Higher Education*, *6*(1), 1-16. doi:10.1016/S1096-7516(02)00158-6

Saxon, D. P., & Morante, E. A. (2014). Effective student assessment and placement: Challenges and recommendations. *Journal of Developmental Education*, *37*(3), 24-31. Retrieved from https://ncde.appstate.edu/publications/journal-developmental-education-jde

Schmit, R., & Saif, S. (2015). Test de Français Laval-Montreal: Does it measure what it should measure? *TESL Canada Journal*, *32*(9), 87-112. doi:10.18806/tesl.v32i0.1219

Scott-Clayton, J. (2012). *Do high-stakes placement exams predict college success?* (CCRC Working Paper No. 41). New York, NY: Community College Research Center, Teachers College, Columbia University.

Scott-Clayton, J., Crosta, P. M., & Belfield, C. R. (2014). Improving the targeting of treatment: Evidence from college remediation. *Educational Evaluation and Policy Analysis*, *36*(3), 371-393. doi:10.3102/0162373713517935

Simon, R. A., Aulls, M. W., Dedic, H., Hubbard, K., & Hall, N. C. (2015). Exploring student persistence in STEM programs: A motivational model. *Canadian Journal of Education*, *38*(1), 1-27. Retrieved from http://cje-rce.ca/

Slomp, D. H., Corrigan, J. A., & Sugimoto, T. (2014). A framework for using consequential validity evidence in evaluating large-scale writing assessments: A Canadian study. *Research in the Teaching of English*, *48*(3), 276-302. Retrieved from https://www.uleth.ca/dspace/handle/10133/3660

Smith, J. L., Cech, E., Metz, A., Huntoon, M., & Moyer, C. (2014). Giving back or giving up: Native American student experiences in science and engineering. *Cultural Diversity and Ethnic Minority Psychology*, *20*(3), 413-429. doi:10.1037/a0036945

Stankov, L. (2014). Noncognitive predictors of academic achievement and intelligence: An important role of self-confidence. *Personality and Individual Differences*, *60*(2014), S37. doi:10.1016/j.paid.2013.07.090

Stankov, L., Morony, S., & Lee, Y. P. (2014). Confidence: The best non-cognitive predictor of academic achievement? *Educational Psychology*, *34*(1), 9-28. doi:10.1080/01443410.2013.814194

Starobin, S. S., Smith, D. J., & Santos Laanan, F. (2016). Deconstructing the transfer student capital: Intersect between cultural and social capital among female transfer students in STEM fields. *Community College Journal of Research and Practice*, *40*(12), 1040-1057. doi:10.1080/10668926.2016.1204964

Stieff, M., & Uttal, D. (2015). How much can spatial training improve STEM achievement? *Educational Psychology Review*, *27*(4), 607-615. doi:10.1007/s10648-015-9304-8

Strayhorn, T. L. (2015). Factors influencing black males' preparation for college and success in STEM majors: A mixed methods study. *Western Journal of Black Studies, 39*(1), 45-63. Retrieved from https://wsu.edu/~wjbs/

Tabachnick, B. G., & Fidell, L. S. (2012). *Using multivariate statistics*. Boston, MA: Pearson.

Texas Higher Education Coordinating Board. (2017). *Overview: Texas success initiative.* Retrieved from http://www.thecb.state.tx.us/

Texas Higher Education Coordinating Board. (2016). The predictive placement validity study of Texas success initiative assessment. Retrieved from http://www.thecb.state.tx.us/

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research*, *45*(1), 89-125. doi:10.3102/00346643045001089

Tinto, V. (1987). *Leaving college: Rethinking the causes and cures of student attrition.* Chicago, IL: University of Chicago Press.

Tinto, V. (1991). Student attrition in higher education. In B. Clark and G. Neave (Eds.), *Encyclopedia of Higher Education* (Vol. 2) (pp.599-623). Oxford: Pergamon Press.

Tinto, V. (1999). Taking retention seriously: Rethinking the first year of college. *NACADA journal*, *19*(2), 5-9. doi:10.12930/0271-9517-19.2.5

Tinto, V. (2000). Linking learning and leaving: Exploring the role of the college classroom in student departure. In J. M. Braxton (Ed.), *Reworking the student departure puzzle* (pp. 81-94). Nashville, TN: Vanderbilt University Press.

Tomasko, D. L., Ridgway, J. S., Waller, R. J., & Olesik, S. V. (2016). Association of summer bridge program outcomes with STEM retention of targeted demographic groups. *Journal of College Science Teaching*, *45*(4), 90-99. doi:10.2505/4/jcst16_045_04_90

Warne, R. T., Nagaishi, C., Slade, M. K., Hermesmeyer, P., & Peck, E. K. (2014). Comparing weighted and unweighted grade point averages in predicting college success of diverse and low-income college students. *NASSP Bulletin, 98*(4), 261-279. doi:10.1177/0192636514565171

Wei, X., Christiano, E. R., Jennifer, W. Y., Blackorby, J., Shattuck, P., & Newman, L. A. (2014). Postsecondary pathways and persistence for STEM versus non-STEM majors among college students with an autism spectrum disorder. *Journal of Autism and Developmental Disorders*, *44*(5), 1159-1167. doi:10.1007/s10803-013-1978-5

Westrick, P. A., & Allen, J. (2014). *Validity evidence for ACT Compass® placement tests.* (ACT Research Report Series 2014 (2)). Iowa City, IA: ACT. Retrieved from http://www.act.org

Westrick, P. A., Le, H., Robbins, S. B., Radunzel, J. M., & Schmidt, F. L. (2015). College performance and retention: A meta-analysis of the predictive validities of ACT® scores, high school grades, and SES. *Educational Assessment*, *20*(1), 23-45. doi:10.1080/10627197.2015.997614

Wilson, D., Jones, D., Bocell, F., Crawford, J., Kim, M. J., Veilleux, N., ... & Plett, M. (2015). Belonging and academic engagement among undergraduate STEM students: A multi-institutional study. *Research in Higher Education, 56*(7), 750-776. doi:10.1007/s11162-015-9367-x

Windsor, A., Russomanno, D., Bargagliotti, A., Best, R., Franceschetti, D., Haddock, J., & Ivey, S. (2015). Increasing retention in STEM: Results from a STEM talent expansion program at the University of Memphis. *Journal of STEM Education:*

Innovations and Research, *16*(2), 11-19. Retrieved from http://digitalcommons.lmu.edu/math_fac/71

Wladis, C., Conway, K. M., & Hachey, A. C. (2015). The online STEM classroom-Who succeeds? An exploration of the impact of ethnicity, gender, and non-traditional student characteristics in the community college context. *Community College Review*, *43*(2), 142-164. doi:10.1177/0091552115571729

Wladis, C., Hachey, A. C., & Conway, K. M. (2015). The representation of minority, female, and non-traditional STEM majors in the online environment at community colleges: A nationally representative study. *Community College Review*, *43*(1), 89-114. doi:10.1177/0091552114555904

Wolniak, G. C. (2016). Examining STEM bachelor's degree completion for students with differing propensities at college entry. *Journal of College Student Retention: Research, Theory & Practice*, *18*(3), 287-309. doi:10.1177/1521025115622782

Wyman, F. J. (1997). A predictive model of retention rate at regional two-year colleges. *Community College Review*, *25*(1), 29-58. doi:10.1177/009155219702500104

Xu, Y. J. (2018). The experience and persistence of college students in STEM majors. *Journal of College Student Retention: Research, Theory & Practice*, *19*(4), 413-432. doi:10.1177/1521025116638344

Ybarra, M. E. (2016). *STEM education: An exploration of its impact on female academic success in high school* (Doctoral dissertation, Chapman University). Retrieved from https://www.waldenu.edu/

Zientek, L. R., Schneider, C. L., & Onwuegbuzie, A. J. (2014). Instructors' perceptions about student success and placement in developmental mathematics courses. *Community College Enterprise*, *20*(1), 67-84. Retrieved from http://www.schoolcraft.edu/ccE/

Zilberberg, A., Finney, S. J., Marsh, K. R., & Anderson, R. D. (2014). The role of students' attitudes and test-taking motivation on the validity of college institutional accountability tests: A path analytic model. *International Journal of Testing*, *14*(4), 360-384. doi:10.1080/15305058.2014.928301