12-2022

Exploring the Relationship Between College Mathematics Remediation Status and Continued Persistence in Mathematics of Community College Students

Morvarid Javadi Pourhassan
mpourhassan17@georgefox.edu

EXPLORING THE RELATIONSHIP BETWEEN COLLEGE MATHEMATICS REMEDIATION STATUS AND CONTINUED PERSISTENCE IN MATHEMATICS OF COMMUNITY COLLEGE STUDENTS

by

MORVARID JAVADI POURHASSAN

FACULTY RESEARCH COMMITTEE:

Chair: Dane Christian Joseph, Ph.D.

Member: Marc Shelton, Ed.D.

Presented to the Doctoral Department

and College of Education in partial fulfillment of the requirements for the degree of

Doctor of Education

GEORGE FOX UNIVERISTY

December 2022

GEORGE FOX UNIVERSITY

COLLEGE OF EDUCATION | EDD

EXPLORING THE RELATIONSHIP BETWEEN COLLEGE MATHEMATICS REMEDIATION STATUS AND CONTINUED PERSISTENCE IN MATHEMATICS OF COMMUNITY COLLEGE STUDENTS, a Doctoral research project prepared by MORVARID JAVADI POURHASSAN in partial fulfillment of the requirements for the Doctor of Education degree in Educational Leadership.

This dissertation has been approved and accepted by:

12-2-22

December 2, 2022	Dane Joseph, Ph.D.	Associate Professor of Education Director of Dissertation Projects

12/2/22

December 2, 2022	Marc Shelton, Ed.D.	Professor of Education Director, Educational Leadership

Abstract

This study analyzed the relationship between community college students' math remediation status and their continued persistence in math. Continued persistence outcomes included college math course completion, seeking a STEM degree pathway, degree attainment (STEM or any degree), and degree completion time (STEM or any degree). Demographic variables and math-placement-level were investigated as predictors. The study used secondary data from students enrolled in math courses at a large Pacific Northwest college between Fall 2016 and Fall 2019. Exploratory data analysis, logistic regression, and chi-square were used to analyze the secondary data. The analysis found a statistically significant impact of age on continued persistence for the entire student population but not the math-remediation subpopulation. Older students were more likely to complete a college-level math course, and younger students were more likely to seek and attain a STEM degree and have faster STEM degree completion times. Pell Grant recipients from both the entire student population and math-remediation subpopulation were more likely to attain a STEM degree than non-Pell Grant recipients. Females were more likely to persist in math than males. Non-Resident Alien (NRA) and Asian (AS) students were found to outperform White (WHI) students in multiple continued persistence outcomes, while Black/African American (BAA) and Hispanic (HIS) students were commonly found to underperform. Regarding math-placement-level, students placed in upper-level remediation and college-level courses were significantly more likely to attain a STEM degree than those placed in lower-level remediation. This study may be used to further evaluate remedial math policies and practices including, but not limited to, the length of the remedial math sequence and placement tests.

Acknowledgements

First and foremost, I would like to praise and thank my Father in Heaven for His love, grace, and countless blessings.

I would like to begin by expressing the deepest appreciation for my kind and brilliant advisor and committee chair, Dr. Dane Joseph. Thank you for your invaluable contributions in shaping this study, including but not limited to your ingenious suggestions, passion, and insightful guidance every step of the way. The completion of my dissertation would not have been possible without your great support, encouragement, patience, compassion, and understanding. Thank you for believing in me and helping me achieve this dream. I also extend my gratitude to the phenomenal faculty at George Fox and committee member, Dr. Marc Shelton. Each of you have impacted my doctoral journey in such a profound way, both academically and spiritually.

The presence of my family and their unwavering support was imperative to my success. I am deeply and forever indebted to my extraordinary parents, Nader Pourhassan and Mojdeh Javadi, who have been a source of unconditional love, nurture, and support through every stage of my life. Growing up, you both profoundly enriched my personal, spiritual, and academic growth. This day wouldn’t have come to fruition without your complete dedication and innumerable sacrifices over the years. I will forever cherish the abundant discussions we had about God. These discussions gave me tremendous strength during my most challenging moments.

This endeavor would not have been enjoyable or possible without the love of my life, Navid Resalat, whose burning passion for my success kept me always moving forward. My dear husband, thank you for helping me and being such a strong pillar for me throughout my doctoral

journey. Your confidence in my abilities and enthusiasm for my achievement is something I will always be eternally grateful for. Having you as my soulmate has been one of God's greatest blessings in my life. I am looking forward to so many more beautiful years by your side along with the new addition to our growing family, baby Shaayaan.

My beautiful little miracle, Shaayaan. Thank you for making me a mom this year. Your birth has been the greatest gift from God. You are the light of our life, and we are so excited to watch you grow, find your passions, and achieve your own dreams. May we support you in your endeavors and celebrate your achievements. We love you with all our heart.

In loving memory of my wonderful grandparents. It has been difficult losing you both just a few short months ago, and I miss you both so dearly. Although I wish you could have witnessed this day by my side, I know you are both watching from heaven.

Becoming part of the Fox family has been such a great privilege. I have been blessed to grown in both faith and knowledge during my time here. The wisdom I have gained and the grace I received from this wonderful Christian university is something I will forever cherish.

"Blessed are those who find wisdom, those who gain understanding, for she is more profitable than silver and yields better returns than gold" (Proverbs 3:13)

Contents

List of Tables

List of Figures

Chapter 1

Introduction

Developmental education has long served as a barrier between students and degree attainment (Bailey, Jeong, & Cho, 2010; Okimoto & Heck, 2015). Remedial coursework is designed to help students who are enrolled in post-secondary education — but are not adequately prepared for college-level coursework — to develop the skills necessary for taking college-level courses (Sanabria, Penner, & Domina, 2020). Needs are significant at community colleges because they are open door institutions (Marwick, 2004). For most community college students, remedial education is the gateway to credit-bearing college-level courses and subsequent degree attainment (Zachry-Rutschow & Schneider, 2011). However, a majority of those enrolled in remedial courses actually have a much lower chance of completing the remedial math sequence and eventually enrolling in a college-level course. There are numerous reasons for students' lack of completion. This includes, but is not limited to, the cost of remedial courses, the numerous courses in the remedial sequence, the length of time needed to complete the sequence, and students giving up. Hence, enrollment in remedial courses has decreased the odds of students completing their degrees, and the lack of college readiness has become a significant cause of low graduation rates (National Center for Public Policy and Higher Education & Southern Regional Education Board [NCPPHE & SREB], 2010; Calcagno, Crosta, Bailey, & Jenkins, 2007).

Remediation is one of the most challenging problems facing community colleges, especially since they are being pressed to increase student graduation rates (Bailey, Jeong, & Cho, 2009). Over the past thirty years, those who have been enrolled in remedial coursework have earned their degrees at a much lower rate than those who were non-remediated (Chen, 2016). Brock (2011) reports that only 28% of remedial students, compared to 43% of non-

remedial students, complete an associate degree or other credentials within eight and a half years of enrollment in a community college.

Specifically, math remediation has very low success rates, and students who are required to take these courses persist to complete the first college-level math course (commonly referred to as a "gateway" course) at an alarmingly low rate. College Algebra is the first college-level, credit-bearing math course. Only 31% of students referred to a remedial math course three-levels below College Algebra eventually enroll into it (Bailey, 2008). This is because the remedial math sequence becomes too lengthy for them. Hence, student under-preparedness has become a significant initial barrier to degree completion. Since most general degree plans require the completion of college-level math, math courses have become a gatekeeper for many students (NCPPHE & SREB, 2010).

Opinions on remediation are highly debated, and research on the effectiveness of remediation has shown mixed results. However, eliminating remediation does not seem to be a solution. This was made evident by Florida's recent legislation. In 2013, Florida passed Senate Bill 1720, which prohibited institutions from requiring placement tests and made remedial education optional regardless of academic preparedness. Once the policy change was implemented in the fall of 2014, there was a smaller percentage of students enrolled in remedial courses (especially in math) than in previous years. Enrollment in gateway math courses such as college algebra increased, and concerningly, passing rates in gateway courses began declining after the policy's implementation. However, a positive observation was that the proportion of students who entered college for the first time and passed math gateway courses increased compared to previous years (Hu, Park, Woods, Tandberg, Richard, & Hankerson, 2016).

The mixed results found in studies on remediation effectiveness have caused colleges to evaluate their remedial programs more carefully and to engage in remediation reforms that may improve student support and success in these courses. Experts have argued that there are two main problems: 1) numerous students are being placed unnecessarily into developmental courses and 2) the structure and traditional instructional practices in developmental education can pose barriers to student success. The Center for the Analysis of Postsecondary Readiness (CAPR), a partnership between Manpower Demonstration Research Corporation (MDRC) and the Community College Research Center (CCRC), is conducting research to examine remediation issues.

Educational Problem of Practice

Community colleges have an open-door policy to serve all students, and they are responsible for teaching college-level material. Approximately two-thirds of all students entering two-year colleges and 40% of all students entering four-year colleges enroll in some form of remedial coursework (Chen, 2016). Remediation rates are generally higher for students who are older, delayed entrants, and Black or Hispanic students. Furthermore, remediation is highest at two-year community colleges than other non-selective colleges and universities since they are open access institutions (Sanabria, Penner, & Domina, 2020). Course failure has been the greatest concern. Less than half of community college students who enroll in remedial courses will pass them. At four-year institutions, the pass rate increases to 50%, which is still concerning (Chen, 2016).

Ill-prepared students make up the majority of the nation’s two and four-year college students who are studying math. Math has one of the highest remediation rates in community colleges. Over 75% of the math students at two-year colleges and 49% percent at four-year

colleges and universities fall under this category (Okimoto & Heck, 2015; Calcagno et al., 2007). Remedial math often becomes more of a roadblock than bridge to college-level courses. Only 45% of students enrolled in remedial coursework eventually earned college-level math credit (Chen, 2016).

Purpose of the Study

The purpose of this study is to explore the relationship between community college students' math remediation status and their continued persistence in math at a large Pacific Northwest college (PNWC). Remediation status is defined as whether a student is placed in remedial or nonremedial coursework; this is most commonly determined by a placement test. Specific math course placement level is also considered such as whether a student places in lower-level or upper-level math remediation or college-level math. Remedial math placement and its relationship with continued persistence in math, such as STEM degree attainment, was explored in this study.

Continued persistence in math includes remediation completion status (whether a student completes the remedial math sequence), college math course completion, seeking a STEM degree pathway, and degree completion. Some of the research questions examine if students complete any degree or specifically a STEM degree. An Associate of Science (AS) or Associate of Science Oregon Transfer in Business (ASORT) are considered STEM degrees for the purposes of this study. Furthermore, this study explores the influence of certain moderators on the relationship between remediation status and continued persistence in math. These moderators include students' age, race/ethnicity, sex, socioeconomic status (through Pell data), and math-placement-level.

Research Questions

1. What are the demographic characteristics (age, race/ethnicity, sex, Pell status) of students who are placed in remedial math?
2. Which demographic variables or characteristics can significantly predict or affect the following outcomes for continued persistence in math:
    - College math course completion
    - Seeking a STEM (AS/ASORT) degree pathway
    - STEM degree (AS/ASORT) attainment, given it was sought
    - STEM degree (AS/ASORT) degree completion time
3. What proportion of math-remediation students attain any degree? What is the average degree completion time of math-remediation students?
4. What does continued math persistence in community colleges look like in terms of the following:
    - Given that the remedial math sequence gets completed, what proportion of students completed at least one college-level math course?
    - Given the remedial math sequence gets completed, what proportion of students end up attaining any degree or a STEM degree?
5. To what extent does age, race/ethnicity, sex, socioeconomic status, and math-placement-level (i.e., lower-level vs. upper-level remedial math placement or college-level math placement) are predictors of:
    - Students (entire student population) attaining a STEM (AS/ASORT) degree, given it was sought

- Math-remediation students (subpopulation) attaining a STEM (AS/ASORT), given it was sought

Significance of the Study

Many researchers have used statewide and national longitudinal data sets to study how remediation impacts numerous postsecondary outcomes such as retention, transfer, and credit accumulation. However, these investigations have illustrated a complex picture leaving little consensus on whether remediation helps, hinders, or has no effect on future student success (Frye, 2014; Horn, McCoy, Campbell, & Brock, 2009). This study hopes to shed more light on this issue.

Moreover, research on math remediation status in relation to community colleges is currently lacking. Most research investigates four-year university students. With community colleges serving a different population than four-year universities, the results of this study will contribute to the literature by specifically addressing the relationship between student remediation status and student continued persistence in math at the community college level. For example, do those who enroll in remedial math courses actually end up finishing and enrolling into a college-level math course?

The results of this study will be disseminated to Oregon state policymakers, local school districts, and practitioners. The findings can help policymakers improve and/or alter their policies and programs to better serve remedial students at the community college level. The results may help policymakers meet the American Association of Community Colleges' (AACC) goal of advancing and improving learning services at community colleges so that staff can have the flexibility to meet the diverse needs of students. In particular, the finding of this study may provide policymakers with useful information regarding math remediation at the community

college level and help create better system alignment amongst postsecondary institutions. Understanding the relationship between math remediation and continued persistence in math may help math educators and math departments make more effective plans for student support, academic success pathways, and degree completion. This can influence departmental decision making in areas such as effective placement policies.

Secondary and postsecondary practitioners and institutions can benefit from this study. By better understanding the relationship between math remediation and continued persistence in math, both groups can form a partnership and create a much-needed bridge between college and high school math instruction. Building this bridge can be instrumental in providing better system alignment and more effective student support. This can be beneficial especially for students transitioning from high school to college.

If positive relationships are found in this study, then policymakers can gain further assurance of the effectiveness of their current policies. If negative or no relationships are found, then it could indicate that policymakers should revisit their policies, request additional research, and/or better understand ways they can refine their policy to further improve student performance.

The hypothesis is that there is a relationship between math remediation status and what students' continued persistence in math will look like at two-year institutions. If the null to this hypothesis is rejected, the study may contribute valuable findings on math remediation and student persistence in math. However, if the null to this hypothesis fails to be rejected, it could mean that other factors may need to be taken into consideration. For example, the issue could lie in the placement system at post-secondary institutions. Placement tests, for example, could be inappropriately placing students into remedial coursework due to under-placement.

Definition of Terms

The following terms are relevant to this research study:

Academic preparedness is the knowledge and skills necessary to be placed in entry-level, credit-bearing college-level courses without remediation.

College readiness includes academic and non-academic characteristics that allow students to access, enroll, and succeed in college.

College Algebra (also referred to as Pre-Calculus I) is the first college-level, or credit-bearing, math course. It is known as the lead "gateway" course.

Community Colleges (also referred to as two-year college or junior college) are open institutions with no admission standards. Their mission is to provide equal opportunity for all by making education more affordable and accessible for those who otherwise would not pursue higher education. Many enroll to attain a two-year degree (associates degree) or to transfer to four-year universities, as it is more economical and affordable than four-year universities (Grubbs, 2020). Due to the open-door policy, many nontraditional students attend community colleges.

Cutoff scores are used in placement tests to determine whether a student will be placed in a college-level course or will need remedial coursework. Even though the placement tests used by colleges may be similar or the same, there are significant variances on how placement scores are interpreted. For example, given the same placement score, a student may be placed in college-level coursework (above 100 level, credit-bearing) at one institution and placed in remedial coursework (below 100 level, non-credit) at another institution.

Secondary cutoffs determine where in the remedial math sequence a student will be placed. For example, will a student only need one remedial course or multiple courses. Institutions usually offer a sequence of remedial courses, and the lower the cutoff score, the more remedial courses a student will need to take to complete the sequence. Once the sequence it completed, students can then enroll in a college-level course.

Entry level credit-bearing courses are freshman level college courses identified by a course code of 100 or above.

Gateway Courses are entry-level, or introductory level, courses required for graduation. Gateway courses have high-level enrollment, but also high withdrawal and failure rates. They are generally included in general education at institutions of higher education.

Guided Pathways is part of the Pathways Project. The Pathways Project is part of a national education reform movement for guiding student choice. The project is conducted by the CCRC and AACC. It uses the cohort model to help students stay on track with a clear and structured pathway. It is being used to redesign and accelerate remediation, establish transfer pathways for those who want to transfer to four-year universities, and is supposed to help create a bridge between K12 and higher education.

Nontraditional Student is defined by the National Center for Education Statistics (2003) as a student meeting one of seven characteristics: delayed enrollment into postsecondary education; attends college part-time; works full time; is financially independent for financial aid purposes; has dependents other than a spouse; is a single parent; or does not have a high school diploma. They are usually adult students (defined as adults older than 25).

Placement Tests are standardized tests most commonly used for determining whether students are either ready for college-level or remedial courses (Kowski, 2013). Based on their placement score, students are either placed into a college-level course or remedial course.

COMPASS and ACCUPLACER are the tests most commonly used for college course placement. It is designed to facilitate the evaluation and placement of college students in three basic skills areas: reading, writing and arithmetic. The purpose of COMPASS and ACCUPLACER tests is to determine which course placements are appropriate for students and whether or not remedial coursework is needed.

Remediation (also referred to as Developmental Education) is coursework assigned to students who lack the academic skills require for college-level, credit-bearing courses. These courses do not count towards degree completion and are designed to prepare students for college-level coursework through a sequence of remedial courses. It focuses on basic skills and assist students in mastering material they should have learning in high school.

Remediation Completion is the completion of the required courses within the remedial math sequence. Remediation completion indicates that a student is academically ready to enroll into college-level coursework.

Remedial math sequence (or remedial sequence) is the sequence of remedial math course offerings that need to be completed before progressing into a college-level math course. Placement tests and student cutoff scores determine whether one remedial course or multiple courses are needed. For example, a student might require one, two, three, or more remedial courses before being able to enroll in college algebra. The remedial program, including the remedial math sequence and course offerings, may differ amongst institutions.

Success rates are different than pass rates. Pass rates include students who earn an A, B, C, or D in a course, while success rates are more restrictive and only include students who earn an A, B, or C. The requirement of students earning at least a C arises from a D not satisfying prerequisites for other courses.

STEM degrees (at PNWC) are degrees that require a minimum of three college-level math courses for which at least MTH 95 or MTH 98 is a prerequisite. PNWC offers two degrees that meet this criterion: Associate of Science (AS) and Associate of Science Oregon Transfer in Business (ASORT) degrees.

Non-STEM degrees (at PNWC) are degrees that either require no college-level math courses or only require one college-level math course. PNWC offers three degrees that meet this criterion: Associate of Applied Science (AAS), Associate of Arts Oregon Transfer (AAOT), or Associate of General Studies (AGS) degrees.

Math-Placement-Level Categories (at PNWC):

Lower-level remedial math placement: MTH 20 through MTH 62

Upper-level remedial math placement: MTH 63 through MTH 98

College-level math placement: courses greater than or equal to MTH 105

Math Pathways (at PNWC) - MTH 60 → 65 → 95 and MTH 58 → 98 are the two math pathways offered

STEM degree pathway (at PNWC) – Students seeking an AS or ASORT degree are on a STEM degree pathway. The MTH 60 → 65 → 95 pathway is designed to prepare students for a STEM degree.

Non-STEM degree pathway (at PNWC) – Students seeking degrees other than an AS or ASORT degree are on a non-STEM degree pathway. The MTH 58 → 98 pathway is designed to prepare students for a non-STEM degree.

Limitations/Delimitations

Any study that is done will have limitations or potential weaknesses that are out of the researcher's control. Delimitations are used to focus a research study (Creswell, 2017). One of the major limitations is the lack of consistency in remediation policies and practices within two-year community colleges. For example, community colleges may implement placement tests differently. This could include the type of placement tests used, cutoff scores, and other metrics used to determine student placement. If a student were to get the same placement score at two different institutions, one institution might place them in a college-level course (above 100-level; credit-bearing), while the other institution might place them in a remedial course (below 100-level; not credit-bearing).

Moreover, colleges may design their remedial program and course offerings differently. In addition to the commonly used multi-semester, remedial math sequence (86% percent of two-year colleges use this model), some institutions might offer additional/alternative options such as compressed courses, multiple math pathways, self-paced courses, corequisite models, etc. (Rutschow, Cormier, Dukes, & Zamora, 2019). Moreover, many colleges emphasize placement test scores, while others might use a blend of placement test scores *and* additional measures such as high school performance, including high school GPA. Hence, there is a lot of uncontrollable inconsistencies in postsecondary remediation policies, practices, and implementations.

Remediation data from a public two-year institution, instead of a four-year institution, was examined to specifically gain a better understanding of remediation at the community

college level; such studies are more scarce and much needed. Secondary data was collected from a large Pacific Northwest college (PNWC). Using data from PNWC allowed for more objective data collection than if collected more subjectively through surveys, focus groups, etc. Secondary data analysis provides a larger sample size that may be of higher quality and more representative of the population.

This study was delimited to students who took math courses at PNWC between Fall 2016 to Fall 2019. Comparing student data across a three-year time span gave an ample timeframe for finding clear distinctions and relationships.

Organization of the Study

Chapter 1 will be an introduction to the study and include background information, discuss the educational problem of practice, purpose of the study, research questions, significance of the study, definition of terms, limitation/delimitations, and an outline of how this dissertation will be structured and organized. In chapter 2, the researcher will present a review of the relevant literature. The literature review includes the history of community colleges and developmental education, the history of College Algebra, the effectiveness of remediation, and the relationship between demographic factors and remediation. The second chapter ends with a discussion on the challenges in developmental education and current reforms. Chapter 3 will outline the methodology the researcher plans to employ to investigate the research questions. Chapter 4 will analyze and discuss the results. Lastly, Chapter 5 will discuss the implications of the study, the need for further research, and serve as a conclusion for the study.

Chapter 2

Review of the Literature

The literature review for this study examines math remediation at community colleges since two-year institutions are the focus of the research. The review will begin with the history of community colleges and developmental education in American postsecondary education. Next, the history of college algebra — the gateway math course for college students — will be discussed. Afterwards, research on the effectiveness of remediation will be examined. This includes research studies that found remediation to have positive, negative, or limited to no effectiveness on student success. Studies on the relationship between student demographics and remediation will then follow. Demographic factors include age, race/ethnicity, sex, and socioeconomic status. The literature review will then end with a discussion of challenges being faced in developmental education and reforms.

Community College Research Center (CCRC) and American Association of Community Colleges (AACC) will be two main sources in this review. Many of the publications examined in this review are associated with the CCRC. The AACC is an advocate for the community college mission and is committed to the community college movement. CCRC focuses on: 1) identifying factors that contribute to low rates of college completion among community colleges students that are assigned to developmental coursework; 2) assessment, placement, and progression of developmental students; 3) developmental education structure, curriculum, and pedagogy; and 4) student persistence, completion, and transfer. Moreover, the Pathways Project — a national educational reform movement — is a project being conducted by the CCRC and AACC.

The Center for the Analysis of Postsecondary Readiness (CAPR) has also been used in this review. The CAPR is a five-year federal center co-led by CCRC and Manpower

Demonstration Research Corporation (MDRC). In terms of developmental assessment and placement, the CAPR gives good information regarding the use of multiple measures for placement.

History of Community Colleges and Developmental Education

Community colleges (also referred to as two-year or junior colleges) began in America. In the past, two-year college were trade and preparatory schools that were alternatives to secondary schools. Most two-year colleges date back to the 1960s. However, the first two-year colleges were found across many states in the 1900s. Most two-year colleges originated as an expansion to high schools as a 13th and 14th grade. The main goal was to further educate the younger people in the community to become good homemakers or local workers and reduce the gap between the educated elite and the masses. Original community colleges began with a bottom-up approach through community advocacy and organizations including the Chambers of Commerce, newspapers, and voters. They were not the open institutions we see today but were derivatives of four-year universities and had admission standards (Grubbs, 2020).

William Rainey Harper, the president of the University of Chicago, is known as the father of junior colleges. He created the idea of splitting the four-year degree into two parts – junior college being the first two years and senior college being the last two years. In 1900, his idea led to the associate degree, which was awarded after the completion of the first two years. The justification of the associate degree was that universities could increase their standards, and it would provide students who wouldn’t have pursued higher education to now pursue it. The general consensus is that Joliet Junior College of Illinois opened the first junior college in 1901. AACC, the advocacy organization for community colleges, was incepted in 1920. Under the Higher Education Act of 1965, federal funding led to large-scale development and expansion of

community colleges. The goal was for 95% of the U.S. population to have access within a reasonable commuting distance. This is when the focus of community college shifted to become open access institutions in order to provide equal opportunity for all. By the 1970s, during the period of vocationalisation of American education, trade skills options also became emphasized at community colleges (Grubbs, 2020).

Today, these open access institutions are continuously working to improve the quality of life of those in the community who otherwise couldn't afford getting an education. The lower costs of tuition, more convenient time offerings, lack of admission standards, etc. have made education possible for many nontraditional students including those who work, are older, have families, are returning students, have delayed enrollment, etc. The goal of remedial coursework is to help underperforming students acquire the skills and knowledge necessary for enrolling and completing college-level coursework. Because of the nature of community colleges and the students they serve, remedial courses are prominent at community college institutions. They have been prominent since community colleges first appeared in postsecondary education in the early 20th century (Cohen & Brawer, 2003; Grubbs, 2020).

College Algebra

According to the American Mathematical Association of Two-Year Colleges (AMATYC) (1995), a strong foundation in math is an absolute requirement for technical education**.** Moreover**,** Ichinose and Clinkenbeard (2016) have identified College Algebra (also referred to as Pre-Calculus I) as the lead "gateway" course. Gateway courses are entry-level, or introductory level, courses required for graduation. They have high-level enrollment, but also high withdrawal and failure rates.

History of College Algebra

College-level math was not always required for undergraduate degree completion. In the early 1800s, engineers were educated by either the U.S. Military Academy or Rensselaer Polytechnic Institute (Tucker, 2013). Soon, there became a growing demand for well-trained engineers, causing other institutions to begin offering engineering programs. It wasn't until after World War II that math would be viewed as important as engineering. (Schoenfeld, 2004).

In 1910, Harvard began requiring students to select academic majors. Princeton expanded this idea by adding a core curriculum which became known as general education requirements (Tucker, 2013). Requiring students to declare a major and to complete core/general requirements became widespread among higher education institutions (Bisesi, 1982). However, it wouldn't be until the mid/late 1900s that general education requirement of math would become widespread amongst institutions (Mitchell, 1974).

E.B. Wilson (1913), an American mathematician, advocated for a year-long freshman math course, mainly referred to as College Algebra, at colleges and universities. His goal was to increase rigor in freshman-level math, and this was the first effort to increase math rigor for freshman students. However, since many college and university institutions did not require math, and math still had not been viewed valuable in the world of education, his initial efforts did not get too far (Tucker 2013).

In 1915, the Mathematical Association of America (MAA) was established by a group of math educators. The MAA formed the Committee of the Undergraduate Program (CUP), which was later renamed as the Committee on the Undergraduate Program in Mathematics (CUPM). CUP created a common freshman-level math course for all natural and social sciences ("MAA History," 2021; Tucker, 2013). This course was called Universal Math and "consisted of one

semester of functions and limits, the real number system, Cartesian coordinates, functions (with focus on exp(x) and log(x)), limits, and elements of derivatives and integrals, followed by one semester of math of sets, logic, counting and probability," (Tucker, 2013, p. 696). However, the course never got fully implemented, as the physics program decided to use calculus as the freshman-level course for its majors.

After World War II, math began gaining more prominence and became viewed as important as engineering, especially since the impact of math was proven to be impactful during war efforts (Tucker, 2013; Schoenfeld, 2004). In 1962, the CUPM surveyed colleges and found that most institutions were offering College Algebra. Furthermore, it was found that most junior colleges also offered remedial math courses such as elementary and intermediate algebra. CUPM worked towards establishing commonality amongst math courses at different universities by creating a general curriculum for math that colleges could adopt — mainly designed for math majors. They also created a recommendation which influenced all majors to require a common math course (Duren, 1965).

By 1974, approximately two-thirds of junior colleges were offering a general education math course. However, only a fourth of those colleges made the course a requirement (Mitchell, 1974). Small (2002) reported that approximately four-hundred-thousand students were enrolled in College Algebra. This made it the credit-bearing course with the highest enrollment nationwide.

Effectiveness of Remediation in Math

Statewide and national longitudinal data sets have been used to study the impact of remediation on postsecondary outcomes such as retention, transfer, and credit accumulation. Moreover, many of the early studies on the effect of remediation suffered from serious

methodological and data limitations, particularly in regard to selection bias – the inability to account for the differences that exist between remedial and nonremedial students (O’Hear & MacDonald, 1995). For example, if remedial and nonremedial students are compared, the performance of the nonremedial students will be far better than remedial students. This difference in outcomes is mainly due to precollege differences, rather than the remediation program itself.

Identifying a causal relationship between remediation and educational outcomes has been difficult since there is no random assignment of students in remedial education. Lesik (2006) explains, “Estimating the causal impact of a developmental math program on student success in college-level math would require randomly assigning all students, including those who are weaker in math, either to the developmental math program or to its alternative” (p. 3). Such random assignment could provide an unbiased estimate of the causal effect of developmental math on student success in college-level math. However, random assignment is not feasible with developmental math since the program is made for students who are not adequately prepared for college-level math.

To overcome such bias, researchers have had to come up with innovative empirical methodologies to better bypass this issue (Grubbs, 2020). The theoretical framework known as the counterfactual model of causal inference has also been used to address selection bias. This framework makes sure that the treatment and control groups are identical on background characteristics. This way any differences overserved can be attributed to the treatment alone. Attewell, Lavin, Domina, and Levey (2006) explain, “Something analogous is achieved in a counterfactual model by first building a model that predicts the dichotomous treatment variable.

This yields a propensity score" (p. 896). The use of propensity score matching reduced selection bias by looking at two groups separately (Crisp & Delgado, 2014).

The regression-discontinuity design is a research design that can be used to make causal inferences when random assignment may not be practical or sensible (Lesik, 2006). It helps researchers investigate the causal impact of remedial coursework on success in subsequent college-level math by examining students who share similar backgrounds but were assigned to different groups (treatment vs. control). Bettinger and Long (2009), as well as other researchers, compared students who were on the margin of needing remediation since they shared similar backgrounds. Most of the newer studies examine students at the margin. However, Hodara and Jaggars (2014) say "this body of research has one key limitation: Because it relies on a regression discontinuity approach, the analytic sample focuses on students who score in a narrow range around a placement exam cutoff" (p. 248). Hence, even more recent regression-discontinuity studies are focused on students near the lower-level cutoff for remediation (Boatman & Long, 2010; Hodara, 2012; Xu & Dadgar, 2018). For example, Xu and Dadgar's (2018) study examined students in remediation with the lowest math skills.

Different studies have left researchers with little consensus on the impact of remediation. Some have found remediation to have a positive effect, some found remediation to have little to no effect, and others have found remediation to have a negative effect on student outcomes. Moreover, there are researchers who believe the effect of remediation is based on the subject matter. For example, Bettinger & Long (2005, 2009) found math remediation to have a positive effect but found English remediation to have no effect. This literature review will discuss different studies, their results, and their implications on what student academic development will look like.

Positive Effects

Fike and Fike (2008) analyzed predictors of first-year student retention in community colleges. They found that taking remedial coursework and internet-based courses were strong predictors of student retention. Bettinger and Long (2009) examined the effects of remediation on college performance and persistence by using a data set of more than 28,000 students who were full-time, traditional-aged (18-20 years old) freshmen students who enrolled in college in Fall 1998. In particular, the study looked at the effects of math and English remediation. Students in this study were tracked over a span of six years and included students from both four-year and two-year colleges in Ohio.

The study focused on students on the margin of needing remedial courses (students who either passed or did not pass the placement test by a small margin). This small margin determines whether students fall into the remedial or nonremedial category. By examining students on the margin of needing remediation, researchers have the ability to study students who share similar backgrounds, and therefore, avoid bias. Longitudinal data from college transcripts, applications, and standardized tests' reports with accompanying student surveys were examined. Since placement policies differ across institutions, this study compared students who were observationally alike and attended different college. This would help avoid the inherent biases.

The effects of remediation were measured using the regression model. The results examined the overall impact of remediation on persistence, transfer behavior, and degree completion for similar students that were placed in and out of remediation. In regard to math, when controlling for ACT math scores (mean 17.68), remedial math students were 14% less likely to drop out of college. Students with higher ACT scores and receiving math remediation were 9% more likely to complete their degrees. Higher ability students were shown to have

benefited from math remediation. The results of the study suggested that students in remediation were more likely to persist in college in comparison to students with similar backgrounds who were not required to take remedial courses. Moreover, it showed that when the focus was narrowed to students on the margin of needing remediation, the estimated effects increased in size and was more positive (Bettinger & Long 2009).

Some states, such as California, don't require standardized placement tests and don't have cutoff scores. Instead, they require institutions to assess the academic preparedness of students and place them accordingly — student placement relies greatly on faculty perceptions. Faculty may encourage students to enroll. But ultimately, the student decides whether to enroll or not (Xu & Dadgar, 2018).

Jespen (2006) examined California community college students who were in remediation to those who were referred by staff to be in remediation but chose not to enroll. He matched students into pairs based on their similarity in preparation for college-level work, which was determined by faculty. Each matched pair included a student who enrolled and a student who chose not to enroll into remedial coursework. Twelve institutions were examined, and preliminary results showed evidence that remediation has positive effects on college persistence and degree completion. However, Martorell and McFarlin (2011) mentioned how there could be confounding variables to Jespen's study. For example, those who were referred to remediation and chose to enroll might have higher levels of academic motivation.

Lesik (2006) collected data at a single four-year metropolitan university located in the Northeast. Data was collected from full-time, first-year students who entered the university between 2000 and 2002. The sample size was 1, 276 students. The purpose of her study was to illustrate the regression-discontinuity design through a study on developmental math. Using the

regression-discontinuity design and an instrumental variables strategy to model selection bias, the study concluded that taking remedial coursework significantly increases the probability of students successfully completing a college-level math on their first try. Lesik (2006) explains that her study illustrates the causal effect of participating in a developmental math course even though there was no random assignment. She writes,

> One key aspect of this study is that an exogenously determined variable such as the student's score on a placement examination can be exploited to make causal inferences. Furthermore, data collection and analyses for a student such as this are relatively simple, given that the only variables that need to be included in a regression-discontinuity model are the treatment indicator and a measure of an exogenous placement score; no other covariates need to be considered but can easily be added to the regression-discontinuity design model to increase the efficacy of the treatment effect estimate. (p. 17)

In a later study, Lesik (2007) confirmed that students who were referred to remediation and took developmental math coursework were significantly less likely of leaving college than students who were referred and chose not to enroll. This study also used the regression-discontinuity design within the framework of discrete-time survival analysis.

Frye (2014) investigated the effect of retention of developmental math students in community colleges in North Carolina. Participants were students who had been referred into one or more developmental math courses and were enrolled in at least one developmental math course during the study. Multilevel propensity matching was used to create two equivalent groups of students matched on the propensity to complete developmental math and to pass college-level math with a C or better.

The goal of the study was to see if there was a difference in outcomes between 1) developmental math students who completed developmental math and attempted, but did not succeed, in college-level math (comparison group) and 2) developmental math students who completed developmental math and then attempted and succeeded in college-level math with a C or better (study group). The results of the study found that the study group did better than the comparison group. Those who completed college-level math earned significantly more associate degrees than those who did not complete college-level math. The completers of college-level math were twice as likely to transfer out of the institution. This study shows that students are found to be more successful long-term if they are retained through developmental coursework and end up successfully completing a college-level math course. However, since this study looks at students who were enrolled in at least one developmental course, it fails to show to show a comparison between those who have to take less developmental courses versus more (such as a full remedial math sequence).

Limited to No Effects

The study by Calcagno and Long (2008) was done to identify the causal effect of remediation on the education outcomes of about 100,000 students attending community colleges in Florida. The state of Florida is unique and can give valuable information nationwide since the state has a broader remediation policy and student diversity than the rest of the nation. The Florida community college system is the third largest in the nation and enrolls about 6% of community college students nationwide. Florida is also one of the ten states that discourages remedial education at four-year institutions — a policy that’s becoming increasing widespread. Calcagno and Long’s (2008) study used a regression discontinuity (RD) design to compare students on the margin of needing remediation (slightly above and below the placement test

cutoff), which makes use of the fact that remedial placement in Florida is largely based on a test score. This approach assumes that a sample of students close to the cutoff will be academically equivalent due to randomness in test outcomes near the discontinuity region. When selection bias exists, this approach is used to find causal inferences. Methodological threats to the validity of the RD design include issues such as the permittance of retesting to be done multiple times in order to place out of the remedial courses.

The study showed that math remediation had limited to mixed benefits for students on the margin of needing remediation. Math remediation appeared to increase early persistence in college, but only slightly. Although remediation showed to increase the total amount of credits earned, there was no statistically significant difference found when it came to total college-level credits (nonremedial credits) earned. Moreover, remediation was not shown to lead to the long-term success of degree attainment. This study indicated that remediation is not detrimental but is also not as supportive as what Bettinger and Long (2009) had found.

Similar to Calcagno and Long (2008), Martorell and McFarlin (2011) examined the effect of remediation in Texas, a state with a single placement exam and cutoff score, similar to Florida. Using a RD design, similar to Calcagno and Long (2008), the study made use of students' remedial placement exam scores to compare students at the margin of needing remediation. Martorell and McFarlin (2011) found little evidence that remediation improves student outcomes. Particularly, some results suggested a small negative effect on the number of academic credits attempted and the likelihood of completing at least one year of college. The effects on degree completion, labor market earnings, and the likelihood of transferring to a four-year university were found to be small and statistically insignificant.

The study concluded that marginal students in Texas received little benefit from remediation. Math remediation had a smaller negative effect on attempted academic credit hours and the likelihood of completing at least one year in college than other subjects. Moreover, the findings of the study indicated that the passing cutoff was not set at an appropriate level. However, it was not clear whether it was set too high or too low.

Hodara and Jaggars' (2014) study explored the impact of the remedial math sequence on various student outcomes without regarding the students' age and how far above or below they were from the cutoff score. In particular, they examined how shorter-length remedial math sequences effected overall credit accumulation for students. The study used longitudinal data the City University of New York System's six community colleges, and propensity score matching was used to control for selection bias. The study found no significant differences between math students who took a shorter-length sequence versus a longer-length sequence.

Negative Effects

Boatman and Long (2010) looked at GPA placement scores slightly above and below the cutoff for remedial placement to examine the effects of remediation on students on the margin. This study used RD based on COMPASS scores and found that students who took remedial coursework received fewer college-level credits over time. Compared to nonremedial students, students who received upper-level math remediation (scoring at or slightly below the cutoff for remediation) took approximately 6.5 fewer college-level credits at the end of their third year. However, students receiving lower-level math remediation took three fewer college-level credits at the end of their third year. These results indicate that remediation could have negative effects on students who are on the margin of needing it.

Bettinger and Long’s (2004) study included 8,600 first-year undergraduate students attending public four-year universities in Ohio. They found that remedial math placement increased the likelihood of students dropping out or transferring to another community college, as compared to non-remediated students. However, students who completed the remedial math sequence were less likely to drop out than those who were placed and chose not to complete it. Bettinger and Long (2004) suggest that the remediation may have a potential positive effect on persistence and may result in student reevaluating their college readiness before choosing to enroll.

Xu and Dadgar (2018) conducted a study to see how effective community college remedial math courses were for students with the lowest math skills. The study examined the causal impacts of the lowest level of remedial math (third level of math remediation) on student academic outcomes. This course is usually referred to as “Pre-Algebra.” The lowest levels of developmental education often take at least three semesters to complete. The study looked at data from the Virginia Community College System, which included twenty-three community colleges. The result of the study showed that students who had the lowest preparation in math were either minimally or negatively affected by the longest developmental sequence. It was found that by having to complete the longest sequence, the likelihood of earning a degree or certificate within four years may have been reduced.

Scott-Clayton and Rodriguez (2012) examined first-year college students from six large urban community colleges. The researchers found no evidence to suggest remediation had improved outcomes and found that students assigned to remediation were more likely to initially delay enrollment. The strong diversion effect of remediation was found to result in high rates of

attrition. This could be likely due to the demands of outside commitments such as family and work, which is common among community college students (Horn & Nevill, 2006).

Students assigned to developmental education are found to spend their limited time in college focused on developmental coursework rather than on college-level coursework (Scott-Clayton & Rodriguez, 2012). Developmental education may build stronger academic skills among those who complete it (Attewell et al., 2006; Bahr, 2010). However, the positive developmental effect was found to be quite negligible in comparison to the larger population affected by the strong diversion effect (Bailey, Jaggars, & Scott-Clayton, 2013).

In addition, for students at the lowest levels of remedial math sequence, remedial coursework can become quite costly (Crisp & Delgado, 2014). It has been estimated that the average community college student pays close to $2000 for remediation (Strong American Schools, 2008). This amount is likely more for students at lower levels of remediation. Attewell et al. (2006) and Scott-Clayton & Rodriguez (2012) have found that remediation may have psychological costs for students, as well. For example, they found that placement into remedial courses can have a negative effect on students' academic aspirations.

Demographics Variables and Remediation

Studies have found that demographic variables can play a significant role on whether a student will progress successfully through remediation. These include variables such as age, race/ethnicity, sex, and socioeconomic status. According to Campbell (2016), most research on remedial education focus on traditional-aged students (ages 18-24) and use age as a control rather than predictor variable.

Age is an important demographic variable when trying to understand the effect of remediation on student success, especially since age is a proxy for many other demographics

such as financial independence, years since high school graduation, having dependents, and employment. They all impact enrollment patterns, retention, transfer, and more. Moreover, literature has shown that adult students have different needs than do traditional-aged college students (Campbell, 2016).

Campbell (2016) examined longitudinal data from ten community colleges in Louisiana. Multiple logistic regression analysis was used, and the goal of the study was to determine if age was a significant predictor of enrollment into remedial math courses, completion of the remedial math sequence, enrollment into a college-level math courses, and completion of a college-level math course with a C or better (referred to as successful remediation). She found that traditional-aged students and adult students (above 25 years old) made up 90.2% and 9.8% of those referred to remedial math, respectively. Of those referred, 6.5% of adult students and 93.5% of traditional-aged students ended up enrolling in a remedial math course. Traditional-aged students who completed the remedial math sequence, enrolled in college-level math, and successfully remediated was 92.3%, 92.1%, and 90.8%, respectively. However, for adult students, these percentages were 7.7%, 7.9%, and 9.2%, respectively.

Calcagno et al. (2007) showed that older students were more likely to need remediation as a short-term refresher course instead of a semester-length course, especially for math remediation. Regarding graduation, older students enrolled in remedial courses were less negatively affected than younger students. Bailey et al. (2010) found that older students were less likely to complete remedial coursework than traditional-aged students.

Davidson and Petrosko (2015) studied persistence patterns of students enrolled in math remediation from the Kentucky Community College System. Persistence was defined as enrollment in the subsequent term, transferring, or receiving a degree or certificate. The

researchers found that age was a significant predictor of persistence, where younger students were more likely to persist than adult students.

Bahr (2010) examined the relationship between race and math remediation. He examined 86,000 freshmen enrolled at 107 community colleges in California. The researcher found that race was highly correlated with the likelihood of successful remediation (defined as passing a college-level course with a C or better). White students were found to be 3.1 times and 1.6 times more likely to successfully remediate than Black and Hispanic students, respectively. One in four students were found to complete a credit-bearing course within six years of enrollment. Higher math deficiency decreased the odds of successful remediation, and on average, Blacks and Hispanics had the greatest math deficiencies. Bahr (2010) discussed how race is not necessarily a causal factor, but a proxy for qualities such a math preparedness. Moreover, in a study of North Carolina community colleges with students who took remedial math courses, Frye (2014) found that Black students were 40% less likely to pass college-level math.

Students of color, many of whom were first-generation college students from low-income backgrounds, were disproportionally placed in remediation courses (Attewell et al., 2006; Bahr, 2010; Chen, 2016). Placement tests were found to be a prominent factor contributing to this disproportionate placement (Davis & Palmer, 2010; Preston, 2017). When compared with their peers, Bailey et al. (2010), found that underserved students were more likely to be placed in lower level of remedial courses.

Campbell’s (2016) study found that females made up the majority of students referred to remedial math (57.2%). The female majority increased with each step in the remedial process: 1) referral; 2) enrollment; 3) completion of remedial math sequence; 4) enrollment in college-level

math; and 5) successful remediation. The researcher found that females made up 64.1% of those who successfully completed remediation.

Frye (2014) found female students were 37% more likely to pass college-level math. Lawrence (2011) studied the North Carolina Community College System. Using logistic regression analysis, the researcher found that gender was a predictor of success for students who took their first remedial math course. Women were more likely to pass their first remedial course. Goldin, Katz, & Kuziemko (2006) also found that women were found to have higher college completion and graduation rates than men.

Remediation, tutorial services, and counseling services were developed to provide equal educational opportunities for the educationally and socioeconomically disadvantaged, many whom would not have been able to attend college. However, retention and graduation rates of students from socioeconomically disadvantaged backgrounds have been shown to be disproportionately lower than those of students from white middle-class families (Adelman, 2007; Brock, 2010; Engle & Tinto, 2008).

In the interviews conducted by the U.S. Department of Education’s NELS:88-2000 longitudinal study, 26-year-olds were asked why they didn’t continue their education. In their responses, 75% said it was because of academic reasons (bad grades, not taking the right classes) and 37% stated that it was because of financial reasons (not being able to afford it, having to support a family, needing to work and make money). The Academic Competitiveness Grants was created by Congress in 2006 (as a supplement to the basic Pell Grant) for low-income students in such situations (Adelman, 2007). However, Frye (2014) still found that Pell recipients were 27% less likely to pass college-level math.

Johnson (2008) found that students who had a higher percentage of receiving free lunch in high school were less likely to stay in college. This could mean that high school socioeconomic characteristics can play a role in the retention of students when they go to college. Lawrence (2011) defined socioeconomic status as whether a student received financial aid or not. She found that socioeconomic status was a predictor of success for students who took their second remedial math course. Students who received financial aid were less likely to pass their second remedial math course than those who did not receive financial aid.

Challenges in Developmental Education

Amos (2011) states that the nation loses $3.7 billion per year as a result of remediation services. How, and if, remediation should be offered is an issue in many states. Two states do not allow remedial courses in their public institutions, and there are at least eight states that only allow remediation in two-year colleges. Many states either have or are considering putting limits on government funding for remediation (Calcagno & Long, 2008). Numerous states have shifted all postsecondary remedial coursework to community colleges (Bettinger & Long, 2007). Hence, one of the greatest challenges currently facing community colleges is the remediation crisis. Since the population of students referred to remedial coursework is very diverse, implementing various approaches to address the diverse population has been a great challenge for community colleges (Levin & Calcagno, 2008).

High School Students and GPA

Thousands of high schoolers graduate each year academically underprepared for college and therefore are referred to remedial coursework (Bettinger & Long, 2009). High school grades, as well as high school rank, have long been accepted as predictors of college persistence and success (Bean & Bradley, 1986; Geiser & Santelices, 2007; Ishitani, 2006; Jamelske, 2009;

Johnson, 2008). Interestingly, it has been found that remediation is not exclusive to only lower-performing high school students. A 2008 survey of students taking college remediation courses, four out of five students said that they earned a 3.0 GPA or better in high (Strong American Schools, 2008).

High school GPA is a metric often used to predict student college preparedness. Countless studies have shown a strong relationship between high school GPA and college preparedness and success (DesJardins & Lindsay, 2008; Rothstein, 2002). For example, Kobrin et al. (2008) found that high school GPA was a moderate predictor (r = 0.53) of college preparedness, while high school GPA combined with SAT scores was a stronger predictor (r =0.61). Belfield and Crosta's (2012) study showed that high school GPA was a more effective predictor of first-year community college success than placement tests. Kowski (2013) found that high school GPA was the most significant predictor for college math course placement, where high school GPA increased the likelihood of testing out of elementary algebra by 2.7 times. Campbell (2016) examined high school GPA and college GPA found that both were significant predictors of remedial math course enrollment.

However, Porter & Polikoff (2012) mention issues with high school GPA. For example, high schools are not standardized in their courses, grading tactics, and more, and there is a lack of diagnostic ability. Moreover, Bishop & Mane (2001) discusses how the significance of high school GPA in college admission process can cause students to take courses with less rigor. This may be why students with a good GPA might still need to take remedial courses.

Returning Students

Many older students returning to school after a number of years are also referred to remedial coursework due to disuse and forgotten skills. In addition, many community colleges

have a significant immigrant population who may have the necessary academic skills for college-level work but are deficient in English. Due to the language barrier, many of these students may take remedial coursework before taking college-level courses (Levin & Calcagno, 2008). Remedial coursework is most common among students from disadvantaged backgrounds (Bettinger & Long, 2007).

According to the CCRC, 60% of students enrolled in community colleges are directed to take at least one remedial course (Bailey, Jenkins, and Leinbach 2005). Attewell et al. (2006) found that about 70% of students pass their reading and writing remedial courses. However, only 30% pass all their remedial math courses – which is an overestimation of student success in math remediation because it does not include those who were referred to remedial courses, but either dropped out or failed to enroll (Levin & Calcagno, 2008).

Remedial math sequences for math have very low success rates, and students who are referred to them persist to complete the first college-level math course at an alarmingly low rate. Only 31% of students referred to a remedial math course three-levels below College Algebra, the first credit-bearing math course, actually enroll in a college-level math course (Bailey, 2008). Student under-preparedness, particularly in math, has become a significant initial barrier to degree completion (National Center for Public Policy and Higher Education & Southern Regional Education Board [NCPPHE & SREB], 2010).

Variances in College Remediation Policies

Colleges are able to establish their own placement and remediation policies independently since they operate autonomously (Attewell et al., 2006). Because of this, there is a great amount of variance in the policies and practices used by colleges when placing students in either college-level or remedial coursework. There is also great variability in the structure of

remediation programs. Despite the differences, most (86%) of two-year colleges use a multi-semester, prerequisite sequence for their remedial programs (Rutschow, Cormier, Dukes, Zamora, 2019).

Placement Tests. Placement tests are standardized tests most commonly used for determining whether students are ready for college-level coursework or need remediation (Kowski, 2013). Based on their placement score, students are either placed into a college-level course or a remedial course. In many states, placement tests are the *only* source used to determine whether students are ready for college-level coursework or need remediation (Collins, 2008; Hughes & Scott-Clayton, 2011).

ACCUPLACER, developed by the College Board, and COMPASS, developed by ACT, are the two frequently administered college placement tests. For decades, colleges have been using standardized exams such as the SAT or ACT for college admission, and they have used placement exams such as ACCUPLACER or COMPASS to measure entering students' skill levels and whether they are ready for college-level coursework (Fields & Parsad, 2012; Hodara, Jaggars, & Karp, 2012). ACCUPLACER and COMPASS are used by colleges to facilitate placement evaluation in three basic skills areas: reading, writing, and math. Their purpose is to determine which course placements are appropriate for students.

Cutoff scores determine whether a student will be placed in a college-level course or will need remedial coursework. Even though the placement tests used by colleges may be similar or the same, there are significant variances on how placement scores are interpreted. For example, given the same placement score, a student may be placed in college-level coursework (above 100 level) at one institution and placed in remedial coursework (below 100 level) at another institution (Fields & Parsad, 2012; Bettinger & Long, 2004).

The organizations that developed ACCUPLACER and COMPASS have supporting documentation regarding the technical quality of their tests. However, the extent to which students have been accurately assigned to courses based on test scores, has not been explained. It has also not been clear whether cutoff scores have been appropriately determined (Scott-Clayton, Crosta, & Belfield, 2014).

Even though the goal of these high-stakes placement tests is to ensure student success (Rosales, 2018), research in the past decade has been beginning to show that a single placement test can underestimate the proficiency level of students. Studies have found that many students taking remedial courses could have been successful in college-level courses (Fulton, 2012; Scott-Clayton, 2012).

A study of New York community college placement test data found that as many as 30% of students were being misplaced in English classes, and slightly lower rates were misplaced in math classes (Belfield & Crosta, 2012). Scott-Clayton (2012) analyzed 42,000 first-year community college students in New York. The researcher found that using placement tests alone were less predictive of success in English and math than using high school GPA. Additionally, it was found that by combining placement test scores with high school GPA, placement error could be reduced by 15%. Belfield & Crosta (2012) also found stronger predictive relationships with the combination of placement test scores and high school GPA. However, the researchers suggest that high school GPA alone may be sufficient in explaining college outcomes.

Reforms

With placement tests possibly hindering students' college success and being a poor predictor of student college readiness, practitioners and policymakers are trying to revise placement policies and procedures (Rutschow, Cormier, Dukes, & Zamora, 2019). Many

colleges have begun using a combination of sources, in addition to placement tests, for determining student college readiness and course placement. Numerous states, including North Carolina, Texas, and Connecticut are in the process of implementing a more holistic approach in determining remedial course placement. However, challenges being faced include integrating data systems, confirming the expiration of high school grades, and withstanding the time it takes to implement systems level policies (Burdman, 2012).

Other reforms include instructional reforms such as re-evaluating course sequencing, content, and pedagogy used in developmental courses (Rutschow, Cormier, Dukes, & Zamora, 2019). Moreover, diagnostic assessments, such as ALEKS and ASSET are becoming a more popular approach. These diagnostic assessments are often being used to modularize developmental courses into smaller modules so that students only take the courses they need before progressing into a college-level course (Rutschow, 2018).

Two-year colleges have been experimenting with different instructional approaches. The majority of public two-year colleges include at least one section of multiple math pathways (instead of a one-size-fits-all traditional pathway), self-paced math courses, corequisite courses, and compressed courses. This is less common in four-year colleges. But, they have been seen to be using these approaches, as well (Rutschow, Cormier, Dukes, & Zamora, 2019)

Pathways Project

Since community colleges have shown high completion rates for students enrolled in vocational programs that use a cohort model with a set curriculum, Guided Pathways have grown in popularity. This is especially true with the pressure for colleges to increase their completion rates. The Guided Pathways approach is highly structured with a map that aligns with students' career and degree goals.

CCRC and AACC Pathways Project is part of a national education reform movement for guiding student choice, creating a clear and structured pathway, helping students stay on track, redesigning remediation and accelerating remediation, creating a bridge between K12 and higher education, establishing transfer pathways, and more. The goal of the Pathways project is to ensure student progression and completion of a degree, reduce the time it takes for students to graduate, prevent students from paying unnecessary money for courses they don't need, and prevent students from losing sight of their goals (The Community College Research Center [CCRC], 2015).

Conclusion of Literature Review

Community colleges are open access institutions with lower costs of tuition, more convenient time offerings, lack of admission standards, and other flexibilities to make education possible for many nontraditional students. This includes those who work, are older, have families, are returning students, have delayed enrollment, etc. The goal of remedial coursework is to help underperforming students acquire the skills and knowledge necessary for enrolling and completing college-level coursework. (Grubbs, 2020; Cohen & Brawer, 2003).

College remediation has an extensive history in the United States, and it has been defined and approached in a variety of ways. Although community colleges are highly regulated and subjugated to state law, policy, and governance, many still operate autonomously and can independently establish their own placement and remediation policies (Attewell et al., 2006). Therefore, there are numerous variances in the policies and practices colleges use in determining student placement in remedial or non-remedial courses (Bettinger & Long, 2004). As a result, similar students might receive very different remedial and non-remedial treatment depending on which college they enroll in.

Placement tests are commonly used for determining whether students are ready of college-level coursework or need to be enrolled in remedial coursework first. However, more and more evidence is suggesting that placement tests lack accuracy, especially when used alone. Due to the inconsistency and variability in remediation policy, the validity of both the instruments and decision-making process has been questioned.

There are mixed beliefs regarding the appropriateness of remediation as a core function of college services. Moreover, there is a mixed body of research confirming both the effectiveness and ineffectiveness of remediation. Some researchers found positive effectiveness, where remediation was found to be a strong predictor of student retention and persistence. These studies found that remediation led to a decrease in dropout rates, an increase in degree competition, and an increase in transfer rates to four-year universities. Other researchers found remediation to have limited to no effects on student persistence and degree completion. They found remediation to be neither supportive nor detrimental to students. There were also researchers that found remediation to be detrimental to students, particularly those on the margin of needing it. These studies found an increase in dropout rates.

Hence, there have been many mixed results from studies on the effectiveness of remediation. Identifying a causal relationship between remediation and educational outcomes has been difficult, especially since there is no random assignment of students in remedial education Lesik (2006). However, researchers have tried to overcome this issue by coming up with innovative empirical methodologies for more accurate and nonbiased results (Grubb, 2011).

Chapter 3

Methods

This study investigated the relationship between community college students' math remediation status and their continued persistence in math at a large Pacific Northwest college (PNWC). Remediation status is whether a student is placed in remedial or nonremedial coursework; this is most commonly determined by a placement test. The specific math-placement-level of students (i.e., lower-level remedial math, upper-level remedial math, or college-level) was examined. Math-placement-level and its relationship with continued persistence in math, such as STEM degree attainment, was also explored.

Continued persistence in math included remediation completion status (whether a student completed the remedial math sequence), college math course completion, seeking a STEM degree pathway, degree attainment (any degree or specifically a STEM degree), and degree completion time. An Associate of Science (AS) or Associate of Science Oregon Transfer in Business (ASORT) were considered STEM degrees for the purposes of this study. Using data obtained from PNWC, this study sought to explore the influence of certain moderators on the relationship between remediation status and continued persistence in math. These moderators included students' age, race/ethnicity, sex, and socioeconomic status (through Pell data), and math-placement-level.

Findings from this study may provide guidance to state policymakers, insitituions, and educators on ways to better improve math remediation policies and programs. This study was framed by the following research questions:

1. What are the demographic characteristics (age, race/ethnicity, sex, Pell status) of students who are placed in remedial math?

2. Which demographic variables or characteristics can significantly predict or affect the following outcomes for continued persistence in math:
    - College math course completion
    - Seeking a STEM (AS/ASORT) degree pathway
    - STEM degree (AS/ASORT) attainment, given it was sought
    - STEM degree (AS/ASORT) degree completion time
3. What proportion of math-remediation students attain any degree? What is the average degree completion time of math-remediation students?
4. What does continued math persistence in community colleges look like in terms of the following:
    - Given that the remedial math sequence gets completed, what proportion of students completed at least one college-level math course?
    - Given the remedial math sequence gets completed, what proportion of students end up attaining any degree or a STEM (AS/ASORT) degree?
5. To what extent does age, race/ethnicity, sex, socioeconomic status, and math-placement-level (i.e., lower-level vs. upper-level remedial math placement or college-level math placement) are predictors of:
    - Students (entire student population) attaining a STEM (AS/ASORT) degree, given it was sought
    - Math-remediation students (subpopulation) attaining a STEM (AS/ASORT), given it was sought

Research Design and Methodology

A quantitative research design using secondary analysis of data was most appropriately matched to this study's purpose. Exploratory research was done in this study using Exploratory Data Analysis (EDA) for the first research question. More robust analytical techniques, including chi-square and logistic regression analyses, were used for all other research questions.

Sampling and Population

This study included students who took math courses at PNWC between Fall 2016 to Fall 2019. Comparing student data across a three-year time span gave an ample timeframe for finding clear distinctions and relationships.

Procedures

Data was collected from PNWC. Using this data allowed for more objective data collection than if collected more subjectively through surveys, focus groups, etc. This was a secondary data analysis study. Secondary data are data that have been collected for another purpose, but where some or all of it can be used for another study or evaluation. Some secondary data is public and some are internal to an organization and require permission. Acquiring data for this study required permission from PNWC. National, state, and local data is usually free, but can be difficult to access. Data from organizations may come with a cost, such as standardized tests or business reports (Goes & Simon, 2016). Secondary analysis provides a larger sample size that may be of higher quality and more representative of the population. To obtain data from PNWC, attaining an IRB approval from George Fox University was necessary. Afterwards, a request was submitted to the Director of Research and Data at PNWC. Upon approval, it became possible to obtain a spreadsheet with the requested data through a secure electronic file transfer.

PNWC included data elements for all enrolled students. Course numbers that were above the 100-level were considered college-level coursework and were credit-bearing courses. Course numbers that fell below 100-level were consisdered remedial coursework and were considered non-credit courses. This study included data from students who took math courses at PNWC between Fall 2016 to Fall 2019.

Measures

The data requested contained data for math courses only. The following variables were included in the data sheet: term (term student took a given math course); PIDM (student ID); birthdate, race/ethnicity, sex, Pell status, first term (students' first term at the college); subject (math); course number; number of credits; grade; degree intention (type of degree student sought or was awarded such as AS, ASORT, AAS, AAORT, AGEN); award status (if a degree was awarded, sought, pending, or denied); and graduation date. Dependent and independent variables were conceptualized and operationalized as follows:

Dependent Variables:

- Continued persistence in math – conceptualized as continued persistence *after* successful completion of the remedial math sequence; operationalized as the following four components:
    - College math course completion: conceptualized as the completion of at least one college-level math course after remediation; operationalized as: yes (1); no (0).
    - Degree attainment – conceptualized as being awarded (AW) any degree; operationalized as: yes (1); no (0).

- Degree completion time – conceptualized as the time it takes for a student to graduate with any degree (graduation date minus first-term date); operationalized as a continuous variable based on time in months.
- Seeking a STEM degree pathway – conceptualized as seeking or being awarded a STEM (AS/ASORT) degree; operationalized as: yes (1); no (0).
- STEM degree attainment – conceptualized as being awarded (AW) a STEM (AS/ASORT) degree; operationalized as: yes (1); no (0).
- STEM degree completion time – conceptualized as the time it takes for a student to graduate with a STEM degree (graduation date minus first-term date); operationalized as a continuous variable based on time in months.

Independent Variables:

- Race/ethnicity – conceptualized and operationalized as a categorical variable based on student self-identification of race/ethnicity: Multi Racial (2+), Caucasian/White (WHI), Black/African American (BAA), Asian (AS), Hispanic (HIS), American Indian/Native American (AI), Non-Resident Alien (NRA), Hawaiian/Pacific Islander (HPI), and Unknown/Not Reported (UNK).
- Sex – conceptualized and operationalized as a categorical variable based on male or female gender identification: Female (F); Male (M).
- Socioeconomic status – conceptualized and operationalized as Pell status, a categorical variable based on the need for a Pell Grant: yes Pell (Y); no Pell (N)
- Age – conceptualized as the age of a student upon initial enrollment at PNWC (first-term date minus birthdate); and operationalized at a continuous variable with time in years (1 or more years)

- Math-Placement-Level – conceptualized as lower-level or upper-level remedial math placement or college-level math placement; Operationalized as the following categories:
    - Lower-level remedial math placement: MTH 20 through MTH 62
    - Upper-level remedial math placement: MTH 63 through MTH 98
    - College-level math placement: courses greater than or equal to MTH 105

Table 1

Relationships of Variables – Data Analysis Table

RQ	Dependent Variable	Independent Variable	Analytics
1		Demographic characteristics (age, race/ethnicity, sex, Pell status)	Exploratory Data Analysis
2	Continued persistence in math: • College math course completion • Seeking STEM degree pathway • STEM (AS/ASORT) degree attainment • STEM (AS/ASORT) degree completion time	Demographic characteristics (age, race/ethnicity, sex, Pell status)	Logistic Regression Analysis and Linear Regression Analysis
3	Continued persistence in math: • Degree (any degree) attainment • Degree (any degree) completion time	None	Chi-Square Analysis, Proportion z-test, and t-test
4	Continued persistence in math: • College math course completion • Degree attainment (either any degree or STEM degree)	None	Chi-Square Analysis and Proportion z-test
5	Continued persistence in math: • STEM (AS/ASORT) degree attainment	Demographic characteristics (age, race/ethnicity, sex, Pell status) and math-placement-level	Logistic Regression Analysis

Research Question One: Exploratory Data Analysis

Research question one (RQ1) employed exploratory data analysis (EDA) of sample demographics. Using data provided by PNWC, EDA was used to explore the demographic variables of all students and specifically math-remediation students. When EDA is done well, it is powerful because it illuminates information that a researcher can then use. There is a lot of flexibility to explore anything that falls within the parameters of the research question. Frequencies and distributions are often used as part of this exploration (Tukey, 1977; Hartwig & Dearing, 1979). The strict EDA used to explore RQ1 was purely observational and only examined what would be observed in the collected data.

Rationale for EDA. EDA is a very basic and powerful way of examining distributions of data. The main philosophy behind EDA is searching. This method is most useful for researchers who are trying to gather useful data without having hypotheses or biases interfere in their analysis and interpretation. The application of EDA techniques determines the other types of techniques a researcher will be able to use to analyze data (Hartwig & Dearing, 1979). EDA techniques usually analyze data with descriptive statistics (numerical representations) (Tukey, 1977) and visual representations of the data (Hartwig & Dearing, 1979). Both representations are equally important, and combined together, they create four categories: numeric displays, numeric summaries, visual displays, and visual summaries. Numeric summaries are the most used technique when researchers want extensive analyses. However, EDA makes a wide use of visual displays, as well.

The systematic search for patterns begins with a variable's distribution. For example, stem-and-leaf plots (also called box-and-whisker plots) can be used for examining univariate distributions, and bivariate distributions can be examined using a scatter plot. In terms of

numeric (statistical) summaries, the exploratory approach relies greatly on resistant statistics. This is because resistant statistics are less affected by a few highly deviant cases, or outliers. Hence, they make it easier for researchers to identify general tendencies and deviant cases. EDA uses numerous techniques (Hartwig & Dearing, 1979). Hartwig and Dearing (1979) argue that:

> A researcher should learn as much as possible about a variable or set of variables before using the data to tests theories of social science relationship. If researchers know as much as possible about their data on the basis of employing EDA, the subsequent data analyses are likely to be sounder than if the researcher did not use EDA techniques. (p. 5)

One of EDA's strengths include allowing a lot of flexibility in exploring the data from numerous angles. EDA is used for hypothesis generation, not hypothesis testing. Since hypothesis generation is an individually driven agenda and still largely considered as much art as science, many researchers can easily generate hypotheses that are not good. Hypothesis generation is often driven by personal interest, biases, and what researchers find in the literature. Hypothesis testing, on the other hand, is driven by methodology. Hence, one limitation of EDA is that it can't be used for hypothesis testing (Hartwig & Dearing, 1979).

Assumptions. The underlying assumption of the exploratory approach is that the more a researcher knows about the data, the more the researcher can effectively use the data to develop, test, and refine a theory. Hence, the goal of EDA is to maximize what is learned from the data, and this requires researchers to be both skeptical and open. Researchers need to be skeptical of the measures used to summarize the data to make sure nothing important is being concealed or misrepresented. They also need to be open to unanticipated patterns which may result in some of the most important findings (Hartwig & Dearing, 1979).

Researchers must be open to alternative models to show the relationship between two variables. Tukey (1977) gives a simple formula to describe data: *Data = Smooth + Rough*. The objective of EDA is to uncover the smooth data. Smooth data refers to the pattern(s) that can be extracted from the raw data. It is not based on the researcher's expectations or hypothesis; it comes straight from the data. Hartwig and Dearing (1979) explains, "instead of imposing a hypothesized model of the smooth *on* the data, a model of the smooth is generated *from* the data" (p. 11). The rough data are the remaining residuals that have no pattern. They are what gets left over after all the patterns have been extracted from the data. However, the rough also needs to be examined carefully, as additional patterns may be hidden within the residuals and should not be overlooked (Tukey, 1977; Hartwig & Dearing, 1979).

With EDA, a researcher must be willing to explore the unexpected and alternative models and not rush to judgment. They must be willing to be an investigator with a detective mentality. No rock should be left unturned. For example, a researcher cannot quickly decide to fit a linear model to the data. If they do so, and the linear model is incorrect, then the statistics found (even if tested to be statistically significant) might be flawed. Hence, EDA requires researchers to be open to the unexpected and the prospect that an alternative model might be more fitting.

EDA should not be taken to mean statistics alone (numerical summaries of the data). Statistical summaries of data can downgrade the importance of visual displays of data, even though they are critical to EDA. A statistic, such as a mean or regression coefficient, is not more informative than a graphical representation of data (which is a common misconception). There is great emphasis on visual representations of data, and there are graphical techniques for looking at individual variables and relationships between them (Hartwig & Dearing, 1979). Hartwig and Dearing (1979) write, "the principle of skepticism also takes two forms when extracting the

smooth from the data: first, a reliance on visual representations of data and, second, the use of resistant statistics" (p. 12).

Research Questions Three and Four: Chi-Square Analysis

Research questions three (RQ3) and four (RQ4) statistically examined proportions of math-remediation students that completed at least one college-level math course, as well as math-remediation students that attained a degree. Both RQ3 and RQ4 examined math-remediation students' attainment of *any* degree. RQ4 specifically examined math-remediation students' attainment of a STEM (AS/ASORT) degree. The test of proportions requires the use of chi-square analysis. The test compares the expected and observed proportions such that the differences in the observed and expected proportions can be examined relative to some test statistic. The test can also be used to examine whether the expected proportion will be significantly lower, higher, or the same as the observed proportion.

Rationale for Chi-Square Analysis. The chi-square test of independence is one of the most useful statistics for testing hypotheses when the variables are nominal. It is also referred to as the Pearson chi-square test, or just chi-square ($\chi 2$). The chi-square test is a statistical procedure used to examine the differences between categorical variables in the same population. Chi-square can provide information on the significance of observed differences, as well as provide thorough information on precisely which categories account for any differences found – which is unlike other statistics. Thus, the amount and information the chi-square statistic can provide makes it an incredible useful tool for analysis (Huck, 2012; McHugh, 2013).

Chi-square analysis is used when a researcher needs to estimate how well an observed distribution matches an expected distribution. This is referred to as the "goodness-of-fit" test. Observed values are the ones gathered by the researcher, and expected values are found from the

frequency distribution. Chi-square tests and analysis compares the difference between observed and expected frequencies or proportions. It is one of the statistical tests that allow us to test for deviations of observed proportions from expected proportions and informs researchers whether there is a statistically significant difference between various categories.

The chi-square distribution is similar to the t-distribution because they are both a series of distributions. However, chi-square is asymmetrical, positively skewed, and will never reach normality. This is why the chi-square test is a non-parametric statistic (or distribution free), as it is not assumed to come from prescribed models such as the normal distribution or linear regression model. The shape varies based on degrees of freedom.

Limitations of chi-square tests is that it is very sensitive to sample size. Even when there is a large sample size, it can still be possible to find statistical significance for trivial relationships. So, statistical significance is not necessarily meaningful. Moreover, chi-square can only inform the researcher on whether two variables are related and does not imply causality between variables (Huck, 2012; McHugh, 2013).

In this study, the null hypotheses for the chi-square model state the expected proportion: there is no difference between the observed and expected proportions. This is why all the hypotheses in this study have an expected proportion of $p = 0.5$. In order to use the chi-squared test, the chi-squared test statistic must be calculated using the following formula:

$$\chi 2 = \sum \frac{(\text{observed} - \text{expected})^2}{\text{expected}}$$

Note that the chi-square statistic can’t be negative since nominal variables don’t have directionality. Using the chi-square goodness-of-fit test, it can be concluded whether we reject the distribution specified in H_0 or fail to reject it. Chi-square goodness-of-fit test allows us to

assess whether the distribution of observed values matches the expected distribution McHugh, 2013).

Assumptions. Chi-square requires data to be randomly selected to eliminate potential biases, and the variables must be nominal/ordinal. However, finding inferential statistics used when data are from convenience samples rather than random samples is not uncommon (as in this study). All categories must be independent, or mutually exclusive. Moreover, the study groups must be independent. The data can't consist of paired samples, otherwise a different test will need to be used. Each subject can contribute to only one cell in the chi-square table. For example, if the same subject is tested over time and contributes to the table more than once, chi-square cannot be used.

The null hypothesis for chi-square is generally the same: there is no relationship between the two variables. However, the research hypothesis states there is a relationship. The result of chi-square testing cannot inform the researcher on the degree of difference between categories. A researcher will not be able to tell which statistic is greater or less than the other. Furthermore, chi-square can only test whether two individual variables are independent if they are binary (i.e., yes or no).

Chi-square is a significance test, and therefore, should always be coupled with an appropriate test of strength. The Cramer's V is the most common strength test used to test the data when significant chi-square results have been found. However, one limitation is that the Cramer's V can produce relatively low correlation measures, even when results are highly significant. The following conditions apply to the data when using non-parametric statistics: 1) the variables are nominal or ordinal and 2) the sample sizes of the study groups are unequal.

However, unlike other non-parametric tests, chi-square is still appropriate to use even when sample sizes are equal (McHugh, 2013).

Research Questions Two and Five: Logistic Regression Analysis

In research questions two (RQ2) and five (RQ5), the data was used to investigate whether the demographic variables of age, race/ethnicity, sex, and socioeconomic status (through Pell data) and math-placement-level (only investigated in RQ5) could significantly affect the outcomes of continued persistence in math for community college students. When looking at binary outcomes, logistic regression needs to be used in the analysis. In this study, logistic regression was used to investigate the binary outcomes of college math course completion, seeking a STEM (AS/ASORT) degree pathway, and STEM (AS/ASORT) degree attainment. The predictors in this study were age, race/ethnicity, sex, Pell status, and math-placement-level. Logistic regression analysis helped explore which predictors could better explain the categorical outcomes of continued persistence in math.

Rationale for Logistic Regression Analysis. Nayebi (2020) explains that "The logistic regression is a statistical technique to show the effects of a set of independent variables on the probability of occurrence of an event" (p. 79). Logistic regression is an extension of linear regression. Similar to linear (simple or bivariate) regression and multiple regression, there is only one dependent variable in logistic regression. However, in comparison to linear and multiple regression, logistic regression is used when the dependent variable is categorical rather than continuous. For example, in this study, a linear regression model was used to explore the outcome of STEM degree completion time since it is a continuous variable.

When the dependent variable is dichotomous or binary in nature, simple linear regression cannot be used and logistic regression gets used instead. In binary logistic regression, the

dependent variable must be binary and the independent variables can be continuous (interval/ratio) or categorical (ordinal/nominal). Even though there needs to be at least one independent variable for logistic regression, two or more independent variables (predictors) are almost always necessary (Huck, 2012). Hence, logistic regression is particularly fitting for studies that test relationships between a binary dependent variable and multiple categorical or continuous independent variables.

Moreover, logistic regression can be used to predict the relationship between the predictors (independent variables) and the dependent variable. In other words, logistic regression predicts the probability of specific outcomes. It also can give information regarding which of the predictors are the strongest. Tests of significance can be conducted with logistic regression which can either target each individual independent variable or target the combined effectiveness of all the independent variables (called multivariate analysis). Moreover, the purpose of logistic regression can either be prediction or explanation (Huck, 2012; Peng, Lee, & Ingersoll, 2002; Mertler & Vannatta, 2005)

Researchers mainly use logistic regression to discuss the explanatory or predictive power of each independent variable using the concept of odds, which is derived to explain the likelihood of an event occurring. Logistic regression is used to obtain the odds ratio in the presence of more than one predictive variable. The concept of odds ratio is not a feature of either linear or multiple regression. Logistic regression calculates the maximum likelihood of the odds of the dependent variable occurring or not. It estimates the probability of an event occurring based on the values of all of the independent variables combined. This is done by converting the dependent variable into a logit variable or a log of odds of occurrence (Foltz, 2016; Muijs, 2011). Odds ratios are found using the following equation:

$$Odds = \frac{p}{1-p}$$

Where p is the probability of the occurrence of the event and $1 - p$ is the probability of the non-occurrence of the event (Nayebi, 2020)

Odds ratios greater than 1 indicate that as an independent variable increases, so will the odds of the outcome occurring. Conversely, an odds ratio less than 1 indicates that as an independent variable increases, the odds of the outcome occurring decreases. An odds ratio equal to 1 means there is no relationship. In this study, the odds ratios described the likelihood of the outcomes of continued persistence in math (college math course completion, seeking a STEM degree pathway, and STEM degree attainment) occurring as the independent variables (demographic variables and math-placement-level) increased or decreased. After performing a logistic regression, researchers usually find the odds ratio for each independent variable, or at least those that aren't used as controls (reference groups). The odds ratio is similar to r^2 since it measures the strength of association between the independent variable and the study's dependent variable.

According to Hosmer, Lemeshow, and Sturdivant (2013), logistic regression requires 10 cases per parameter (independent variable). In this study, five independent variables were included, requiring a minimum sample size of 50. The logistic regression model for this study used the following predictors: $X_1 =$ age, $X_2 =$ race/ethnicity, $X_3 =$ sex, X_4= Pell status, and X_5 = math-placement- level (only RQ5). These independent variables were used to predict the likelihood of the outcomes of continued persistence in math occurring (college math course completion, seeking a STEM degree pathway, and STEM degree attainment) using the following equation (the natural logarithm of the odds ratio):

$$logit\ (Y) = \ln\left[\frac{\pi}{1-\pi}\right] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n$$

where π is the probability of the event (remediation completion) occurring and is between 0 and 1, α is the y-intercept, β_n are the regression coefficients, and X_n are the independent variables (Peng, Lee, & Ingersoll, 2002). This model explains the extent to which the independent variables will increase and decrease the likelihood of remediation completion.

The regression coefficients for logistic regression are calculated using maximum likelihood estimation (MLE). When the regression coefficients (β_n) of an independent variable (X_n) are positive, it indicates the increase in the probability of the occurrence of the event (odds ratio will be greater than 1). So, positive regression coefficients show that the independent variable increases the odds. For example, if we wanted to assess a female's odds of being recommended for remediation and the odds ratio was 2.5, this would mean that females are 2.5 times more likely, than not, to be recommended for remediation than males.

Conversely, when the regression coefficient is negative, it indicates the decrease of the probability of the event occurring (odds ratios will be less than 1). So, negative regression coefficients show that the independent variable lowers the odds. However, if the regression coefficient of an independent variable is 0, the probability neither increases nor decreases. This means the odds don't change (odds ratio will be equal to 1). The assumed causal relationships are verified when all regression coefficients of independent variables are non-zero and considered significant (Nayebi, 2020).

The null hypothesis for RQ2 and RQ5 is that there is no relationship between the predictors and continued persistence in math. If the null hypothesis is true (odd ratio equal to 1), it means there is no relationship between the dependent variable and independent variables. In this case, B_n would be zero. For the null hypothesis to be rejected, the odds ratio's deviation from 1 must be statistically significant. The Wald test gets used to see if the odds ratio is

statistically significant or not. A rejection of the null hypothesis means that the regression does predict the outcome and that there is a relationship between the predictors and remediation completion. In this case, β_n values would be greater than or less than 1 (Huck, 2012; Peng, Lee, & Ingersoll, 2002).

The equation $logit(Y)$ takes the probability, Y, as the input. However, since probability is what needs to be found, the inverse- logit function will be needed to provide the probability of an event occurring as an output. The inverse-logit function is:

$$predicted\ probability\ = \frac{e^{\ \alpha+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\cdots+\beta_n X_n}}{1+e^{\ \alpha+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\cdots+\beta_n X_n}}$$

The inverse-logit function allows us to find the estimated regression equation (or solve for, p, the probability). When it’s graphed, we get a sigmoid function curve (or “S” curve), which shows the probability of each independent variable occurring.

A researcher can assess the reliability of a logistic regression model by examining the (a) overall model evaluation, (b) statistical tests of individual predictors, (c) goodness-of-fit statistics, and (d) validations of predicted probabilities. The goodness-of-fit statistics assess the fit of a logistic model against actual outcomes, such as whether remediation gets completed. In other words, goodness-of-fit reveals the discrepancy between observed and expected values. Two descriptive measures of goodness-of-fit are presented as R^2 indices, representing the proportion of variance explained by the model (Cox & Snell, 1989; Nagelkerke, 1991; Peng, Lee, & Ingersoll, 2002).

Assumptions. The logistic regression model has a few key assumptions. First, the multicollinearity assumption is that the independent variables are independent from each other. Multicollinearity exists if two or more independent variables are too highly correlated with each other. This causes inferences about individual predictor variables to lack reliability. The

assumption can be tested by using the tolerance measure of collinearity and variance inflation factor (VIF) for each independent variable (Huck, 2012; Mertler & Vannatta, 2005).

Secondly, the model specification assumption is that the model has been specified properly and misspecification has been avoided. Model specification depends on the variables the researcher decides to include in the regression model. When important variables get overlooked, or if irrelevant variables are included, the regression model is said to be misspecified (Huck, 2012)

Third, with a binary dependent variable being used in logistic regression, linearity in logistic regression assumes there is a linear relationship between continuous independent variables and the binary outcome. This assumption can be tested by investigating the interaction between each independent variable and the outcome. There is also an assumption that each observation is independent. This assumption can be tested by examining the dispersion parameter, such as variance and standard deviation, produced in the analysis (Mertler & Vannatta, 2005).

Next, logistic regression does not follow the assumption of normality and equal variances of errors. However, errors should be independent. Logistic regression assumes that the binomial distribution describes the distribution of the errors that equal the actual Y minus the predicted Y and is also the assumed distribution for the conditional mean of the dichotomous outcome. This assumption implies that the same probability is maintained across the range of predictor values. The binomial assumption may be tested by the normal z test (Peng, Lee, & Ingersoll, 2002).

Lastly, the distinction between statistical significance and practical significance is important to keep in mind. Many researchers glorify findings that seem small and barely significant. Sometimes, researchers do not mention whether their results were statistically

significant or practically significant. Sometimes the results lack statistical significance but are found to be practically significant by the researcher. Readers should be aware of examining the research report's summary (Huck, 2012; Mertler & Vannatta, 2005).

Research Ethics

This study required exempt status approval from George Fox University's IRB. Approval was also needed from PNWC. Hence, I submitted a formal request to the Director of Research and Data at PNWC for their college's data.

Upon approval, PNWC's staff produced and delivered a spreadsheet containing the requested data via secure electronic file transfer. Ethical concerns mainly revolved around data sharing and the confidentiality and security of the data. De-identified data was requested so that subjects would remain anonymous. Hence, no personally identifiable information wase under my possession or used in the data analysis, interpretations, and conclusions of this study. Data has been securely stored. Data will be kept for three to four years after the study has finished in the case further analysis comes up. Afterwards, the file will be destroyed by permanent deletion.

Role of the Researcher

The researcher is a graduate student completing a doctoral degree in education (Ed.D.). She is also a part-time math instructor with eight years of community college teaching experience and has been involved in implementing innovative and learner-centered teaching methodologies, including flipped teaching, to enhance student success. The researcher has witnessed the shifts and changes in placement testing, remedial programs, and student support services within community colleges, in particular math. She hopes to further learn and support these efforts with this study.

Chapter 4

Results

This study aimed to investigate the relationship between community college students' select demographic and academic-status variables, including their initial math-placement level and their continued persistence in math courses at the community college. Continued persistence in math was defined as 1) college math course completion, 2) seeking a STEM (AS/ASORT) degree pathway, 3) STEM degree (AS/ASORT) attainment, and 4) STEM degree (AS/ASORT) completion time. The demographic variables used in this study were students' age, race/ethnicity, sex, and socioeconomic status (through Pell data). Math-placement-level was explored by the examination of three placement categories: lower-level remediation, upper-level remediation, and college-level.

Data from a large Pacific Northwest college (PNWC) was used in this study. PNWC offers a variety of remedial courses, math pathways, and degree and certificate options. Math course requirements differ for each student depending on the degree or certificate they pursue. Hence, contextualizing the data by describing the college's academic policies and math course offerings is vital so readers can understand the results and analysis later in this chapter. The college will remain anonymous in this dissertation per the institution's request.

Contextualization of Data

A math placement test is a student's first step when admitted to PNWC. The math placement test determines if the student needs to take remedial coursework or if they can begin with college-level coursework. Table 2 lists all remedial math course offerings and initial college-level math courses (gateway math courses) at PNWC. College-level math course requirements differ based on students' math pathways.

Table 2

Remedial Math Courses and Gateway College-Level Math Courses

Course Name	Applicability
MTH 15: Conquering Math Anxiety	Supplemental (optional)
MTH 20: Fundamentals of Math	Core remedial math course • The is the lowest level math remediation course offered (no prerequisite) • Competency required for all PNWC students
MTH 25C: Fractions	Supplemental (optional) to MTH 20
MTH 25D: Decimals	Supplemental (optional) to MTH 20
MTH 58: Math Literacy	Core remedial course for the MTH 58 → 98 pathway
MTH 60: Introductory Algebra (first term)	Core remedial course for the MTH 60→ 65→ 95 pathway
MTH 65: Introductory Algebra (second term)	Core remedial course for the MTH 60 → 65→ 95 pathway
MTH 70: Review of Introductory Algebra	Optional to take instead of MTH 65 or student may choose to take both
MTH 95: Intermediate Algebra	Core remedial course for the MTH 60 → 65 → 95 pathway
MTH 98: Math Literacy II	Core remedial course for the MTH 58 → 98 pathway
MTH 105: Math in Society	College-level math course for the MTH 58 → 98 pathway • MTH 95 or MTH 98 can serve as a prerequisite MTH 105 or MTH 243 fulfills degree requirement
MTH 111: Precalculus	College-level math course for the MTH 60 → 65 → 95 pathway

Course Name	Applicability
MTH 211: Foundations of Elementary Math I	College-level math course for both pathways (MTH 58 → 95 and MTH 60→ 65 → 95 • Only for education students seeking to teach K-8 math • Students taking this course will need to complete the 211/212/213 series (Foundations of Elementary Math) to fulfill their degree requirement.
MTH 243: Statistics I	College-level math course for the MTH 58 → 98 pathway • Student can take either MTH 105 or MTH 243 to fulfill degree requirement College-level math course for the MTH 60→ 65 → 95 pathway • Will not fulfill the students' degree requirements if student requires higher level math courses.

Core remedial math courses at PNWC include MTH 20, 58, 60, 65, 95, and 98. The math department's other remedial math courses are supplemental (optional) courses, usually for additional support. For example, MTH 25C and MTH 26C are supplemental to MTH 20 for students who are struggling with fractions and decimals. They do not fulfill a student's remedial course requirements but are designed to support a student in completing MTH 20. Another example is MTH 93 Intro to Graphing Calculators. This course gives students additional support with using graphing calculators but does not count as a remedial math course.

PNWC offers two math pathways: MTH 60 → 65 →95 and MTH 58 → 98. Both pathways require placement above MTH 20, the lowest core remedial math course offered. Students choose their required math courses based on their math pathway. The MTH 60 → 65 → 95 pathway is

designed to prepare students for higher-level math classes. Students who major in healthcare or in science, technology, engineering, and math (STEM) or require advanced math, chemistry, biology, or physics for their degrees will need to choose this pathway. I refer to such majors as STEM degree pathways. The MTH 58 → 98 pathway is designed for students who plan to major in humanities, arts, or social science and do not plan to major in healthcare or STEM fields. This pathway focuses on real-world math and does not require higher-level math classes such as precalculus, trigonometry, or calculus. I refer to such majors as non-STEM degree pathways.

Each community college may have different pathways and course offerings. Alternative math pathways and course offerings are not universal amongst all institutions. Although MTH 111 might be numbered differently at different institutions, it is one of the gateway courses considered universal to all colleges and universities. MTH 111 is usually referred to as either College Algebra or Pre-Calculus I. It explores relations and functions such as exponential, logarithmic, polynomial, and rational functions graphically, numerically, symbolically, and verbally. Ichinose and Clinkenbeard (2016) identified this course as the lead "gateway" course. Gateway courses are entry-level courses required for graduation with high-level enrollment and high withdrawal and failure rates. This is one reason why alternative pathways began – many students' degrees required MTH 111 per college policy, but in reality, these students did not need MTH 111 content knowledge. As a result, such students were either being held back or failing to complete their degrees because of the MTH 111 requirement.

By offering the MTH 58 → 98 alternative math pathway, PNWC has tried to make math more accessible and applicable to students' individual needs, increasing student success rates in math and degree completion. The college-level math requirements for the MTH 58 → 98 pathway are either MTH 105 or 243. A student choosing this pathway only needs to take one of

these college-level courses to fulfill their degree requirement. Both MTH 95 and MTH 98 serve as prerequisites for MTH 243. Only MTH 98 serves as a prerequisite for MTH 105. MTH 105 and MTH 243 serve as terminal college-level math courses for most students on this pathway.

The number of college-level math courses required for a student choosing the MTH 60→ 65 → 95 pathway depends on students' majors, especially if they plan to transfer. Most students on this pathway will need upper-level math courses for their degrees. MTH 111 is a *prerequisite* college-level math course for all upper-level math courses. MTH 95 is a prerequisite for either MTH 111 or MTH 243. Moreover, MTH 111 and MTH 243 can serve as terminal college-level math courses for some degrees.

Remedial courses of MTH 61, 62, and 63 are no longer offered at PNWC. When offered, MTH 61/62 were equivalent to MTH 60, and MTH 62/63 were equivalent to MTH 65. They were designed for students who needed to get through MTH 60 and MTH 65 at a slower pace. Since these courses existed in the dataset before the policy change, they were considered in this study. MTH 70 reviews the content covered in MTH 60 and MTH 65. Hence, if a student completes and passes MTH 70, it is equivalent to them completing the MTH 65 requirement. Therefore, placement tests that place students at this level give them the option to take MTH 65 or 70 – some students may choose to take both courses if they want an extra review of algebra.

For this study and analysis, I have defined the following categories for math-placement-level:

- Lower-level remedial math placement: MTH 20 through MTH 62
- Upper-level remedial math placement: MTH 63 through MTH 98
- College-level math placement: courses greater than or equal to MTH 105

The core remedial courses (MTH 20, 58, 60, 65, 95, and 98) have been split between the lower-level and upper-level categories – three core remedial courses in each category. I have grouped MTH 20, 58, and 60 into the lower-level category and MTH 65, 95, and 98 into the upper-level category.

PNWC offers five-degree programs: Associate of Applied Science (AAS) degree; Associate of Arts Oregon Transfer (AAORT) degree; Associate of General Studies (AGEN) degree; Associate of Science (AS) degree; and Associate of Science Oregon Transfer in Business (ASORT) degree. All degrees offered at PNWC are two-year degrees. The college also offers numerous certificates with two-year, one-year, and less-than-one-year options.

Most certificates are building blocks for an AAS degree, and some are standalone. Certificates that are building blocks allow students to pursue additional credits after certification to attain an AAS degree in their desired career technical program. For example, the course requirements for a Biotechnician certificate are also contained in the Bioscience Technology AAS degree requirements. Certificates and the AAS degree do not require college-level math. Some certificates, such as Addiction Counseling or Auto Collison Repair Technology, do not require math courses. All other certificates require competence in MTH 58 or MTH 65 or competence in program-specific math courses. For example, BCT 104 Construction Math is a course specific to the Building Construction Technology program. The math department does not offer program-specific math courses, as they are specific to (and only offered by) individual career technical programs.

This study only examined students who either sought or attained *degrees*. Therefore, all students who did not pursue a degree and only sought and/or attained a certificate were discarded from the dataset used in this study. Moreover, the dataset in this study only included students who

took math courses offered by the math department. These course names start with “MTH”. Hence, program-specific math courses, such as BCT 104, were not included in the dataset given to me by PNWC.

Out of the five degrees offered at PNWC, AAS and AGEN are the only degrees that *do not* require college-level math courses. Both AGEN and AAS degree programs require students to either receive 1) a grade of C or higher, 2) a pass (P) in MTH 58 or MTH 65, or 3) pass a competency exam for MTH 65. AAS students can also meet competency requirements by taking program-specific math courses (i.e., BCT 104 Construction Math for the Building Construction Technology program). The AAS degree is a terminal degree designed for career technical programs only. This degree is not designed for students planning to further their education.

The AAORT degree is the only one that requires the completion of *one* college-level math course. This math course could be MTH 105 or any other college-level math course where MTH 95/MTH 98 is a prerequisite, such as MTH 111 or MTH 243. Since the degrees of AAS, AGEN, and AAORT either require one math course or none, they have been defined as non-STEM degrees, and students pursuing them are defined to be on a non-STEM degree pathway.

The AS and ASORT degrees are the only two degree programs that require at least three college-level math courses (for which at least MTH 95 or MTH 98 is a prerequisite). The ASORT degree requires at least one of those college-level math courses to be statistics. For this study, AS/ASORT are defined as STEM degrees since they require at least three college-level math courses. Students pursuing such degrees are defined to be on a STEM degree pathway. PNWC’s degree offerings and their STEM statuses are summarized in Table 3.

Table 3

College Degree Programs (STEM and non-STEM)

STEM Degrees	Non-STEM degrees
• Associate of Science (AS) • Associate of Science Oregon Transfer in Business (ASORT)	• Associate of Applied Science (AAS) • Associate of Arts Oregon Transfer (AAOT) • Associate of General Studies (AGS)

Introduction to Data Analysis

This study used exploratory data analysis (EDA) with data provided by PNWC to explore the demographic variables of *all* (remedial and nonremedial) students and specifically *math-remediation* students. Tests of proportions (chi-square and Z-test) were used to explore the effects of remedial coursework on math-remediation students in terms of college math course completion and degree attainment (STEM degree attainment vs. attainment of any degree). I also used the data to investigate whether demographic variables and math-placement-level could significantly predict continued persistence in math. For data modeling, I used logistic regression and linear regression models.

The logistic regression models were used for binary outcomes such as college math course completion, seeking a STEM degree pathway, and STEM degree attainment. The linear model was used for the continuous outcome of STEM degree completion time. The predictors of the models were age, race/ethnicity, sex, socioeconomic status (through Pell data), and math-placement-level. Math-placement-level was defined as the initial math course students were placed in upon enrollment at the college. Presumably, if a student were placed into college-level math, the probability of attaining a STEM degree would be higher than those placed in remedial math. The math-placement-level variable was only included to investigate STEM degree attainment further.

Explanation of Data

This study used two data sources: 1) student datasheet; and 2) award datasheet. In the student datasheet, each row represented a single student record, such that each student had an individual record for each math course they had taken. Students were identified by their ID numbers. If a student with a given ID had taken three math courses, three separate records were reported (equivalent to three rows) with the same ID. Since most students took multiple math courses, the total number of records surpassed the total number of students.

In this study, the total number of the records were 91,788, and the total number of individual students (identified through student IDs) were 43,345. In the award datasheet, each row showed each student's degree status, degree intention, and graduation date. The degree intention column represented if a student chose AAS, AGEN, AAORT, AS, and ASORT as their degree pathway. The degree status column indicated if a degree was awarded (AW), sought (SO), denied graduation application (DE), or pending graduation application (PE). The graduation date column either indicated the date a degree was awarded or the anticipated graduation date if a student was still seeking (SO) a degree. Tables 4 and 5 show example records from each of the datasheets. The "First Term" column is coded as the year followed by quarter (01= Winter, 02, Spring, 03 = Summer, 04 = Fall). For example, the fall term of 2019 would be 201904. First-term data was used to derive the age variable (difference between the first-term date and birthdate).

Table 4

Example Records of the Student Datasheet

Race/Ethnicity	Sex	Pell	Course No.	Grade
WHI	N	N	243	A
WHI	F	N	243	A
BAA	F	N	20	A
BAA	F	N	60	B
BAA	F	N	65	C
BAA	F	N	70	P
BAA	F	N	95	C
WHI	F	N	111	W
WHI	F	N	243	W
2+	F	N	58	P

Table 5

Example Records of the Award Datasheet

Degree Intention	Graduation Date	Award Status
AAS	6/13/1992	AW
AAS	6/17/2018	SO
AS	12/16/2018	AW
ASORT	6/17/2018	SO

The student datasheet, which was the primary source for the analyses in this study, contained the following variables: race/ethnicity; sex; Pell status (whether or not a student received a Pell Grant); birthdate; the first term (date when a student first enrolled at the college); course number; and grade. To compute the age of students when they first attended the college, the birthdate was subtracted from the first term. The demographic variables had subcategories. For example, sex had three subcategories – Male (M), Female (F), and Not Reported (N). Race/ethnicity had nine subcategories – WHI (Caucasian/White), BAA (Black/African American), AS (Asian), HIS (Hispanic), AI (American Indian/Native American), NRA (Non-Resident Alien), HPI (Hawaiian/Pacific Islander), and UNK (Unknown/Not Reported), 2+ (multi-Racial).

Historically underserved groups included BAA, HIS, AI, HPI, NRA, and UNK. Pell status had two subcategories – Yes Pell Grant (Y) and No Pell Grant (N). It is important to note that Pell status was used to operationalize students' socioeconomic status.

The award datasheet contained the following variables: degree intention (AAS, AGEN, AAORT, AS, and ASORT), award status (AW, SO, DE, or PE), and graduation date. For degree intention, this study only considered the Associate of Science (AS) and Associate of Science Oregon Transfer (ASORT) degree subcategories – referred to as STEM degrees. For award status, this study only considered degrees awarded (AW) or sought (SO) by students. Notice the linking variable for these two sources was the student ID.

Data Cleaning

In this study, I observed that for race/ethnicity, sex, first-term date, and birthdate, there were discrepancies in values reported for some students. For example, sex was reported as both male and female for some students. Students with these flawed records were entirely discarded from the dataset. Out of 43,345 students, I excluded the data for 120 students due to such discrepancies. Notice no discrepancies were observed for the first-term date. Students with discrepancies in Pell status were included since it could be possible for students to have Pell Grants for only a portion of their time at the college. For example, a student might not have had a Pell Grant when they started at the college but might have attained one later. After removing students with flawed records, I preserved 91,339 records from 43,225 students.

Furthermore, I removed the records of those students whose sex entries were blank in the dataset. Out of the remaining 91,339 records, I dropped 59 records from 47 students due to blank entries. Therefore, the number of records was reduced to 91,280 from 43,178 students. The sex variable had a third category denoted as "N" in the dataset. This represented "not reported" cases.

I did not discard these students from the dataset since the datasheet guidelines treated “N” as a relevant category.

There were some blank values for first-term date and birthdate. Since age calculation depended on these variables, I discarded students with blank values for first-term date and birthdate from the student dataset. For the first-term date, I found six blank records, and for birthdate, I found three. These nine records were from a total of eight students. These students were discarded from the dataset. A total of 175 students were discarded due to blanks and discrepancies in their demographic data. Therefore, the total number of records and students used in this study was further reduced to 91,271 records from 43,170 students.

In addition, I observed that some of the recorded courses in the student dataset were irrelevant to this study, as they are either unidentifiable courses or supplemental remedial courses (not remedial math courses). These irrelevant math courses were MTH 07, 08, 15, 30, 25C, and 26C. The records containing these courses were discarded from the student dataset. The total number of remaining records was reduced to 90,978 from 43,045 students.

The total number of records was further reduced based on the guidelines of the datasheet. The guidelines indicated that the records for this study were pulled from live Banner, and students with first-term years in the 1990s and early 2000s were highly likely to have inaccurate first terms due to the Banner being implemented in 1994. Findings showed that many students had earlier first terms than those manually imported into Banner upon the system’s implementation, and therefore, the first-term dates for student IDs less than 445000 may not represent the true first-term date since low ID numbers reflected those which were imported from the legacy system (the system that was used before Banner). According to the program analyst who prepared the data, solving this issue would not be feasible, given their current resources and time constraints. Hence,

the datasheet was further filtered for students with IDs greater than 445000 to extract accurate first-term dates. Implementing these conditions reduced the total records to 84,230 from 39,795 students.

In the last step of data cleaning, the student IDs of the remaining 84,230 records from 39,795 students from the student datasheet were matched with student IDs in the award datasheet. Relevant records from the award datasheet were of students who either sought (SO) or attained (AW) any of the five degrees offered at PNWC (AS, ASORT, AGEN, AAS, AAORT). All records related to certificates or degrees with pending graduation application (PE) or denied graduation application (DE) statuses were discarded. Therefore, the total number of records was further reduced to 61,828 from 28,316 students. This became the sample used in the study and is referred to as the *cleaned student dataset* and *cleaned award dataset* throughout this dissertation.

Data Analysis

This section shows and discusses the results of EDA and the data modeling. RQ1 presents the distribution of each demographic variable for the entire student population and the subpopulation of math-remediation students. In RQ2, the results of the logistic and linear regression analyses over the demographic variables on the continued persistence in math for the entire student population are demonstrated. McFadden’s pseudo-R-squared was used for the logistic models in this study (RQ2 and RQ5) and will be referred to as McFadden’s R^2. In RQ3, the results of the proportion test analysis (chi-square and Z-test) of math-remediation students who attained any degree are presented. In RQ4, the results of the proportion test analysis (chi-square and Z-test) of math-remediation students who completed the remedial math sequence *and* completed a college-level math course are presented. RQ4 also presents the results of the proportion test analysis (chi-square and Z-test) of math-remediation students who completed the

remedial math sequence *and* attained a degree (either any degree or a STEM degree). RQ5 shows the logistic regression analysis results over the demographic variables and math placement level on STEM degree attainment for the entire student population and the subpopulation of math-remediation students.

RQ1 Results and Analysis

RQ1 illustrates the distribution of demographic variables extracted from the cleaned student dataset for the entire student population and math-remediation students. To extract a subset of records for students who took remedial courses, remedial courses were considered any course with a number less than or equal to 98 (any course number above 98 is a college-level math course). By imposing this constraint, I extracted 30,473 records from 16,691 math-remediation students. The distribution of each demographic variable (Pell status, race/ethnicity, sex, age) is shown in Table 6 and Figure 1.

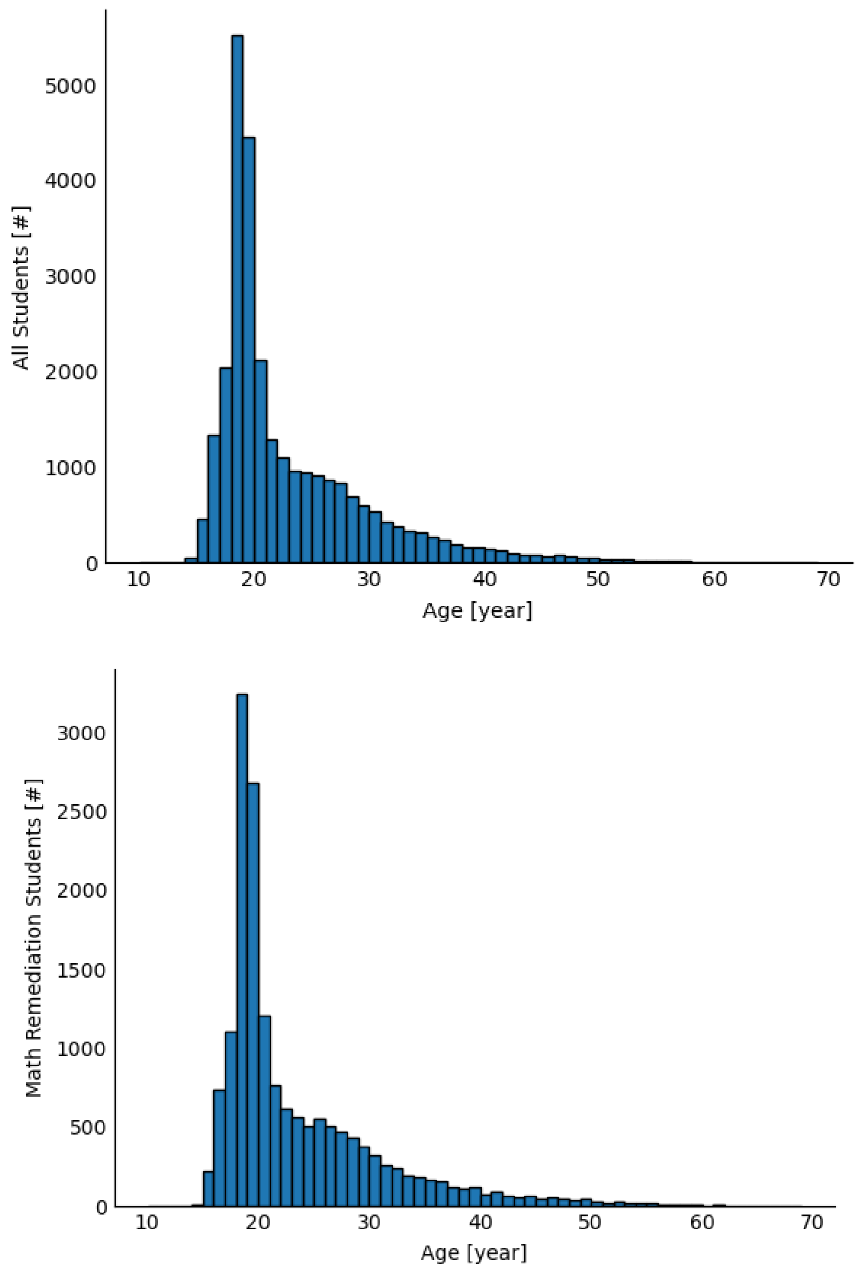
Table 6

Distributions of Pell, Race, and Sex for All Students and Math-Remediation Students

Demographic Variables		Frequency for all students	Frequency for math-remediation students
Pell	N	26984 (95.3 %)	15768 (94.4 %)
	Y	1332 (4.7 %)	931 (5.6 %)
Race	WHI	15366 (54.3 %)	8937 (53.5 %)
	HIS	4088 (14.4 %)	2751 (16.5 %)
	2+	2162 (7.6 %)	1302 (7.8 %)
	UNK	1938 (6.8 %)	1099 (6.6 %)
	BAA	1476 (5.2 %)	1015 (6.1 %)
	AS	2066 (7.3 %)	933 (5.6 %)
	NRA	740 (2.6 %)	334 (2.0 %)
	AI	234 (0.8 %)	166 (1.0 %)
	HPI	246 (0.9 %)	162 (1.0 %)
Sex	Female	14037 (49.6 %)	8611 (51.6 %)
	Male	13304 (47 %)	7433 (44.5 %)
	Not Reported	975 (3.4 %)	655 (3.9 %)

Figure 1

Distribution of Age of the Entire Student's Population [top] and Math-Remediation Students [bottom]



Most math-remediation students still need to receive a Pell Grant. Only 5.6% of math-remediation students received a Pell Grant, indicating that most of the math-remediation students were not socioeconomically fragile. The race/ethnicity of most of the math-remediation students was White (WHI, 53.5%). Asians (AS), who are not historically underserved, made up 5.6% of the math-remediation students. Hispanics (HIS), who are historically underserved, had the subsequent highest frequency and made up 16.5% of math-remediation students.

Historically underserved groups included Black/African American (BAA), Hispanic (HIS), American Indian/Native American (AI), Hawaiian/Pacific Islander (HPI), Non-Resident Alien (NRA), and Unknown/Not Reported (UNK). Together, they made up 33.1% of the math-remediation students' population. In particular, the race/ethnicities of 2+, UNK, and BAA each contributed approximately 8%, 7%, and 6%, respectively. The race/ethnicities of NRA, AI, and HPI each contributed less than 2% to the population of math-remediation students.

RQ2 Results and Analysis

RQ2 investigated if any of the demographic variables could significantly predict or affect the following outcomes for continued persistence in math:

A. College math course completion

B. Seeking a STEM (AS/ASORT) degree pathway

C. STEM (AS/ASORT) degree attainment

D. STEM (AS/ASORT) degree completion time

I used the cleaned dataset containing 61,828 records from 28,316 students for parts A-C. However, I only used the dataset for part D students who attained a STEM degree.

College Math Course Completion (Part A). In this part, I investigated the significance of the demographic variables on college math course completion. I first checked if the students

enrolled in college-level math courses. These math courses included 105, 111, 112, 211, 212, 213, 241, 243, 244, 251-254, 256, and 261. I used the cleaned students' data and found that 16,349 students enrolled in at least one college-level math course. Secondly, I checked if the students had passing grades in at least one of the courses. A passing grade was defined as either a P (pass) or a grade of C or higher. Out of 16,349 students, 12,699 passed at least one college-level math course, and 3,650 students did not.

For data modeling, I used a logistic regression model. The model requires the dependent variable to be either 0 or 1. Since, in this section, the dependent variable was categorical (completed college-level math vs. not completed college-level math), I encoded the students who passed at least one college-level math course as 1 and the rest of the students as 0.

In addition, the logistic regression model can determine the significance of each demographic variable in completing at least one college-level math course. These variables should also be converted from categories to numerical values for the data modeling. The Statsmodels library in Python converts the categorical variables into numerical variables using the one-hot encoding (also known as dummy variable conversion) method.

In the logistic regression model, the following were set as the reference groups: WHI (race/ethnicity), F (sex), and N (Pell). The results after fitting the logistic regression model into the data are shown in Table 7. The model accounted for 1.5% of the information in the dependent variable (McFadden's $R^2 = 0.0153$) and the degree of freedom was 12.

Table 7

Summary of Logistic Regression Coefficients for College Math Course Completion

		β [95% CI]	Standard error	Statistics	p-value	OR [95% CI]
β_0		1.04 [0.89-1.19]	0.077	13.55	<0.001	2.83 [2.44-3.3]
Race	2+	-0.25 [-0.39- -0.12]	0.07	-3.6	<0.001	0.78 [0.68-0.89]
	AI	-0.38 [-0.81-0.06]	0.22	-1.7	0.089	0.69 [0.45-1.06]
	AS	0.25 [0.11-0.39]	0.074	3.39	0.001	1.28 [1.11-1.48]
	BAA	-0.79 [-0.96- -0.63]	0.084	-9.46	<0.001	0.45 [0.38-0.53]
	HIS	-0.32 [-0.43- -0.21]	0.057	-5.61	<0.001	0.73 [0.65-0.81]
	HPI	-0.83 [-1.19- -0.46]	0.186	-4.46	<0.001	0.44 [0.3-0.63]
	NRA	0.76 [0.49-1.03]	0.137	5.54	<0.001	2.14 [1.64-2.8]
	UNK	-0.02 [-0.17-0.13]	0.076	-0.31	0.759	0.98 [0.84-1.13]
Sex	M	-0.12 [-0.19- -0.04]	0.039	-3.05	0.002	0.89 [0.82-0.96]
	N	-0.08 [-0.3-0.14]	0.112	-0.69	0.49	0.93 [0.74-1.15]
Pell	Y	-0.38 [-0.56- -0.21]	0.09	-4.26	<0.001	0.68 [0.57-0.81]
Age		0.02 [0.01- 0.02]	0.003	5.19	<0.001	1.02 [1.01-1.02]

OR – odds ratio, [95% CI] - lower and upper bound of 95% confidence interval

The logistic regression model revealed nine significant predictors for college math course completion: race (2+, AS, BAA, HIS, HPI, NRA), sex (M), Pell (Y), and age. All these variables had $p < 0.05$. Positive beta values (odds ratios greater than 1) for any independent variable indicated more odds of completing a college math course than the reference group. In contrast, negative beta values (odds ratios less than 1) demonstrated lower odds of completing a college-level math course than the reference group. For example, NRA and AS were the only statistically significant races/ethnicities with positive beta values. The odds ratio of NRA and AS were 2.14 and 1.28, respectively. This meant that NRA students had 2.14 times the odds and AS students had 1.28 times the odds of completing a college-level math course than WHI students (the

reference group), given that the other independent variables remained constant. In other words, the NRA and AS students had 114% and 28% more odds of completing a college-level math course than WHI students, given that the other independent variables remained constant.

The other races/ethnicities that were statistically significant had negative beta values. This meant that the odds of completing a college-level math course (OR = 0.78, 0.45, 0.73, 0.44, respectively) for students with race/ethnicities of 2+, BAA, HIS, and HPI decreased by 22%, 55%, 27%, and 56%, respectively, compared to WHI students (reference group), given that the other independent variables remained constant. The odds of completing a college-level math course for students with a sex of M (OR=0.89) was 11% lower than that of students with a sex of F (reference group), given that the other independent variables remained constant. The odds of completing a college-level math course for students with a Pell of Y (OR=0.68) was 32% lower than those with a Pell of N (reference group), given that the other independent variables remained constant.

Age was a continuous variable and did not have a reference group. The results found that a 1 unit increase in age (i.e., 20 vs. 21-year-old) was associated with a 2% increase (OR= 1.02) in the odds of the students completing a college-level math course.

All the above comparisons assumed that the other demographic variables were consistent. The odds should be computed in a different way for students with different demographic variables. For example, for 20-year-old, BAA male students with a Pell Grant, the odds of completing at least one college-level math were ($e^{[20\times (0.02) - 0.79 - 0.12 - 0.38]}$ = 0.41) 89% lower than 30-year-old, NRA, female students without a Pell Grant ($e^{[30 \times (0.02) + 0.76 + 0 + 0]}$ = 3.9).

Seeking a STEM Degree Pathway (Part B). This part investigated if demographic variables could significantly affect students seeking a STEM degree pathway. The demographic

variables for each student were extracted from the cleaned student dataset used in part A. I used the cleaned award dataset to find students who sought a STEM degree pathway. In this dataset, I checked the award status of each student. In the award status column, degree entries included: awarded (AW) and sought (SO). AW and SO were selected since they were relevant award statuses for identifying students' degree pathways. Furthermore, I used the degree intention column of the cleaned award dataset to determine the degrees students sought. I filtered AS and ASORT degrees out of all degree intentions since I defined them as STEM degrees (requiring at least three college-level math courses).

With these two conditions, I extracted the subset of students who sought a STEM degree pathway. Of 28,316 students, 14,019 sought a STEM degree pathway, and 14,297 did not. I encoded those students who sought a STEM degree pathway as 1, and the rest were labeled as 0. The label of 0 meant that the students did not seek a STEM degree pathway. In other words, they sought non-STEM degrees such as AGEN, AAS, or AAORT.

The logistic regression model determined the significance of each demographic variable on students seeking a STEM degree pathway. Like part A, I used the logistics regression model from the Statsmodels library in Python. In the model, the following were set as the reference groups: WHI (race/ethnicity), F (sex), and N (Pell). The results after fitting the logistic regression model into the data are shown in Table 8. The model accounted for 0.2% of the information in the dependent variable (McFadden's $R^2 = 0.0023$), and the degree of freedom was 12.

Table 8

Summary of Logistic Regression Coefficients for Seeking a STEM Degree Pathway

		β [95% CI]	Standard error	Statistics	p-value	OR [95% CI]
β_0		0.32 [0.23-0.4]	0.044	7.14	<0.001	1.37 [1.26-1.5]
Race	2+	0 [-0.09-0.09]	0.046	0.07	0.948	1 [0.92-1.1]
	AI	-0.21 [-0.47-0.05]	0.133	-1.57	0.117	0.81 [0.63-1.05]
	AS	0.08 [-0.01-0.17]	0.047	1.73	0.083	1.08 [0.99-1.19]
	BAA	0.04 [-0.07-0.15]	0.055	0.75	0.453	1.04 [0.94-1.16]
	HIS	-0.08 [-0.15- -0.01]	0.036	-2.17	0.03	0.93 [0.86-0.99]
	HPI	-0.03 [-0.28-0.22]	0.129	-0.25	0.803	0.97 [0.75-1.25]
	NRA	-0.04 [-0.19-0.11]	0.075	-0.56	0.574	0.96 [0.83-1.11]
	UNK	-0.02 [-0.12-0.07]	0.048	-0.45	0.655	0.98 [0.89-1.08]
Sex	M	-0.13 [-0.18- -0.08]	0.024	-5.35	<0.001	0.88 [0.84-0.92]
	N	-0.17 [-0.3- -0.04]	0.067	-2.61	0.009	0.84 [0.74-0.96]
Pell	Y	0.06 [-0.05-0.17]	0.056	1.11	0.269	1.06 [0.95-1.19]
Age		-0.01 [-0.01- -0.01]	0.002	-6.93	<0.001	0.99 [0.99-0.99]

OR – odds ratio, [95% CI] - lower and upper bound of 95% confidence interval

The logistic regression model revealed four significant predictors in seeking a STEM degree pathway: race (HIS), sex (M, N), and age. All these variables had $p < 0.05$. The positive beta values (odds ratios greater than 1) increased the likelihood of seeking a STEM degree pathway, compared to the reference group. However, the negative beta values (odds ratios less than 1) decreased the likelihood of seeking a STEM degree pathway compared to the reference group.

For example, HIS students were 7% (OR=0.93) less likely to seek a STEM degree pathway than WHI students (reference group), given that the other independent variables remained constant. The odds of students with the sex of M and N seeking a STEM degree pathway decreased by 12% (OR= 0.88) and 16% (OR=0.84) compared to female students

(reference group), given that the other independent variables remained constant. Age was a continuous variable and did not have a reference group. The results found that a 1 unit increase in age (i.e., 20 vs. 21-year-old) was associated with a 1% decrease in the odds of students seeking a STEM degree pathway.

STEM Degree Attainment (Part C). This part investigated if demographic variables could significantly affect attaining a STEM degree. The population for this analysis was the students who sought or were awarded a STEM degree. Of 28,316 students, 13,910 sought or were awarded a STEM degree. The demographic variables for each student were extracted from the cleaned student dataset used in part A. I used the cleaned award dataset to determine if the students were awarded a STEM degree. Since I was only interested in students awarded a degree, I filtered the award status column for AW only. Like part B, the degree intention column was filtered for AS/ASORT. Out of 13,910 students, 3,772 students attained a STEM degree, and they were encoded as 1.

To determine the students who did not attain a STEM degree, I analyzed the cleaned award dataset and extracted the students who *sought* a STEM degree but *did not* attain it. Out of 13,910 students, I found 10,138 students who sought a STEM degree. Before encoding these students as 0 and passing the data into the logistic regression model, I further filtered the 10,138 students. In the award datasheet, the award status column for some students was reported as SO, but their projected graduation dates were 2023 or 2024. In the award datasheet, graduation dates for the awarded students were *actual* graduation dates. However, for students who sought a degree, the graduation dates were *projected* graduation dates. It would not be accurate to encode students with projected graduation dates greater than March 2022 as 0 in this analysis. Since

such encoding could distort my results, these students were discarded from the analysis in the following manner:

1) The maximum graduation date in my dataset for students who were awarded a STEM degree (students that had an AW status for an AS/ASORT degree) was determined from the award dataset. The maximum graduation date in my dataset (max degree attainment date) was March 2022.
2) Given that the maximum first-term date across all students in my dataset was Fall 2019 (since my dataset consisted of data from students who took math classes between Fall 2016 and Fall 2019), I assumed there was enough time for students who sought a STEM degree to graduate by March 2022. Therefore, if a student's projected graduation date was March 2022 or less, I assumed they failed to receive the STEM degree they sought. These students are the only ones I encoded as 0 in the analysis.

I discarded 1,646 out of 10,138 students who sought a STEM degree since either their projected graduation date was greater than March 2022 or no projected graduation dates were reported. I encoded 3,772 and 8,492 students as 1 and 0, respectively.

The logistic regression model from the Statsmodels library in Python was used to determine the significance of each demographic variable on STEM degree attainment. In the model, the following were set as reference groups: WHI (race/ethnicity); F (sex); and N (Pell). The results after fitting the logistic regression model into the data are shown in Table 9. The model accounted for 1.6% of the information in the dependent variable (McFadden's R^2 = 0.0163) and the degree of freedom was 12.

Table 9

Summary of Logistic Regression Coefficients for STEM Degree Attainment

		β [95% CI]	Standard error	Statistics	p-value	OR [95% CI]
β_0		-0.45 [-0.61- -0.29]	0.081	-5.55	<0.001	0.64 [0.54-0.75]
Race	2+	-0.11 [-0.26-0.05]	0.078	-1.38	0.167	0.9 [0.77-1.05]
	AI	0.14 [-0.31-0.58]	0.228	0.6	0.551	1.15 [0.73-1.79]
	AS	0.23 [0.09-0.38]	0.074	3.11	0.002	1.26 [1.09-1.46]
	BAA	-0.27 [-0.46- -0.08]	0.096	-2.83	0.005	0.76 [0.63-0.92]
	HIS	-0.01 [-0.13-0.11]	0.06	-0.14	0.885	0.99 [0.88-1.12]
	HPI	-0.41 [-0.88-0.06]	0.238	-1.72	0.085	0.66 [0.42-1.06]
	NRA	1.48 [1.25-1.71]	0.117	12.65	<0.001	4.4 [3.5-5.53]
	UNK	0 [-0.15-0.16]	0.08	0.04	0.972	1 [0.86-1.17]
Sex	M	-0.02 [-0.1-0.06]	0.04	-0.52	0.601	0.98 [0.9-1.06]
	N	-0.14 [-0.38-0.09]	0.119	-1.22	0.222	0.87 [0.69-1.09]
Pell	Y	0.25 [0.05-0.46]	0.104	2.42	0.016	1.29 [1.05-1.58]
Age		-0.02 [-0.02--0.01]	0.003	-5.45	<0.001	0.98 [0.98-0.99]

OR – odds ratio, [95% CI] - lower and upper bound of 95% confidence interval

The logistic regression model revealed five significant predictors for STEM degree attainment since the p-values were less than 0.05. These predictors were race/ethnicities of AS, BAA, and NRA, Pell of Y, and age. The positive beta values (odds ratios greater than 1) indicated higher odds of attaining a STEM degree than the reference group. The negative beta values (odds ratios less than 1) showed lower odds of attaining a STEM degree compared to the reference group.

AS and NRA had positive beta values (OR= 1.26 and 4.4, respectively). This meant that students with the race/ethnicities of AS and NRA were 26% and 340% more likely to attain a STEM degree than WHI students (reference group), given that the other independent variables remained constant. However, students with the race/ethnicity of BAA were 24% (OR=0.76) less

likely to attain a STEM degree than WHI students (reference group), given that the other independent variables remained constant. The odds of students receiving a Pell Grant was 29% (OR=1.29) more than the odds of the students without the Pell Grant for attaining a STEM degree. One unit increase in age (i.e., 20 vs. 21-year-old) was associated with a 2% decrease in the odds of students attaining a STEM degree.

STEM Degree Completion Time (Part D). This part investigated if the demographic variables could significantly affect STEM degree completion time. In this part, I only used the data from 3,772 students who attained a STEM degree. This dataset was also used in part C. However, in part C, I also included the data for students who did not attain a STEM degree which was not used in this part. To compute the degree completion time, I subtracted the graduation date (extracted from the cleaned award dataset) from the first-term date (date the student first attended the college; extracted from the cleaned student dataset). I observed that 17 students attained both an AS and ASORT degree. These students had more than one graduation date in the dataset. For these students, the earliest graduation date was considered.

I used a linear regression model from the Statsmodels library in Python for the data modeling. I defined the time of completion as the dependent variable and the demographic variables as the independent variables. The model was then fitted using the OLS (ordinary least square) method. Its results were shown in Table 10. The results show that race/ethnicity of NRA, sex (N), Pell (Y), and age are statistically significant predictors of STEM degree completion time.

Table 10

Summary of Linear Regression Model for STEM Degree Completion Time

		β [95% CI]	Standard error	Statistics	p-value
β_0		61.78 [59-64.55]	1.413	43.72	<0.001
Race	2+	-0.78 [-3.58-2.03]	1.432	-0.54	0.587
	AI	2.88 [-5.08-10.85]	4.063	0.71	0.478
	AS	-0.28 [-2.83-2.26]	1.3	-0.22	0.827
	BAA	2.37 [-1.18-5.92]	1.812	1.31	0.191
	HIS	1.42 [-0.71-3.55]	1.086	1.31	0.191
	HPI	-5.21 [-14.15-3.73]	4.559	-1.14	0.253
	NRA	-7.16 [-10.17- -4.15]	1.534	-4.67	<0.001
	UNK	-2.1 [-4.94-0.74]	1.449	-1.45	0.148
Sex	M	-0.04 [-1.45-1.37]	0.721	-0.06	0.956
	N	-9.3 [-13.59- -5.01]	2.189	-4.25	<0.001
Pell	Y	7.91 [4.35-11.46]	1.812	4.36	<0.001
Age		-0.65 [-0.77- -0.54]	0.057	-11.57	<0.001

[95% CI] - lower and upper bound of 95% confidence interval

Negative beta values represented shorter degree completion times. For instance, the STEM degree completion time of students with sex of N was approximately 9.3 months (beta = -9.3) shorter than the female students (reference group), given that the other independent variables remained constant. The degree completion time of students with the race/ethnicity of NRA was approximately 7.2 months (beta = -7.16) shorter than the WHI students (reference group), given that the other independent variables remained constant. In addition, one unit in age was associated with approximately a 0.7-month reduction in STEM degree completion time, given that the other independent variables remained constant.

Positive beta values represented longer degree completion times. For example, the STEM degree completion time of students receiving a Pell Grant was approximately 8 months longer than those without a Pell Grant, given that the other independent variables remained constant.

RQ3 Results and Analysis

RQ3 explored if enrolling in remedial math courses increased degree attainment (part A). This part examined if the proportion of math-remediation students who attained a degree (any degree) was statistically different from a pre-defined proportion. In addition, RQ3 statistically tested if the average degree (any degree) completion time of math-remediation students differed significantly from a predefined value (part B).

Tests of Proportions for Degree Attainment of Math-Remediation Students (Part A). In this part, I investigated if remedial math courses affected student degree attainment by computing the proportion of math-remediation students who attained a degree. I used the cleaned student dataset and filtered those who took courses less than or equal to 98. MTH 98 was the highest course number math-remediation students could enroll in. I analyzed 16,699 math-remediation students.

The null hypothesis for part A was that the proportion of math-remediation students who attained any degree was p_0=0.5. I used the award status column from the cleaned award dataset to test the null hypothesis to find math-remediation students awarded (AW) degrees. The total number of math-remediation students who attained a degree was 3,558, and the number of students who did not attain a degree was 13,141. The proportion of math-remediation students who attained a degree was p_1=0.21.

To test my hypothesis, I used two statistical models. The reason for using an additional model was for reassurance. In one statistical model, I used chi-square from the SciPy library in

Python, and in the other statistical model, I used the proportion Z-test from the Statsmodels library in Python. These models tested if a null hypothesis equaled a given proportion. I ran the model using the values of 3,558 (math-remediation students who attained a degree), 16,699 (total number of math-remediation students), and p_0=0.5 (null hypothesis). The proportion of p_1=0.21 was significantly different from the expected proportion of p_0=0.5. Hence, the null hypothesis was rejected. Table 11 shows the test statistics along with the p-values for these two methods.

Table 11

Summary of Chi-square and Proportion Z-test Methods for Degree Attainment of Math-Remediation Students

	Test Statistic	*p*-value
Chi-Square	5500.2	<0.001
Z-test	-90.6	<0.001

Average Completion Time of Math-Remediation Students (Part B). In this part, I investigated if the average degree completion time of math-remediation students was statistically different than a predefined value. The null hypothesis for this test was that math-remediation students would take 24 months (2 years) to complete their degrees (μ_0=24). This null hypothesis was chosen since the degrees offered by PNWC are 2-year degrees. However, it does not necessarily mean students will complete their degrees in that timeframe.

The sample for this analysis was 3,558, which was the number of math-remediation students who attained a degree. I subtracted the graduation date from the first-term date to compute the degree completion time. The graduation and first-term dates were extracted from the cleaned award and student datasets. The minimum graduation date was used if students had two graduation dates for two awarded degrees.

The t-test statistical model was used to assess the null hypothesis from the SciPy library in Python. The t-test was used because the dependent variable was continuous and its distribution across the 3,558 students was close to normal. Figure 2 shows the distribution of the degree completion time of the students.

The average degree completion time for math-remediation students was 50.9 months or approximately 4.2 years. The result of the t-test, shown in Table 12, demonstrated that the null hypothesis was rejected, and there was a significant difference between the null assumption of 24 months and the actual degree completion time of math-remediation students.

Table 12

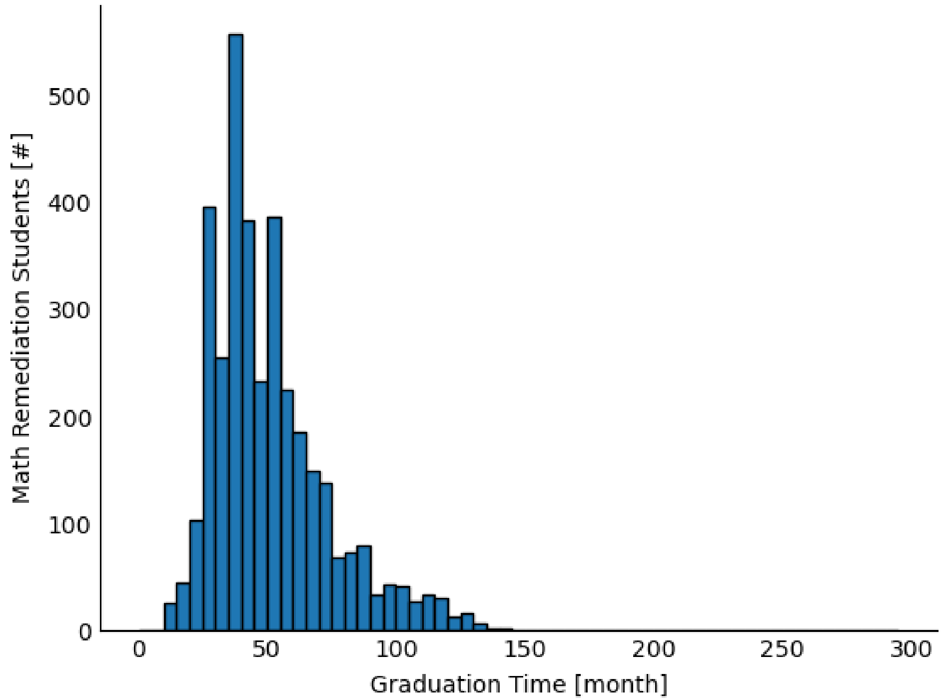
T-test for Equality of Means for Degree Completion Time

t	df	Sig (2-tailed)	Mean difference	Std. Error Difference	95% Confidence Interval of the Difference		p-value
					Lower 95%	Upper 95%	
71.2	3557	22.6	26.9	0.38	26.1	27.7	<0.001

t: t-statistics, df: degree of freedom, Sig: standard deviation

Figure 2

Distribution of Degree Completion Time of Math-Remediation Students



RQ4 Results and Analysis

In RQ4, I further examined the effect of remedial math courses on continued math persistence in community colleges. I mainly investigated if completing the remedial math sequence impacted college-level math course completion and degree attainment. Notice, in RQ3, math-remediation students were examined. However, in RQ4, math-remediation students who completed the remedial math sequence were examined.

Tests of Proportions for Math-Remediation Students and College Math Course Completion (Part A). In this part, I investigated the impact of remedial math sequence completion on college math course completion. Students were extracted from the cleaned student dataset, which contained 61,828 records from 28,316 students including 16,699 math-remediation students. The remedial math sequence was completed if a student passed either

MTH 95 or 98. Pass grades were defined as either P or a grade of C or higher. Out of 16,699 math-remediation students, there were 6,101 students that completed the remedial math sequence.

To extract the number of math-remediation students who completed one or more college-level math courses, I investigated whether they received a pass grade for at least one of the following course numbers: MTH 105, 111, 112, 211-213, 241-244, 251-254, 256, and 261. Out of 6,101 math-remediation students who completed the remedial math sequence, there were 3,346 students that completed at least one college-level math course (p_1=0.55).

Two statistical models were used to evaluate the null hypothesis for this part, the chi-square method from SciPy library and proportion Z-test from the Statsmodels library in Python. The null hypothesis was that the proportion of math-remediation students who completed the remedial math sequence *and* completed at least one college-level math course was p_0=0.5. Table 13 shows the test-statistics and p-values for both methods. The results showed that the null hypothesis was rejected, and the proportion was significantly different from 0.5.

Table 13

Summary of Chi-Square and Proportion Z-test Methods for Math-Remediation Students That Completed At Least One College-Level Math Course

	Test Statistic	*p*-value
Chi-Square	57.5	<0.001
Z-test	7.6	<0.001

Tests of Proportions for Math-Remediation Students and Degree Attainment (Part B). This part investigated the effect of remedial math sequence completion on students' degree attainment. In particular, I investigated if remedial math sequence completion increased the number of degree attainments for math-remediation students. As shown in part A of RQ4, the

total number of math-remediation students who completed the remedial math sequence was 6,101. Out of 6,101 students, 2,098 students ended up attaining any degree. This was found in the award status column in the award dataset. The proportion of math-remediation students who completed the remedial math sequence and attained any degree was p_1=0.34, or 34%.

Out of 6,101 students, 1,115 of them attained a STEM degree (AS/ASORT). The value of 1,115 was found by first filtering math-remediation students who were awarded (AW) a degree from the award status column in the award dataset. Then, the students were filtered for those who were specifically awarded an AS/ASORT degree from the degree intention column in the award dataset. Hence, the proportion of math-remediation students who completed the remedial math sequence and attained a STEM degree was p_1=0.18, or 18%.

Two statistical models were used to evaluate the null hypotheses for this question, Chi-square, and proportion Z-test:

- The first null hypothesis (Null_1) was: the proportion of math-remediation students who completed the remedial course sequence *and* attained any degree equals p_0=0.5.
- The second null hypothesis (Null_2) was: the proportion of the math-remediation students who completed the remedial math sequence *and* attained a STEM degree equals p_0=0.5.

Tables 14 and 15 show the test-statistics and the p-values for both methods and both null hypotheses. The results showed that both null hypotheses were rejected, and the proportions were significantly different than 0.5.

Table 14

Summary of Chi-Square and Proportion Z-test Methods for Math-Remediation Students That Attained Any Degree

	Test Statistic	p-value
Chi-Square	594.3	<0.001
Z-test	-25.7	<0.001

Table 15

Summary of Chi-Square and Proportion Z-test Methods for Math-Remediation Students That Attained a STEM Degree

	Test Statistic	p-value
Chi-Square	2455.2	<0.001
Z-test	-64.1	<0.001

RQ5 Results and Analysis

RQ5 examines the extent in which age, race/ethnicity, sex, socioeconomic status (through Pell data), and math-placement-level (i.e., lower-level vs. upper-level remedial math placement or college-level math placement) are predictors of:

A. All students (entire population) attaining a STEM degree

B. Math-remediation students (subpopulation) attaining a STEM degree

Part A examines the entire student population regardless of math remediation status. However, part B) examines only math-remediation students. RQ5 attempted to provide an extension to RQ2-part-C by examining an additional variable – math-placement-level. Particularly, I examined three placement categories: lower-level remedial math; upper-level remedial math; and college-level math. The following math courses were included in each placement category:

- Lower-level remedial math: MTH 20, 58, 60-62
- Upper-level remedial math: MTH 63, 65, 70, 76, 84, 93, 95, 98
- College-level math: MTH 105, 111-112, 211-213, 241, 243, 244, 251-254, 256, and 261

STEM Degree Attainment of All Students (Part A). I analyzed the cleaned student dataset to evaluate the math-placement-level of the entire student population. The math-placement-level variable was used to demonstrate the course level students were placed in after taking the math placement test.

To begin the analysis, I extracted each student's first math course at the PNWC and checked if it fell into one of three subcategories: lower-level remedial, upper-level remedial, or college-level math. Then, using the award dataset, I investigated whether any students were awarded a STEM degree. This was done by selecting students awarded (AW) a degree from the award status column. Then, I filtered the students specifically awarded an AS/ASORT degree from the degree intention column. If they were awarded an AS/ASORT degree, they were labeled as 1, and if they were not, they were labeled as 0 in the analysis. This subset of data was further explained in part C of RQ2.

The logistic regression model determined the significance of each of the demographic variables, as well as math-placement-level, for students who were awarded a STEM degree. I used the Statsmodels library in Python for this part of the analysis. In the logistic regression model, the following were set as the reference groups: WHI (race/ethnicity), F (sex), and N (Pell) and lower-level remedial math placement. The results after fitting the logistic regression model into the data are shown in Table 16. The model accounted for 4.5% of the information in the dependent variable (McFadden's $\mathrm{R}^2 = 0.0449$), and the degree of freedom was 14.

Table 16

Summary of Logistic Regression Coefficients for STEM Degree Attainment for All Students with the Additional Independent Variable of Math-Placement-Level

		β [95% CI]	Standard error	Statistics	p-value	OR [95% CI]
β_0		-1.17 [-1.36- -0.98]	0.098	-11.95	<0.001	0.31 [0.26-0.38]
Race	2+	-0.08 [-0.23-0.08]	0.079	-0.98	0.326	0.93 [0.79-1.08]
	AI	0.21 [-0.24-0.67]	0.232	0.92	0.356	1.24 [0.79-1.95]
	AS	0.14 [-0.01-0.29]	0.076	1.86	0.063	1.15 [0.99-1.33]
	BAA	-0.15 [-0.35-0.04]	0.098	-1.57	0.117	0.86 [0.71-1.04]
	HIS	0.06 [-0.06-0.18]	0.061	1.04	0.296	1.07 [0.95-1.2]
	HPI	-0.35 [-0.83-0.12]	0.243	-1.46	0.144	0.7 [0.44-1.13]
	NRA	1.41 [1.18-1.65]	0.119	11.84	<0.001	4.1 [3.25-5.18]
	UNK	-0.01 [-0.17-0.15]	0.081	-0.1	0.92	0.99 [0.85-1.16]
Sex	M	-0.09 [-0.17- -0.01]	0.041	-2.2	0.028	0.91 [0.84-0.99]
	N	-0.13 [-0.36-0.11]	0.121	-1.04	0.299	0.88 [0.7-1.12]
Pell	Y	0.37 [0.16-0.58]	0.106	3.5	<0.001	1.45 [1.18-1.79]
Math placement	upper level	0.36 [0.23-0.49]	0.066	5.5	<0.001	1.44 [1.26-1.63]
	college level	1.04 [0.92-1.15]	0.059	17.58	<0.001	2.83 [2.52-3.17]
Age		-0.01 [-0.02- -0.01]	0.003	-4.52	<0.001	0.99 [0.98-0.99]

OR – odds ratio, [95% CI] - lower and upper bound of 95% confidence interval

The logistic regression model revealed six significant predictors for the entire student population attaining a STEM degree. These predictors were race/ethnicity (NRA), sex (M), Pell (Y), upper-level remedial math, college-level math, and age since the p-values for these independent variables were less than 0.05. When an independent variable has a positive beta value (odds ratio greater than 1), the likelihood of the outcome (attaining a STEM degree)

occurring increases compared to the reference group. However, a negative beta value (odds ratio less than 1) decreases the likelihood of the outcome occurring compared to the reference group.

The race/ethnicity of NRA, Pell (Y), upper-level remedial math, and college-level math had positive beta values (OR= 4.1, 1.45, 1.44, and 2.83, respectively). This meant that the students with race/ethnicities of NRA were 310% more likely to attain a STEM degree than WHI students (reference group), given that all other independent variables remained constant. Students who received a Pell Grant were 45% more likely to attain a STEM degree than the students who did not receive a Pell Grant, given that all other independent variables remained constant. Students who were placed in upper-level math remediation and college-level math courses were 44% and 183%, respectively, more likely to attain a STEM degree than those placed in lower-level math remediation (reference group), given that all other independent variables remained constant. On the contrary, the beta value for the sex (M) was negative, demonstrating that the odds of male students attaining a STEM degree were 9% lower than the odds of female students. In addition, age was a continuous variable and did not have a reference group. The results found that a 1 unit increase in age (i.e., 20 vs. 21-year-old) was associated with a 1% decrease in the odds of students attaining a STEM degree.

STEM Degree Attainment of Math-Remediation Students (Part B). Part B investigated if any of the demographic variables (age, race/ethnicity, sex, and Pell status) and the additional variable of math-placement-level were predictors of math-remediation students attaining a STEM degree. The difference between part A and part B of RQ5 is that part A examined the entire student population and part B only examined the subpopulation of math-remediation students. The methodology for the analysis was the same for both parts. As discussed above, part B was designed to be an extension to RQ2.

As in part A, I began by using the cleaned student dataset with 28,316 students. I selected the subpopulation of math-remediation students by only examining student records for course numbers less than or equal to 98. I ended up getting records from 16,699 students for this subpopulation. Next, I checked if the first math course taken for each of the math-remediation students fell into the lower-level remedial math category or the upper-level remedial math category. Again, the lower-level category included courses MTH 20, 58, 60-62, and the upper-level category included courses MTH 63, 65, 70, 76, 84, 93, 95, 98.

Afterwards, I chose the lowest math course number a student took in their first term. The first term was examined since placement tests were taken before a student could enroll into their first math course at the college. I also used the award dataset to investigate if math-remediation students attained a STEM (AS/ASORT) degree. If they were awarded a STEM degree, they were labeled as 1, and if they were not awarded, they were labeled at 0 in the analysis. The selection of this subset of data was further explained in part C of RQ2. I used the logistic regression method from the Statsmodels library in Python for the data modeling.

In the logistic regression model, the following were set as the reference groups: WHI (race/ethnicity), F (sex), N (Pell), and lower-level remedial math placement. The results after fitting the logistic regression model into the data are shown in Table 17. The model accounted for 2.5% of the information in the dependent variables ($\text{McFadden's } R^2 = 0.0245$), and the degree of freedom was 13. The degree of freedom was reduced to 13 compared to 14 in part A of RQ5 since math-remediation students could either be placed in lower or upper-level remedial math courses. The college-level math placement did not apply to math-remediation students.

Table 17

Summary of Logistic Regression Coefficients for STEM Degree Attainment for Math-Remediation Students with the Additional Independent Variable of Math-Placement-Level

		β [95% CI]	Standard error	Statistics	p-value	OR [95% CI]
β_0		-1.54 [-1.8- -1.28]	0.133	-11.56	<0.001	0.21 [0.16-0.28]
Race	2+	0.01 [-0.22- 0.24]	0.118	0.09	0.925	1.01 [0.8-1.27]
	AI	0 [-0.67-0.68]	0.343	0.01	0.99	1 [0.51-1.97]
	AS	0.14 [-0.12-0.41]	0.134	1.07	0.286	1.15 [0.89-1.5]
	BAA	-0.32 [-0.6- -0.04]	0.145	-2.22	0.027	0.73 [0.55-0.96]
	HIS	0 [-0.17-0.18]	0.091	0.03	0.974	1 [0.84-1.2]
	HPI	-0.62 [-1.37-0.13]	0.382	-1.62	0.105	0.54 [0.25-1.14]
	NRA	1.98 [1.58-2.38]	0.205	9.66	<0.001	7.23 [4.84-10.8]
	UNK	0.11 [-0.14-0.36]	0.128	0.85	0.397	1.11 [0.87-1.43]
Sex	M	-0.06 [-0.18-0.07]	0.065	-0.87	0.382	0.94 [0.83-1.07]
	N	-0.12 [-0.46-0.22]	0.174	-0.69	0.492	0.89 [0.63-1.25]
Pell	Y	0.41 [0.13-0.68]	0.14	2.9	0.004	1.5 [1.14-1.97]
Math placement	upper-level	0.36 [0.23-0.49]	0.066	5.48	<0.001	1.43 [1.26-1.63]
Age		0 [-0.01-0.01]	0.005	0.12	0.902	1 [0.99-1.01]

OR – odds ratio, [95% CI] - lower and upper bound of 95% confidence interval

The logistic regression model revealed four significant predictors in attaining a STEM degree for math-remediation students since the p-values for these independent variables were less than 0.05. These predictors were race/ethnicity (NRA and BAA), Pell (Y), and upper-level math remediation. Like the previous section, the positive and negative beta values represented higher and lower odds of attaining a STEM degree compared to the reference group.

According to the results shown in Table 17, the race/ethnicity of NRA, Pell (Y), and upper-level math remediation had positive beta values and odds ratios greater than 1 (OR= 7.23,

1.5, and 1.43, respectively). This meant that math-remediation students with race/ethnicity of NRA were 623% more likely to attain a STEM degree than WHI math-remediation students (reference group), given that all other independent variables remained constant. The math-remediation students who received a Pell Grant had 50% more odds of attaining a STEM degree than the students who did not receive a Pell Grant, given that all other independent variables remained constant. The math-remediation students placed in upper-level math remediation courses were 43% more likely to attain a STEM degree than the math-remediation students placed in lower-level math remediation courses (reference group), given that all other independent variables remained constant.

On the contrary, the beta value for race/ethnicity of BAA was negative, demonstrating that the odds of math-remediation students with race/ethnicity of BAA (OR= 0.73) was 27% lower than the odds of WHI students attaining a STEM degree given that all other independent variables remained constant.

Summary

In conclusion, logistic regression analysis was performed to determine the predictors of continued persistence in math of community college students. The predictors were the demographic variables of age, sex, race/ethnicity, Pell status, and math-placement-level. Math-placement-level was only considered for RQ5, where predictors of STEM degree attainment were explored. The outcomes of continued persistence in math included college math course completion, seeking a STEM degree pathway, degree attainment, and degree completion time. I evaluated degree attainment and completion time for any degree and specifically STEM. I used Chi-square as a test of proportions for some of these outcomes. I used the Z-test of proportions as

an additional test to further verify the chi-square test results. Moreover, I used a t-test to investigate the degree completion time outcome since it was a continuous variable.

Age, a continuous variable in this study, was a predictor of college math course completion. Older students were more likely to persist and complete a college-level math course than younger students. Younger students were more likely to persist, seek and attain a STEM degree, and have faster completion times for STEM degrees.

Sex was a significant predictor of seeking a STEM degree pathway. The students with sex “F” had more odds of pursuing a STEM degree pathway than the students with the sex “M” and “N.”

Race/Ethnicity was a significant predictor of college math course completion. The odds of completing at least one college-level math course for historically underserved groups, except the NRA students, were significantly lower than the WHI students. Compared to the WHI reference group, none of the race/ethnicities, except HIS, were found to be a significant predictor for seeking a STEM degree pathway. Race/Ethnicity was a significant predictor for attaining a STEM degree. Results showed that BAA students underperform compared to WHI students, while AS and NRA students outperformed WHI students in attaining a STEM degree. For math-remediation students, BAA and NRA race/ethnicities were significant predictors of STEM degree attainment compared to WHI students. The BAA students had a lower likelihood of attaining a STEM degree, while the NRA students had a higher chance of attaining a STEM degree than WHI students.

This study examined socioeconomic status through Pell data. The Pell variable was a predictor of college math course completion. Students with Pell Grants were less likely to pass at least one college-level math course. Receiving a Pell Grant also increased the likelihood of

attaining a STEM degree. Pell status was also a significant predictor for STEM degree completion time. Students who received a Pell Grant had a significantly longer degree completion time than those who did not.

The math-placement-level variable was a significant predictor of STEM degree attainment. The odds of students in upper-level remedial math or college-level math attaining a STEM degree were significantly higher than those in lower-level remedial math.

Math-placement-level was a significant predictor of STEM degree attainment. Students placed in upper-level remedial courses had 43% more odds of attaining a STEM degree than those in lower-level remedial courses.

Chi-Square analysis showed that the proportion of math-remediation students who attained a degree (21%), the proportion of math-remediation students who completed one or more college-level math course (55%), the proportion of math-remediation students who completed the remedial math sequence and attained any degree (34%), and the proportion of math-remediation students who completed the remedial math sequence and attained specifically a STEM degree (18%) were all statistically significant. Lastly, math-remediation students' average degree completion time was 50.9 months or approximately 4.2 years. The result of the t-test demonstrated a significant difference between the null assumption of 24 months and the actual degree completion time of math-remediation students.

Chapter 5

Discussion and Conclusions

This study analyzed the relationship between community college students' math remediation status and their continued persistence in math at a large Pacific Northwest college (PNWC). Continued persistence in math included the following outcomes: college math course completion, seeking a STEM degree pathway, degree attainment, and degree completion time. Degree attainment and degree completion time were analyzed for students who chose any degree (STEM or non-STEM), as well as those who specifically chose a STEM degree. Specific math course placement level was also considered such as whether a student placed in lower-level or upper-level math remediation or college-level math. An Associate of Science (AS) or Associate of Science Oregon Transfer in Business (ASORT) were considered STEM degrees and Associate of General Studies (AGEN), Associate of Applied Science (AAS), and Associate of Arts Oregon Transfer (AAORT) were considered as non-STEM degrees for the purposes of this study.

Numerous studies have been conducted on how remediation impacts numerous postsecondary outcomes such as remediation completion, college-level math completion, retention, transfer, credit accumulation, degree attainment, and more. Most of these studies have illustrated a complex picture leaving little consensus on whether remediation helps, hinders, or has no effect on future student success (Bailey, Jeong, & Cho, 2009; Bettinger & Long; 2005; Bettinger & Long, 2009; Brock, 2011; Calcagno, Crosta, Bailey, & Jenkins, 2007; Chen, 2016; Frye, 2014; Horn, McCoy, Campbell, & Brock, 2009; Lesik, 2006; National Center for Public Policy and Higher Education & Southern Regional Education Board [NCPPHE & SREB], 2010). Moreover, there are researchers who believe the effectiveness of remediation is based on the subject matter. For example, Bettinger & Long (2005, 2009) found math remediation to have a

positive effect on outcomes such as student success and persistence but found English remediation to have no effect. My study sheds light on this issue. Moreover, research on math remediation status in relation to community colleges is currently lacking. Most research investigates four-year university students. One of the reasons why it has been difficult to identify a causal relationship between remediation and educational outcomes is because there is no random assignment of students in remedial education.

In this study, logistic regression models were used to answer the research questions that examined the relationship between demographic variables and math-placement-level on continued persistence in math of community college students. Logistic regression was used to identify predictors for outcomes of continued persistence in math. Chi-square and Z-test was used as a test of proportions for some of these outcomes. Moreover, a t-test was used to test the outcome of degree completion time since it was a continuous variable.

The demographic variables in this study were race/ethnicity, sex, socioeconomic status (through Pell data), age, and math-placement- level. Some of the demographic variables had subcategories. For example, sex had three subcategories: Male (M), Female (F), and Not Reported (N). Race/ethnicity had nine subcategories: 2+ (Multi Racial), WHI (Caucasian/White), BAA (Black/African American), AS (Asian), HIS (Hispanic), AI (American Indian/Native American), NRA (Non-Resident Alien), HPI (Hawaiian/Pacific Islander), and UNK (Unknown/Not Reported). Historically underserved groups included BAA, HIS, AI, HPI, NRA, and UNK. Pell had two subcategories: Yes Pell Grant (Y) and No Pell Grant (N) and math-placement-level had three subcategories: lower-level vs. upper-level remedial math placement or college-level math placement. In this chapter, I will summarize the findings of the study and

discuss implications for practitioners. In addition, I will explain the limitations of the study and make suggestions for future research.

Summary of Results

College Math Course Completion

The outcome of college math course completion was explored for all students, regardless of remediation status. Evidence from Table 7 suggested that odds of completing at least one college level math course for historically underserved groups, except the NRA students, were significantly lower than the WHI students, suggesting that their completion rate was lower than WHI students. For example, out of 681 BAA students, 429 (63%) completed at least one college level math course, and out of 8,986 WHI students, 7107 (79.1%) completed at least one college level math course. Moreover, the NRA students were significantly outperforming WHI students such that odds of completing at least one college math course were 114% more than the odds of the WHI students. Out of 563 NRA students, 501 (89%) completed at least one college level math course.

Bahr (2010) and Frye (2014) found similar results to my study, particularly when it came to the Black race/ethnicity. However, my study examined the outcome of college math course completion for all students, whereas Bahr (2010) and Frye (2014) examined the outcome for math-remediation students. Bahr (2010) also examined the relationship between race and math remediation and found that race was highly correlated with the likelihood of passing a college-level course. Bahr (2010) found that White students were 3.1 and 1.6 times more likely to pass a college-level course than Black and Hispanic students, respectively. In a study of math-remediation students at North Carolina community colleges, Frye (2014) found that Black

students were 40% less likely to pass college-level math. Bahr (2010) discussed how race is not necessarily a causal factor, but a proxy for qualities such a math preparedness.

Students with a Pell Grant were less likely to pass at least one college level math course, suggesting that rate of students who did not receive a Pell Grant and passed at least one college-level math course was higher than the rate of students who received a Pell Grant and passed at least one college-level math course. Out of 623 students who received a Pell Grant, 438 (69.3%) students completed at least one college math course, while out of 15,717 students without the Pell Grant, 12,261 (78%) students completed at least one college math course. Hence, receiving a Pell Grant didn’t seem to contribute to students’ ability to complete a college math course.

Analysis from the data alone gives very limited information regarding students’ socioeconomic background. The results from my study could suggest that students with low socioeconomic backgrounds could have a more difficult time persisting through college-level coursework due to numerous other factors in addition to financial reasons. This includes, but is not limited to, the numerous courses in the remedial sequence, the length of time it takes to complete the sequence, and students giving up (Calcagno, Crosta, Bailey, & Jenkins, 2007; NCPPHE & SREB, 2010). Even though the Pell Grant helped cover the cost of remedial courses and subsequent college-level courses, living expenses, children, and other financial costs outside of academics could be contributing socioeconomic factors holding such students back from continued persistence in math. Moreover, the older the students’ ages were, the more likely they were to persist and complete a college-level math course than younger students.

Seeking a STEM Degree Pathway

Evidence from Table 8 indicated that the younger the students’ age, the more likely they were to seek a STEM degree pathway. Moreover, Table 8 suggested that none of the races,

except the HIS race, were significant predictors for seeking a STEM degree pathway, compared to WHI race. This suggested that the rates of students seeking a STEM degree pathway were not substantially different than WHI students. For example, out of 740 NRS students, 360 (48.6%) sought a STEM degree pathway, while, out of 15,366 WHI students, 7601 (49.5%) sought a STEM degree pathway. Table 18 shows the number of students who sought or did not seek a STEM degree pathway for all the demographic variables.

Table 18

Frequency of Students Seeking a STEM Degree Pathway in Each Demographic Variable

Demographic Variables		Seeking STEM Degree Pathway		Total Number of Students
		Yes	No	
Race	WHI	7601 (49.5%)	7765 (50.5%)	15366
	2+	1084 (50.1%)	1078 (49.9%)	2162
	AI	102 (43.6%)	132 (56.4%)	234
	AS	1076 (52.1%)	990 (47.9%)	2066
	BAA	745 (50.5%)	731 (49.5%)	1476
	HIS	1979 (48.4%)	2109 (51.6%)	4088
	HPI	121 (49.2%)	125 (50.8%)	246
	NRA	360 (48.6%)	380 (51.4%)	740
	UNK	951 (49.1%)	987 (50.9%)	1938
Sex	F	7181 (51.2%)	6856 (48.8%)	14037
	M	6385 (48%%)	6919 (52%)	13304
	N	453 (46.5%)	522 (53.5%)	975
Pell	N	13338 (49.4%)	13646 (50.6%)	26984
	Y	681 (51.1%)	651 (48.9%)	1332

For most of the demographic variables, no substantial difference was observed compared to WHI students. Although the difference between the race of AI and WHI for seeking a STEM degree pathway was non-negligible (43.6% and 49.5%, respectively), the model was statistically insignificant due to AI having a smaller sample size. This scenario did not occur for HIS

students. Although the difference between HIS and WHI students who sought a STEM degree pathway were smaller (48.4% and 49.5%, respectively), the model was statistically insignificant since the sample size was larger, approximately 18 times of the AI students. Notice, for more accurate comparisons, these groups of students should be compared for all identical combinations of the demographic variables (Sperandei, 2014). The rates shown in Table 18 are the aggregated results over the entire dataset, irrespective of other demographic variables. Considering all identical combinations of the demographic variables to compare two groups is out of the scope of this study. The students with sex of “F” had more odds of seeking a STEM degree pathway than the students with sex of “M” and “N”. For example, Table 18 shows that out of 14,037 female students, 7,181 (51%) and out of 13,304 male students, 6,385 (48%) sought a STEM degree pathway.

STEM Degree Attainment

The outcome of STEM degree attainment was explored for the entire student population (RQ2 and RQ5) and specifically math-remediation students (RQ5). RQ2 solely explored STEM degree attainment for the entire student population, and demographic variables were the only predictors. RQ5 explored STEM degree attainment for the entire student population in part A and specifically math-remediation students in part B. Both demographic variables and math-placement-level were explored as predictors in RQ5.

STEM Degree Attainment (All Students). Evidence from Table 9 suggested that BAA students underperform WHI students while AS and NRA students outperform WHI students for attaining a STEM degree. This suggested that rate of BAA students who attained a STEM degree was lower than the rate of WHI students who attained a STEM degree. The rates of AS, and NRA students who attained a STEM degree were higher than WHI students who attained a

STEM degree. For example, out of 636 BAA students, 155 (24.4%) students attained a STEM degree while out of 921 AS and 342 NRA students, 329 (35.7%) and 224 (65.5%) attained a STEM degree compared to 1988 out of 6714 (29.6%) WHI students who attained a STEM degree.

By adding the math-placement-level (see Table 16) the AS and BAA variables were no longer significant predictors, although their odds ratios followed the same pattern observed in Table 9. This suggested that there was insufficient evidence to conclude there was a performance difference between AS, BAA and WHI students at the population level for each set of demographic variables. For example, out of 99 BAA students only 10 (10.1%) students attained a STEM degree – given all other variables stayed constant (female, received no Pell Grant, and placed in lower-level math remediation). This rate was 11.3% (7/62), 17.5% (123/705) and 62.5% (10/16) for AS, WHI and NRA students with the same demographic conditions. Although race of AS and BAA were no longer significant predictors, the race of NRA remained as a significant predictor since the rate of NRA students (62.5%) was substantially higher than the rate of WHI students (17.5%). The same pattern existed in the other set of demographic variables. Adding the math-placement-level variable as another independent variable increased the McFadden R^2 value of the model. However, this caused less distinctive rates among the races, which resulted in observing less significant race predictors.

Receiving a Pell Grant increased the likelihood of attaining a STEM degree (Table 9), suggesting that the rate of students who received a Pell Grant and attained a STEM degree was higher than the rate of students who did not receive a Pell Grant and attained a STEM degree. Out of 427 students who received a Pell Grant, 151 (35.4%) attained a STEM degree, which was higher than the rate of students who did not receive a Pell Grant and attained a STEM degree

(3621/11,837 = 30.6%). This situation also existed when observing more granular demographic variables; that is, variables with a 'larger' number of factors. For example, the rate of attaining a STEM degree for BAA, HIS, HPI, 2+ female students who received a Pell Grant (37.5%, 31.7%, 40%, 40%, respectively) were higher than the same-race female students who did not receive a Pell Grant (22.2%, 30.7%, 19.6%, 29.3% respectively). Adding the math-placement-level variable in RQ5 when examining STEM degree attainment for the entire student population did not change the effect of the Pell status predictor, as it remained as a significant predictor (Table 16). Additionally, it was found that the younger the students' age, the more likely they were to persist and attain a STEM degree.

With an increased focus on encouraging students to pursue STEM degrees, students from disadvantaged backgrounds may choose this pathway due to possible improvements in their quality of life. A study by Broton and Monaghan (2018) indicated that students with STEM degrees are shown to have higher pay than those with non-STEM degrees. The study also suggested that a crucial factor in low-income students not seeking a STEM degree comes from a lack of financial resources. According to the study, need-based aid recipients, such as Pell Grant recipients, were almost 8 percent more likely to major in STEM fields than their peers. Hence, with necessary financial resources such as Pell Grants, students who are socioeconomically disadvantaged are more likely to pursue and attain a STEM degree. Moreover, a study from Harvard supports the claim that financial aid impacts students choosing STEM degrees as they found suggestive evidence that aid offers increase degree attainment in STEM fields" (Castleman, Long, & Mabel, 2017).

STEM Degree Attainment with Math-Placement-Level (All Students). The main difference between part C of RQ2 and RQ5 was the math-placement-level variable. The math-placement-level variable was added as another predictor in RQ5. The math-placement-level variable showed significant effect on STEM degree attainment (Table 16). The odds of upper-level remedial and college-level math placement were significantly higher than the odds of lower-level remedial math placement, hypothesizing that the students who were placed in higher math levels had higher likelihood of attaining a STEM degree. The students' and the award datasets also supported this hypothesis. For example, out of 3,503 and 6,276 students who were placed in upper-level remedial course and college-level math course, 863 (24.6%) and 2,460 (39.2%) students attained a STEM degree, respectively while out of 2,485 students who were placed in lower-level remedial course, 449 (18.1%) students, attained a STEM degree.

STEM Degree Attainment with Math-Placement-Level (Math-Remediation Students). For the math-remediation students, BAA and NRA were significant predictors compared to WHI students (see Table 17). The BAA students had lower likelihood of attaining a STEM degree while the NRA students had higher likelihood of attaining a STEM degree compared to WHI students. NRA students, or nonresident alien students are immigrants. Many community colleges have a significant immigrant population who may have the necessary academic skills for college-level work but are deficient in English. Due to the language barrier, many of these students may take remedial coursework before taking college-level courses (Levin & Calcagno, 2008). Remedial coursework is most common among students from disadvantaged backgrounds (Bettinger & Long, 2007). The sex and age variables were not significant predictors, demonstrating that there were no substantial and distinctive rates of attaining a STEM degree among different groups of students with different sex and age.

Math-placement-level and Pell status were significant predictors of STEM degree attainment for math-remediation students. Adding math-placement-level as an additional predictor in RQ5 did not change the effect of the Pell status predictor, as it remained significant for math-remediation students (Table 17). Even with the math-placement-level predictor, math-remediation students who received a Pell Grant were more persistent in attaining their STEM degree. Students who were placed in upper-level remedial course had 43% more odds than students who were placed in lower-level remedial course for attaining a STEM degree. The rates extracted from the students' and award datasets also supported this scenario. Out of 3,586 students who were placed in upper-level remedial course, 880 (24.5%) attained a STEM degree, while out of 2,492 students who were placed in lower-level remedial course, 451 (18.1%) attained a STEM degree.

For students at the lowest levels of remedial math sequence, remedial coursework can become quite costly (Crisp & Delgado, 2014). In 2008, the estimated average community college student paid close to $2000 on remediation courses (Strong American Schools, 2008). The cost is likely much more in current times. This amount is likely more for students at lower levels of remediation since they must pay for more remedial courses. Attewell et al. (2006) and Scott-Clayton & Rodriguez (2012) have found that remediation may have psychological costs for students, as well. For example, they found that placement into remedial courses can have a negative effect on students' academic aspirations, especially if they are placed in the lowest levels and have a tall ladder to climb.

STEM Degree Completion Time

In this study, the Pell Grant variable significantly impacted STEM degree completion time (Table 10). Students who received a Pell Grant could attain a STEM degree approximately

8 months later than the students who did not receive a Pell Grant. The average STEM degree completion time for 151 students who received a Pell Grant was 54.9 months compared to 46.7 from 3,621 students who did not receive a Pell Grant. This demonstrated that the students who received a Pell Grant, despite setbacks that slowed their progression, were more persistent in attaining their STEM degree. This could be due to the presence of financial resources to support them through their necessary courses. Moreover, students who are socioeconomically disadvantaged are working outside of school, which could contribute to their delayed degree completion time. Additionally, it was found that the younger the students' age, the more likely they were to have faster STEM degree completion times.

Attainment and Completion Time of Any Degree

The attainment and completion time of any degree was only investigated for math-remediation students. The results from RQ3 showed that only 21% of math-remediation students attained any degree. The degrees considered in RQ3 were AS, ASORT, AGEN, AAS and AAORT. I also observed that the average degree completion time (50.9 months) for the math-remediation students who attained any degree was significantly higher than 24 months. The low rate of degree attainment could be attributed to the lack of strong math foundation in math-remediation students and having to take many remedial math courses. This could cause many to give up and withdraw from college. The extensive degree completion time of math-remediation students who attained their degree in a timeframe substantially higher that the pre-defined 24 months could be attributed to the extra investment of time in taking remedial math courses before progressing to required college-level math courses.

Other studies support these findings. Over the past thirty years, those who have been enrolled in remedial coursework have earned their degrees at a much lower rate than those who

were non-remediated (Chen, 2016). Brock (2011) reports that only 28% of remedial students, compared to 43% of non-remedial students, complete an associate degree or other credentials within eight and a half years of enrollment in a community college. Specifically, math remediation has very low success rates, and students who are required to take these courses persist to complete the first college-level math course at an alarmingly low rate. College Algebra (MTH 111 at PNWC) is the first college-level math course, and only 31% of students referred to a remedial math course three-levels below College Algebra (equivalent to lower-level math placement in this study) eventually enroll into it (Bailey, 2008). This low degree attainment rate is thought to because the remedial math sequence becomes too lengthy for them. Hence, student under-preparedness has become a significant initial barrier to degree completion. Since most general degree plans require the completion of college-level math, math courses have become a gatekeeper for many students (NCPPHE & SREB, 2010).

I also observed that receiving a Pell Grant did not affect degree attainment rates for math-remediation students. Out of 931 math-remediation students who received a Pell Grant, 195 (20.9%) students attained any degree, while out of 15,768 math-remediation students who did not receive a Pell Grant, 3,363 (21.3%) students attained any degree. These rates were compatible with the overall 21% any-degree attainment rate, stating that receiving a Pell Grant did not affect any-degree attainment rate. GPA could probably be used to further evaluate the withdraw rate of the math-remediation students from attaining any degree.

Although any-degree attainment rate was 21% among the math-remediation students, it was higher for the math-remediation students who completed the math remediation sequence (see RQ4). The math remediation sequence was completed if a student passed either MTH 95 or 98. From 6,101 math-remediation students who completed the math remediation sequence, 2,098

(34%) attained a degree. Compared to 21% any-degree attainment rate, this 34% rate demonstrated that completing the initial math remediation courses was the major challenge for the math-remediation students. Once they completed the math remediation sequence, the rate of any-degree attainment increased. Indeed, out of 16,699 math remediation students, only 6,101 (36.5%) students completed the math remediation sequence while 10,598 (63.5%) did not, showing that most of the math-remediation students could not complete the math remediation sequence.

Implications for Policymakers and Practitioners

The results of this study will be disseminated to Oregon state policymakers, local school districts, and practitioners. They can help policymakers improve and/or alter their policies and programs to better serve remedial students at the community college level. The results will also help policymakers meet the goals of the American Association of Community Colleges (AACC). In particular, the findings of this study may provide policymakers with useful information regarding math remediation at the community college level and help create better system alignment amongst postsecondary institutions. Understanding the relationship between math remediation and continued persistence in math will help math educators and math departments make more effective plans for student support, academic success pathways, and degree completion. This can influence departmental decision-making in areas such as effective placement policies, pathway options, and degree requirements.

Evidence from the Pell data in this study suggest that providing financial assistance to students, particularly from disadvantaged socioeconomic backgrounds, could help address the growing need for students to pursue STEM degrees. This is especially true for community colleges which have higher populations of socioeconomically disadvantaged students. Based on

the results from my study and previous studies in the literature, it is important for policymakers and practitioners to understand how the lack of financial resources is often an overlooked barrier to STEM degree attainment in colleges.

Moreover, examining the low degree attainment rate of math-remediation students in both my study and other studies could indicate a need for change in math pathways, including the alternative pathways already in place. The remedial math sequence may be too lengthy and have negative repercussions in math-remediation students' persistence. Students assigned to remedial education are found to spend their limited time in college focused on remedial coursework rather than on college-level coursework (Scott-Clayton & Rodriguez, 2012). The financial and psychological repercussions of having a lengthy remedial math sequence and the extensive costs that accumulate for students to take these noncredit bearing courses need to be further evaluated. Often the psychological repercussions, such as losing motivation, of having to take one or more remedial courses are overlooked and should be studied in more detail.

Age is an important demographic variable when trying to understand the effect of remediation on student success, especially since age is a proxy for many other demographics such as financial independence, years since high school graduation, having dependents, and employment. They all impact enrollment patterns, retention, transfer, and more. Moreover, literature has shown that adult students have different needs than do traditional-aged college students (Campbell, 2016). Hence, the unique population of community colleges and the variety of age ranges need to be taken into careful consideration when examining policies.

Colleges may also need to further evaluate the effectiveness of the alternative pathways. In particular, PNWC needs to further evaluation the effectiveness of their MTH 58 → 98 alternative math pathway. The MTH 58 → 98 pathway is what was referred to as a non-STEM

pathway in this study. It was designed for students majoring in humanities, arts, or social science and not in healthcare or STEM fields. This pathway does not require higher-level math classes such as precalculus, trigonometry, or calculus. Given that this alternative pathway is relatively new could mean that more data needs to be collected to better understand the effectiveness it in student degree attainment. Moreover, this study could indicate a need for policymakers to reevaluate degree requirements. For example, do all AAORT degrees need at least one college-level math course. PNWC also began offering alternative learning courses, which are math labs (using the ALEKS diagnostic assessment system) that provide personalized math content to support student success in current math courses, preparation for a required math course, or pacing through math at a comfortable pace. Since the math labs are personalized, the labs are designed to identify students' math strengths and weaknesses and help students focus on specific areas they are struggling in. Since alternative learning courses are also relatively new, more data collection and further research needs to be done on their effects on continued math persistence, particularly degree attainment and college math course completion.

Having policymakers and practitioners implement and do more studies on diagnostic assessments, such as ALEKS and ASSET, is important. These are becoming a more popular approach but are still very new. These diagnostic assessments are often being used to modularize developmental courses into smaller modules so that students only take the courses they need before progressing into a college-level course (Rutschow, 2018). PNWC has already begun implementing these types of diagnostic assessments in their alternative learning courses. Data should be collected and the effect of these courses on students' continued persistence in math should be examined.

Just as PNWC has included the alternative math pathway of MTH 58 → 98, many other two-year colleges have also been experimenting with different instructional approaches. The majority of public two-year colleges include at least one section of multiple math pathways (instead of a one-size-fits-all traditional pathway), self-paced math courses, corequisite courses, and compressed courses. This is less common in four-year colleges (Rutschow, Cormier, Dukes, & Zamora, 2019). Policymakers should take into careful consideration how each college is implementing alternative pathways differently and how this can affect analysis on their effectiveness on continued persistence in math in the long run.

Limitations of the Research

There are many important limitations associate with this study. First, data was only selected from only one community college. Moreover, remediation is defined in a variety of ways, and each institution has its own remediation policies and independent practices (Attewell, Lavin, Domina, & Levey, 2006). Given the vast differences in policies and practices of math programs at different community colleges, it may be difficult to extend the results of this study to all community colleges in the nation, or even the region or state within which the institution originated. Moreover, the way in which a STEM degree vs. non-STEM degree were defined affected the results of this study. The definition of these terms was determined by me, the researcher, by the number of college-level math courses required by the degree program. It is important to recognize that the degrees offered at PNWC can differ from degree offerings at other community colleges. Hence, this is another reason why it may be difficult to extend the results of the study to all other community colleges. Furthermore, given the substantial differences in both policies, student population, degree offerings, programs, and more, the results found in this study for community colleges cannot be easily extended to four-year institutions.

Other limitations include the limitations in data that could be provided by PNWC. For example, high school GPA and SAT math scores could not be provided, as there were many missing records in their dataset. Moreover, socioeconomic status was derived from Pell Grant data. Pell Grants are very limited in giving a full pictures of students' socioeconomic statuses. Hence, limited conclusions could be made from the results attained through the Pell data. Furthermore, the records in this study were pulled from live Banner and students with first-term years in the 1990s and early 2000s were highly likely to have inaccurate first terms due to Banner being implemented in 1994. Hence, all data for students with first terms in that timeframe had to be discarded from the dataset used in this study due to this possible inaccuracy. The first-term date was used to calculate degree completion time. Missing this bulk of study data may have affected the results of degree completion time. According to the program analyst who prepared the data, solving this issue would not be feasible given their current resources and time constraints.

The sample size for some of the races were too small, which may have influenced some results such as seeking a STEM degree pathway to be deemed insignificant. For example, when examine the effect of race/ethnicity in seeking a STEM degree pathway, AI had a small size, while HIS had a large sample size (18 times larger than AI). This may have caused the results to indicate the difference between AI and WHI (43.6% vs. 49.5%) to be insignificant, but the difference between HIS and WHI (48.4% vs. 49.5%) to be significant even though the difference between the percentages of AI and WHI were more.

This research study was designed to examine the relationship between continued persistence in math for math-remediation students. Some research questions, such as RQ2, examined the relationship between continued persistence in math for all students (regardless of

remediation status). However, it was unfeasible to further compare remedial vs. nonremedial students in their continued persistence in math, as the performance of nonremedial students would be inherently much better. This difference in outcomes is mainly due to precollege difference, rather than the remediation program itself. Identifying a causal relationship between remediation and educational outcomes, since there is no random assignment of students in remedial education, is difficult. Lesik (2006) explains that finding a causal relationship would require the random assignment of students into college-level math or remedial math. Such random assignment could provide an unbiased estimate of the causal effect of developmental math on student success in college-level math. However, Lesik (2006) made it clear that random assignment is not feasible with developmental math since the program is made for students who are not adequately prepared for college-level math.

Even though the R^2 values for the models in this student were small, the models in this study were still valid. However, the higher the R^2 of a model, the better the model fits the data. In other words, a model can predict outcomes more accurately with higher R^2 values. For example, to get a better fitting model for this study, additional relevant independent variables would have needed to be included such as GPA, household income, SAT scores, rank of high school, etc.

Suggestions for Future Study

In RQ2 of this study, demographic predictors for the outcomes of continued persistence in math (college math course completion, seeking a STEM degree pathway, STEM degree attainment, and STEM degree completion time) were considered for the entire PNWC student population. However, in a future study, examining this relationship specifically for math-remediation students would be valuable. Moreover, in RQ5, math-placement-level was included

as an additional predictor to the demographic variables. However, RQ5 only examined these predictors for the outcome of STEM degree attainment. This was done using the entire PNWC population, as well as the math-remediation subpopulation. In a future study, examining these predictors for all of the outcomes of continued persistence in math, not just STEM degree attainment, would be even more informative.

Furthermore, in a future study, further examining math-remediation students' completion of the remedial math sequence, such as identifying predictors of completing the remedial math sequence, would be useful. Further examination of the completion time of the remedial math sequence would be beneficial. Previous studies found that a majority of math-remediation students actually had a much lower chance of completing the remedial math sequence and eventually enrolling in a college-level course (Calcagno, Crosta, Bailey, & Jenkins, 2007; NCPPHE & SREB, 2010). Further studies can examine this, as well.

The mixed results found in studies on remediation effectiveness have caused colleges to evaluate their remedial programs more carefully and to engage in remediation reforms that may improve student support and success in these courses. Experts have argued that there are two main problems: 1) numerous students are being placed unnecessarily into remedial courses; and 2) the structure and traditional instructional practices in remedial education can pose barriers to student success. In particular, placement tests were found to be a prominent factor contributing to this disproportionate placement (Davis & Palmer, 2010; Preston, 2017). When compared with their peers, Bailey et al. (2010), found that underserved students were more likely to be placed in lower level of remedial courses.

With placement tests possibly hindering students' college success and being a poor predictor of student college readiness, practitioners and policymakers are trying to revise

placement policies and procedures (Rutschow, Cormier, Dukes, & Zamora, 2019). Many colleges have begun using a combination of sources, in addition to placement tests, for determining student college readiness and course placement. Therefore, doing more research on math placement policies is of great importance, especially when it comes to the issues of under-placement or over-placement particularly for historically underserved students.

This study didn’t examine the effect of degree attainment given that students completed at least one college level math course. A further study could examine the relationship between degree attainment and the completion of college level math courses. For example, the degree attainment of math-remediation students who complete college-level math courses could be compared with non-math-remediation student who complete college-level math courses. Another research option would be to investigate the degree attainment of math-remediation students who complete college-level math versus the degree attainment of math-remediation students who don’t complete college-level math. For example, Frye (2014) found that math-remediation students who completed college-level math earned significantly more associate degrees than those who did not complete college-level math. The completers of college-level math were twice as likely to transfer out of the institution. The study showed that students were found to be more successful long-term if they were retained through remedial coursework and ended up successfully completing a college-level math course. However, since Frye’s (2014) study looked at students who were enrolled in at least one remedial course, it failed to show a comparison between those who took fewer remedial courses versus the entire remedial math sequence.

Remedial education may build stronger academic skills among those who complete it (Attewell et al., 2006; Bahr, 2010). However, the strong diversion effect of remediation have been found to result in high rates of attrition. This likely is due to the demands of outside

commitments such as family and work, which is common among community college students (Horn & Nevill, 2006). This is also worth further investigating, especially in community colleges where most of the population has such outside commitments in addition to academics.

Conclusion

In conclusion, this study found a relationship between college math remediation status and continued persistence in math. Age was a significant predictor for all research questions that involved the entire student population but was not significant when examining the subpopulation of math-remediation students. Older students were more likely to persist and complete a college-level math course than younger students. However, younger students were more likely to seek and attain a STEM degree and have faster STEM degree completion times. This difference between older and younger students can guide policymakers and practitioners in providing the right support for students of different age groups, particularly traditional and non-traditional students.

The results from the Pell data show policymakers and practitioners that when given the financial resources, students from low-income will pursue and attain STEM degrees. Pell Grant recipients from both the entire student population and math-remediation subpopulation were more likely attain a STEM degree than non-Pell Grant students. This was true with and without the inclusion of math-placement-level. Moreover, regardless of remediation status, males from the entire student population were less likely than female students to complete a college-level math course, seek a STEM degree pathway, and attain a STEM degree.

AS and the historically underserved BAA, HIS, and NRA races/ethnicities were significant predictors for many of the outcomes of continued persistence in math. The overperformance of NRA students was remarkable and unexpected. In particular, the odds of

NRA students completing a college-level course and attaining a STEM degree was alarmingly higher than the WHI reference group in almost every outcome. NRA students were more than twice as likely to complete a college-level math course and attain a STEM degree. Even more fascinating was that NRA math-remediation students were more than 5 times more likely to attain a STEM degree than WHI math-remediation students. No other race/ethnicity had such overwhelmingly high likelihoods. Moreover, the STEM degree completion time of NRA students was about 7 months shorter than WHI students.

This study found that students placed in upper-level math remediation and college-level math courses were significantly more likely to attain a STEM degree than those placed in lower-level math remediation. For particularly math-remediation students, those placed in upper-level math remediation courses were significantly more likely to attain a STEM degree than the math-remediation students placed in lower-level math remediation courses. This indicates that math-placement-level has a substantial effect on students' continued persistence in math. Given the effects of math-placement-level shown in this study, policymakers and practitioners may want to further explore the effects of placement tests and the remedial math sequence's length on students' persistence in math.

References

Adelman, C. (2007). Do we really have a college access problem? *Change, 39* (4).

Attewell, P., Lavin, D., Domina, T., & Levey, T. (2006). New evidence on college remediation. *Journal of Higher Education, 77*(5), 886-924.

Amos, J. (2011). Saving now and saving later: How high school reform can reduce the nation's wasted remediation dollars. Alliance for Excellent Education. http://all4ed.org/articles/saving-now-and-saving-later-united-states-loses-5-6- billion-providing-college-remediation-according-to-new-alliance-brief/

Bailey, T., Jenkins, D., &. Leinbach, T. (2005). Community college low-income and minority student completion study: Descriptive statistics from the 1992 high school cohort. Available from https://ccrc.tc.columbia.edu/media/k2/attachments/low-income-minority-completion-study.pdf.

Bailey, T. (2008). *Challenge and opportunity: Rethinking the role and function of developmental education in community college*. Community College Research Center.

Bailey, T.R., Jeong, D.W., & Cho, S.W. (2009). Referral, enrollment, and completion in developmental education sequences in community colleges. https://ccrc.tc.columbia.edu/publications/referral-enrollment-completion-developmental-education.html

Bailey, T., Jeong, D.W., & Cho, S. (2010). Referral, enrollment, and completion in developmental education sequences in community colleges. *Economics of Education Review*, *29* (2), 255-270. https://doi.org/10.1016/j.econedurev.2009.09.002

Bailey, T., Jaggars, S. S., & Scott-Clayton, J. (2013). *Characterizing the effectiveness of developmental education: A response to recent criticism*. Columbia University, Teachers College, Community College Research Center.

Bailey, T., Jaggers, S., & Jenkins, D (2015). *Redesigning America's community colleges*. Harvard University Press.

Bahr, P. R. (2010). Preparing the underprepared: An analysis of racial disparities in postsecondary mathematics remediation. *The Journal of Higher Education, 81*(2), 209-237.

Bean, J. P., & Bradley, R. K. (1986). Untangling the satisfaction-performance relationship for college students. *The Journal of Higher Education, 57*(4), 393- 412.

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

Bettinger, E. P., & Long, B. T. (2004). Shape up or ship out: The effects of remediation on students at four-year colleges (Working Paper No. 10369). National Bureau of Economic Research.

Bettinger, E.P., & Long, B.T. (2005). Remediation at the community college: Student participation and outcomes. *New Directions for Community Colleges, 2005*(129), 17-26.

Bettinger, E., Long, B. (2005a). *Addressing the needs of under-prepared college students: Does college remediation work?* National Bureau of Economic Research.

Bettinger, E., Long, B. (2005b). Remediation at the community college: Student participation and outcomes. In C.A. Kozeracki (Ed.). *Responding to the challenges of developmental education* (New Directions for Community Colleges, No. 129, pp. 17-26). Jossey-Bass.

Bettinger, E., Long, B. (2007). Institutional responses to reduce inequalities in college outcomes: Remedial and developmental courses in higher education. In S. Dickert-Conlin & R. Rubenstein (Eds.), *Economic inequality and higher education: Access, persistence and success* (pp. 69-100). Russell Sage Foundation.

Bettinger, E., & Long, B. (2009). Addressing the needs of under-prepared college students: Does college remediation work? *Journal of Human Resources*, *44*, 736-771. doi:10.3368/ jhr.44.3.736

Bettinger, E.P., & Long, B.T. (2009). Addressing the needs of underprepared students in higher education. *Journal of Human Resources, 44*, 736-771.

Bisesi, M. (1982). Historical developments in American undergraduate education: General education and the core curriculum. *British Journal of Educational Studies, 30*(2), 199-212. doi:10.1080/00071005.1982.9973625

Boatman, A., & Long, B. T. (2010). *Does remediation work for all students? How the effects of postsecondary remedial and developmental courses vary by level of academic preparation*. National Center for Postsecondary Research.

Brock, T. (2010). Young Adults and Higher Education: Barriers and Breakthroughs to Success. *The Future of Children*, *20*(1), 109- 132.

Broton, K. M., & Monaghan , D. B. (2018). *Seeking STEM: The Causal Impact of Need-Based Grant Aid on Undergraduates' Field of Study*. Lumina Foundation. https://www.luminafoundation.org/wp-content/uploads/2018/09/seeking-stem.pdf

Burdman, P. (2018). *The mathematics of opportunity: Rethinking the role of math in educational equity.* Just Equations. https://justequations.org/wp-content/uploads/je-report-summary-r12.pdf

Brock, T. (2011). Young adults in higher education: Barriers and breakthroughs to success. *Future of Children, 20*(1), 109-132.

Calcagno, J.C (2007). *Evaluating the impact of developmental education in community colleges: a quasi-experimental regression-discontinuity design*. Unpublished doctoral dissertation, Columbia University.

Calcagno, J.C., Crosta, P., Bailey, T., & Jenkins, D. (2007). Stepping stones to a degree: The impact of enrollment pathways and milestones on community college student outcomes. *Research in Higher Education*, *48*(7), 775–80. https://doi.org/10.1007/s11162-007-9053-8

Calcagno, J., & Long, B. (2008, April). *The impact of postsecondary remediation using a regression discontinuity design: Addressing endogenous sorting and noncompliance* (NBER Working Paper No.14194). National Bureau of Economic Research.

Campbell, E. (2016). *The remedial math process: Age and other factors affecting attrition among students in community colleges* (Publication No. 2248) [Doctoral dissertation, University of New Orleans]. University of New Orleans Theses and Dissertations. https://scholarworks.uno.edu/td/2248

Castleman, B. L., Long, B. T., & Mabel, Z. (2017). Can Financial Aid Help to Address the Growing Need for STEM Education? The Effects of Need-Based Grants on the Completion of Science, Technology, Engineering, and Math Courses and Degrees: The Effects of Need-Based Grants on STEM attainment. *Journal of Policy Analysis and Management*. https://doi.org/10.1002/pam.22039

Chen, X. (2016). Remedial coursetaking at U.S. public 2- and four-year institutions: Scope, experiences, and outcomes (NCES 2016-405). U.S. Department of Education. National Center for Education Statistics.

Community College Research Center (CCRC). (2015). *What we know about guided pathways*. Teachers College, Columbia University.

Cohen, A. M., & Brawer, F. B. (2003). *The American community college*. John Wiley & Sons.

Collins, M. (2008). *It's not about the cut score*. Jobs for the Future

Cox, D. R., & Snell, E. J. (1989). *The analysis of binary data (2nd ed.).* Chapman and Hall.

Crisp, G., & Delgado, C. (2014). The impact of developmental education on community college persistence and vertical transfer. *Community College Review*, *42*(2), 99-117.

Davidson, J.C., & Petrosko, J.M. (2015). Predictors of persistence for developmental math students in a community and technical college system. *Community College Journal of Research and Practice*, *39*(2), 163-178.

Davis, R. J., & Palmer, R. T. (2010). The role of postsecondary remediation for African American students: A review of research. *The Journal of Negro Education*, *79*(4), 503-520.

DesJardins, S. L., & Lindsay, N. K. (2008). Adding a statistical wrench to the "Toolbox." *Research in Higher Education, 49*(2), 172-179.

Duren Jr, W. L. (1965). A general curriculum in mathematics for colleges. *The American Mathematical Monthly, 72*(8), 825-831.

Engle, J., & Tinto, V. (2008). Moving Beyond Access: College Success for Low-Income, First-Generation Students. *Pell Institute for the Study of Opportunity in Higher Education.*

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

Fike, D.S., & Fike, R. (2008). Predictors of first-year student retention in the community college. *Community College Review, 36*(2), 68-88. doi: 10.1177/0091552108320222

Foltz, B. (2016). Statistics 101: Logistic regression, an introduction. https://www.youtube.com/watch?v=zAULhNrnuL4&feature=youtu.be&list=PLIeGtxpvyG-JmBQ9XoFD4rs-b3hkcX7Uu.

Frye, B.J. (2014). Using propensity score matching to model retention of developmental math students in community colleges in North Carolina (PhD dissertation). North Carolina State University, Graduate School, Raleigh, NC.

Fulton, M. (2012). *Using state policies to ensure effective assessment and placement in remedial education.* Education Commission of the States.

Geiser, S., & Santelices, M. V. (2007). *Validity of High-School Grades in Predicting Student Success Beyond the Freshman Year.* University of California-Berkely.

Goes, J., & Simon, M. (2016). Using secondary data in doctoral research. http://dissertationrecipes.com/wp-content/uploads/2011/04/Using-Secondary-Data-inDoctoral-Research.pdf.

Goldin, C., Katz, L. F., & Kuziemko, I. (2006). The Homecoming of American College Women: The Reversal of the College Gender Gap. *The Journal of Economic Perspectives, 20*(4), 133-156.

Grubbs, S. J. (2020). The American community college: History, policies and issues, *Journal of Educational Administration and History, 52* (2), 193-210. https://doi.org/10.1080/00220620.2019.1681385

Hartwig, F., & Dearing, B. (1979). *Exploratory data analysis*. Sage Publications

Hodara, M. (2012). Language minority students at community college: *How do developmental education and English as a second language affect their educational outcomes?* (Doctoral dissertation).

Hodara, M., & Jaggars, S. S., & Karp, M. M. (2012). *Improving developmental education assessment and placement: Lessons from community colleges across the country* (CCRC Working Paper No. 51). Columbia University, Teachers College, Community College Research Center.

Hodara, M., & Jaggars, S.S. (2014). An examination of the impact of accelerating community college students' progression through developmental education. *Journal of Higher Education, 85*(2), 246-273.

Horn, L., & Nevill, S. (2006). *Profile of undergraduates in U.S. postsecondary education institutions, 2003–04: With a special analysis of community college students* (NCES 2006–184). U.S. Department of Education. National Center for Education Statistics.

Horn, C., McCoy, Z., Campbell, L., & Brock, C. (2009). Remedial testing and placement in community colleges. *Community College Journal of Research and Practice*, *33*(6), 510-526.

Hu, S., Park, T. J., Woods, C. S., Tandberg, D. D., Richard, K., & Hankerson, D. (2016). *Investigating developmental and college-level course enrollment and passing before and after Florida's developmental education reform (REL 2017-203).* U.S. Department of Education, Institute of Education Sciences, National Center for Education Evaluation and Regional Assistance, Regional Educational Laboratory Southeast.

Huck, S. (2012). *Reading statistics and research.* Boston, MA: Pearson Education.

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

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). *Applied logistic regression*. John Wiley & Sons, Inc.

Ichinose, C., & Clinkenbeard, J.(2016). Flipping college algebra: Effects on student engagement and achievement. *Learning Assistance Review (TLAR)*, *21*(1), 115-129.

Ishitani, T. T. (2006). Studying Attrition and Degree Completion Behavior among First-Generation College Students in the United States. *The Journal of Higher Education, 77*(5), 861-885.

Jamelske, E. (2009). Measuring the impact of a university first-year experience program on student GPA and retention. *Journal of Higher Education*, *57*(3).

Johnson, I. (2008). Enrollment, Persistence and Graduation of In-State Students at a Public Research University: Does High School Matter? *Research in Higher Education, 49*(8), 776-793.

Kowski, L. E. (2013). Does high school performance predict college math placement? *Community College Journal of Research and Practice, 37*(7), 514-527.

Lawrence, D.M. (2011). *Evaluating the effectiveness of remedial mathematics at a community college.* [Doctoral dissertation, North Carolina State University]. ProQuest LLC.

Lesik, S. A. (2006). Applying the regression-discontinuity design to infer causality with non-random assignment. *The Review of Higher Education*, *30*(1), 1-19.

Lesik, S. (2007). Do developmental math programs have a causal impact on student retention? An application of discrete-time survival and regression-discontinuity analysis. *Research in Higher Education, 48,* 583-608. doi:10.1007/s11162-006-9036-1

Levin, H., & Calcagno, J. C. (2008). Remediation in the community college: An evaluator's perspective. *Community College Review, 35*, 181-207. doi:10.1177/0091552107310118

MAA History. (2021). https://www.maa.org/about-maa/maa-history

Marwick, J. D. (2004). Charting a path to success: The association between institutional placement policies and the academic success of Latino students. *Community College Journal of Research and Practice, 28,* 263-280.

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

McHugh, M.L. (2013). The chi-square test of independence. *Biochem Med (Zagreb), 23*(2),143-9. doi: 10.11613/bm.2013.018

Mertler, C. A., & Vannatta, R. A. (2005). *Advanced and multivariate statistical methods*. Pyrczak Publishing.

Mitchell, W. (1974). Improving general education mathematics. *The Two-Year College Mathematics Journal, 5*(2), 32-38. doi:10.2307/3026568

Muijs, D. (2011). *Doing quantitative research in education with SPSS (2nd ed.)*. SAGE Publications Ltd.

Nagelkerke, N. J. D. (1991). A note on general definition of the coefficient of determination. *Biometrika, 78*(3), 691-692.

Nayebi, H. (2020). *Advanced statistics for testing assumed causal relationships: Multiple regression analysis, path analysis, logistic regression analysis*. Springer. https://doi.org/10.1007/978-3-030-54754-7

National Center for Education Statistics [NCES] (2003). *Remedial Education at Degree-Granting Postsecondary Institutions in Fall 2000*. Department of Education

National Center for Public Policy and Higher Education & Southern Regional Education Board [NCPPHE & SREB]. (2010). *Beyond the rhetoric: Improving college readiness through coherent state policy.* Atlanta: National Center for Public Policy and Higher Education. http:// publications.sreb.org/2010/ Beyond%20th%20Rhetoric.pdf

O'Hear, M.F., & MacDonald, R.B. (1995). A critical review of research in developmental education, Part I. *Journal of Developmental Education 19*,(2), 2-6.

Okimoto, H., & Heck, R. (2015). Examining the impact of redesigned developmental math courses in community colleges. *Community College Journal of Research and Practice, 39*(7), 633-646. http://dx.doi.org/10.1080/10668926.2013.873004

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.

Preston, D. C. (2017). *Untold barriers for Black students in higher education: Placing race at the center of developmental education.* Southern Education Foundation.

Rosales, J. (2018, spring). The racist beginnings of standardized testing. *NEA Today*, 68– 69.

Rothstein, J. M. (2002). College performance predictions and the SAT. *Journal of Econometrics, 121*(1), 297-317.

Rutschow, E. Z. (2018). *Making it through: Interim findings on developmental students' progress to college math with the Dana Center Mathematics Pathways*. Center for the Analysis of Postsecondary Readiness.

Rutschow, E. Z., Cormier, M. S., Dukes, D., & Cruz Zamora, D. E. (2019). *The changing landscape of developmental education practices: Findings from a national survey and interviews with postsecondary institutions.* Center for the Analysis of Postsecondary Readiness.

Sanabria, T., Penner, A., Domina, T. (2020). Failing at remediation? College remedial coursetaking, failure and long-term student outcomes. *Research in High Education, 61*, 459-485. https://doi.org/10.1007/s11162-020-09590-z

Schoenfeld, A. H. (2004). The math wars. *Educational Policy*, *18*(1), 253-286.

Scott-Clayton, J. (2012). *Do high-stakes placement exams predict college success?* Columbia University, Teachers College, Community College Research Center.

Scott-Clayton, J., & Rodriguez, O. (2012). *Development, discouragement, or diversion? New evidence on the effects of college remediation* (NBER Working Paper No. 18328). National Bureau of Economic Research.

Scott-Clayton, J., Crosta, P.M., & Belfield, C. R. (2014). Improving the targeting of treatment: Evidence from college remediation. (Working Paper 18457). National Bureau of Economic Research.

Small, D. (2002). An urgent call to improve traditional college algebra programs. *Focus: The Newsletter of the Mathematical Association of America*, 12-13.

Sperandei S. (2014). Understanding logistic regression analysis. *Biochemia medica*, *24*(1), 12–18. https://doi.org/10.11613/BM.2014.003

Strong American Schools. (2008). *Diploma to nowhere*. Strong American Schools. http://www.broadeducation.org/asset/1128-diploma%20to%20nowhere.pdf

Tucker, A. (2013). The history of the undergraduate program in mathematics in the United States. *The American Mathematical Monthly, 120*(8), 689-705. doi:10.4169/amer.math.monthly.120.08.689

Tukey, J. (1977). *Exploratory data analysis*. Addison-Wesley Publishing Company.

Wilson, E. B. (1913). Let us have our calculus early. *Bulletin of the American Mathematical Society, 20*(1), 30-36.

Writing Team and Task Force of the Standards for Introductory College Mathematics Project. (1995). Crossroads in Mathematics: Standards for Introductory College Mathematics Before Calculus. *American Mathematical Association of Two-Year Colleges*. http://www.amatyc.org/?page=GuidelineCrossroads

Wyatt, J., Kobrin, J., Wiley, A., Camara, W. J., & Proestler, N. (2011). *SAT benchmarks: Development of a college readiness benchmark and its relationship to secondary and postsecondary school performance*. (College Board Research Report 2011–5). The College Board.

Zachry-Rutschow, E., & Schneider, E. (2011). *Unlocking the gate: What we know about improving developmental education*. MDRC. http://www.mdrc.org/publication/unlocking-gate

Xu, D., & Dadgar, M. (2018). How effective are community college remedial math courses for students with the lowest math skills? *Community College Review*, *46* (1), 62-81.

Appendix A

George Fox IRB Agreement

GEORGE FOX UNIVERSITY HSRC INITIAL REVIEW

2211118

QUESTIONNAIRE Title: Exploring the Relationship between College Mathematics Remediation Status and the Continued Mathematics Development of Community College Students

Principal Researcher(s): Morvarid (Megan) Pourhassan

Date application completed: 11/1/2021

(The researcher needs to complete the information above on this page.)

COMMITTEE FINDING:

__√__ (1) The proposed research makes adequate provision for safeguarding the health and dignity of the subjects and is therefore approved.

_____ (2) Due to the assessment of risk being questionable or being subject to change, the research must be periodically reviewed by the **HSRC** on a basis throughout the course of the research or until otherwise notified. This requires resubmission of this form, with updated information, for each periodic review.

_____ (3) The proposed research evidences some unnecessary risk to participants and therefore must be revised to remedy the following specific area(s) on non-compliance:

_____ (4) The proposed research contains serious and potentially damaging risks to subjects and is therefore not approved.

____
Chair or designated member

11/1/21
Date