University of Nevada, Reno

Using an Adaptive Learning Platform to Promote Underprepared Students' Success in Corequisite Mathematics Courses: A Logistic Regression Analysis

A dissertation submitted in partial fulfillment of the

requirements for the degree of Doctor of Philosophy in Education

by

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May 2024

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THE GRADUATE SCHOOL

We recommend that the dissertation
prepared under our supervision by

PING WANG

entitled

Using an Adaptive Learning Platform to Promote Underprepared Students' Success in Corequisite Mathematics Courses: A Logistic Regression Analysis

be accepted in partial fulfillment of the
requirements for the degree of

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ABSTRACT

The issue of college readiness persists in higher education, with many students entering college unprepared for the demands of college-level coursework. This challenge is particularly pronounced in math-intensive fields, where students frequently encounter struggles in corequisite math courses. The problem statement asserts that underprepared students, lacking essential math skills and knowledge and requiring varying levels of remediation, need personalized instruction and support to ensure their success in corequisite math courses.

This study investigates whether an adaptive learning platform (EdReady) promotes the success of underprepared students in corequisite math courses. Through a two-sample proportion test comparing the proportion of students passing corequisite math courses between the treatment group (utilizing EdReady) and the control group (not using EdReady), the data analysis reveals a significant difference. More importantly, logistic regression analysis in the study demonstrates that the use of EdReady and students' prior math experience in Arithmetic are significant predictors of passing corequisite math courses.

The findings of this study carry substantial implications for the design of targeted interventions and support systems aimed at enhancing the academic outcomes of underprepared students in math-intensive fields. By exploring the differentiation of passing rates and the relationship between the utilization of adaptive learning platforms and student success in their corequisite math courses, this study contributes to the ongoing dialogue on innovative strategies for supporting underprepared students in higher education.

ACKNOWLEDGMENTS

Fourteen years ago, when I graduated with my Master's degree in Applied Mathematics, I embarked on a dream: to earn my Ph.D someday. Today, as that dream is about becoming a reality, I find myself overflowing with gratitude toward many individuals. While words may not suffice to express my appreciation, I endeavor to convey my heartfelt thanks here.

First and foremost, I extend my sincerest gratitude to my advisor, Dr. Leping Liu. Her invaluable guidance, profound knowledge, extensive research experience, unwavering patience, and steadfast support have been instrumental throughout this arduous journey. Without her mentorship, I would not have completed this dissertation. Equally, I am deeply thankful to my committee members: Dr. Li-Ting Chen, Dr. Robert Quinn, Dr. Teruni Lamberg, and Dr. Xiaoshan Zhu. Their expertise, constructive feedback, and dedication to teaching and research have been a constant source of inspiration. Their unwavering support and valuable guidance were vital to my success.

I am also grateful to Dr. Ping Sa, my advisor for my master's thesis, whose guidance ignited my passion for research and set me on this path. Starting my research journey with her and continuing it with the professors on my current committee has been a rewarding experience.

Additionally, I am deeply grateful to my husband, Di (pronounced as dee), our son Jason, and my mother, for their boundless love and support, and devoted faith in me. My husband has taken on all household responsibilities lately, while our son's playful reminders to "never give up" serve as constant motivation. Though my mother may not fully understand the significance of a “Ph.D.”, her trust and faith in me have never hesitated.

Last but not least, I wish to honor my father, who watches over me from above. Our close bond and his unwavering support were a driving force in my pursuit of higher education. I still remember seeking his opinion on whether to pursue a Ph.D. when I was about to graduate from my master’s study, to which he responded simply but firmly, "Why not?!" This dissertation is a tribute to remember him, and I carry his spirit with me always.

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Chapter One: Introduction

Chapter One delves into the critical topic of college readiness in higher education, a subject of significant concern for educators and policymakers alike. It begins by elucidating the concept of college readiness as defined by Conley (2007) and explores the common approaches used to measure it, including high school GPAs, standardized tests, and completion of advanced courses. Through detailed examination, the chapter underscores the importance of academic indicators in predicting college success and highlights the prevalence of under-preparedness among incoming college students, particularly in mathematics.

Using a compelling example of a fictional student named John, the chapter portrays the challenges faced by underprepared students entering college and the implications of remediation models like the developmental and co-requisite approaches. It outlines John's journey through remedial mathematics courses, illustrating the time-consuming nature of remediation and the potential for prolonged academic pathways. Moreover, it sets the stage for the study's focus on exploring the effectiveness of adaptive learning platforms, specifically EdReady, in enhancing the success of underprepared students in co-requisite math courses.

The chapter concludes by outlining the study's objectives, research questions, and significance, emphasizing the importance of personalized academic support and the potential of adaptive learning technologies to promote students' performance. By filling a critical gap in existing literature and offering empirical evidence on the impact of EdReady, the study aims to contribute to the development of more effective strategies for supporting underprepared students in their academic journey, particularly in mathematics.

College Readiness-Not-Ready

College readiness garnered significant attention from researchers, educators, policymakers, and practitioners in the field of education. Conley (2007, p.5) provided a clear definition of college readiness as “the level of preparation a student needed to enroll and succeed - without remediation - in a credit-bearing general education course at a postsecondary institution that offers a baccalaureate degree or transfer to a baccalaureate program.” To measure a student’s college readiness, two common approaches were employed: the usage of Course Titles completed by students and their high school Grade Point Averages (GPA), and the adoption of standardized tests (Tierney & Duncheon, 2015).

Studies have revealed that a combination of academic measures, including high school courses with challenging curriculum, advanced courses completed at high school, and student’s high school GPA, was a strong indicator of college performance (Adelman, 2006; DesJardins & Lindsay, 2008). These findings supported that high school students consistently exhibited a higher likelihood of graduating from college and achieving academic success if they earned high GPAs and finished advanced placement courses during their high school study, compared to those with lower GPAs. A high school graduate who had completed advanced courses with a high GPA was reasonably assumed to have the knowledge, skills, and behaviors to successfully complete a college course of study. Such students were typically referred to as “college-ready” (Mijares, 2007).

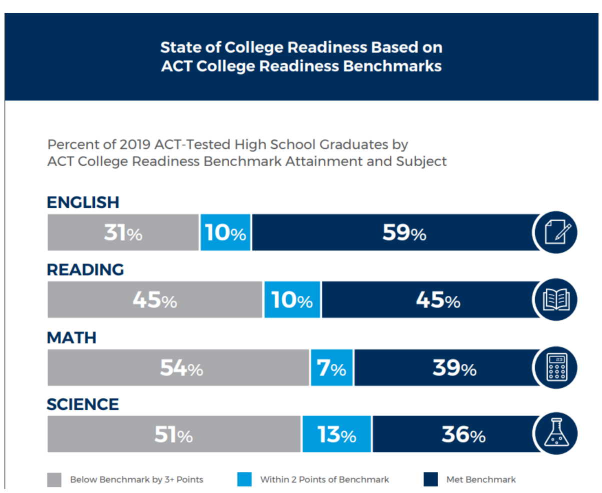
Beside the utilization of high school GPAs and advanced courses completed in high school as important measurements for students’ college readiness, standardized tests were also frequently employed to measure college readiness. Postsecondary institutions in the United States usually adopt two primary types of standardized tests: college admission tests, such as the SAT and ACT (Conley, 2007), and placement tests, such as Accuplacer and Compass (Belfield & Crosta, 2012). College admission tests assessed students' readiness for college-level work through established benchmarks. Let's take the ACT as an example. ACT, a nonprofit organization and a respected leader in college and career readiness solutions, defined ACT College Readiness Benchmarks as "the minimum ACT test scores required for students to have a reasonable chance of success in first-year credit-bearing courses at a typical postsecondary institution" (The ACT's National Report: The Condition of College & Career Readiness 2019). These minimum ACT test scores were referred as cut-off points. Students, whose ACT test scores exceeded these cut-off scores to meet ACT college readiness benchmarks, were marked as "college-ready" and could take entry-level college courses directly without the need for remediation. Conversely, students whose scores did not meet ACT college readiness benchmarks were required to complete the necessary remediation before taking a college credit-bearing course. In this study, students who were not "college-ready" were referred as "underprepared" students.

In addition to college admission tests, placement tests were other types of standardized tests adopted by colleges and universities to determine appropriate course placement for incoming students, particularly when students' GPAs, ACT, or SAT test scores were not available or did not meet college admission criteria. Like college admission tests, postsecondary institutions also set up "cut off scores" for placement tests to identify students' readiness (Grubb et al., 2011; Venezia & Voloch, 2012). Calcagno and Long (2008) stated that students would be marked as "underprepared" and placed into different levels of remedial courses if their placement test results did not meet the designated "cut scores". As an educator, I believed that it was reasonable to expect that a high school graduate admitted by a postsecondary institution possessed the necessary knowledge and skills to qualify for entry-level, credit-bearing college courses without the need for remediation. However, the state of college readiness in the United States was problematic: students' college readiness was not sufficient.

Taking the subject of Mathematics as an example, according to The ACT's National Report: The Condition of College & Career Readiness 2019 (See Figure 1.1), only 39% of 2019 ACT-tested high school graduates met the ACT college readiness benchmark for mathematics. In other words, 61% of students who took the ACT tests in 2019 would encounter one of two scenarios: either not enrolling in college or being accepted by a postsecondary institution but facing gaps and requiring remediation in mathematics. The college readiness in mathematics is not ready at all.

Figure 1.1

The ACT's National Report: The Condition of College & Career Readiness 2019



An Illustrative Example

To solve the issue of remediation, higher education institutions employed two primary models: the Developmental Model, also known as the Traditional Remedial Model, and the Co-requisite Model. In the Developmental Model, students were placed into a linear sequence of remedial or developmental courses designed to target specific academic deficiencies and establish foundational skills needed for college-level coursework. Each developmental course served as a prerequisite for the subsequent one. Conversely, the Co-requisite Model I nvolved students concurrently receiving remediation alongside enrollment in a college-level credit-bearing course (Boylan, 1999). In essence, while remediation in the Developmental Math Model progressed in a linear sequence and had to be completed prior to undertaking college-level math courses, the Co-requisite Math Model allowed for simultaneous progression in remediation alongside the study of college-level math material.

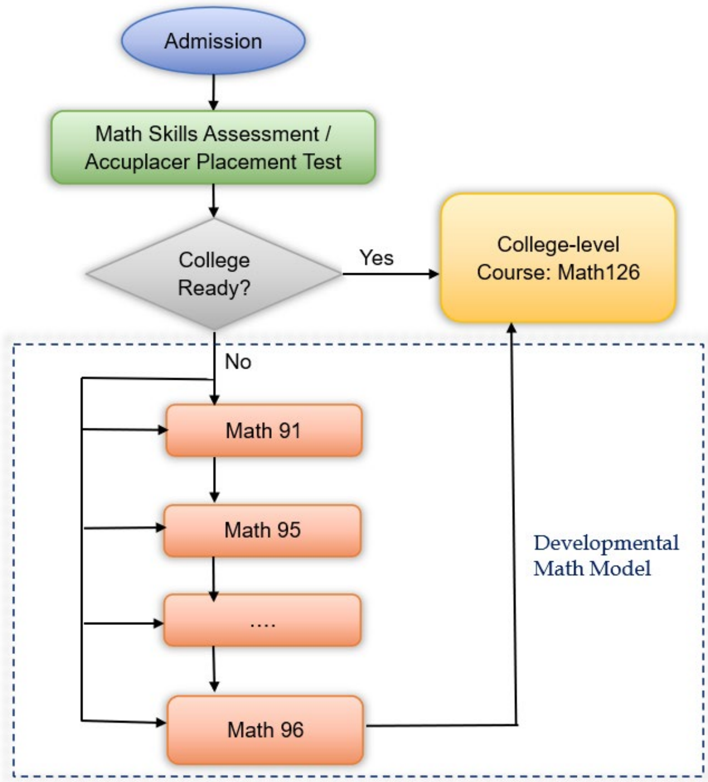
John was a freshman recently admitted to College ABC, a small 2-year college in Nevada. Due to his extended absence from formal education and the lack of information regarding his high school GPAs and ACT scores, a school advisor at ABC suggested that he take the Accuplacer placement test to assess his college readiness and determine the appropriate math course for him. Upon completion of the Accuplacer math placement test and referencing the established Accuplacer "cut scores" at ABC, John was identified as an underprepared student requiring significant remediation to acquire the necessary mathematical knowledge and skills before enrolling in Math 126 – Precalculus I, a foundational college credit-bearing math course essential for his major and degree.

At ABC, students underwent math remediation following the developmental math model until the Fall 2021 semester. Starting from this semester, the Nevada System of Higher Education (NSHE) fully adopted the NSHE Co-Requisite and College-Ready Gateway Policy across all eight public institutions in the state. Consequently, College ABC transitioned to implementing the co-requisite model to assist students in obtaining the necessary math remediation. The following paragraphs utilized John's story as an illustrative example to introduce the statement of the problem for the study.

Under the developmental model, and based upon John's Accuplacer math test results, he was required to complete a sequence of three remedial math courses. John began by enrolling in the lowest level of developmental math course: Math 91 – Basic Mathematics, indicating that he needed the most amount of math remediation. Assuming John successfully completed Math 91 in the first semester, he progressed to the second developmental math course, Math 95 – Elementary Algebra, in the next semester, which indicated a medium level of math remediation at ABC. If John passed Math 95 by the end of the second semester, he was then required to enroll in Math 96 – Intermediate Algebra in the third semester. Math 96 was the last course in the sequence of three remedial math courses, indicating the least amount of remediation needed. Again, assuming John successfully completed Math 96 in the third semester, he became eligible to enroll in Math 126, four semesters later starting from the day he was admitted at ABC. John's journey of math remediation through a developmental math model was depicted in the flowchart below. See Figure 1.2.

Figure 1.2

Developmental Math Model

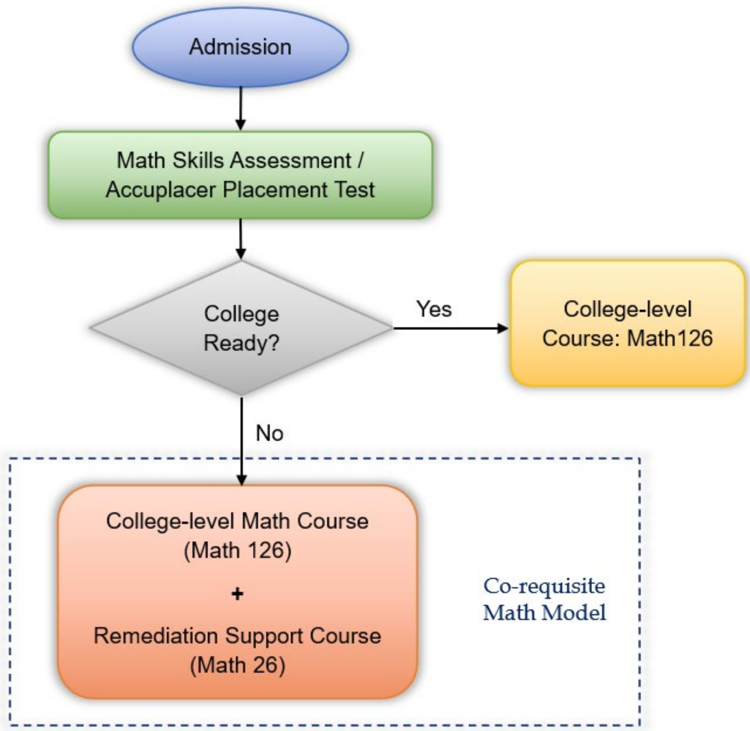


Boylan (2011) argued that the design of developmental mathematics followed a lengthy linear model. John's experience clearly illustrated it: at least three semesters were needed for John to complete the required remediation sequence under a traditional developmental math model. If John failed any one or more courses while completing the sequence of three developmental math courses, his remediation journey would be extended by one or more semesters, potentially requiring 4 to 6 semesters to finish all three developmental math courses before taking his first college-level math course: Math126 – Precalculus I. John's scenario represented the situation when students were least prepared for college coursework and required the most degree of remediation. Other students may have begun their remedial pathways by being placed into Math 95 (a medium level of math remediation) or Math 96 (the least level of math remediation), based on their Accuplacer math placement results. For these students, their remedial journey would have been slightly shorter by one or two semesters.

As mentioned earlier, NSHE fully adopted a co-requisite policy starting from the Fall 2021 semester. Again, using John's experience as an example, under a co-requisite math model, John would have taken Math 126E paired with Math 26, where Math126E was completely equivalent to Math126 (the letter "E" was used to label it as a co-requisite course) and Math 26 served as a learning support course for the purpose of remediation. John would have completed both courses concurrently in the same semester. In other words, John's pathway to gain the needed college-level math credits could have been shortened to one semester. Comparing this with at least four semesters required under a developmental math model, theoretically, the co-requisite math model was more effective and efficient in completing the first credit-bearing college-level math course. John's journey of remediation under a co-requisite math model was depicted in the flowchart below. See Figure 1.3.

Figure 1.3

Co-Requisite Math Model



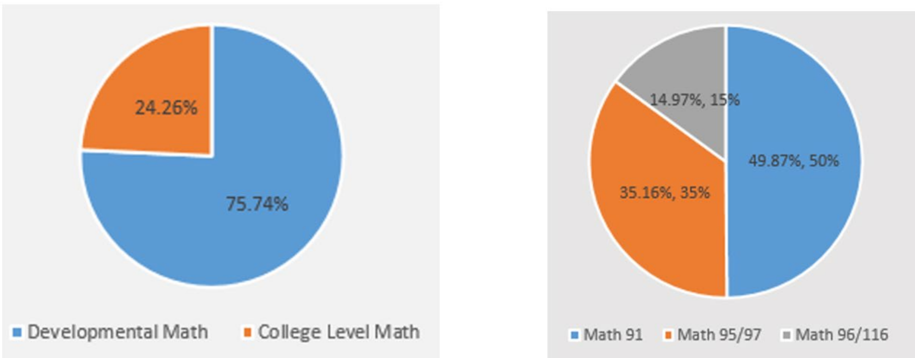
Statement of Problem

While the co-requisite math model demonstrated numerous benefits, one challenge that the model faced was addressing the varying degrees of remediation needed by different students. Kosiewicz, Ngo, and Fong (2016) questioned whether the co-requisite model had helped increase completion rates, particularly for students requiring significant remediation support. Unfortunately, those students, who required substantial remediation, were not a minority in community colleges. Accuplacer math placement test data from 2017-2018 at the college in my study revealed that 75.74% of freshmen were identified as "underprepared" students, with more than 50% of freshmen requiring the highest degree of remediation before entering a college-level credit-bearing math course.

See Figure 1.4.

Figure 1.4 Accuplacer math placement result in 2017-2018

Accuplacer Math Placement Results in 2017-2018



Although students did not always display the same level of remediation, the co-requisite model placed them into the same co-requisite courses. Some underprepared students may have only needed minor remedial support to succeed in the credit-bearing course, for example, those placed into Math 96 – Intermediate Algebra. Others may have required more intensive remediation to bridge significant gaps in their knowledge and skills, such as John, who needed to start his remediation from taking Math 91 – Basic Mathematics, indicating the highest degree of remediation needed.

To address the "one-size-fits-all" issue with the co-requisite model, providing personalized support and resources tailored to individual students' needs could have helped solve the problem. With the emergence and advancement of technology in the past two decades, a number of computer-assisted and web-based products had been integrated into both classroom teaching and independent learning. Adaptive learning systems offered the opportunity for personalized learning by providing individual learning paths to target and meet specific needs (Department for Education and Skills, 2004). Within adaptive learning systems, adaptive diagnostic assessments and online lessons were usually integrated to deliver personalized instruction tailored to each student's needs (Diziol et al., 2010). Integrating adaptive learning systems with co-requisite math courses are targeting to provide students with flexible learning pathways that accommodate their unique learning styles and preferences. Students can work at their own pace, revisit challenging topics, and access additional practice exercises or instructional resources as needed. This flexibility empowers students to take control of their learning and engage with the material in a way that works best for them. By incorporating adaptive learning systems into these corequisite math model, it is hopeful to help underprepared students overcome the barriers of needed remediations, and to enhance their success in corequisite math courses by providing personalized instruction, targeted remediation, and continuous progress monitoring.

Purpose of the study

The purpose of this study is to investigate the effectiveness of utilizing an adaptive learning platform, EdReady, as a supplemental learning resource, in helping underprepared students succeed in their corequisite math courses. To achieve this purpose, the study focused on three specific objectives:

Firstly, the study aimed to examine whether there is a difference in passing rates of corequisite math classes between underprepared students who utilized EdReady and those who did not. By comparing the passing rates of these two groups, the study sought to determine if the utilization of EdReady enhanced student success in corequisite math courses. This objective provided insights into the potential benefits of integrating adaptive learning technologies into mathematics remedial education.

Secondly, the study sought to explore variations in the proportions of underprepared students passing corequisite math classes across different levels of needed math remediation. By categorizing students into groups based on the degree of their math remediation needs (Least, Medium, and Most), the study aimed to analyze whether there are significant differences in success rates among these groups. Understanding how passing rates differ based on varying levels of math preparation will help customize interventions and support strategies to meet the diverse needs of underprepared students.

Lastly, the study endeavored to identify significant factors that predict the probability of underprepared students passing corequisite math courses. Through logistic regression analysis of various factors, the study aimed to uncover elements significantly related to student success. Additionally, it targeted to develop a predictive model for the probability of underprepared students passing the course. This objective enhances our understanding of the complex factors influencing student success and provides practical implications for designing effective academic programs to support underprepared students, particularly in learning mathematics.

Research Questions

To achieve these three objectives, the study employed the "Two-Sample Proportion Test" and "Binary Logistic Regression." The former is a hypothesis test that determines whether the proportions of success or failure in two groups are significantly different from each other. The latter is a commonly used statistical analysis method to analyze the relationship between a binary dependent variable (with two categories) and one or more independent variables. The following research questions were addressed in this study:

1) Research Question 1:

Were the proportions of passing co-requisite math courses significantly different between students who utilized EdReady and those who did not?

2) Research Question 2:

Were the proportions of passing co-requisite math courses significantly different among students who required different levels of math remediation (Least, Medium, and Most)?

3) Research Question 3:

What were the significant factors predicting the likelihood of underprepared students passing a co-requisite college-level math class? If such significant factors existed, to what extent did they influence this probability, and what was the developed logistic regression model?

Significance of the Study

The significance of this study was underscored by its focus on the relationship between underprepared students' success in corequisite math courses and the adoption of an adaptive learning platform – EdReady, as well as comparisons on passing rates among different groups. More importantly, the study was aimed to identify significant predictors related to students' success in co-requisite math course, furthermore, using them to develop a predictive model to predict the likelihood of underprepared students passing their courses. This study addressed a critical need in higher education, particularly in Nevada, where the success of underprepared students in corequisite courses was pivotal for their academic advancement and degree attainment.

Moreover, the scarcity of existing studies examining EdReady's relationship to students' success in co-requisite math courses highlighted the novelty and importance of this research. While some studies explored adaptive learning systems and mathematics learning, not many compared proportions of passing co-requisite math courses among students who required different levels of math remediation. In addition, it barely discovers the studies in the similar setting, which employ binary logistic regression to examine significant predictors, followed by developing a regression model to predict the likelihood of underprepared students passing co-requisite math courses. Thus, this study filled a significant gap in the literature by providing empirical evidence on the utilization of EdReady in supporting underprepared students in their corequisite math education.

Furthermore, the potential implication of the findings from the study may extend beyond the scope of this study. If the findings would demonstrate that the utilization of EdReady is significantly and positively related to student success, the insights gained could be shared with other peer institutions in Nevada and beyond. This dissemination of knowledge and best practices could contribute to the development of effective strategies and programs using adaptive learning systems, to enhance underprepared students in their academic journey.

Definition of Terms

Academically underprepared - A term to describe students assigned to developmental courses in one or more areas, typically reading, writing, or mathematics (McCabe, 2000).

Adaptive learning - An instructional method that utilizes technology as a means of lesson delivery, allowing teachers to spend more time with students and offer personalized learning (Lishon-Savarino, 2016).

Artificial intelligence – refers to research that seeks to create machines that behave intelligently; a central assumption inherent to this topic is that human cognition and behavior can be analyzed and replicated by machines (McCarthy, 1956).

Developmental Education - Also referred to as remedial education, which includes courses and services offered to help under-prepared college students attain their academic goals. Students who needed developmental education usually refer as under-prepared students, and they required remediation on cognitive or affective abilities to succeed in a postsecondary education experience (Boylan, 2002).

College Board ACCUPLACER® Test – The CollegeBoard ACCUPLACER (n.d.) test is an integrated system of computer-adaptive assessments. These assessments are all designed to evaluate and measures a student's skills in reading, writing, and mathematics. (Wilson, 2008)

Summary

In Chapter One, the focus was on the pervasive issue of college readiness in higher education. It delved into the definitions and measurement of college readiness, exploring both traditional markers such as high school GPA and standardized tests like the ACT and SAT. Through an illustrative example of student John, the chapter vividly illustrated the challenges faced by underprepared students entering college and the implications of remediation models like the developmental and co-requisite approaches. Moreover, it set the stage for the study's exploration on adopting adaptive learning platforms, particularly EdReady, in enhancing the success of underprepared students in co-requisite math courses, addressing a critical need in higher education.

The chapter also outlined the study's objectives, research questions, and significance. It underscored the importance of personalized support for underprepared students and the potential of adaptive learning technologies to address the "one-size-fits-all" approach of remediation.

Outline of Chapters

This study is organized into five chapters. As concluded in the summary of Chapter One, John's story was utilized as an illustrative example to highlight a challenging issue on college readiness. Chapter One also described the purpose of the study, introduced the three main objectives aimed to be achieved, and illustrated the significance of the study. At the end of Chapter One, a list of definitions of key terms used in the study was provided.

Chapter Two provided a thorough overview of the current literature and set the stage for further investigation into how EdReady enhances the success of underprepared students in co-requisite math courses. It explored indicators of college readiness, as well as strategies for math remediation, revealing the complex nature of student readiness for higher education. The review on conceptual and theoretical frameworks highlighted its potential to personalize learning experiences and effectively address individual student needs. Moreover, the synthesis of research on the effectiveness of adaptive learning systems across diverse educational settings emphasized their versatility and utility in improving student outcomes.

Chapter Three provided a detailed description of the methodology employed in this study. It began with an overview of two commonly used statistical analysis methods: the Two-Sample Proportion Test and Binary Logistic Regression. Following this, it revisited the research questions in detail, offering comprehensive insights into each query. Furthermore, the chapter elaborated on the research design, offering detailed descriptions of dependent and independent variables, and elucidated the procedures for data collection. Additionally, it introduced the study's setting, providing essential context for understanding the research environment.

Chapter Four presented the results of data analysis of this study. Firstly, it provided detailed data analysis and results, focusing on various research questions and aiming to understand the factors influencing the success rates of underprepared students in co-requisite math courses. The chapter began with a detailed overview of the response variable, success, and key independent variables such as EdReady usage, gender, course enrollment, and remediation level. Following this, the chapter presented comprehensive data analysis and the corresponding results of statistical tests conducted for Research Questions 1, 2, and 3.

Chapter Five synthesized the findings and provided discussions on both theoretical and practical implications of these findings. Additionally, the chapter addressed the limitations of the study and outlined recommendations for future research.

Chapter Two: Literature Review

The integration of technology in education has increasingly become prevalent, offering new opportunities to enhance student learning outcomes and address academic challenges. Salvin and Lake (2002) highlighted that technology integration in mathematics education has been achieved through computer-assisted instruction programs aimed at supporting and improving students' efforts to learn mathematics. Adaptive learning systems have further expanded these opportunities by providing personalized learning experiences, offering tailored learning pathways, targeted feedback, and catering to the diverse academic needs of individual students. This chapter reviews the existing literature on the impact of adaptive learning in mathematics education.

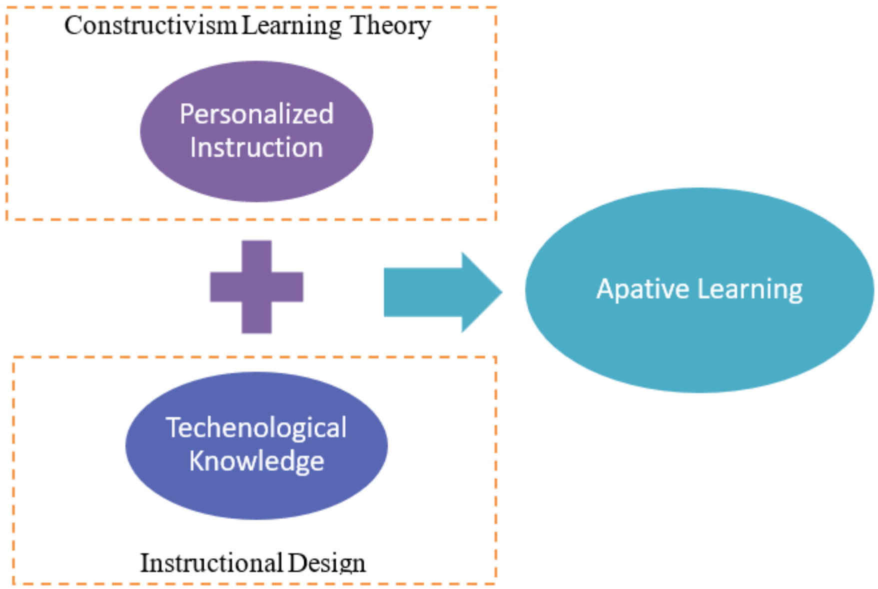
Moreover, the significance of this research lies in its potential contribution to understanding how adaptive learning platforms can support underprepared students in mastering mathematical concepts and succeeding in math remediation. By synthesizing findings from previous studies and integrating them with the specific context of co-requisite math courses, this chapter aims to inform educational practitioners, policymakers, and researchers about the implications of implementing adaptive learning platforms for co-requisite math models in higher education settings.

Theoretical Framework

The theoretical framework of the study was anchored in Adaptive Learning, which was defined by Lishon-Savarion (2016) as an instructional approach that leverages technology for lesson delivery, thereby enabling teachers to allocate more time to personalized instruction. Adaptive learning represents a harmonious amalgamation of personalized learning and technology integration. The related theoretical and conceptual foundation is provided as below. See Figure 2.1.

Figure 2.1

Theorectical Framework



Personalized Instruction and Technological Knowledge (TP)

Constructivism, along with technological knowledge, formed the foundational elements of the theoretical framework. Learning theories, encompassing behaviorism, cognitivism, and constructivism, provided systematic frameworks and perspectives on the learning process, aiming to integrate individuals' internal and external learning characteristics to enhance learning outcomes. As emphasized by Merriam and Caffarella (1999, p. 250), while learning theories may not have offered direct solutions, they drew attention to crucial variables essential for effective solutions. Therefore, integrating constructivist principles with technological knowledge facilitated the development of instructional designs and content that promoted effective and efficient teaching and learning practices.

Prouix (2006) advocated for learner-centered instruction within a constructivist classroom. This approach entailed encouraging students to actively discover knowledge through interaction with the material, engaging in reflection, analysis, and problem-solving. Such an approach contrasted with traditional teacher-centered instruction, where the teacher primarily imparted information. Furthermore, according to Schuman (1996), constructivism viewed knowledge as constructed by individuals through their experiences. Personalized instruction emerged as a valuable application of constructivism, wherein lessons were tailored to accommodate the unique needs of students, considering their existing knowledge and past experiences. This personalized approach enabled teachers to facilitate the construction of knowledge in a manner that resonated with each student's individual context.

Keller (1968) introduced a method to personalize learning for college students, comprising five key components. Firstly, courses were designed to be self-paced, allowing learners to progress at their own speed. Secondly, learners were required to demonstrate mastery at a level of 100% before moving on to the next unit. Thirdly, formal instructional techniques such as lectures and demonstrations were employed primarily for motivational purposes rather than the transmission of critical information. Fourthly, there was a strong focus on written expression to convey concepts effectively. Finally, proctors, as part of extensive teaching teams, facilitated multiple testing opportunities for students on an individual basis.

Burns (1987) conducted a study comparing two instructional approaches in mathematics. One approach allowed students to progress through the math course at their own pace, while the other approach followed a more traditional teacher-paced format.

Both groups consisted of eighth-grade students at the same school studying the same curriculum. Burns found that students in the student-paced group completed more assignments throughout the year compared to those in the teacher-paced group. Additionally, when comparing pace rates, the teacher-paced group progressed similarly to the lower third of the student-paced classes. Tullis and Benjamin (2011) conducted an experimental study to examine the impact of self-pacing on word recall. First-year psychology students were divided into two groups and tasked with studying a list of 160 words using computer software. In the treatment group, students could determine the length of time spent studying each word, while in the control group, students viewed each word for a predetermined duration. Results from a word recognition test revealed that students in the self-paced group demonstrated significantly better recall of the words compared to the control group. To further investigate whether improved recall was solely due to spending more time with difficult words, a follow-up study was conducted. This study introduced a third group where students were given extra time to study challenging words within a predetermined timeframe. Despite the additional time for difficult words enhancing recall, the self-paced group still exhibited the most accurate recall among all three groups. The researchers concluded that entrusting learners with their own learning had the potential to enhance their learning outcomes.

Many studies have affirmed that the uniqueness of personalized learning lay in its focus on meeting the needs of students by emphasizing student voice and choice, as well as flexibility in the pace and location of learning (Burns, 1987; Deci et al, 1996; Gray & Chanoff, 1986; Keller, 1968; Loyens et al., 2008; Reeve & Halusic, 2009; Shernoff, 2013; Zimmerman, 2002). Houchens et al. (2014, p23) summarized four key indicators to evaluate personalized learning:

a) *Assessment – the extent to which students are assessed based strictly on their mastery of explicit skills and learning objectives, that assessments are performance-based measures of applied learning, and that students play an active role in the assessment process themselves.*
b) *Flexibility of Pacing – the extent to which students may move their curricular material at a flexible pace that meets their own individualized needs.*
c) *Flexibility of Location – the extent to which school schedules support seamless student learning across a variety of school-based, home, and community-locations.*
d) *Student Choice – the extent to which students demonstrate evidence of extensive choice in their learning goals, pace of learning, location of learning, and method of assessment.*

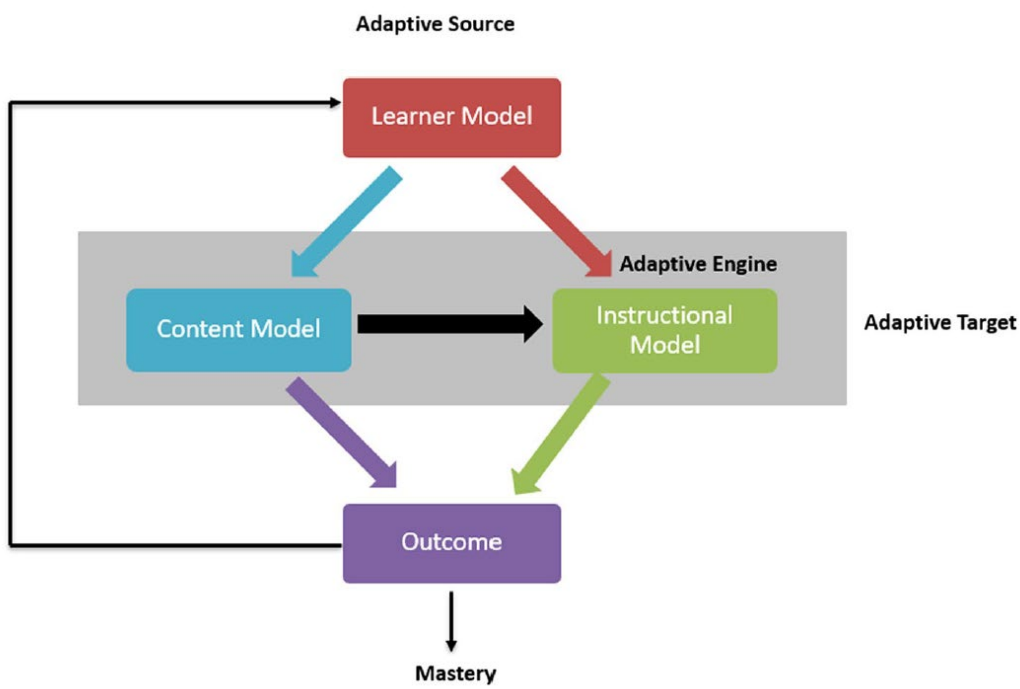
After reviewing personalized learning, it was imperative to revisit a pivotal instructional design model - TPACK. Developed by Mishra and Koehler (2006), TPACK comprised three main components: Technological Knowledge (TK), Pedagogical Knowledge (PK), and Content Knowledge (CK). The purpose of TPACK was for teachers to understand how to use technology to teach concepts with the purpose of enhancing student learning experiences. TK, one of the three components, pertained to effectively integrating technology to teach concepts in a manner that enhanced student learning experiences. The integration of technology within adaptive learning assumed critical significance as adaptive learning systems relied on artificial intelligence technologies, algorithms, and data analytics to dynamically adjust the content, pace, and delivery of instruction in response to each learner's performance and learning outcomes

Adaptive Learning Framework

The Adaptive Learning Framework, as conceptualized by Florence Martin, Yan Chen, Robert L. Moore, and Carl D. Westine in 2020, emerged from a systematic review of research on adaptive learning. Drawing inspiration from the works of Shute and Towle (2003) and Vandewaetere et al. (2011), Martin et al. developed their own adaptive learning framework. This framework, outlined in Martin et al. (2020, p. 1907), comprises several key elements: the Learner Model, Content Model, Instructional Model, Adaptive Source and Adaptive Target, and Adaptive Engine. See Figure 2.2.

Figure 2.2

Adaptive Learning Framework (Martin et. al., 2020, p.1907)



a) Learner Model

Also referred to as the Student Model, this component encompasses the characteristics of learners, including their knowledge, skills, and behaviors. It serves as an adaptive source within the framework, allowing for the customization of educational approaches to suit individual learners (Vandewaetere et al., 2011). Martin and Markant (2019) further elaborate that the learner model comprises attributes, preferences, knowledge, proficiency, motivational or emotional factors, and individual differences, all of which are utilized to tailor the learning experience to each student.

b) Content Model

Also referred to as the expert or domain model, the Content Model encompasses the content or knowledge base relevant to the course being taught (Vandewaetere et al., 2011). As discussed by Martin and Markant (2019), the Content Model consists of interconnected concepts that are designed to progressively build upon one another. These concepts are often represented through a learning map, illustrating the relationships among various ideas and topics within the course. Additionally, the Content Model outlines how course content is structured and delivered to facilitate effective learning experiences for students.

c) Instructional Model

Also known as the pedagogical model or the adaptation model, the Instructional Model refers to the algorithmic process that assists in adapting instruction based on the content and learner model. This model defines what, when, and how adaptation can occur during the learning process (Paramythis & Loidl-Reisinger, 2004). As summarized by Martin and Markant (2019), adaptation techniques within this model may include pacing, the format of instruction, and sequencing. Vandewaetere et al. (2011) argued that the Instructional Model provides the foundation for determining what content is presented to the learner and how it is adapted to meet individual learning needs.

d) Adaptive Source and Adaptive Target

Vandewaetere et al. (2011) referred to the learner model as the adaptive source, while referring to the combination of the content model and the instructional model as the adaptive target.

e) Adaptive engine

The Adaptive Engine functions as an artificial intelligence (AI) sequence generator, creating a learning map with instructional content tailored to the learner within the instructional model. According to Shute and Towle (2003), the adaptive engine is responsible for selecting topics, identifying objectives, sequencing them, and presenting them in a manner that caters to the learner's needs until mastery is achieved. This intelligent engine aids the learner by gradually enhancing their knowledge through content that builds on their existing understanding (Vandewaetere et al., 2011). AI techniques integrate models of content, instruction, and the learner to determine and recommend the appropriate instructional material for the learner.

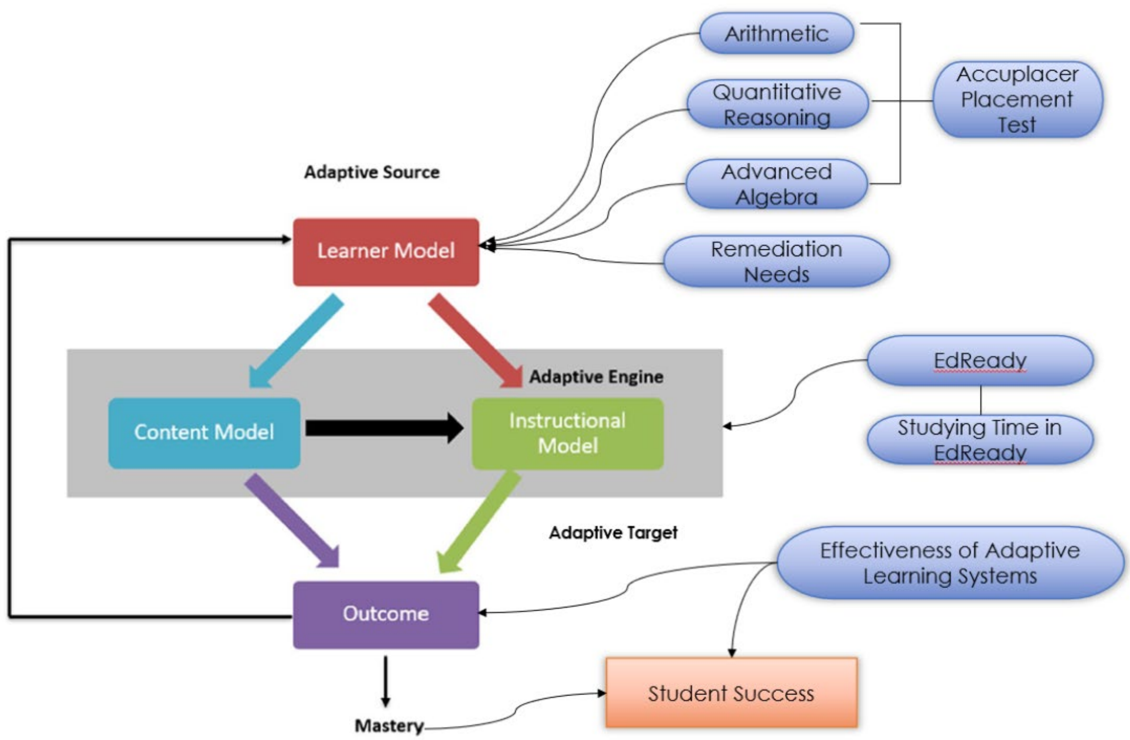
In summary, Adaptive Learning seamlessly merges principles of personalized learning with the transformative capabilities of technology, providing an ideal fit for the study. At its core, adaptive learning acknowledges the inherent diversity among learners, recognizing that each individual possesses unique strengths, weaknesses, and learning preferences, mirroring the characteristics of underprepared students in the study. By leveraging technology, adaptive learning platforms can analyze extensive data in real-time and customize learning experiences to meet individualized needs of each student. This offers an effective solution for addressing the math remediation needs of underprepared students.

Conceptual Framework

The detailed literature review provided in this chapter underpins the overall conceptual framework (see Figure 2.8). This framework integrates elements and factors studied in this research into the adaptive learning model, providing a robust basis for understanding the potential of the adaptive learning platform EdReady in promoting students' success in corequisite math education. The literature reviews on the related elements and factors are illustrated in the following sections.

Figure 2.8

Conceptual Framework



College Readiness

Tierney and Duncheon (2015, p. 8) succinctly categorized various components of college readiness into three main categories: cognitive academic factors (encompassing content knowledge and cognitive skills), non-cognitive academic factors (comprising mindsets and behaviors), and campus integration factors (including college knowledge and relationships with self and others).

Studies have underscored that college readiness hinges not solely on cognitive factors like subject core content knowledge and critical thinking skills but also on non-cognitive factors such as attitudes, motivations, and time management skills. While success in entry-level college coursework necessitated core content knowledge, subject basics, and cognitive skills (Adelman, 2006; Barnett et al., 2012; Conley, 2010); non-cognitive abilities, mindsets, and behaviors also played pivotal roles in preparing students for college and persevering to graduation without the need for remediation (Conley, 2012; Dweck, Walton & Cohen, 2013; Farrington et al., 2012).

Furthermore, Conley (2007, 2012) polished college readiness, through a subsequence of conducted studies, into four keys: Key Content Knowledge, Key Cognitive Strategies, Key Learning Skills and Techniques, and Key Transition Knowledge and Skills. Burdman & Jobs for the Future (2012) argued that only key content knowledge and key cognitive skills were measurable with standardized tests.

Many studies affirmed that it was more effective at measuring an individual's college readiness and future college success by using "multiple measures" (Lawallen, 1994; Desjardins and Lindsay, 2008; Geiser and Santelices, 2007; Jaffe, 2012). By employing multiple measures, educators and administrators gained a better understanding of students' abilities, experiences, and potential. The utilization of multiple measures enhanced the accuracy and fairness of placement decisions by providing a more comprehensive view of each student's educational journey and capabilities.

Accuplacer Placement Test

Wilson (2018) suggested that employing "multiple measures" for student placement led to more accurate course assignments and greater success rates in completing assigned courses for more students. Among multiple measures for college readiness, the Accuplacer placement test was one traditional measure. Developed by College Board in 1985, Accuplacer was designed to assess and gauge students' readiness for college-level coursework, as well as to identify areas where students may need additional support to succeed. The main goal of the ACCUPLACER test was to identify students' strengths and weaknesses in particular subject areas, allowing for placing students into the most appropriate courses tailored to address their individual areas of improvement (Atkinson & Geiser, 2009).

The website of College Board introduced three subtests included in the Accuplacer math placement test, which were Arithmetic, Quantitative Reasoning, Algebra, and Statistics (QAS), and Advanced Algebra and Functions (AAF). Each of the three tests had a score range of 200 – 300. Many colleges had their own cut-off scores from at least one of the three tests to identify college readiness or determine the corresponding placement results if identified as not college ready.

1) The Arithmetic test evaluated fundamental mathematical abilities essential for success in various academic settings. It covered a range of topics including computation, order of operations, estimation, rounding, comparing, and ordering values in different formats, and identifying equivalent values across formats. Specifically, the test assessed knowledge and skills in whole number

operations, fraction operations, decimal operations, understanding percentages, and proficiency in number comparisons and equivalents.

2) The Quantitative Reasoning, Algebra, and Statistics test evaluated a broad spectrum of mathematical competencies essential for academic success. It covered topics such as rational numbers, ratio and proportional relationships, exponents, algebraic expressions, linear equations, applications of linear equations and graphs, probability sets, descriptive statistics, and fundamental geometry concepts.

3) The Advanced Algebra test delved deeper into algebraic concepts, including linear equations, applications and graphs, factoring, quadratics, functions, radical and rational equations, polynomial equations, and exponential and logarithmic equations. Additionally, it assessed proficiency in trigonometry, providing a comprehensive evaluation of advanced mathematical skills.

Although placement exams were widely used in educational institutions to determine students' readiness for college-level coursework, recent research suggested that these exams may not have been as effective as once thought. Burdman and Jobs for the Future (2012) found that placement exams were weak predictors of student success in gateway courses. Similarly, research by Scott-Clayton et al. (2013) supported this notion, indicating that unnecessary placement in developmental courses could complicate the challenge of completing college-level coursework. These findings highlighted the ineffectiveness of placement tests and raised questions about their necessity in accurately assessing students' readiness for higher education. Many community colleges were open-admissions colleges, which meant freshmen enrolled had wide ranges of ability and preparation (Smith & Vellani, 1999), and prior to enrolling in courses, they were usually required to take a placement test to determine the start of their college career (Bailey et al., 2008).

Remediation in Mathematics

Mathematics was notorious for its abstract nature, posing challenges for students in grasping its intricate concepts (Ramani & Patadia, 2012). Consequently, several studies (Bailey, 2009; Bailey et al., 2010; Hoyte, 2013) demonstrated that remedial math exhibited the lowest pass rates compared to subjects like writing and reading. Math remediation endeavored to rectify deficiencies in cognitive academic factors, particularly content knowledge and cognitive skills, crucial for success in mathematics. Typically, remedial math courses concentrated on revisiting fundamental mathematical concepts and fostering essential skills to equip students for college-level coursework.

Two primary approaches were employed in higher education to address the challenge of math remediation for underprepared students: the developmental math model and the co-requisite math model. The traditional developmental model had a rich history dating back to the mid-19th century, where the terms "developmental" and "remedial" had often been used interchangeably (Arendale, 2005). In the United States, developmental education courses were introduced in postsecondary institutions with the aim of helping students prepare for college-level coursework as early as the mid-19th century (Arendale, 2002). The University of Wisconsin established one of the earliest college preparatory programs in 1849, offering courses in reading, writing, and arithmetic to students who did not possess academic readiness for college (Boylan & White Jr, 1987). These programs focused on remedying skills that students were expected to possess upon entering postsecondary institutions.

Using Mathematics as an example, a developmental math education typically comprised a sequence of up to three remedial courses tailored to address various gaps in students' foundational academic skills and equip them for success in college-level math coursework. It was noteworthy that at least 50% of students were assigned to enroll in at least one remedial course during their college career (Bailey, 2009; Barry & Dannenberg, 2016; Chen & Simone, 2016; Scott-Clayton & Rodriguez, 2015).

Despite the intention of developmental math courses to support students in achieving necessary academic competencies, several research findings criticized their effectiveness. Bailey (2009) argued that, on average, developmental education had not been very effective in addressing academic weaknesses. Bahr (2013) discovered that among students required to take remedial math courses, more than half never completed their developmental requirements or went on to obtain a degree or certificate. Bailey, Jeong, and Cho (2015) also reported that only 16% of community college students referred to mathematical remediation completed a required college-level math course within three years. As Adelman insisted in his studies (Adelman, 1996, Adelman, 1998), if the completion of remediation took longer than one year, the degree completion rate dropped significantly; the longer students remained in the stage of remediation, the less likely they were to achieve their academic goals.

The low retention and completion rates of remedial math courses raised significant concerns among researchers. In response to the limitations of the traditional developmental model and the need to enhance remediation effectiveness, educators and institutions began offering co-requisite/accelerated mathematics courses to overcome the barrier posed by the lengthy course sequence of traditional remedial pathways (Schak et al., 2017). Consequently, the Co-requisite Model, integrating remediation alongside college-level coursework, garnered considerable attention across post-secondary institutions (Vandal, 2014b). Jaggars et al. (2015) also suggested that co-requisite courses not only expedited the time required to earn college credits but also offered financial benefits by reducing costs and alleviating student debt burdens.

Co-requisite courses had become increasingly popular in recent years, particularly in the United States (Rutschow & Mayer, 2018). Many states had switched from the traditional development math model to co-requisite math model, such as the Florida College System, the California Community College and State University System, the College System of Tennessee, and the Texas public colleges and universities. Not only in the United States, but the study about the effectiveness of the co-requisite model in Chile also showed positive results. Boatman, Claro, Fresard, and Kramer (2022) proposed that at a technical college, students enrolled in a corequisite math course experienced improved grades in their college-level math course and had a slightly lower likelihood of withdrawing during the first semester compared to those enrolled in just a single college-level math course. However, authors also pointed out that being required to take an additional developmental math course on top of a full co-requisite course load had the potential to overwhelm students, particularly those with very low levels of incoming levels of academic preparation.

Adaptive Learning Platform - EdReady

EdReady is an adaptive learning platform that "*has been adopted by districts, systems, and states to personalize math and English instruction and to empower data-*

driven, student-success decisions" (source: https://www.nroc.org/edready). It was created by The NROC Project, a non-profit organization initially known as the National Repository of Online Courses and Monterey Institute for Technology and Education, established in 2003. NROC was a trailblazer in the creation and dissemination of Open Educational Resources (OER) (The NROC Project, 2017).

EdReady enables learners to identify the concepts they have mastered and those they still need to learn. This helps them create a personalized study plan to address their knowledge gaps and effectively prioritize their time and effort to achieve their academic goals. For educators, EdReady quickly diagnoses students' math and English proficiency, indicating how and when to choose the appropriate intervention, whether for an individual, a group, or the entire class.

The following section reviews how EdReady works by embedding personalized and adaptive learning concepts. First, a schoolteacher or staff member with an EdReady administrator role creates several study goals based on the purpose of using EdReady. In the study, several goals are established in EdReady, all of which focus on preparing students for college readiness. These topics may range from very basic math concepts such as whole numbers, fractions, and mixed numbers to intermediate algebra topics such as exponential and logarithmic functions and trigonometry. See Figure 2.4.

Figure 2.4

Topics in EdReady

- Unit 1: Whole Numbers
- Unit 2: Fractions and Mixed Numbers
- Unit 3: Decimals
- Unit 4: Ratios, Rates, and Proportions
- Unit 5: Percents
- Unit 6: Measurement
- Unit 7: Geometry
- Unit 8: Concepts in Statistics
- Unit 9: Real Numbers
- Unit 10: Solving Equations and Inequalities
- Unit 11: Exponents and Polynomials
- Unit 12: Factoring
- Unit 13: Graphing
- Unit 14: Systems of Equations and Inequalities
- Unit 15: Rational Expressions
- Unit 16: Radical Expressions and Quadratic Equations
- Unit 17: Functions
- Unit 18: Exponential and Logarithmic Functions
- Unit 19: Trigonometry

Then, students log in EdReady to choose a study goal which they feel more appropriate. After a goal is selected, EdReady requires students to take a diagnostic pre-assessment (about 30-45 minutes) to evaluate student's previous knowledge. Based on the result of pre-assessment, EdReady can generate an individualized study path for each student by recognizing which topic students have mastered and which topics students need to review or re-learn. In this way, learning contents are tailored to accommodate the unique needs of students, considering their existing knowledge and past experiences. To learn for a topic, there are various instructional approach students can choose to help them master the contents, such as presentation, e-textbook, more online practice, additional worked examples, etc. See Figure 2.5 and 2.6.

Figure 2.5

Individualized Study Plan in EdReady

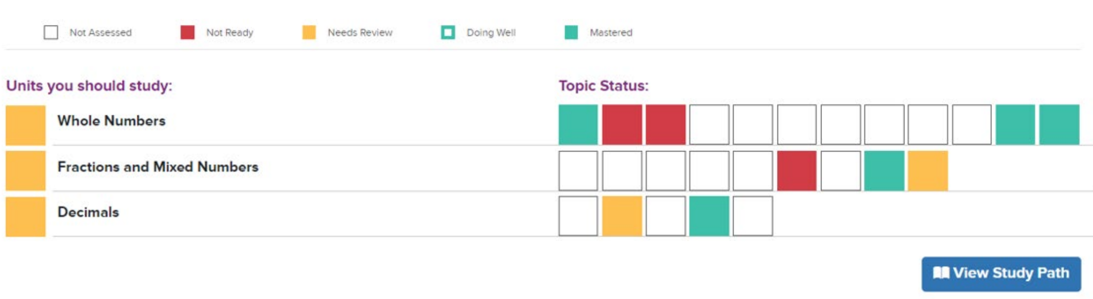
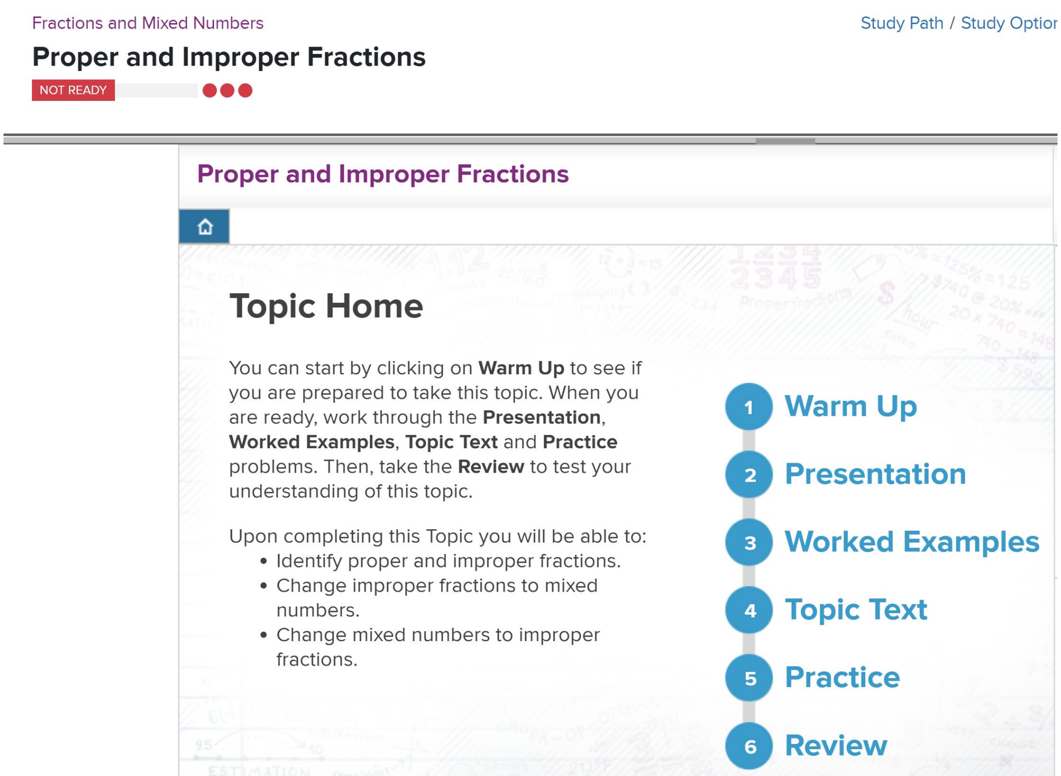


Figure 2.6

Learning Resources in EdReady



During the process of learning, students always have options to choose either re-learn or re-test for a small topic or a whole unit to evaluate their mastery level. After a topic is mastered, student's individualized study plan will be updated accordingly.

Figure 2.7

Study in EdReady

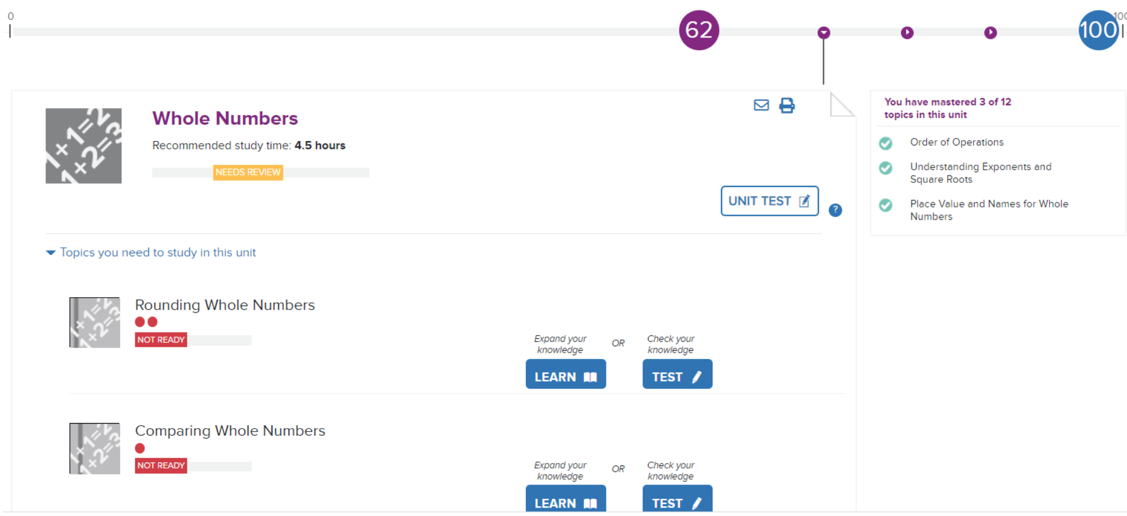
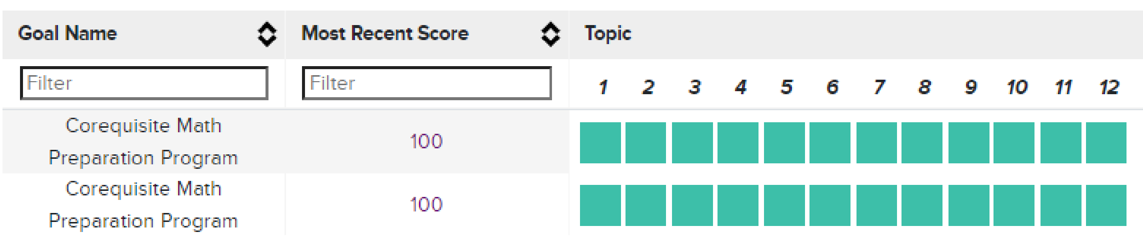


Figure 2.8

Mastery in EdReady



Applying Martin et. al's Adaptive Learning Model, it is evident that EdReady is an adaptive learning platform which consists of learner model, content model, instructional model, as well as the adaptive process which includes selection of topics, identification of objectives, determination of sequences, and presentation of these contents to them to meet the learner's needs until mastery is achieved..

Effectiveness of Adaptive Learning

Both the developmental math model and the co-requisite math model have demonstrated numerous benefits, as well as challenges, in helping students resolve their remediation in mathematics. Alongside the emergence and advancement of technology in the past two decades, a variety of computer-assisted and web-based products have been integrated into remedial math courses to overcome these challenges. Shute and Towle (2003) state that "enhancing learning and performance is a function of adapting instruction and content to suit the learner" (p. 105), which generally highlights what adaptive learning systems do.

Many studies have examined the effectiveness of utilizing adaptive learning technologies/systems/programs in different educational settings, ranging from K-12 to post-secondary, across various subjects. Yakin and Linden (2021) conducted a mixed-method study to assess the effectiveness of adaptive lessons - Smart Sparrow, used in dental education. Yakin and Linden claimed that the study is the first of its kind to demonstrate the potential of adaptive learning technology to enhance both measured and perceived student performance in dental education. In their study, students reported high levels of perceived improvement in performance and comprehension, with significantly higher exam performance observed in the experimental group compared to the control group. The Smart Sparrow lessons were perceived as helpful, engaging, motivating, and conducive to independent learning, which is a critical graduate competency. Adaptive learning platforms offer convenience, on-demand availability, and flexibility, aligning well with the expectations of Generation Z students who value instant and personalized learning experiences. Despite the success of adaptive lessons in engaging students, face-to-face teacher-learner interactions remain crucial, particularly for developing key graduate competencies such as professionalism and communication. While the number of exercises was considered relatively small, students expressed enthusiasm and motivation to engage in active learning. The specificity required for free text answers to be recognized as correct may be perceived as a limitation, but efforts were made to mitigate this issue. Overall, the study underscores the significant potential of adaptive learning platforms in engaging students, improving perceived knowledge, and enhancing exam performance, especially in the context of the COVID-19 pandemic and the transition to online education.

Adaptive learning systems are popular to be used in math education. Crowley (2018) conducted a quasi-experimental research study to investigate the effect of the adaptive learning system - LGL Math Edgeon. Crowley's study aimed to assess the LGL Math Edgeon on elementary students' mathematics achievement in a large urban school district. Using a quasi-experimental design, the study involved 7,114 students in Grades 3–6 as the control group (2015–2016 school year) and 7,733 students in Grades 3–6 as the treatment group (2016–2017 school year). The treatment group received supplemental adaptive mathematics lessons during their regular mathematics sessions, utilizing the LGL Math Edge adaptive learning system. The study analyzed the effects of adaptive learning on various subgroups and explored the relationship between time spent in LGL Math Edge and mathematics achievement from pretest to posttest. Secondary data were used to compare the mean gain score of the adaptive diagnostic mathematics assessment (ADAM) pretest and posttest between the control and treatment groups. Results indicated a statistically significant difference in student achievement when students received the adaptive learning treatment, across all subgroups examined. Additionally, there was a significant relationship between the time spent in LGL Math Edge and mathematics achievement on ADAM, suggesting that supplemental adaptive lessons, combined with conventional instruction, improved student mathematics achievement.

Mathematics education in higher education is also greatly employed with adaptive learning systems. Holt (2019) performed a quasi-experimental study at a two-year college, implementing independent sample t-tests to determine if adaptive learning technology - ALEK, impacted remedial math learning outcomes for nontraditional students compared to traditional students. Findings indicated no significant difference in final grade scores for remedial math learners when ALEKS was included. However, a statistically significant difference in completion rates was observed among nontraditional students in ALEKS sections compared to traditional instruction sections. Regarding the performance of nontraditional students versus traditional students in remedial math with ALEKS, no statistical difference was found in final grade scores or ALEKS posttest scores. In Holt's work, analysis by gender showed a significant difference in grade scores for females in ALEKS sections compared to traditional instruction, but no significance among ethnic groups.

The most recent study about the effects of adaptive learning and mathematics achievement is from William Roberts. Roberts (2023) conducted a quantitative study to investigate the effects of Adaptive Learning Technology (AT) on students' mathematics achievement in a rural, low socioeconomic (SES) context, considering the correlation between low SES and poor mathematical performance. AT programs assess students' existing knowledge and target areas for improvement, aiming to supplement traditional teaching methods. The study includes pretests followed by personalized instruction through computer-generated questions and examples. Additionally, a student survey captures feedback on the experience with AT. Given the challenges faced by students in low SES settings, the study aims to assess the effectiveness of technology in enhancing mathematics achievement and to gauge students' perceptions of mathematics before and after AT implementation. The results contribute insights into the efficacy of AT, demonstrating improved mathematical achievement and changes in students' perceptions of mathematics following AT utilization.

Although there is much research demonstrating the effectiveness of adaptive learning systems on students' learning, only a few adopted the adaptive learning platform – EdReady. In 2014, the Dennis and Phyllis Washington Foundation contributed $2.4 million to the Montana Digital Academy at the University of Montana to establish EdReady Montana, an innovative statewide math readiness program. In its first three years, EdReady Montana significantly improved college math placement exam scores for incoming freshmen, assessed algebra readiness for middle school students, and kept high school students on track in their math classes. Additionally, the program supported adult learners throughout the state in preparing for the high school equivalency test and college-level math courses, enrolling over 51,000 students and adult learners. (Dennis Phyllis Washington Foundation, 2016).

Following the success story of implementing EdReady in the state of Montana, the NROC Project (NROC) partnered with the Texas Education Agency (TEA) and The Commit Partnership (Commit) to design and implement Texas College Bridge using EdReady in the state of Texas. This program offers each participating student an individualized college readiness pathway, which improves student knowledge and provides the opportunity to register for credit-bearing, college math and English courses without an SAT, ACT, or TSIA (Texas Success Initiative Assessment) score. The program data indicated that students who took advantage of the program significantly outperformed other students who did not use the program, in both non-algebraic and algebraic math courses, as well as English composition (The NROC Project, 2021).

Smajstrla (2018) conducted a quasi-experimental study, using to examine if there was a difference in the performance of students in their first credit-bearing math class, comparing between using EdReady vs. Compass as placement tools. She performed both t-tests and Chi-squared tests to answer her research questions and found a significant difference in the performance of Jacksonville State University students in their first credit-bearing math class after the use of the EdReady placement approach, indicating the effectiveness of EdReady. In her study, Enrollment data indicated a significant decrease in developmental math enrollment after EdReady implementation, from 761 students in fall 2014 to 168 students in fall 2017. Statistical analysis revealed a significant difference in student performance between the two approaches. Notably, following the use of EdReady, Science, Technology, Engineering & Math students demonstrated an improvement in pass rates, with 64.3% passing with a C or better compared to 52% previously. Similarly, Non-Science, Technology, Engineering & Math students saw enhanced performance, with 75.2% passing with a C or better, up from 70%. The population in her study is students who are identified as “college-ready” after taking either EdReady or Compass as placement tests. Moreover, Smajstrla’s work studied students’ performance in regular entry-level college math classes, not co-requisite math courses. this study can perfectly fill in these gaps.

Similar to Smajstrla’s research, Thornton, Case, and Peppers (2019) conducted a study using data from the same university, Jacksonville State University, to evaluate the effectiveness of using EdReady as a placement approach. The authors concluded that employing EdReady to replace traditional high-stakes testing resulted in positive outcomes. These included students progressing to credit-bearing math courses more quickly, at reduced costs, and with higher success rates in subsequent math courses. They also found that enrollment in developmental courses decreased from over 500 students to fewer than 140 over three years, while undergraduate enrollment increased by 1.5 percent with consistent demographics. The study indicated that the decline in demand for developmental courses reflects improved student progress and reduced financial strain on the university due to decreased need for extra faculty.

Summary

In this extensive literature review, an in-depth exploration was undertaken into various aspects of college readiness, Accuplacer placement tests, math remediation, and the efficacy of adaptive learning platforms. By analyzing indicators of college readiness and exploring strategies for math remediation, insight into the multifaceted nature of student preparedness for higher education was gained. Additionally, the review surrounding adaptive learning highlighted its potential to personalize learning experiences and effectively address individual student needs.

Furthermore, the synthesis of research on the effectiveness of adaptive learning systems across diverse educational settings emphasized their versatility and utility in improving student outcomes. This chapter provided a comprehensive overview of current literature and set the stage for further investigation into the effectiveness of the utilization of the adaptive learning platform - EdReady in enhancing underprepared students' success in corequisite math courses. Additionally, examination of the extent to which students' success could be predicted by the implementation of this platform and other relevant factors was aimed for.

Chapter Three: Methodology

This chapter provided a detailed overview of the methodology utilized in this study. It began by elucidating the chosen research design – a quasi-experimental design. Then, the chapter meticulously detailed the sample selection process, encompassing 367 underprepared freshmen enrolled in co-requisite math courses over three semesters, sourced from historical academic records. Additionally, it provided comprehensive definitions and descriptions of both dependent and independent variables. Moreover, the chapter subsequently delved into two key quantitative methods: the two-sample proportion test and binary logistic regression, and discussed quantitative data analysis techniques, highlighting their relevance to each research question. Furthermore, ethical considerations, including data confidentiality and IRB approval, underscored the study's adherence to rigorous ethical standards and guidelines. This chapter played an important role in setting the stage for further analysis of data results in the subsequent chapters.

Research Design

Quantitative research designs are typically classified into three primary categories: non-experimental, quasi-experimental, and experimental (Maxwell & Delany, 2004; Johnson & Christensen, 2014; Shadish, Cook & Campbell, 2002). This classification is determined by the extent of control researchers hold over the independent variable(s) and the level of randomization involved.

In non-experimental designs, researchers observe phenomena without intervening or manipulating any variables, aiming to observe and describe characteristics, and to understand or explore relationships or differences between variables without any interventions. In contrast, experimental designs involve the random assignment of subjects to different groups and manipulate variables to examine the effects on the dependent variable(s). Experimental designs are well-suited for establishing cause-and-effect relationships. Although experimental designs offer high internal validity, they may not always be feasible or ethical in educational research settings (Maxwell & Delany, 2004).

Quasi-experimental designs, lying between non-experimental and experimental, involve interventions on the independent variable(s) but lack complete random assignment of subjects to groups. This type of design allows researchers to evaluate the effects of an intervention or treatment in a real-world setting while considering practical constraints and limitations (Johnson & Christensen, 2014). Despite not achieving the same level of control and randomization as experimental designs, quasi-experimental designs offer valuable insights into the practical application of interventions, as well as many advantages in practical research settings (Trochim & Donnelly, 2008).

In the study, a quasi-experimental design was conducted, aimed at comparing the success rates of underprepared students in corequisite math courses between two groups: one that utilized an adaptive learning platform – EdReady, and another group that did not use EdReady. Additionally, the study sought to investigate the effectiveness of EdReady and other relevant factors. EdReady had been introduced to the college starting from the Fall 2017 semester, serving as an open, free, and online supplemental learning platform to help students refresh and review their mathematical knowledge and skills at any time, either before or after enrolling in their math courses. While all students were recommended by the college to utilize EdReady after its implementation, its usage was voluntary, not mandatory.

Based on the study's setting, an intervention was introduced involving the utilization of EdReady versus non-utilization. The treatment group comprised students who utilized EdReady, while the control group consisted of students who did not use it. Importantly, students were not randomly assigned to these groups; instead, they made their own choices regarding EdReady utilization after its implementation on campus. Consequently, the two groups naturally formed based on students' enrollment in the EdReady program, rather than through random assignment. This approach resulted in a quasi-experimental design involving an intervention without the manipulation of variables and lacking a full level of random assignment.

Sample

Students in the study were freshmen at a small two-year public community college located in northern Nevada, identified as "underprepared," and enrolled in a co-requisite math course, either Math120E (Fundamentals of Mathematics) or Math126E (Precalculus I), during three semesters - Fall 2021, Spring 2022, and Fall 2022. The student population at this 2-year college exhibited a variety of characteristics, ranging from non-traditional to traditional students, encompassing dual enrollment high school students to older adult learners, and representing both in-state and out-of-state residents, from urban to rural areas.

The research relied on historical academic records sourced from the student information systems at the college, retrieved by the office of institutional research, as the dataset. Therefore, it was more accurate to refer to the "participants" as "students or student records" in the study. A total of 871 student records were retrieved from all corequisite math classes of Math120E and Math126E within three semesters - Fall 2021, Spring 2022, and Fall 2022. However, only 367 records were selected and used as the sample of the study due to a specific inclusion criterion, which was explained later.

Beginning in the Fall 2021 semester, the Nevada System of Higher Education (NSHE) fully adopted the NSHE Co-Requisite and College-Ready Gateway Policy across all eight public institutions in the state, including this 2-year college. Students admitted by the college were recommended to take Accuplacer math placement tests before enrolling in a math class. Accuplacer placement tests were performed at this college to determine if students were college-ready. If their test results did not meet the "cut scores," students were identified as "underprepared" and could only enroll in a co-requisite math course.

Since one primary objective of the study aimed to explore variations in the proportions of passing co-requisite math classes among students who had different levels of math remediation, the remediation level, determined by taking an Accuplacer math placement test at the college, was required to be included in the dataset. However, after the implementation of NSHE Co-Requisite and College-Ready Gateway Policy, an Accuplacer placement test was only recommended, not required anymore. Many students decided to enroll in a co-requisite math class without taking placement tests to measure their college readiness. Due to this reason, only 367 out of 871 student records, containing measurements of Accuplacer placement results, were selected as the sample of the study.

In summary, the sample of the study comprised 367 students who were freshmen at the college, took Accuplacer math placement tests, were identified as "underprepared" students, and took one co-requisite math class (either Math120E or Math126E) from Fall 2021 to Fall 2022.

Variables

In this study, there was one dependent variable (also referred to as the response) and a number of independent variables (also referred to as predictors). The dependent variable was Success, while the independent variables were EdReady, Course, Gender, Age, Advanced Algebra (AdvAlgebra), Arithmetic, Quantitative Reasoning (QuanReasoning), Remediation Level (Remediation), Most Remediation (MostRemed, a dummy variable of Remediation), Least Remediation (LeastRemed, another dummy variable of Remediation), and Studying Time in EdReady (Time). Detailed descriptions of each variable are provided below.

Dependent Variable (Response)

Y = Success

Success is a binary variable with two values: 1 or 0. A value of 1 indicated that a student successfully passed the class, while a value of 0 meant that a student failed the class. At the college, any grades of D or above were counted as passing grades.

Independent Variables (Predictors)

X_1 = EdReady, which was a categorical variable with values 1 and 0. A value of 1 indicated that a student utilized the adaptive learning platform – EdReady, while a value of 0 indicated non-utilization. The EdReady platform tracked how many times students logged into the platform. In the study, students with a login count greater than one were classified as having "utilized EdReady," denoted by the value of 1; otherwise, they were assigned a value of 0.

X_2 = Time, which represented the studying time in EdReady, measured by the EdReady platform, with "minute" as the measuring unit. It is a continuous variable recording the total duration of time a student spent studying in EdReady.

X_3 = Gender, which was a categorical variable with values 1 and 0. A value of 1 indicated a female, while a value of 0 represented a male.

X_4 = Age, which was a continuous variable indicating the age of the student at the time of taking a corequisite math course.

X_5 = Course, which was a categorical variable with values 1 and 0. The value of 1 indicated the co-requisite math course Math120E (Fundamental of Mathematics), and the value of 0 represented the co-requisite math course Math126E (Precalculus I).

Based on the college catalog, Fundamentals of Mathematics is a math course that fulfills the lower-division mathematics requirements for Bachelor of Arts or Associate of Arts degrees. The course content covers topics such as real numbers, consumer mathematics, variation, functions, relations, graphs, geometry, probability, and statistics.

On the other hand, Precalculus I is a math course that fulfills the lower-division mathematics requirements for Bachelor of Applied Science, Bachelor of Science, Associate of Applied Science, or Associate of Science degrees. This course is often referred to as "A third course in Algebra" and covers topics such as polynomial, quadratic, rational, exponential, and logarithmic functions, as well as graphs and their applications. Additionally, it includes complex numbers, systems of equations, basic operations with matrices and determinants, and Cramer's rule.

X_6 = MostRemed and X_7 = LeastRemed

Before introducing both variables, it was necessary to describe the variable Remediation. Remediation, which represented the degree of math remediation students required, was a categorical variable with three values: 1, 2, and 3. These values were determined by Accuplacer placement results: Math 91, Math 95, or Math 96, corresponding to three remedial math courses. The Accuplacer placement results, available and retrieved from the student information system at the college, were included in the sample dataset.

The value of Remediation was assigned as 1 when the placement result was Math 91, indicating the highest level of remediation. Similarly, it was assigned as 2 when associated with the placement result of Math 95, indicating a moderate level of remediation, and as 3 when associated with Math 96, representing the lowest level of remediation.

Both MostRemed and LeastRemed are dummy variables related to Remediation. The dummy variable MostRemed was generated by assigning the value of 1 in Remediation to the value of 1 for MostRemed and assigning all other values in Remediation to 0 for MostRemed. Hence, MostRemed had two values: 1 and 0, with 1 representing the highest level of remediation and 0 representing the other two levels.

Similarly, the dummy variable LeastRemed was generated by assigning the value of 3 in Remediation to 1 for LeastRemed and assigning all other values in Remediation to 0 for LeastRemed. Therefore, LeastRemed also had two values: 1 and 0, with 1 representing the lowest level of remediation and 0 representing the other two levels.

X_8 = Arithmetic, which is a continuous variable, representing the testing score a student obtained from the first section of Accuplacer math placement test - Arithmetic

X_9 = QuantReasoning, which is a continuous variable, representing the testing score a student obtained from the second section of Accuplacer math placement test – Quantitative Reasoning.

X_{10} = AdvAlgebra, which is a continuous variable, representing the testing score a student obtained from the third section of Accuplacer math placement test – Advance Algebra.

Quantitative Data Analysis

All data analysis in the study was conducted using SPSS statistical software. Both two-sample proportion test and binary logistic regression were performed to analyze the data. Before delving into detailed statistical techniques, let's revisit three research questions.

Revisit of Research Questions

Research Question 1 (RQ1): Were the proportions of passing co-requisite math courses significantly different between students who utilized EdReady and those who did not?

Research Question 2 (RQ2): Were the proportions of passing co-requisite math courses significantly different among students who required different levels of math remediation (Least, Medium, and Most)?

RQ2 was further subdivided into three sub-questions, because of the existence of three levels of remediation: Least, Medium, and Most.

Research Question 2a (RQ2a): Were the proportions of passing co-requisite math courses significantly different between students who required the most math remediation and those who only needed the medium level of math remediation?

Research Question 2b (RQ2b): Were the proportions of passing co-requisite math courses significantly different between students who required the most math remediation and those who only needed the least math remediation?

Research Question 2c (RQ2c): Were the proportions of passing co-requisite math courses significantly different between students who required the medium level of math remediation and those who needed the least math remediation?

Research Question 3 (RQ3): What were the significant factors predicting the likelihood of underprepared students passing a co-requisite college-level math class? If such significant factors existed, to what extent did they influence this probability, and what was the developed logistic regression model?

Among the investigation of these research questions, two-sample proportion tests were conducted to answer RQ1 and RQ2 (i.e., RQ2a, RQ2b and RQ2c), and a binary logistic regression was performed to answer RQ3. The following section provided detailed introduction about these two quantitative approaches.

Two-sample Proportion Test

A two-sample proportion test is a type of hypothesis test that compares the proportions of two distinct populations. They are used to determine whether the difference between the proportions is statistically significant. The test statistic is calculated as:

$$z = \frac{p_1 - p_2}{\sqrt{p(1-p)(\frac{1}{n_1} + \frac{1}{n_2})}}$$

where:

p = total pooled proportion, $p = (p_1 n_1 + p_2 n_2)/(n_1 + n_2)$

p_1 = sample 1 proportion

p_2 = sample 2 proportion

n_1 = sample 1 size

n_2 = sample 2 size

The hypothesis statements performed in a two-sample proportion test were formulated as follows:

Null hypothesis: H_0: $p_1 = p_2$

Alternative hypothesis: H_1: $p_1 \neq p_2$

Here, p_1 , represents the first sample proportion, and p_2 , denotes the second sample proportion. The null hypothesis assumes that there is no difference in two proportions. Conversely, the alternative hypothesis suggests that the two proportions are significantly different. Additionally, the significance level α is set at 0.05 to determine the threshold for rejecting the null hypothesis.

RQ1 (EdReady V.S Not EdReady)

To investigate Research Question 1, a two-sample proportion test was employed to compare the proportions of passing co-requisite math courses between students who utilized EdReady and those who did not. The hypothesis statements were formulated as follows:

Null hypothesis: H_0: $p_1 = p_2$

Alternative hypothesis: H_1: $p_1 \neq p_2$

Here, p_1 , represents the first sample proportion, indicating the proportion of students passing co-requisite courses after using EdReady. Similarly, p_2 , denotes the second sample proportion, representing the proportion of students who passed co-requisite courses without using EdReady.

The null hypothesis posited that there was no difference in the proportions of students passing co-requisite math courses between underprepared students who utilized

EdReady and those who did not. Conversely, the alternative hypothesis suggested that the two proportions were significantly different, indicating a potential effect of EdReady on students' success rates in co-requisite math courses. Additionally, the significance level α was set at 0.05 to determine the threshold for rejecting the null hypothesis.

RQ2a (Most Remediation V.S Medium Remediation)

Applying a two-sample proportion test to investigate RQ2a, the test was performed to compare the proportions of passing co-requisite math courses between students who needed the most remediation and those who required the medium level of remediation. The hypothesis statements were formulated as follows:

Null hypothesis: H_0: $p_1 = p_2$

Alternative hypothesis: H_1: $p_1 \neq p_2$

Here, p_1 represented the proportion of success for students who required the most remediation, while p_2 represented the proportion of success for students who needed the medium level of remediation. The null hypothesis assumed that there was no difference in the proportions of passing co-requisite math courses between underprepared students who required the most math remediation and those who needed the medium level. Conversely, the alternative hypothesis suggested that the two proportions were significantly different.

RQ2b (Most Remediation V.S Least Remediation)

Similar with RQ2a, to investigate Research Question 2b, a two-sample proportion test was employed to compare the proportions of passing co-requisite math courses between students who needed the most remediation and those who only required the least level of remediation. The hypothesis statements were formulated as follows:

Null hypothesis: $H0: p1 = p2$

Alternative hypothesis: $H1: p1 \neq p2$

This statistical test compares the success rates between two groups—students who needed the most remediation and those who needed the least level of remediation. Here, p_1 , the first sample proportion, representing the proportion of passing co-requisite math course among students who required the most remediation. Similarly, p_2 the second sample proportion, represents the proportion of students passing corequisite math class, who needed the least math remediation.

The null hypothesis posited that there was no difference in the proportions of passing co-requisite math courses between underprepared students who required the most math remediation and those who needed the least level. Conversely, the alternative hypothesis suggested that the two proportions were significantly different, Again, the significance level was chosen as $\alpha = 5\%$.

RQ2c (Medium Remediation V.S Least Remediation)

Like RQ2a and RQ2b, to investigate Research Question 2c, a two-sample proportion test was employed to compare the proportions of passing co-requisite math courses between students who needed the medium remediation and those who required the least level of remediation. The hypothesis statements were formulated as follows:

Null hypothesis: H_0: $p_1 = p_2$

Alternative hypothesis: H_1: $p_1 \neq p_2$

This statistical test compares the success rates between two groups. Here, p_1 , the first sample proportion, representing the proportion of passing co-requisite math course among students who required the medium remediation. Similarly, p_2 the second sample proportion, represents the proportion of students passing corequisite math class, who needed the least remediation.

The null hypothesis posited that there was no difference in the proportions of passing co-requisite math courses between underprepared students who required the medium math remediation and those who needed the least level. Conversely, the alternative hypothesis suggested that the two proportions were significantly different, Again, the significance level was chosen as $\alpha = 5\%$.

Binary Logistic Regression

To gain a better understanding of binary logistic regression, let's first conduct a quick review of linear regression analysis. Linear regression is a well-known statistical analysis used to predict the value of a numerical dependent variable (response), Y, based on a set of independent variables (predictors). The general form of a regression equation is expressed as:

$$Y = b_0 + b_1X_1 + \ldots + b_iX_i$$

Here, each X_i is a predictor and each b_i is the regression coefficient. Given a set of X_i values, we can predict the corresponding Y value using this linear regression equation.

While linear regression is suitable for predicting continuous numeric outcomes, binary logistic regression is specifically designed for binary outcomes. Binary logistic regression is employed when the dependent variable is dichotomous, meaning it has only two possible outcomes (commonly coded as 0 and 1). In educational research, for instance, binary logistic regression could be used to predict whether a student passes (1) or fails (0) a final exam based on various independent variables such as study time, attendance, and previous performance.

In linear regression, the predicted values can range from negative to positive infinity, making it unsuitable for modeling binary outcomes. In contrast, binary logistic regression employs the logistic function to constrain predicted values between 0 and 1, aligning with the probabilities associated with binary outcomes. Understanding the distinctions between linear regression and binary logistic regression is fundamental for researchers to choose the appropriate model based on the nature of their dependent variable.

Again, Binary Logistic Regression is the appropriate statistical analysis to predict a binary outcome for a response variable based on the values of a set of predictors or independent variables, which can be categorical and/or numerical. Assume p is the probability of an event occurring, the general form of a binary logistic regression equation is expressed as:

$$logit(p) = b_0 + b_1X_1 + \ldots + b_iX_i$$

Here, each X_i is a predictor and each b_i is the regression coefficient. Given a set of X_i values, we can predict the corresponding $logit(p)$ value using this regression equation. Since $logit\ (p) = \ln\left(\frac{p}{1-p}\right)$, we can rewrite:

$$\ln\left(\frac{p}{1-p}\right) = b_0 + b_1X_1 + \ldots + b_kX_k$$

By solving this equation for p, the probability of an event occurring is:

$$p = \frac{\exp\left(b_0 + b_1X_1 + \ldots + b_kX_k\right)}{1 + \exp\left(b_0 + b_1X_1 + \ldots + b_kX_k\right)}$$

All statistical methods have assumptions that must be met to ensure the validity of the analysis. Here are the assumptions for binary logistic regression (Hosmer, Lemeshow & Sturdivant, 2013):

a) Binary outcome: The dependent variable must be dichotomous which must have only two possible outcomes, converting to 1 or 0.

b) Linearity: The relationship between each independent variable and the log odds of the outcome must be linear. This assumes that the change in log odds is constant for a one-unit change in the independent variable.

c) Independence: Observations must be independent of each other. This means that the occurrence of the outcome for one observation should not influence the occurrence of the outcome for any other observation.

d) No multicollinearity: The independent variables should not be highly correlated with each other. High multicollinearity can lead to unstable estimates of the coefficients and reduce the reliability of the model.

e) Adequate sample size: The sample size should be large enough to ensure stable estimates of the coefficients. Small sample sizes can lead to imprecise and unreliable parameter estimates.

RQ3

To explore Research Question 3, a binary logistic regression was employed to investigate significant factors to predict the likelihood of underprepared students passing a co-requisite college-level math class. The hypothesis statements for RQ3 were formulated as follows:

Null hypothesis: H_0: $B_1 = B_2 = \ldots = B_9 = B_{10} = 0$

Alternative hypothesis: H_1: At least one $B_i \neq 0$

The null hypothesis states that all coefficients for the ten independent variables in the model are equal to zero. In other words, it assumes that none of the ten predictor variables has a statistically significant relationship with the response variable, Success. Conversely, the alternative hypothesis suggests that at least one of the coefficients is not equal to zero, indicating that at least one independent variable is significant to predict the likelihood of underprepared students passing a co-requisite college-level math class. The significance level (α=5%) was set to determine the threshold for rejecting the null hypothesis.

Data Collection and Ethical Considerations

As mentioned earlier, the research relied on historical academic records sourced from the student information systems at the college. The data were not actually "collected" but retrieved by the office of institutional research. The data for all variables needed to address all five research questions in the study were contained in the retrieved students' records; therefore, no data recruitment process was necessary. Additionally, all personal identifiers were removed from the data.

To ensure the confidentiality and security of the data, strict steps were implemented during the data collection process. The data were securely transferred from the Office of Institutional Research at the college using a portable flash drive and stored in a password-protected folder. Furthermore, access to the data was restricted, with an additional passcode protecting the information itself.

Ethical considerations were also addressed, as the study underwent review by the institutional review board (IRB) at the University of Nevada, Reno (UNR). This approach aligned with IRB policy, specifically policies regarding exempt research that involved minimal risk and did not require participant recruitment. The study received the determination of an exempt research from the IRB office at UNR, affirming its adherence to ethical standards and guidelines for research involving human subjects.

Summary

Chapter Three of this study provided a comprehensive exploration of the research design, sample characteristics, variables studied, and quantitative data analysis techniques employed. It began by explaining the three primary categories of quantitative research designs: non-experimental, experimental, and quasi-experimental. The chapter then delved into the sample selection process, detailing the criteria for inclusion and the retrieval of historical academic records from the college's student information systems. Ethical considerations regarding data confidentiality and IRB approval were underscored, ensuring compliance with rigorous ethical standards.

Furthermore, the chapter explained the dependent and independent variables examined in the study. These variables were crucial for understanding the factors influencing students' performance in co-requisite math courses. Additionally, the chapter discussed the quantitative data analysis techniques employed, namely the two-sample proportion test and binary logistic regression, which were utilized to address the research questions formulated in the study. Through a rigorous methodological approach and adherence to ethical guidelines, Chapter Three set the stage for the subsequent analysis of data results, advancing our understanding of factors contributing to underprepared students' success in co-requisite math education.

Chapter Four: Data Analysis and Results

Chapter 4 delves into the descriptive results and data analysis of the study, focusing on various research questions aimed at understanding the factors influencing the success rates of underprepared students in co-requisite math courses. The chapter begins with a detailed overview of the response variable, success, and key independent variables such as EdReady usage, gender, course enrollment, and remediation level. Descriptive statistics, including frequency tables and bar charts, provide insights into the distribution of students across these variables. Following this, the chapter presents comprehensive data analysis and the corresponding results of statistical tests conducted for Research Questions 1, 2, and 3.

For Research Question 1, which explores the impact of EdReady usage on success rates, a two-sample proportion test reveals a significant difference in success rates between students who utilize EdReady and those who do not. Moving to Research Question 2, which investigates success rates based on different levels of remediation, mixed results are found. While no significant difference is observed between students needing the most and medium levels of remediation (RQ2a), a significant difference is found between those needing the most and least levels of remediation (RQ2b), as well as those needing medium and least levels of remediation (RQ2c). Finally, Research Question 3 focuses on identifying significant predictors of student success, leading to the development of a logistic regression model. The refined model highlights EdReady usage, arithmetic test scores, and time spent studying in EdReady as significant factors predicting success in co-requisite math courses. The chapter concludes by presenting the refined logistic regression model's equation and interpretations of coefficients, providing valuable insights into the relationship between predictor variables and the likelihood of student success.

Descriptive Results

Response: Success

Success served as the dependent variable (response) in this study, characterized as a binary variable with two values: 1 or 0. A value of 1 denoted that a student successfully passed the class, while a value of 0 indicated failure. The frequency table below illustrates the distribution of students based on their success in the course. Out of 367 students, 145 students (39.5%) failed their co-requisite math courses, while 222 students (60.5%) successfully passed. The frequency table and bar chart were provided below as Table 4.1 and Figure 4.1.

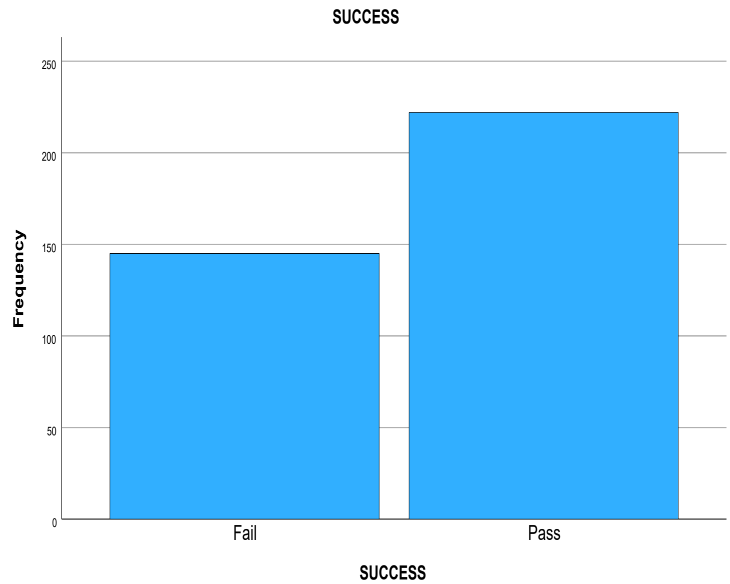
Table 4.1

Frequency Table of Success

	N	%
Fail	145	39.5
Pass	222	60.5

Figure 4.1

Bar Chart of Success



Predictor: EdReady

EdReady served as an independent variable (predictor) in this study, a categorical variable with values 1 and 0. A value of 1 denoted that a student utilized the adaptive learning platform – EdReady, whereas a value of 0 indicated the opposite. Among the total of 367 students in the study, 155 students (42.2%) did not use EdReady, while 212 students (57.8%) used EdReady. The frequency table and bar chart illustrating the distribution of students based on their utilization of EdReady are provided below. See Table 4.2 and Figure 4.2.

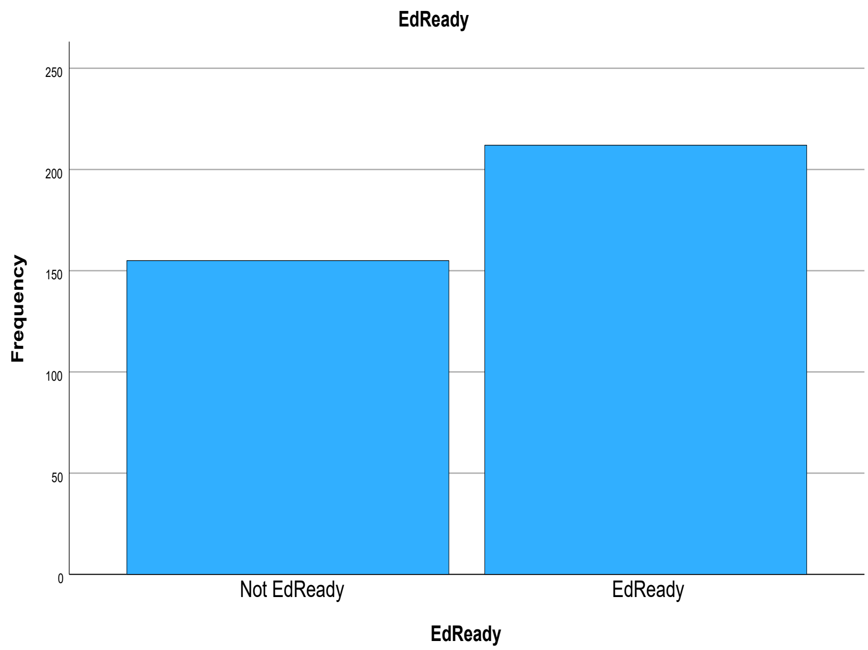
Table 4.2

Frequency Table of EdReady

	N	%
Not EdReady	155	42.2
EdReady	212	57.8

Figure 4.2

Bar Chart of EdReady



Predictor: Gender

Gender was a categorical variable represented by values 1 and 0, where 1 indicated female and 0 represented male. It served as a predictor in the study. Among the 367 students, 114 students (31.1%) were male, and 253 students (68.9%) were female. The frequency table and bar chart illustrating this distribution are provided below. See Table 4.3 and Figure 4.3.

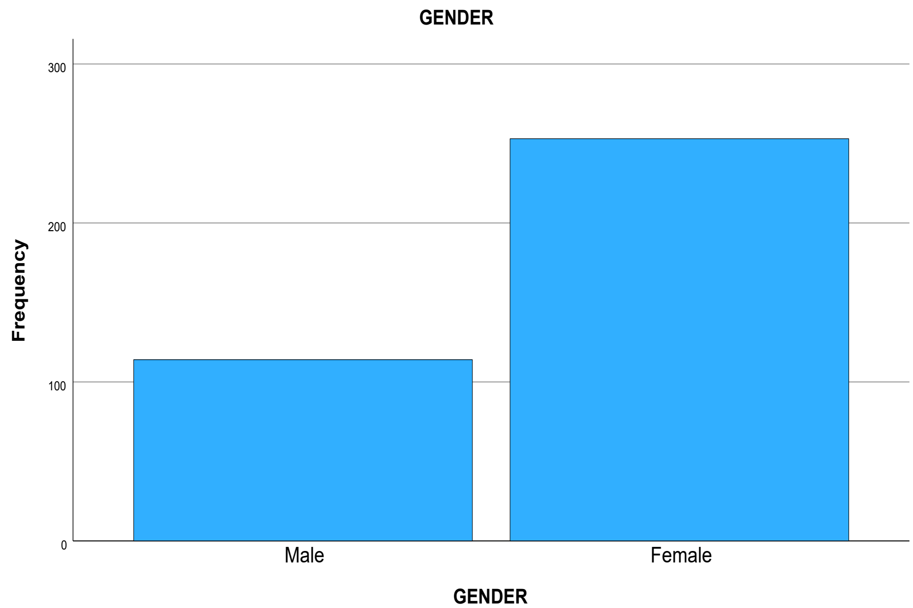
Table 4.3

Frequency Table of Gender

	N	%
Male	114	31.1
Female	253	68.9

Figure 4.3

Bar Chart of Gender



Predictor: Course

Course, functioning as a predictor, was a categorical variable with values 1 and 0. A value of 1 corresponded to enrollment in the co-requisite math course Math120 (Fundamental of Mathematics), while 0 indicated enrollment in Math126E (Precalculus I). Among the 367 students, 178 students (48.5%) were enrolled in Math126, and 189 students (51.5%) were enrolled in Math120E. The frequency table and bar chart depicting this distribution are provided below. See Table 4.4 and Figure 4.4.

Table 4.4

Frequency Table of Course

	N	%
Math126E	178	48.5
Math120E	189	51.5

Figure 4.4

Bar Chart of Course

Predictors: MostRemed & LeastRemed

Remediation was a categorical variable with three values: 1, 2, and 3, representing the three levels of math remediation that students needed. The values 1, 2, and 3 corresponded to the most, medium, and least levels of remediation, respectively. Among the 367 students in the sample, 105 students (28.6%) required the most level of remediation, 223 students (60.8%) needed a medium level of math remediation, and only 39 students (10.6%) required the least level of math remediation. The frequency table and bar chart illustrating these proportions are provided below. See Table 4.5 and Figure 4.5.

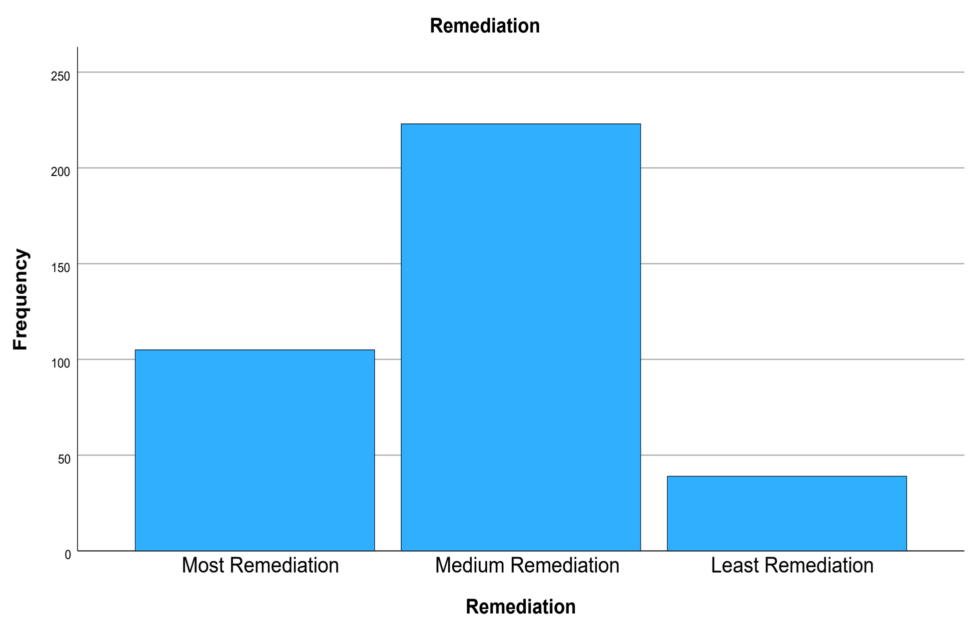
Table 4.5

Frequency Table of Remediation

	N	%
Most Remediation	105	28.6
Medium Remediation	223	60.8
Least Remediation	39	10.6

Figure 4.5

Bar Chart of Remediation



For the dummy variable MostRemed, the value of 1 represented the most remediation, while the value of 0 represented either the moderate or the lowest level of remediation needed. Among the 367 students in the sample, 105 students (28.6%) were identified as needing the most remediation, while 262 students (71.4%) required either medium or the least math remediation. The frequency table and bar chart for MostRemed are provided below. See Table 4.6 and Figure 4.6.

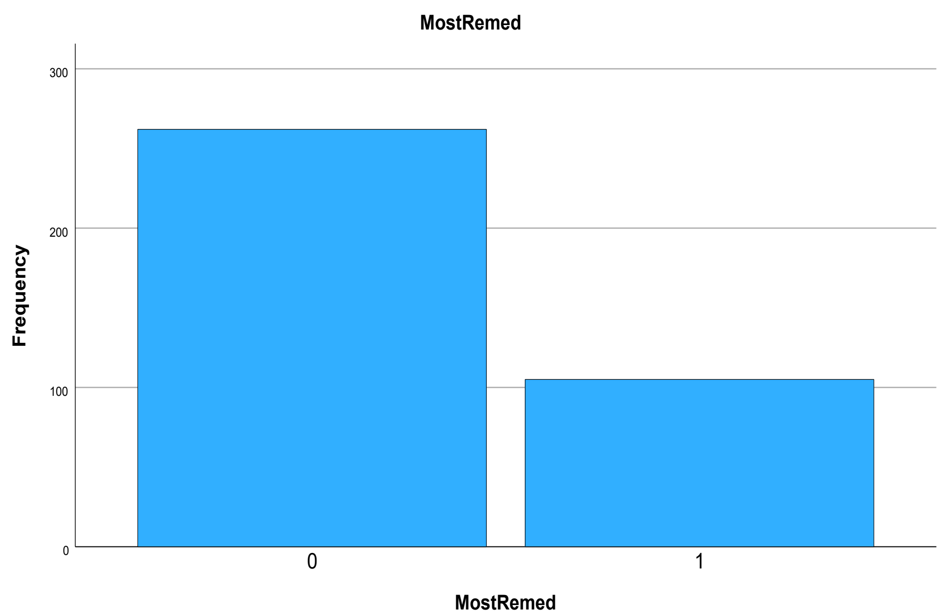
Table 4.6

Frequency Table of MostRemed

	N	%
Medium or Least Remediation	262	71.4
Most Remediation	105	28.6

Figure 4.6

Bar Chart of MostRemed



For the dummy variable LeastRemed, the value of 1 indicated the lowest level of remediation, while the value of 0 indicated either the most or the medium remediation needed. Among the 367 students in the sample, only 39 students (10.6%) were identified as needing the lowest level of remediation, while 328 students (89.4%) required either the most or medium level of math remediation. The frequency table and bar chart for LeastRemed are provided below. See Table 4.7 and Figure 4.7.

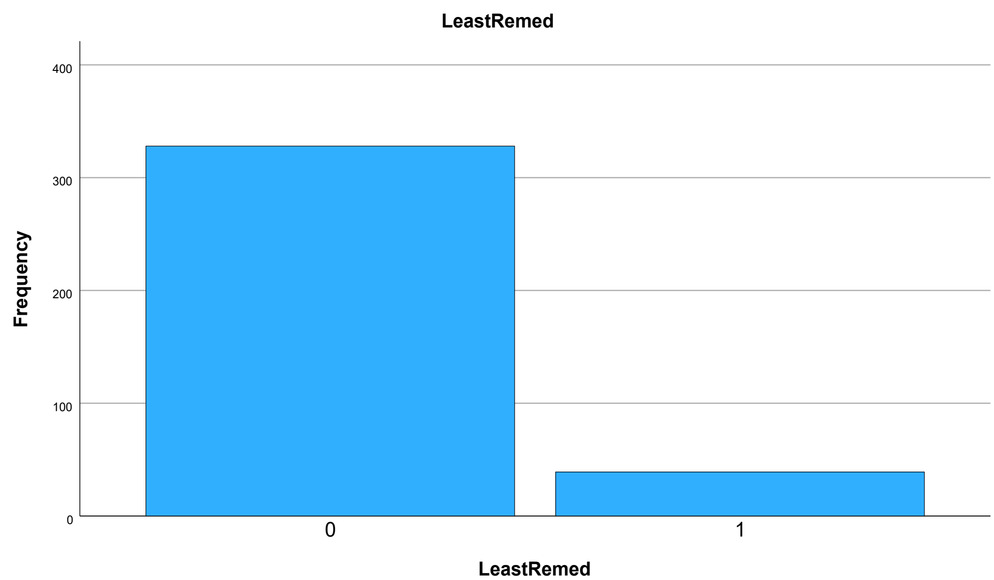
Table 4.7

Frequency Table of LeastRemed

	N	%
Most and Medium Remediation	328	89.4
Least Remediation	39	10.6

Figure 4.7

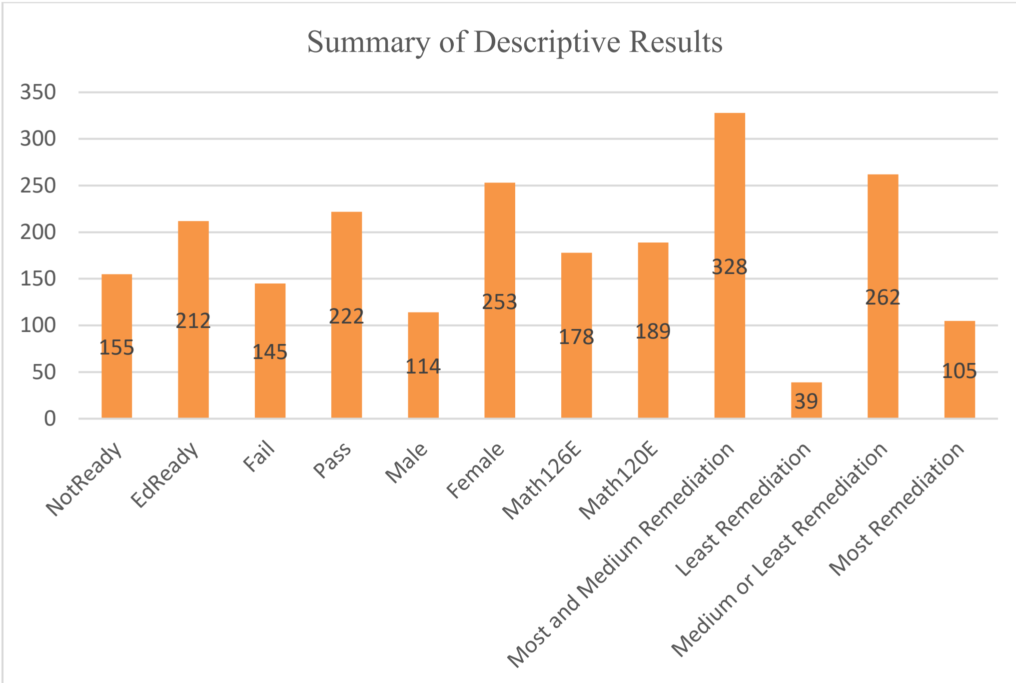
Bar Chart of LeastRemed



Putting the above descriptive results together, an overall bar graph is illustrated in Figure 4.8.

Figure 4.8

Summary of Descriptive Results



Predictors: Arithmetic, QuantReasoning, AdvAlgebra and Time

Arithmetic, Quantitative Reasoning (QuanReasoning), and Advanced Algebra (AdvAlgebra) were continuous independent variables, recording students' Accuplacer test scores for three sections of placement tests. Time, another continuous independent variable, recorded the time (measured in minutes) that students spent studying in EdReady. Descriptive statistics showed that Arithmetic had an average of 255.65 with a standard deviation 16.109, its minimum and maximum values were 200 and 300; Quantitative Reasoning had an average 246.56 with a standard deviation of 14.399, a minimum of 200 and a maximum of 282. Advanced Algebra had an average 203.48 with a standard deviation 10.699, a minimum of 200 and a maximum of 258. Time had a mean of 42.54 with a standard deviation of 129.855, a minimum of 0 and a maximum of 920 minutes. See Table 4.8.

Table 4.8

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
AdvAlgebra	367	200	258	203.48	10.669
Arithmetic	367	200	300	255.65	16.109
QuantReasoning	367	200	282	246.56	14.399
Time	367	0	920	42.54	129.855

Data Analysis and Results for RQ1

Research Question 1: Were the proportions of passing co-requisite math courses significantly different between students who utilized EdReady and those who did not?

Upon analyzing the data using SPSS, the output results of the two-sample proportion test are provided below. See Table 4.9, Table 4.10, and Table 4.11.

Table 4.9

Proportions Statistics - EdReady V.S Not EdReady

	EdReady	Successes	Trials	Proportion	Asymptotic Standard Error
SUCCESS = Pass	= EdReady	148	212	.698	.032
	= Not EdReady	74	155	.477	.040

Table 4.10

Two-sample Proportion Test - EdReady V.S Not EdReady

	Test Type	Difference in Proportions	Asymptotic Standard Error	Z	Significance	
					One-Sided p	Two-Sided p
SUCCESS = Pass	Wald H0	.221	.051	4.272	<.001	<.001

Table 4.11

95% Confidence Interval of the Difference (EdReady minus Not EdReady)

	Interval Type	Difference in Proportions	Asymptotic Standard Error	95% Confidence Interval of the Difference	
				Lower	Upper
SUCCESS = Pass	Agresti-Caffo	.221	.051	.119	.318
	Newcombe	.221	.051	.119	.317

The SPSS test results uncovered that p_1 = 69.8% and p_2 = 47.7%. It meant that 69.8% of students who utilized EdReady successfully passed their co-requisite math courses, however, only 47.7% of students who did not use EdReady passed their co-requisite math courses. A notable difference of 21.1% was observed, comparing p_1 with p_2. However, was this difference statistically significant? Further examination from the test results indicated a rejection of the null hypothesis, suggesting a statistically significant distinction in the proportions of students passing co-requisite math courses between those who utilized EdReady and those who did not, because the statistical output revealed a substantial test statistic ($Z = 4.272$) and a remarkably low p-value (< 0.001), and both surpassing the conventional threshold for statistical significance ($\alpha = 5\%$).

Additionally, the computation of a 95% Confidence Interval of the Difference, utilizing the Newcombe interval type, reinforced the significance of this discrepancy, as the interval (11.9% to 31.7%) did not encompass zero.

In a summary, based the two-sample proportion test results, enough evidence was found to reject the null hypothesis, and to support that the proportion of students passing co-requisite math courses after the utilization of EdReady was significantly different from those who did not use EdReady. The statistical analysis conclusively demonstrated that students who utilized EdReady exhibited markedly higher success rates in passing co-requisite math courses compared to those who did not use the platform. These findings underscore a potential efficacy of EdReady as a supportive learning platform in facilitating student success in math education.

Data Analysis and Results for RQ2a

Research Question 2a: Were the proportions of passing co-requisite math courses significantly different between students who required the most math remediation and those who only needed the medium level of math remediation?

Upon analyzing the data using SPSS, the output results were provided as below. See Table 4.12, Table 4.13, and Table 4.14.

Table 4.12

Proportions Statistics - Most Remediation V.S Medium Remediation

	RemedLevel	Successes	Trials	Proportion	Asymptotic Standard Error
SUCCESS = Pass	= Most Remediation	58	105	.552	.049
	= Medium Remediation	135	223	.605	.033

Table 4.13

Two-sample Proportion Test - Most Remediation V.S Medium Remediation

	Test Type	Difference in Proportions	Asymptotic Standard Error	Z	Significance	
					One-Sided p	Two-Sided p
SUCCESS = Pass	Wald H0	-.053	.059	-.910	.181	.363

Table 4.14

95% Confidence Interval of the Difference (Most Remediation minus Medium Remediation)

	Interval Type	Difference in Proportions	Asymptotic Standard Error	95% Confidence Interval of the Difference	
				Lower	Upper
SUCCESS = Pass	Agresti-Caffo	-.053	.059	-.167	.061
	Newcombe	-.053	.059	-.167	.060

The SPSS test results showed that p_1 = 55.2% and p_2 = 60.5%. It meant that 55.2% of students who needed the most remediation passed their co-requisite math courses, and 60.5% of students who needed the medium level of math remediation passed their co-requisite math courses. A difference of 5.3% was observed, comparing p_1 with p_2.

To find out if this difference is statistically significant, a further examination was followed. The SPSS test results indicated it was failed to reject the null hypothesis, suggesting no significant difference in the proportions of students passing co-requisite math courses existed, between those who needed the most remediation and who needed the medium level, because of a test statistic Z = -0.910 and a p-value 0.363 which was greater than the level of significance (α = 5%).

Additionally, the computation of a 95% Confidence Interval of the Difference, utilizing the Newcombe interval type, reinforced the non-significance of this discrepancy, as the interval (-16.7% to 6%) included zero.

In a summary, the outcomes of the two-sample proportion test signified a failure to reject the null hypothesis, suggesting no significant difference in passing rates of co-requisite math classes between two groups. Therefore, the conclusion was made that the proportions of passing co-requisite math courses were not significantly different between students necessitating the most extensive math remediation and those requiring a medium level.

Data Analysis and Results for RQ2b

Research Question 2b: Were the proportions of passing co-requisite math courses significantly different between students who required the most math remediation and those who only needed the least math remediation?

Upon analyzing the data using SPSS, the output results were provided as below. See Table 4.15, Table 4.16, and Table 4.17.

Table 4.15

Proportions Statistics - Most Remediation V.S Least Remediation

	RemedLevel	Successes	Trials	Proportion	Asymptotic Standard Error
SUCCESS = Pass	= Most Remediation	58	105	.552	.049
	= Least Remediation	29	39	.744	.070

Table 4.16

Two-sample Proportion Test - Most Remediation V.S Least Remediation

	Test Type	Difference in Proportions	Asymptotic Standard Error	Z	Significance	
					One-Sided p	Two-Sided p
SUCCESS = Pass	Wald H0	-.191	.085	-2.085	.019	.037

Table 4.17

95% Confidence Interval of the Difference (Most Remediation minus Least Remediation)

	Interval Type	Difference in Proportions	Asymptotic Standard Error	95% Confidence Interval of the Difference Lower	Upper
SUCCESS = Pass	Agresti-Caffo	-.191	.085	-.345	-.015
	Newcombe	-.191	.085	-.337	-.012

The SPSS test results showed that p1 = 55.2% and p2 = 74.4%. It meant that 55.2% of students who needed the most remediation passed their co-requisite math courses, and 74.4% of students who needed the least level of math remediation passed their co-requisite math courses. A difference of 19.1% was observed, comparing p_1 with p_2.

To find out if this difference is statistically significant, a further examination was followed. The SPSS test results indicated enough evidence to reject the null hypothesis, suggesting significant difference in the proportions of students passing co-requisite math courses existed, between those who needed the most remediation and who needed the least level, with a test statistic Z = -2.085 and a p-value 0.037 which was less than the level of significance ($\alpha = 5\%$).

Additionally, the computation of a 95% Confidence Interval of the Difference, utilizing the Newcombe interval type, reinforced the non-significance of this discrepancy, as the interval (-33.7% to -1.2%) included zero.

In a summary, the outcomes of the two-sample proportion test demonstrated enough evidence to reject the null hypothesis, suggesting there was significant difference in passing rates of co-requisite math classes between two groups. Therefore, the conclusion was made that the proportions of passing co-requisite math courses were significantly different between students necessitating the most math remediation and those requiring the least level.

Data Analysis and Results for RQ2c

Research Question 2c: Were the proportions of passing co-requisite math courses significantly different between students who required the medium level of math remediation and those who needed the least math remediation?

Upon analyzing the data using SPSS, the output results were provided as below. See Table 4.18, Table 4.19, and Table 4.20.

Table 4.18

Proportions Statistics - Medium Remediation V.S Least Remediation

	RemedLevel	Successes	Trials	Proportion	Asymptotic Standard Error
SUCCESS = Pass	= Medium Remediation	135	223	.605	.033
	= Least Remediation	29	39	.744	.070

Table 4.19

Two-sample Proportion Test - Medium Remediation V.S Least Remediation

	Test Type	Difference in Proportions	Asymptotic Standard Error	Z	Significance One-Sided p	Significance Two-Sided p
SUCCESS = Pass	Wald H0	-.138	.077	-1.646	.050	.100

Table 4.20

95% Confidence Interval of the Difference (Medium Remediation minus Least Remediation)

	Interval Type	Difference in Proportions	Asymptotic Standard Error	95% Confidence Interval of the Difference	
				Lower	Upper
SUCCESS = Pass	Agresti-Caffo	-.138	.077	-.277	.023
	Newcombe	-.138	.077	-.267	.028

The SPSS test results showed that p1 = 60.5% and p2 = 74.4%. It meant that 60.5% of students who needed the medium level of remediation passed their co-requisite math courses, and 74.4% of students who needed the least level of math remediation passed their co-requisite math courses. A difference of 13.8% was observed, comparing p_1 with p_2.

To find out if this difference is statistically significant, a further examination was followed. The SPSS test results indicated it was failed to reject the null hypothesis, suggesting no significant difference in the proportions of students passing co-requisite math courses existed, between those who needed the medium level of remediation and who needed the least remediation, with a test statistic Z = -1.646 and a p-value 0.1 which was greater than the level of significance (α = 5%).

Additionally, the computation of a 95% Confidence Interval of the Difference, utilizing the Newcombe interval type, reinforced the non-significance of this discrepancy, as the interval (-26.7% to 2.8%) included zero.

In a summary, the outcomes of the two-sample proportion test demonstrated a failure to reject the null hypothesis, suggesting no significant difference in passing rates of co-requisite math classes between two groups. Therefore, the conclusion was made that the proportions of passing co-requisite math courses were not significantly different between students necessitating the medium level of math remediation and those requiring the least remediation.

Data Analysis and Results for RQ3

Research Question 3: What were the significant factors predicting the likelihood of underprepared students passing a co-requisite college-level math class? If such significant factors existed, to what extent did they influence this probability, and what was the logistic regression model?

To investigate for Research Question 3, a binary logistic regression was conducted in SPSS, aiming to investigate significant factors to predict the likelihood of underprepared students passing a co-requisite college-level math class. The list of variables was provided as blow. See Table 4.21 and Table 4.22.

Table 4.21

Dependent Variables Utilized in Binary Logistic Regression

Name	Type	Value
Success	Dichotomous	1 = Success/Pass; 0 = Failure/Fail

Table 4.22

Independent Variables Utilized in Binary Logistic Regression

Name	Type	Value
EdReady	Categorical	1 = Used EdReady; 0 = Not use EdReady
Course	Caterorical	1 = Math120E (Fundamental of Mathematics); 0 = Math126E (Precalculus I)
Gender	Categorical	1 = Female; 0 = Male
RemedLevel	Categorical	1 = Most Remediation 2 = Medium Remediation

		3 = Least Remediation
MostRemed	Dummy variable	1 = Most Remediation 0 = Medium or Least Remediation
LeastRemed	Dummy variable	1 = Least Remediation 0 = Most or Medium Remediation
Age	Continuous	Student's age
Arithmetic	Continuous	Student's placement test score in Arithmetic
QuantReasoning	Continuous	Student's placement test score in Quantitative Reasoning
AdvAlgebra	Continuous	Student's placement test score in Advanced Algebra
Time	Continuous	Student's studying time in EdReady (minutes)

The hypothesis statements for RQ3 were formulated as follows:

Null hypothesis: H_0: $B_1 = B_2 = \ldots = B_9 = B_{10} = 0$

Alternative hypothesis: H_1: At least one $B_i \neq 0$

The null hypothesis stated that all coefficients for these ten predictors in the model were equal to zero. In other words, it assumed that none of ten independent variables had a statistically significant relationship with the response variable, Success. Conversely, the alternative hypothesis suggested that at least one of the coefficients was not equal to zero, indicating that at least one predictor was significant in predicting the likelihood of underprepared students passing a co-requisite college-level math.

Analysis of Test Results

Upon the statistical test outputs after running a binary logistic regression is SPSS, the analysis of test results was provided as follows.

1) Significance of The Full Model

To evaluate the significance of the full model, the Omnibus Tests of Model Coefficients was used and analyzed. See Table 4.23.

Table 4.23

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	42.776	10	<.001
	Block	42.776	10	<.001
	Model	42.776	10	<.001

In this table, the Chi-square statistic with 10 degrees of freedom, χ^2 (10), yielded a value of 42.776, with a p-value of less than .001. The rejection of the null hypothesis suggested that the full model significantly differed from a null model, which assumed even odds. Consequently, the full model comprising ten independent variables was deemed statistically significant.

2) Goodness-of-Fit Test

A goodness-of-fit test was conducted to evaluate how well the model aligns with the observed data, utilizing the Hosmer and Lemeshow Test, see Table 4.24.

Table 4.24

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.730	8	.460

In this table, the chi-square statistic with 8 degrees of freedom, χ^2 (8), yielded a value of 7.730, with a corresponding p-value of 0.460, which was greater than the chosen significance level of 0.05. The failure to reject the null hypothesis indicated that there was no significant difference between the observed and expected frequencies, suggesting that the model adequately fits the data.

3) Strength of Association

To assess the strength of the association between the model and the dependent variable, the Model Summary table was utilized. See Table 4.25.

Table 4.25

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	449.718[a]	.110	.149

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

The strength of the association between the model, consisting of ten independent variables, and the dependent variable was represented by a Nagelkerke R^2 value of 0.149. This implies that 14.9% of the variation in the dependent variable could be explained by the model. While the model demonstrated statistical significance in predicting the dependent variable, the relatively modest percentage of explained variation suggests that there might be other independent variables not included in the model that could serve as significant predictors. Indeed, the strength of the association was one of the limitations in the study to be discussed later in the next chapter.

4) Significance of Independent Variables

The table of Variables in the Equation from the SPSS output was utilized to assess the significance of each independent variable. See Table 4.26.

Table 4.26

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	COURSE(1)	.356	.241	2.194	1	.139	1.428
	GENDER(1)	-.082	.266	.095	1	.757	.921
	AGE	-.002	.013	.014	1	.905	.998
	AdvAlgebra	-.033	.024	1.942	1	.163	.967
	Arithmetic	.025	.012	4.777	1	.029	1.026

QuantReasoning	.011	.018	.346	1	.556	1.011
EdReady(1)	.792	.237	11.208	1	<.001	2.208
Time	.004	.002	5.515	1	.019	1.004
MostRemed(1)	.570	.437	1.703	1	.192	1.768
LeastRemed(1)	1.091	.917	1.416	1	.234	2.977
Constant	-2.820	6.252	.203	1	.652	.060

a. Variable(s) entered on step 1: COURSE, GENDER, AGE, AdvAlgebra, Arithmetic, QuantReasoning, EdReady, Time, MostRemed, LeastRemed.

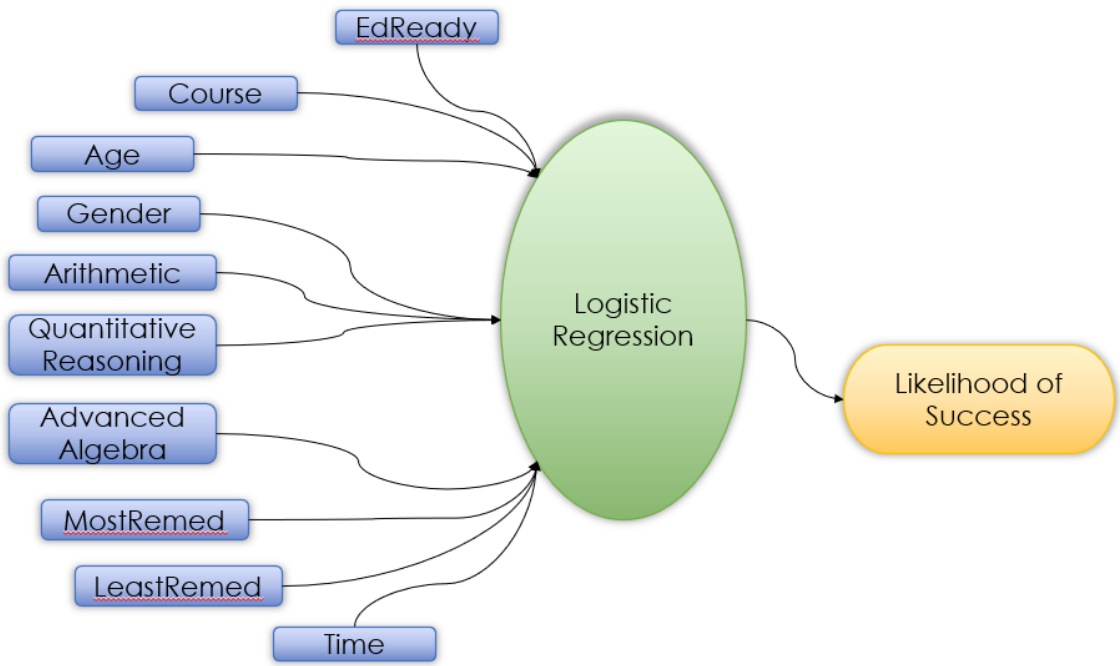
The Wald statistic and associated p-values were used to assess the significance of individual coefficients in the model. Notably, at a significance level of 0.05, the Wald statistics and p-values for the variables EdReady, Arithmetic, and Time were $\chi^2(1)$ = 11.208, p-value < 0.001, $\chi^2(1)$ = 4.777, p-value = 0.029, and $\chi^2(1)$ = 5.515, p-value = 0.019, respectively. Since the p-values for these three predictors were less than 0.05, it was concluded that the coefficients for EdReady, Arithmetic, and Time were significantly different from zero. Therefore, these variables were identified as significant factors in predicting the likelihood of underprepared students passing a co-requisite college-level math class.

Conversely, the Wald statistics and p-values for all other independent variables, including COURSE, GENDER, AGE, AdvAlgebra, QuantReasoning, MostRemed, and LeastRemed, were $\chi^2(1)$ = 2.194, p-value = 0.139, $\chi^2(1)$ = 0.095, p-value = 0.757, $\chi^2(1)$ = 0.014, p-value = 0.905, $\chi^2(1)$ = 1.942, p-value = 0.163, $\chi^2(1)$ = 0.346, p-value = 0.556, $\chi^2(1)$ = 1.703, p-value = 0.192, and $\chi^2(1)$ = 1.416, p-value = 0.234, respectively. As the p-values for these predictors were greater than 0.05, it was suggested that the coefficients for Course, Gender, Age, AdvAlgebra, QuantReasoning, MostRemed, and LeastRemed were not significantly different from zero. Hence, these variables were not identified as significant factors in predicting the likelihood of underprepared students passing a co-requisite college-level math class.

The original full model involving ten predictors was illustrated in Figure 4.9.

Figure 4.9

The Full Model of Student Success in Corequisite Math Course



5) Model Accuracy

The overall accuracy of the model was 64.9% correct, calculated as the total number of correctly predicted cases (59 + 179) divided by the total number of cases (59 + 86 + 43 + 179). This meant that the logistic regression model correctly predicted the outcome for 64.9% of the total cases. It was also observed that the model performed better in predicting "Pass" outcomes, with a higher percentage of correct predictions (80.6%). See Table 4.27.

Table 4.27

Classification Table (Full Model)

Observed			Predicted		
			SUCCESS		Percentage Correct
			Fail	Pass	
Step 1	SUCCESS	Fail	59	86	40.7
		Pass	43	179	80.6
	Overall Percentage				64.9

a. The cut value is .500

Model Refinement

In the context of logistic regression, the process of iteratively improving the model by selecting the most relevant predictor variables and eliminating those that do not contribute significantly to the prediction of the outcome variable was referred as Model Refinement (Hosmer, Lemeshow & Sturdivant, 2013). Hosmer, Lemeshow and Sturdivant emphasized that the model refinement process helped create a more interpretable model, meanwhile maintaining predictive accuracy.

Upon the previous logistic regression analysis and outputs in SPSS, a follow-up binary logistic regression, including only three significant predictors was conducted to refine and determine the final model. In the process of model refinement, the list of variables included one dependent variable and three independent variables. See Table 4.28. All other non-significant factors were eliminated from the model.

Table 4.28

Variables Utilized in Refined Model

Name	Type	Value
Success	Dichotomous	1 = Success/Pass; 0 = Failure/Fail
EdReady	Categorical	1 = Used EdReady; 0 = Not use EdReady
Arithmetic	Continuous	Student's placement test score in Arithmetic
Time	Continuous	Student's studying time in EdReady (minutes)

The hypothesis statements for the refined model were formulated as follows:

Null hypothesis: H_0: $B_1 = B_2 = B_3 = 0$

Alternative hypothesis: H_1: At least one $B_i \neq 0$

Similarly, the null hypothesis in the refined model stated that all three coefficients for three predictors in the model were equal to zero, which assumed that none of three predictor variables had a statistically significant relationship with the response variable, Success. Conversely, the alternative hypothesis suggested that at least one of the coefficients was not equal to zero, indicating that at least one independent variable was significant in predicting the likelihood of underprepared students passing a co-requisite college-level math.

A binary logistic regression was employed again in SPSS to ensure that the refined model was statistically sound and more accurate for predicting the dependent variable, Success.

1) Significance of The Refined Model

Based upon the SPSS outputs, the Omnibus Tests of Model Coefficients was used to evaluate the significance of the refined model. See Table 4.29.

Table 4.29

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	35.916	3	<.001
	Block	35.916	3	<.001
	Model	35.916	3	<.001

In this table, the Chi-square statistic with 3 degrees of freedom, χ^2 (3), yielded a value of 35.916, with a p-value of less than .001. The rejection of the null hypothesis suggested that the full model significantly differed from a null model, which assumed even odds. Consequently, the full model comprising three independent variables, EdReady, Arithmetic, and Time, was deemed statistically significant.

2) Goodness-of-Fit Test

A goodness-of-fit test was conducted to evaluate how well the refined model aligned with the observed data, utilizing the Hosmer and Lemeshow Test. See Table 4.30.

Table 4.30

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	7.494	8	.484

In this table, the chi-square statistic with 8 degrees of freedom, χ^2 (8), yielded a value of 7.494, with a corresponding p-value of 0.484, which was greater than the chosen significance level of 0.05. The failure to reject the null hypothesis indicated that there was no significant difference between the observed and expected frequencies, suggesting that the model adequately fits the data.

3) Strength of Association

To assess the strength of the association between the model and the dependent variable, the Model Summary table was utilized. See Table 4.31.

Table 4.31

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	456.578[a]	.093	.126

a. Estimation terminated at iteration number 5 because parameter estimates changed by less than .001.

In this refined model, the strength of the association between the model, consisting of three independent variables, and the dependent variable was represented by a Nagelkerke R^2 value of 0.126. This implied that 12.6% of the variation in the dependent variable could be explained by the model. Similar to the original full model, while the model demonstrated statistical significance in predicting the dependent variable, the relatively modest percentage of explained variation suggested that there may be other independent variables not included in the model that could serve as significant predictors.

4) Significance of Independent Variables

The table of Variables in the Equation from the SPSS output was utilized to assess the significance of each independent variable in this refined model. See Table 4.32.

Table 4.32

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	Arithmetic	.021	.007	8.282	1	.004	1.021
	Time	.003	.002	4.925	1	.026	1.003
	EdReady(1)	.774	.232	11.095	1	<.001	2.167
	Constant	-5.380	1.848	8.481	1	.004	.005

a. Variable(s) entered on step 1: Arithmetic, Time, EdReady.

The Wald statistic and associated p-values were used to assess the significance of individual coefficients in the model. Again, at a significance level of 0.05, the Wald statistics and p-values for the variables EdReady, Arithmetic, and Time were $\chi^2(1) = 11.095$, p-value < 0.001, $\chi^2(1) = 8.282$, p-value = 0.004, and $\chi^2(1) = 4.925$, p-value = 0.026, respectively. Since the p-values for these three predictors were less than 0.05, it was confirmed that the coefficients for EdReady, Arithmetic, and Time were significantly different from zero. Therefore, these three variables were identified as significant factors in predicting the likelihood of underprepared students passing a co-requisite college-level math class after the process of model refinement.

5) Model Accuracy

The overall accuracy of the refined model was 62.1% correct, calculated as the total number of correctly predicted cases (54 + 174) divided by the total number of cases (54 + 91 + 48 + 174). This meant that the logistic regression model correctly predicted the outcome for 62.1% of the total cases. It was also observed that the model performed better in predicting "Pass" outcomes, with a higher percentage of correct predictions (78.4%). See Table 4.33.

Table 4.33

Classification Table (Refined Model)

Observed			Predicted		
			SUCCESS		Percentage Correct
			Fail	Pass	
Step 1	SUCCESS	Fail	54	91	37.2
		Pass	48	174	78.4
	Overall Percentage				62.1

a. The cut value is .500

Equation of Predictive Model

In addition to identifying significant factors for predicting the likelihood of underprepared students passing a co-requisite college-level math class, Research Question 3 (RQ3) also aimed to develop a binary regression model and formulate an equation for predicting the likelihood.

Upon analyzing the SPSS outputs for the refined model, and assuming p is the probability of an underprepared student passing a co-requisite math class, the equation of the refined binary logistic regression model, consisting of three significant predictors (EdReady, Arithmetic, and Time), was formulated as follows:

$$logit(p) = B_0 + B_1 * EdReady + B_2 * Arithmetic + B_3 * Time$$

where Bi represented coefficients associated with individual predictors, obtained from the Variables in the Equation table in the SPSS outputs. Specifically, $B_0 = -5.380$, $B_1 = 0.774$, $B_2 = 0.021$ and $B_3 = 0.003$.

Therefore, the equation of the refined model in the study was expressed as:

$$logit(p) = -5.380 + 0.774 * EdReady + 0.021 * Arithmetic + 0.003 * Time \qquad (1)$$

Since $logit\ (p) = \ln\left(\frac{p}{1-p}\right)$, the equation could also be rewritten as:

$$\ln\left(\frac{p}{1-p}\right) = -5.380 + 0.774 * EdReady + 0.021 * Arithmetic + 0.003 * Time \qquad (2)$$

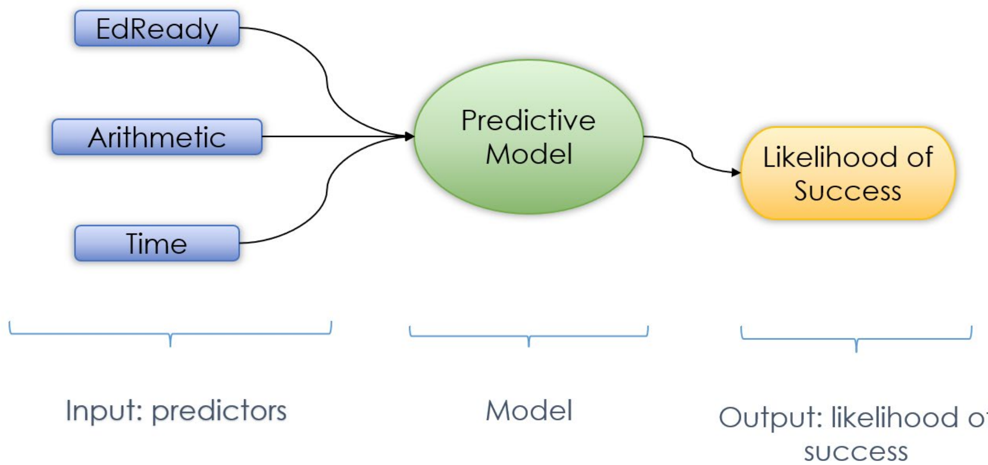
By solving this equation for p, the likelihood of an underprepared student passing a corequisite math course could be obtained by:

$$p = \frac{\exp\left(-5.380 + 0.774 * EdReady + 0.021 * Arithmetic + 0.003 * Time\right)}{1 + \exp\left(-5.380 + 0.774 * EdReady + 0.021 * Arithmetic + 0.003 * Time\right)}$$

The refined model was illustrated in Figure 4.10.

Figure 4.10

The Refined Predictive Model of Student Success in Corequisite Math Course



Interpretation of Coefficient and Exp(Coefficient)

Interpreting the coefficients and their exponentials (Exp(coefficient)) from a binary logistic regression is crucial for understanding the relationship between the predictor variables and the response variable. Upon reviewing the Variables in the Equation table from the statistical outputs in SPSS, the interpretations on the coefficients and their exponentials (Exp(coefficient)) for three predictors EdReady, Arithmetic, and Time were provided previously in Table 4.30.

EdReady

The coefficient of the predictor variable EdReady was $B_1 = 0.774$, indicating that the logit of the probability of passing a corequisite math course increased by 0.774 for students who utilized EdReady compared to those who did not. Exp $(B_1) = 2.167$, indicating that the odds of passing a corequisite math course are 2.167 times higher for students who utilized EdReady compared to those who did not. In practical terms, this meant that students who utilized EdReady had 2.167 times greater odds of passing the corequisite math course compared to students who did not use EdReady. Moreover, it was important to note that because Exp (B_1) was greater than 1, it suggested a positive association between the predictor variable (EdReady) and the likelihood of passing the corequisite math course.

Arithmetic

The coefficient of the predictor variable Arithmetic was $B_2 = 0.021$, indicating that for every one-point increase in the Arithmetic test score, the log-odds of the probability of passing a corequisite math course increases by 0.021 units. Exp (B_2) = 1.021, indicating that the odds of passing a corequisite math course are 1.021 times higher for students who scored one point higher on the Arithmetic test compared to those who scored one point lower. In other words, for every one-point increase in the Arithmetic test score, the odds of passing the corequisite math course increased by a factor of 1.021. Moreover, It was important to note that because the Exp (B_2) is greater than 1, it suggested a positive association between the Arithmetic test score and the likelihood of passing the corequisite math course.

Time

The coefficient of the predictor variable Time was $B_3 = 0.003$, indicating that for every one-minute increase in the time of study in EdReady, the log-odds of the probability of passing a corequisite math course increases by 0.003 units. Exp (B_3) = 1.003, indicating that the odds of passing a corequisite math course are 1.003 times higher for students who studied one minute more compared to those who studies one minute less. In other words, for every minute increase in the studying time, the odds of passing the corequisite math course increased by a factor of 1.003. Moreover, it was important to note that because the Exp (B_3) is greater than 1, it suggested a positive association between the studying time in EdReady and the likelihood of passing the corequisite math course.

Summary

In a summary, this chapter focused on investigating the impact of various factors on the success rates of students in co-requisite math courses. The chapter utilized two-sample proportion tests to seek answers to Research Question 1 (RQ1) and Research Question 2 (specifically, RQ2a, RQ2b, and RQ2c), as well as binary logistic regression to investigate into Research Question 3 (RQ3).

Analysis for RQ1 revealed a significant difference which suggested that students who used EdReady demonstrated a notably higher success rate compared to non-users.

Investigation into Research Question 2 (RQ2) yielded mixed results:

RQ2a: The passing rates of corequisite math courses for students requiring the most remediation and those needing a medium level of remediation were statistically equivalent.

RQ2b: The passing rate of corequisite math courses for students requiring the most remediation was significantly lower than those only needing the least remediation.

RQ2c: The passing rates of corequisite math courses for students requiring the medium level of remediation and those needing the lowest level of remediation were statistically equivalent.

Analysis for RQ3 identified three significant predictors of student success in a co-requisite math class, including EdReady usage, arithmetic test score, and time spent studying in EdReady.

1) The odds of passing a corequisite math course was 2.167 times higher if students utilized EdReady, comparing to those who did not use.
2) The odds of passing a corequisite math course was 1.021 times higher if students scored one point higher on the Arithmetic test.
3) The odds of passing the corequisite math course was 1.003 times higher if students spent one more minute studying in EdReady.

The refined model was formulated as:

$$\ln\left(\frac{p}{1-p}\right) = -5.380 + 0.774 * EdReady + 0.021 * Arithmetic + 0.003 * Time$$

Where p was the probability of an underprepared student passing a co-requisite math class. Additionally, if given the measures of EdReady, Arithmetic, and Time, p could be calculated by:

$$p = \frac{\exp(-5.380 + 0.774 * EdReady + 0.021 * Arithmetic + 0.003 * Time)}{1 + \exp(-5.380 + 0.774 * EdReady + 0.021 * Arithmetic + 0.003 * Time)}$$

Chapter Five: Discussion and Conclusion

This final chapter synthesizes the findings from the empirical investigation into the effectiveness of the adaptive learning platform, EdReady, on underprepared students in co-requisite math courses, as well as the impact of students' initial remediation needs on their success in co-requisite math courses. It provides further discussion about the theoretical and practical implications of these findings. Additionally, the chapter addresses the limitations of the study and outlines recommendations for future research.

Discussion on Impact of EdReady

The study's findings clearly revealed that EdReady significantly enhanced the success rates of underprepared students in co-requisite math courses. Notably, students who utilized EdReady exhibited markedly higher passing rates compared to their peers who did not engage with this adaptive learning platform.

Firstly, the results provided significant evidence to demonstrate that a higher percentage of students who chose to use EdReady passed their corequisite math classes, compared to those who chose not to use EdReady.

Furthermore, the findings from the binary logistic regression underscored EdReady's significance in predicting the likelihood of underprepared students passing a co-requisite college-level math class. This analysis revealed a clear positive relationship between students' success in their co-requisite math courses and their utilization of EdReady. These results reinforced and validated the earlier conclusions drawn from the two-sample proportion test, indicating that students who engaged with EdReady achieved higher success rates in passing co-requisite math courses compared to those who did not utilize this adaptive learning platform.

As discussed in the literature review chapter, numerous studies (Yakin & Linden, 2021; Crowley, 2018; Roberts, 2023; Smajstrla, 2018) have demonstrated the effectiveness of utilizing adaptive learning technologies, systems, or programs across various educational settings, from K-12 to post-secondary, and spanning various subjects. The adaptive learning system, which integrates personalized learning with technology, aims to enhance learning and performance by tailoring instructions and content to suit individual learners (Shute & Towle, 2003). EdReady, as a representative platform employing adaptive learning technologies, aligns closely with previous research findings.

Discussion on Impact of Remediation

In the comparison of passing rates for co-requisite math courses among students requiring different levels of math remediation (Least, Medium, and Most), mixed results were observed from two-sample proportion tests. Firstly, no significant difference was found in success rates between students requiring the most remediation and those needing a medium level of remediation, or between students requiring medium remediation and those needing the least remediation. The significant difference in success rates was detected only between students necessitating the most remediation and those requiring the least remediation, with the most remediation group exhibiting a lower success rate in their co-requisite math courses.

One common assumption applied in the traditional developmental model was that students would be more likely to experience a higher passing rate in their math courses if they had a lower level of remediation needs. Bettinger and Long (2005) suggested that better-prepared students were likely to do better in college. The theory about remediation was that students needed to pass the remedial courses to have the knowledge and skills necessary to pass the college-level courses. However, the findings from this study suggested that the majority of underprepared students did not show a significant difference in their passing rates in the corequisite math course, regardless of their remediation levels. The significant variation only occurred between students who needed a lot of remediation and those who just required a little.

Valentine, Konstantopoulos, and Goldrick-Rab (2017) suggested that Mathematics is the most frequently assessed remedial need. Attewell, Lavin, Domina, and Levey (2006) argued that the completion of mathematics remediation was one of the largest academic barriers to increasing overall college graduation rates. These studies implied that remediation in mathematics was a significant element with the potential to impact student success. However, after further examination of the impact of remediation on students' success conducted by binary logistic regression in the study, the findings concluded that remediation was not identified as a significant factor in predicting the likelihood of underprepared students passing a co-requisite college-level math class. This analysis revealed that remediation (most, medium, or least) did not impact students' success in their co-requisite math courses.

Additionally, over the past two decades, a significant number of studies have argued and demonstrated the inefficiency and ineffectiveness of the developmental model. This model required students to take a series of remedial math courses before enrolling in a college-level course, with the series of remedial math courses determined by the level of their remediation needs. If the remediation level was not necessarily related to or impacting students' success in math education, as discovered in this study, then a series of remedial courses would not be needed anymore, supporting the argument that the corequisite math model became more popular than the developmental math model.

Last but not least, the finding that the impact of remediation was not significant also further strengthened an earlier conclusion regarding EdReady. It suggested that the capacity of adaptive learning technologies in EdReady effectively addressed diverse educational needs and reduced the disparity in educational outcomes among students with varying levels of academic preparation.

Theoretical and Practical Implications

The findings of this study carry significant implications across various domains. Firstly, from a theoretical perspective, this research enriches the literature on adaptive learning by furnishing empirical evidence of its effectiveness within higher education, particularly in the realm of mathematics education for underprepared students. By validating the theoretical framework outlined in Chapter Two, it underscores the capacity of personalized instruction integrated with adaptive learning technologies to enhance learning outcomes. Specifically, the study highlights adaptive learning systems as valuable applications of constructivism. Taking EdReady as an example, its effectiveness in improving student success in co-requisite math courses, as explored and demonstrated in this study, indicated the notion that personalized, technology-assisted learning environments could substantially enhance students' success in their math education because EdReady's adaptive learning environment effectively supported underprepared students by offering tailored content that addressed their individual learning gaps, as well as adapting to each student's learning pace and providing immediate feedback.

Reflecting on the statement of the problem, addressing the "one-size-fits-all" issue with the co-requisite model necessitates providing personalized support and resources tailored to individual students' needs. The findings of this study suggest that adaptive learning systems possess the capabilities to tailor learning resources and facilitate the construction of knowledge based on students' varying remedial needs in math. Therefore, adaptive learning systems such as EdReady could serve as a viable solution to mitigate the "one-size-fits-all" issue in the co-requisite mathematics model.

Second, from a practical perspective, the finding of the effectiveness of EdReady suggests that not only this college but also others that have implemented the corequisite math model should consider broader implementation of adaptive learning platforms like EdReady. These technologies not only support underprepared students' learning but also help educators tailor instructions more effectively. For policymakers, the results in the study advocate that adaptive learning systems can be included as supplemental learning resources and integrated into the educational framework of colleges, especially those with a significant proportion of underprepared students. This aligns with Bryk and Treisman's (2010) proposal that colleges should examine the support available to these students beyond the classroom to develop a remedial system capable of meeting the diverse needs of students from various backgrounds.

Additionally, the findings that remediation was not significantly associated with underprepared students' success in their corequisite math courses imply that it may not be necessary for colleges to categorize students into different groups based on their degree of under-preparedness. Instead, the primary focus should be on recognizing students who lack adequate knowledge and skills in Arithmetic, and providing additional academic support to help them review Arithmetic. The more arithmetic knowledge they acquire, the higher the likelihood they will pass their corequisite math courses.

Limitations and Future Research

While the study yielded many informative and meaningful findings, it is not without limitations.

The first limitation relates to the generalizability of the results. The sample was drawn from a small 2-year college, which may not adequately represent larger institutions. Additionally, as discussed in Chapter 3, specific inclusion criteria were employed to determine the sample for the study. Data records were required to include the level of remediation determined by students' Accuplacer placement results. Out of a total of 871 student records available from the college's student information systems for Fall 2021, Spring 2022, and Fall 2022, only 367 records included Accuplacer placement results. Consequently, the sample was limited to these 367 students. These factors may restrict the generalizability of the study's findings.

Since one of the study's findings indicated that the level of remediation was not significantly associated with the success rate of corequisite math courses, this suggests that Accuplacer placement results may not be necessary for data collection purposes. Therefore, in future research, the consideration of including all 871 student records as the sample could enhance the generalizability of the study's results.

The second limitation concerns the strength of the association captured by the logistic regression model, as indicated by the Nagelkerke R^2 value of 0.126. This value suggests that only 12.6% of the variation in student success in corequisite math courses can be explained by the variables included in the model. While the model demonstrated statistical significance in predicting the likelihood of students' success based on the usage of EdReady, Arithmetic test score, and study time in EdReady, the relatively modest percentage of explained variance indicates the existence of additional significant factors. These unknown factors may contribute to a higher percentage of variance to be explained by the model. Therefore, another interesting avenue for future research may involve exploring additional relevant factors and incorporating them into a further study, which could potentially offer a more comprehensive understanding of the determinants of student success in corequisite math courses.

Conclusion

In conclusion, this dissertation has demonstrated that adaptive learning platforms, particularly EdReady, offer significant benefits for improving the success rates of underprepared students in corequisite math courses. The study aimed to investigate the effectiveness of implementing the adaptive learning platform, EdReady, in aiding underprepared students to succeed in their corequisite math courses, and the purpose of the study was achieved. Moreover, the utilization of EdReady, by facilitating personalized learning experiences for students, not only helps to overcome educational disparities but also enriches the overall learning environment. The findings from this study provide a strong foundation and meaningful implications for the continued integration of adaptive learning technologies in higher education, promising to enhance educational outcomes and student success in the face of diverse academic challenges.

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