The Impact that A New Co-Requisite Model for Entry-Level College Courses is Having on Students' Success in Mathematics

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ABSTRACT

This study used a quantitative descriptive design and the CIPP model to evaluate the impact a co-requisite model had on students' passing rates in entry-level college math courses. The co-requisite model has become the alternative to the traditional developmental education sequence, and understanding how it impacts students' passing rates is important. The study was conducted in a small liberal arts private university in Southwest Georgia. Even though the research about the benefits of the co-requisite model is growing, there are still not enough literature about how this model is affecting students' passing rates in entry-level math courses at small private universities.

The study used archived data from 300 students' records who took the entry-level math course with and without the co-requisite support lab from Fall 2014 through Fall 2019. The CIPP model was integrated into the research design to aid in the evolution. Four research questions guided the study. A 2 x 2 Factorial ANOVA was used to analyze the data. The results from the Factorial ANOVA data analysis produced one significant result for the main effect gender and two nonsignificant results, one for the main effect co-requisite support lab and one for the interaction effect. However, there was enough evidence to indicate that the co-requisite support lab had an impact on students' passing rates in the entry-level math course. Results produced by the descriptive statistics revealed that the passing rate for the entry-level math courses was 76.5% (229) and for students who took the lab was 75.3%. In addition, descriptive data analysis showed that women had higher passing rates than men. Overall, the CIPP model, descriptive statistics results and 2 x 2 Factorial ANOVA results were combined to form a bigger picture of the co-requisite program which showed a positive outcome. However, due to the limitations of the study these results cannot be generalized beyond the university's co-requisite program.

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Chapter I

INTRODUCTION

Mathematics is a subject that most students have to take in college to earn a degree. At present more and more majors require students to take at least one math course. Society has become a more technological society where knowing mathematics is very important. Students need to know "basic mathematics and how to apply it in unfamiliar settings" (University System of Georgia Mathematics, 2013, p. 3) as well as "knowledge of statistics and data analysis to make sense of and to manage the inescapable reality of uncertainty in both physical systems and humans affairs . . . to make sense of the world around them" (University System of Georgia Mathematics, 2013, p. 3).

The researcher's interest was to learn more about developmental math and how it can be improved to help students who lack the skills to succeed in their college math courses. The idea of just getting rid of developmental math is not one that the researcher agrees with, but at the same time it is understandable why developmental math needs to be improved or reformed. According to one developmental education scholar, Hunter Reed Boylan (who will be referred in this paper as Boylan) who was interviewed by Levine-Brown and Anthony (2017), "it is either idiotic or deceitful to misrepresent developmental education and then blame it for the complexity of student attrition and assume the problem is solved by getting rid of it" (p. 20). On the other hand, the current proposed changes to developmental math seem promising, one clear example of these new approaches to developmental education is the co-requisite model (Levine-Brown & Anthony, 2017).

Barriers, Challenges, and Cost of Developmental Education

Barriers

Students enrolled in developmental math encounter many barriers in achieving their goal of getting a college degree. Two of the barriers that students placed in developmental math have to face are cost and time. According to Fong, Melguizo, and Prather (2015) it takes a long time to complete developmental courses in California, where students take up to two developmental math courses before reaching entry-level college courses for an associate degree and even more courses for a four-year degree. Thus, when combining these two factors (time and cost); it becomes very expensive for both the colleges and students (Fong et al., 2015). Similarly, Xu and Dadgar (2018) stated that having a developmental math sequence with multiple courses will only add to the high cost students have to pay for their education and increase the stress that students have to go through when taking developmental courses, which do not count towards degree attainment, thus increasing the time to earn their college degree. In addition, schools have to spend and allocate plenty of resources to developmental education (para. 34).

Supporters of developmental education suggest that the amount of resources spent and allocated to developmental education are not wasted since it is better to use these resources to help underprepared students rather than leaving them to fend for themselves in entry-level college courses without the proper preparation (Lazarick, 1997, as cited in Fong et al., 2015, p. 720). Other experts consider developmental math courses “a barrier to educational opportunity” (Bonham & Boylan, 2012, p. 14). This issue has posed a challenge for colleges and universities in the United States of America that report many of these students dropping out of college before earning a college degree (Guevara, 2007). As a potential solution to the issue of losing students who enroll in developmental courses before degree attainment, Georgia has adopted the new co-requisite model. Fixing this issue "will raise the economic prospects, well-being, and civic engagement" (Guevara, 2007, p. 1) of undergraduate students seeking to earn a bachelor's degree. Quarles and Davis (2017) also stated that developmental education is an obstacle for students enrolled in two-year colleges; and as a consequence, there has been an increased interest in reforming developmental education, which has resulted in the current changes being implemented nationally (p. 33). To truly reform developmental math in a way that helps students succeed in their first entry-level college math courses, colleges would have to identify two things: the first one is to identify what knowledge and abilities students must possess to success in their college courses, and the second one is to identify teaching methodologies to foster the students' knowledge and abilities needed to pass their entry-level college courses (Quarles & Davis, 2017).

Challenges

Developmental math has challenges that students and colleges need to address. Although some students taking many developmental math courses or failing a developmental math course multiple times is the reason for withdrawing from college, the researcher would argue that it is not the only reason for students not continuing taking and succeeding in their entry-level college courses. Colleges need to research and understand what other factors could be affecting their students' success and ability to earn college math credits. For example, students may encounter personal and motivational challenges that ultimately contribute to a lack of academic success. Additionally, some students fail in college because they were not well prepared in high school; they perhaps never learned basic mathematics like they should have. According to Howard and Whitaker (2011):

> For the younger group of students, arithmetic skill and years of high school mathematics correlated strongly with final course averages; levels of motivation also correlate strongly with academic success . . . Although the group of students in the younger age category not demonstrating proficiency in their basic arithmetic skills may have forgotten them quickly; it is likely that many never sufficiently learned these skills in the first place. (p. 2)

Howard and Whitaker (2011) go on to say that for the non-traditional group of students remembering basic mathematics is difficult because they might have been out of school for a long time, and for others of the same age group, these skills where never part of their curriculum when they were in school (Howard & Whitaker, 2011, p. 2). According to Merseth (2011), to understand the reasons and complexity for the high failure rates in developmental math education, it is important to consider asking the following questions, "Was it a high school preparation problem? A curriculum matter? A faculty concern? A psychosocial issue for many first-generation college students who had no knowledge of what it means to 'do college?' Or all of the above, and then some?" (p. 32).

All of these reasons must be researched in more detail to have a clear understanding about what factors are hindering students from earning college-level math credits. Wheeler and Bray (2017) also suggested that colleges and high schools should create a partnership so both entities understand each other better. As a result of such partnerships, high school students can learn more about the different college processes needed to have a successful transition between high school and college such as applying for admissions and for scholarships, creating their course schedules, attending events, learning where to get help and assistance, and joining clubs and organizations, to name a few. Moreover, institutions should provide effective counseling to make sure that students are aware of the potential significant negative impacts that the lack of understanding of these processes might have on their future college academics and experiences short- and long-term (Wheeler & Bray, 2017). This partnership should be created with the intent of understanding what helps and affects students' success so colleges can use that knowledge to develop better academic environments and students' activities that would help students to succeed in their college courses (Wheeler & Bray, 2017).

Taking developmental math courses can be time consuming. In many cases, students spend a few years passing all the levels in developmental programs. This is both time consuming and very expensive, as Hunter Reed Boylan stated in an interview conducted by Levine-Brown and Anthony (2017), "for some people, developmental has become a for profit industry" (p.19) since many students only take developmental courses before dropping out of school without earning a college credit. Thus, developmental education could be a good business model for some for-profit schools that claim that they have found the solution to developmental education, but do not really address what is affecting the field of developmental education. In Levine-Brown and Anthony's (2017) interview with Boylan, he mentioned that there has been a massive amount of economical investment to fix developmental math and degree attainment (p. 19). Subsequently, such investment has attracted many organizations and some "with more integrity than others . . . some have found it profitable to become instant experts and sell their 'solutions' to naïve legislators and policy makers" (p. 19).

Boylan went on to say that there is not a single solution to this problem, but that a combination of methods, which have shown to work in the past, can be used to solve the current issues of developmental education, including in the field of mathematics (Levine-Brown & Anthony, 2017). Similarly, Bailey (2009) stated that due to the lack of cooperation among states as well as the complexities of reforming developmental education, the manner in which states approach developmental education varies drastically (para. 12). However, according to Xu and Dadgar (2018) given the huge cost and obstacles that the current developmental education system poses to students and institutions, a popular nationwide movement has emerged to move towards a shorter developmental education system similar to or in line with the co-requisite model (para. 4).

Cost

Developmental education is costly for both the state and the nation, according to Pretlow III and Wathington (2012). In the year 2004-2005, the overall estimated cost of developmental education to the nation's public colleges and universities was about $1.13 billion, which was an increase of about 13% from the late 1990's when the amount was about $1 billion (p. 4). A more recent report conducted in 2017 puts this figure much higher, to about seven billion per year (Butrymowicz, 2017). So developmental math is both costly to students and to our nation. Similarly, Bailey (2009) stated that since many students fail their placement tests, the cost of education increases for the students, colleges, and the nation in general with states spending hundreds of millions a year. This is why it is important to look for alternatives to the current traditional developmental education system, especially in math. We need to find a better alternative such as the co-requisite model. The co-requisite model addresses the issue of developmental sequences by reducing or in some cases eliminating the number of developmental math courses in a developmental sequence; since students can take college level math courses at the same time they take a developmental math lab or co-requisite supporting course.

On the other hand, according to Wheeler and Bray (2017), the cost of providing assistance to all the underprepared students entering higher education is not as high as some research suggested. They argued that since the number of underprepared students entering college is so large, the overall cost for each student served is not as high as predicted, and in fact, since developmental education serves all of these underprepared students, who otherwise would be left to fend for themselves, the cost or investment in developmental education is money well spent (p. 10).

Background

The study of developmental math is nothing new; it has been done in the past. The issue of fixing developmental math has been a concern of experts in the field at the states level, as well as faculty and administrators, and universities across the country for many years. In fact, since the early 1990's addressing the short comings of developmental education to increase students' success rates has become a topic of interest. This issue has attracted the interest of both experts in the field of higher education and lawmakers seeking to pass legislature that could address the short coming of developmental education at the state and national level (Melguizo, Kosiewicz, Prather, & Bos, 2014). Most research about developmental math indicates that it does not work in its current form, but the researcher believes that there must be a support system in place to help all underprepared students who come to college missing and lacking the skills to succeed in their entry-level college courses. According to Wheeler and Bray (2017) "increased efficiency to enhance student success and proficiency should be the aim of any group vested in the education of the country's citizenry" (p. 15).

The reason many people do not support developmental education is because they confuse it with remediation. In remediation, schools only provide instructional support, whereas in developmental education the university or college provides different services aimed to guide students and to assist with classwork and academic related matters (Levine-Brown & Anthony, 2017). Developmental education is a more comprehensive system, one where students do not stop receiving help once they leave the classroom and it entails more than just remediation of the subject. The argument made by experts is that if people knew the difference, then they would support developmental education because it works; however, "the challenge is separating meaningful research from propaganda and making sense of it all" (Levine-Brown & Anthony, 2017, p. 19).

The misunderstanding of the difference between remedial and developmental education has caused some people to say that developmental education causes attrition in colleges, which is just wrong, because "as any competent researcher would point out, however, correlation does not imply causality" (Levine-Brown & Anthony, 2017, p.19) even if the research shows that there is a correlation between remediation and students dropping out of college (Levine-Brown & Anthony, 2017). On the other hand, wheeler and Bray (2017) conducted a study in a two-year college and they found that even though most people do not feel or believe that developmental education works their findings showed that developmental education in fact does help students pass their entry-level math courses and even graduating from college.

Another reason why the researcher conducted this type of study was because as a professional who personally has experienced developmental math as a student and as an instructor; he wanted to be an active participant of the current proposed changes rather than being a passive observer. Adult educators need to be active participants of the current changes to developmental education, especially in mathematics. Educators in higher education need to provide their expertise and advice to those working on the current reform to developmental education (Levine-Brown & Anthony, 2017), both at the local college and at the state legislative level.

Renowned experts in developmental education such as Boylan also have questioned the expertise of self-appointed experts who have an opinion or claimed to have found the solution to this issue, but have not taught at a community college or met a student in a developmental course. Experts who have spent most of their careers studying developmental education would say that there is not one single solution; there is not a "silver bullet" (Levine-Brown & Anthony, 2017, p. 19).

Higher education educators need to know which reforms at the state level are working and which are not. It is important to have this knowledge in order to participate in the discourse about developmental mathematics with legislators who are pushing these reforms. It is important to the researcher to study a co-requisite model implemented at one small, private liberal arts college in the state of Georgia to determine its efficacy. The most important goal is to ensure that underprepared students entering college complete their college education. Looking for and promoting reforms and practices that work to increase college degree attainment among underprepared students currently taking developmental courses must be a constant endeavor of higher education (Levine-Brown & Anthony, 2017).

Statement of the Problem

The aim of the researcher was to further contribute to the body of the literature by conducting research about this important and current topic in higher education. About two thirds of entering college students in the U.S. need academic assistance in their entry level-college math courses and many are placed in developmental education courses. These students lack the basic math academic skills needed to succeed in such courses (Bailey, 2009; Howard & Whitaker, 2011; Park, Woods, Hu, Bertrand Jones, & Tandberg, 2018). This study will address the impact a new co-requisite model is having on students' success rates in entry-level college math courses.

In this study the researcher examined a new co-requisite model for entry-level math college courses that was implemented in Fall 2014 in a small liberal-arts private university in southwest Georgia. The Co-requisite Model allows students who need developmental support to take entry-level courses with a co-requisite support lab (Complete College America, n.d.). The researcher focused on the university's co-requisite program implemented on its campus-based entry-level college math courses. This new co-requisite model, like similar models implemented by other states is being embraced as a way to reform their developmental curriculums. However, this topic about the co-requisite model is new and there are not enough quantitative and qualitative research data to produce an accurate picture that describes how it is helping students. As a result, there are not enough data to determine whether it should be applied and replicated everywhere in the U.S., including at small private universities that do not have the same student population and resources as larger public or larger private universities do.

Given the importance and relevance of the topic there has been a significant economical investment in the past decade to find solutions for improving developmental education as well as to improve students' passing rates in entry-level college math courses. This investment is generating new research, but given the importance of the topic and its impact on students' future, the production of quality research on the topic remains paramount and it is to that end that this study seeks to contribute.

This study used a quantitative descriptive design. This research design is used to study a segment in time of a phenomenon that is still currently happening, and the phenomenon is measured as it naturally occurs to describe the relation between variables (Waugh, 2018). The researcher did not manipulate the independent variables, the event naturally happened. The researcher did not decide who took the supporting math lab and who did not (application of the treatment). Secondary archival data were used to look at how the program performed in a specific period of time. The study was used to compare the relationship between variables, and the findings could be used for program improvement, but caution must be made about generalizing the findings beyond the institution where the study took place. Therefore, a quantitative descriptive design was the best design to conduct this study (Ary, Jacobs, Sorensen, & Walker, 2014).

Integrated into the quantitative descriptive research design the researcher also used The Context, Input, Process, and Product model (CIPP) model ("The CIPP Evaluation Model," 2003) as the theoretical framework through which to view the results to add to the results in the form of a program evaluation. The quantitative design and The CIPP model blended perfectly since both used quantitative data.

Theoretical Framework

The CIPP model for program evaluation will be used as the theoretical framework for this study's program evaluation. The CIPP model was developed by Daniel L. Stufflebeam in the 1960s. It was created to evaluate educational programs but overtime it has been used in a wide range of professions. The model's main goal is to provide evaluators data for program improvement and decision-making (Stufflebeam, 2003) during and after the evaluation (Zhang et al., 2011). The CIPP model can be used to evaluate the strengths and weakness of a program's curriculum (Akpur, Alci, & Karatas, 2016) as well as the effectiveness and implementation of such curriculum (Thurab-Nkhosi, 2019). The program is composed of four factors: Context, Input, Process, and Product. The Context factor "assess[es] needs, problems, and opportunities within a defined environment . . . [it aids] evaluation users to define and assess goals" (Stufflebeam, 2003, p. 31) to provide an educated judgement about the program. The Input factor evaluates program's plans, strategies, and resources. This evaluation helps evaluators to create plans for improvement, "funding proposals, [and] detail action plans" (Stufflebeam, 2003, p. 31).

The Process factor assesses the implementation of the program. It observes, records, and assesses what is happening with the program; it helps evaluators implement "improvement efforts and maintain[s] accountability records of their execution of action plans" (Stufflebeam, 2003, p. 31). The final factor is Product, the main goal of this factor is to aid evaluators to know if the needs of program participants are being met or have been met by assessing and recording data. The Product evaluation assesses and identifies "short-term, long-term, intended, and unintended outcomes . . . and [provides evaluators data to] make informed decisions to continue, stop, or improve the effort" (Stufflebeam, 2003, p. 32).

Purpose of the Study

The purpose of this quantitative descriptive study was to use a 2 x 2 Factorial ANOVA and the CIPP model to determine if the co-requisite model implemented in a small private liberal arts university had an impact on students' end of course grades for their entry-level math courses. The co-requisite model used a supporting math lab that students had to take with their entry-level math course based on their placement scores. The purpose was to evaluate the program's success and how it affected students' success rates, which was defined as passing the class with a grade of C or better. To accomplish this task the following data were collected and analyzed: secondary archival data from Fall 2014 through Fall 2019, demographics data, resources put in place to help students in the co-requisite model, and placement policies/processes. The following research questions were used to accomplish this task.

Research Questions

Context:

1. What are the current demographics of college students enrolled in entry-level college math?

Input:

2. What resources are in place to support the delivery of entry-level college math?

Process:

3. What methods are used to place students in the entry-level math courses and co-requisite math course?

Product:

4. Are there statistically significant differences in passing rates between men and women college students who took an entry-level college math course using the new co-requisite model compared to those students who did not?

Definition of Terms

Entry-level college math course(s). The first math course that students are required to take to complete their general education at a given college (Williams & Siwatu, 2017). For this study it will also refer to MTH 1 and MTH 2. The first math course(s) that students are required to take, depending on their chosen major, to complete their general education.

Developmental level. Courses not counting for college credit. Math courses required to be taken before entry-level college math courses (Levine-Brown & Anthony, 2017).

Developmental education (DE). In this study it will be used instead of using remediation or learning support, and it will be used to indicate courses designed to assist students either at the developmental level (meaning math courses required to be taken before entry-level college math courses), or at the college level. This definition follows what Levine-Brown and Anthony (2017) stated about DE, “in developmental education the university or college provides different services aim to guide students; and to assist with classwork and academic related matters” (p. 18).

Co-requisite Model. Allows students who need developmental support to take entry-level courses with a co-requisite support lab (Complete College America, n.d., para. 1).

Co-requisite support course or learning support labs or co-requisite support lab or supporting math labs (MTHL 1 and MTHL 2). In this study it will refer to the supporting math labs that are designed to help students who according to the institution’s placement policies need additional assistance with their entry-level college math courses (Beamer, 2020, p. 2).

Significance of the Study

This problem is important because it affects a huge percentage of college applicants nation-wide. According to Howard and Whitaker (2011) between “60% and 75%” (p. 2) of students enrolling in college needed or were placed in one or more developmental courses and an even higher percentage of students entering college do not have the necessary skills to succeed (Bailey, 2009). Melguizo et al. (2014) also found that the lower the level in a sequence of developmental math courses a student is placed the lower the chance that such student will enroll in college or in a math course. They found that “approximately 20% of students placed in five levels below transfer-level math did not enroll in college within a year of assessment, only 6% of students placed one level below transfer made the same decision . . . roughly 45% students placed five levels below transfer never enrolled in a math course compared with 18% of students placed in one level below transfer” (p.711, 714).

Melguizo et al. (2014) also reported that the same pattern was observed throughout the four levels of developmental math courses where 28% of students who took the lowest level of developmental math earned transferable college math credits, followed by "35%, 36%, and 42%" at each respective developmental math level. On the other hand, students who only had to take one entry-level college course passed the course at a success rate of 70% (Melguizo et al., 2014, p. 714); therefore, it is important to improve placement procedures across the nation's colleges and universities.

This point was also corroborated by Fong et al. (2015). They suggested that when policymakers and colleges make modifications to their placement policies that they need to include multiple measures of assessing students' readiness for college level work rather than just using one standardize test score; the use of multiple measures provide a better indicator for students' readiness and students' success. Hence, lawmakers need to approach this matter with objectivity, data driven processes, and without politics in mind (Breneman & Haarlow, 1999).

Thus, it is extremely important that universities across the country understand whether the changes to developmental education are working or not; especially for states where the new co-requisite models, or supporting labs, or supporting instruction are being provided and implemented to improve developmental math passing rates. This is a very important time in developmental math; changes made now will have a lasting impact on students' success in entry-level college courses. Therefore, it is important that this study is conducted to add to the literature and to aid future decisions about the future of developmental math.

Limitations

The study had one limitation; the study used archived quantitative data. As a result, this quantitative descriptive design is affected by interval validity and external validity threats. According to Waugh (2018) internal validity is when the researcher manipulates the independent variable to measure if there is a true change in the dependent variable. External validity is when the manipulation of the independent variable has a true effect of the dependent variable and the results can be generalized (Waugh, 2018). According to Ary et al. (2014) a quantitative descriptive study suffers from both internal and external validity threats because (a) the researcher did not manipulate or control the independent variable(s), (b) did not assign participants to each group (those who received the treatment and those who did not), and (c) the researcher could not control other external factors that could have impacted the DV.

The groups being compared were selected because they "already possess[ed] the variable of interest" (p. 360); for example, co-requisite lab vs not lab. Thus because of the lack of control of the IVs this type of study has "less internal validity" (p. 361). If the results show a change in the DV. It cannot be assumed that the changed occurred because of the IVs, and alternative explanations must be considered for the change in the DV. According to Creswell (2014) a great concern with threats to validity is that it could be hard to conclude if the treatment applied, in the case of this study the co-requisite support lab, had any effect on the DV and not other factors.

To reduce the threats to the internal validity of the study the researcher used stratified random sampling to select participants records from the population for the two factors (Co-requisite support) and gender (See Table 2 and sampling section in Chapter 3). To reduce the threat to external validity reliable testing tools were used such as SPSS 26.0 (Creswell & Plano Clark, 2018) and a 2 x 2 Factorial ANOVA. In SPSS 26.0 F tests were calculated to determine where the difference occurred in the main effects and interaction effect (Ary et al., 2014).

In addition, a Pairwise Comparisons test was conducted to pinpoint where that difference occurred within the levels of each group. Also, the fact that the study had two IVs helped. According Ary et al. (2014) increasing the number of external IVs reduces the threat to external validity because when more external IVs that could affect the DV are considered, the chances of other external factors affecting the change in the DV are reduced. Therefore, the generalization of the researcher's findings will also be limited to the universities' co-requisite program.

Delimitation

The study had one delimitation; this study is limited to one small private university in Southwest Georgia. The university is a non-for-profit university that offers undergraduate and graduate degrees with a student enrollment of about 1300 students from which about one third are student athletes (Integrated Postsecondary Education Data System, 2019). The majority of the students who took the entry level math courses MTH 1 and MTH 2 on the campus-based co-requisite program were student athletes. Sixty percent of the undergraduate population is under 24 years old and 95% of the graduate students are 24 years old or older. In 2018 about seventy eight percent of its undergraduate and graduate population were distant learners (Integrated Postsecondary Education Data System, 2019). This study is also limited to the university's on campus population. Therefore, this institution differs significantly from large public universities in the University System of Georgia which in 2019 had an overall enrollment of 333,507 students in its 26 colleges and universities (University System of Georgia Enrollment, 2019). Therefore, the results of the study cannot be generalized beyond the university's co-requisite program.

Organization of the Study

This dissertation is organized in five chapters. The first chapter contains an introduction, background about the topic, statement of the problem, theoretical framework, purpose of the study, research questions, definition of terms, purpose of the study, limitation, significant of the problem, and summary. Chapter 2 contains a review of the literature highlighting important topics such as (a) the importance of placement policies, (b) current changes to developmental education, (c) barriers, cost, and challenges of developmental education, (d) the co-requisite model, (e) developmental education in Georgia, and f) the CIPP model. Chapter 3 was organized as follows: description of the methodology, research questions, research design, and a description of the process for collecting and analyzing the data. Chapter 4 contains the results obtained from the data analysis using the 2 x 2 Factorial ANOVA and data collected for the CIPP model. The final chapter, Chapter 5, provides a full discussion of the findings and how they relate to the literature, in addition to the study's conclusions and suggested recommendations for future research are also included.

Summary

This study will be an evaluation of the co-requisite model implemented in a small private university in Southwest Georgia. The purpose was to evaluate its success and to determine whether or not it had an impact on students' success rate in the entry-level college math courses. This study is important because many students entering college lack the math skills needed to success in their college math courses (Bailey, 2009). The co-requisite model is being implemented in many institutions of higher education across the U.S.A. and research like this that looks at its impact on small universities' co-requisite programs must be conducted to add to the literature. The body of research has shown that the co-requisite model is having a positive impact on students' success at public colleges and universities, but there remains insufficient research that addressed the implementation of the co-requisite model in small liberal arts private universities.

The study will use a quantitative descriptive design and the CIPP model to conduct the program evaluation. The two approaches blend well because both use quantitative data. The CIPP model will be used as the study's framework. There are four research questions addressing a wide range of factors such as students' demographics, placement process, resources put in place to assist students in the co-requisite model, and the impact the co-requisite model is having on students' passing rate in entry-level math courses.

Chapter II

REVIEW OF THE LITERATURE

Developmental math is an important and current topic of conversation in most states of the U. S.. However, the concept of developmental or remedial education is nothing new; this concept has been in existence for the past four centuries addressing the needs of students in postsecondary education (Williams & Siwatu, 2017, p. 24). The importance of increasing the number of developmental students earning a college degree and improving their passing rates in developmental courses has become a priority for colleges and universities across the United Stated of America (Fong et al., 2015, p. 721). There has been an increase in the amount of interest in improving developmental education specifically mathematics both at the state and federal level (Wheeler & Bray, 2017) due to the large number of students in need of remediation. Given the importance, cost, and lack of research of developmental education, it is very important that the people in charge of evaluating it do so in an efficient and valuable way (Wheeler & Bray, 2017). Cox (2015) noted that since the topic of developmental math has become a topic of concern for colleges, especially in terms of improving students' passing rates, the first thing colleges should do to address this issue is to know what students enrolled in developmental math have to face to succeed.

Another issue in the literature is that most research on developmental education is concerned with passing rates and students progressing through their developmental math courses, but there is little research about what actually happens in the developmental math classes. According to Cox (2015), by neglecting what occurs in the classroom, such as different teaching techniques and learning differences among students, the current research about developmental math-which is strongly focused on how students perform at the end of the semester-is not able to recognize and address how these in-class conditions affect students’ performance in developmental courses (p. 266). These incapacities are important to understand since almost half of students entering college need to take a developmental course, and of those who take developmental math, about half pass the course and even fewer complete their degree (Cox, 2015). Other factors that could hinder or help students’ success in developmental math involve the vast differences that take place among developmental math classrooms. For example, in Cox’s (2015) study, she saw how differently professors taught their lessons, how differently they assessed their students’ learning, and how differently they all understood what students reaching proficiency meant. Each professor had their own opinion, and this could result in measuring students’ success differently across classrooms (Cox, 2015).

The Importance of Placement Practices in Developmental Education

Scott-Clayton and Rodriguez (2015) conducted a study in an urban college. They found that about 80% of applicants took a placement test provided by the college, and of those who took the placement test, about 72% were placed in developmental math. Their results also showed that students who scored below the cutoff scores were more prone to take developmental courses and were less prone to enroll and succeed in their college level courses. Understanding what different states do around the country is very important in developmental education given the large number of students placed in developmental math courses. Improving placement policies and procedures must begin with faculty and administrators setting clear and consistent cut scores (Melguizo et al., 2014). A study conducted in the state of California by Melguizo et al. (2014) to examine “assessment and placement” (p. 692) policies, or “A and P”, found that policy makers are doing their best to determine what constitutes the best practices to A and P. However, they also found that this task is very complex and that most people involved in establishing the most appropriate way of determining A and P neither know how nor are sufficiently trained to accomplish this task (Melguizo et al., 2014).

One factor affecting the full understanding of A and P is the lack of statewide or national standards colleges have for policies about placement and cut scores. Melguizo et al. (2014) found that a little over a dozen states have such standards for placement scores. This finding was corroborated by Bailey (2009), who stated that the reason why it is difficult to understand how to measure students' readiness for college-level math is because there is a lack of standardization regarding which placement tests and cutoff scores to use in each state.

Melguizo et al. (2014) found that colleges have their own placement assessments and are allowed to set their own placement scores. They also found that some colleges required students to take up to four courses in their developmental programs. Thus, in one college a student can be placed in a much lower developmental course while at another college a student could be placed at a much higher level with the same placement scores (Melguizo et al., 2014). For example, one of the colleges Melguizo et al. (2014) studied "placed roughly 53% of its students four levels below transfer" (p. 707). Meanwhile, another college they studied "placed only 2% at that level" (p. 707), which would result in a different math progression outcome for these students.

Another thing Melguizo et al. (2014) found was that using multiple measures in conjunction with placement scores from tests like ACCUPLACER could help, but that unfortunately faculty, administrator, and staff do not understand how to properly use them. Colleges and universities need to do a better job at creating a systematic approach on how to properly use placement guidelines and procedures and to properly train everyone involved in the placement process. According to Fong et al. (2015), if colleges and universities create and successfully implement a systematic approach, they will see an increase in degree attainment and student success in developmental courses.

Current Changes to Developmental Education in Different States

Some states like Florida have made developmental education optional for students who graduated from its public high schools after 2003 (Park et al., 2018). This finding was corroborated by Williams and Siwatu (2017) who noted that many states have stopped funding developmental education at universities and colleges across the nation (p. 25). Other states like Georgia have transitioned into a co-requisite model, where students who used to be placed in developmental math now are placed in an entry-level college math course along with a co-requisite course. The co-requisite course serves as a supporting course to help those students pass the entry-level college math course. According to Weisburst, Daugherty, Miller, Martorell, and Cossairt (2017), many states and universities, including community colleges, have started to modify developmental math in multiple formats:

> Including augmenting coursework with content intended to improve study skills, adding tutoring resources and building learning communities, compressing or accelerating coursework, pairing developmental education (DE) courses with college-level courses, and incorporating technology in the classroom . . . Studies on the effectiveness of various interventions are essential to ensure that the reforms . . . are effective in improving student outcomes. However, research on recent innovations in DE has only just started to emerge. (p. 183-184)

States like Louisiana are restricting where students can take developmental math courses. The state of Louisianan passed legislation to only allow community colleges to teach developmental courses. Therefore, if a student needs to take developmental courses, the student needs to go to a community college first and then transfer to a four-year college (Williams & Siwatu, 2017).

Community Colleges Helping Developmental Education

Williams and Siwatu (2017) found that the location where DE courses are taught is important. They conducted a study in Louisiana and found that students who completed their developmental sequence at a community college had a 20% better probability of successfully passing their entry-level college math course compared to students who completed their developmental sequence at a four-year university (p. 35). Thus, this finding seems to indicate that students at community colleges perhaps received a more individualized education.

Dasinger (2013) mentioned how community colleges offer an opportunity to underprepared college students to achieve their goal of getting a college degree. This is particularly true for non-traditional students who very often start their college education at two-year colleges with the intention of earning an associate degree or transferring to a four-year university (p. 2). Thus, community colleges play a crucial role in preparing underprepare and non-traditional students seeking to earn a post-secondary education.

This point was also corroborated by Fong et al. (2015), who found that both the size of the college and the size of the classes have an impact on students' success in developmental math courses. They found that when both colleges and classes are small, students in developmental math courses performed better. This could be due to the fact that when colleges are small, and classes are also small these institutions can "provide a more conductive environment for successfully passing" (p. 740) developmental math. So, it would be prudent to consider small class sizes of developmental courses especially in mathematics, when developing a new developmental math model such as the co-requisite model being implemented in the state of Georgia. Changes to improve developmental education must be done to ensure that students receive the best level of education preparing them to succeed at a community college or at a four-year college.

Math Strategies, Support Models, and Does Developmental Math Work?

In the past years there has been an increased number of underprepared students enrolling in higher education (Dasinger, 2013). According to Bailey (2009), many students arrive to college with not enough math skills to do well in college-level math. Hobbs (2018) reported that the percentage of students who took the ACT and met the benchmarks, which indicate whether a student is ready for entry-level college courses, has dropped and has been dropping in the past few years, especially in math where it reached its lowest level since 2004. The report released by the ACT showed that 60% of 2018 high school graduates who took the ACT did not meet the necessary benchmark that indicates whether a student would succeed in their entry-level college math courses (Hobbs, 2018).

Therefore, the findings based on the ACT scores indicated that this group of students will need some form of developmental math. Thus, this study corroborates what the research has found about the percentage of students entering college underprepared and in need of developmental help. This trend should be of concern for everyone involved in industry and in higher education, as ACT chief executive Marten Roorda told Hobbs that math is one of his concerns given the trend in our society to become technologically-oriented and in which "'the economy needs more students with STEM . . . education, and good math skills are vital to the STEM orientation. There is a high risk for the U.S. economy coming to a slowdown or a standstill'" (Hobbs, 2018, para. 4). Thus, the importance of improving developmental math programs at the college level as well as high school math curriculums. Fong et al. (2015) corroborated these finding by stating that a large number of students arrive to college underprepared to handle college class work.

Colleges have made modifications to their enrollment and retention practices, but they have not tried to study the reason(s) why students do not graduate from college or pass their entry-level college math courses (Vásquez, Offer, Ward, & Dochen, 2011). There is a need for research that could explain the reason(s) why students are withdrawing from college and why they are not succeeding in developmental math courses. Vásquez et al. (2011) found that "supplemental instruction" or "SI" does help students succeed in developmental courses. So perhaps the new models where there is a co-requisite course taken at the same time that the entry-level college course is taken will have a positive impact on students' success. Vasquez et al. (2011) stated that students who receive SI do better and feel more confident than students who do not because they feel that they are in an atmosphere where everyone in the class or lab is there for the same reason so they do not feel like they are the non-smart students of the class. Everyone in the class needs help, making everyone equal. Therefore, collaboration is most likely to occur, and students participate more.

Pedagogically, the instructor teaching the course can focus more on topics relevant to the students rather than trying to teach a predetermined curriculum or chapters regardless of students' understanding of such curriculum. Students' needs are what guide the curriculum selection and instruction. Fong et al. (2015) corroborated this point by stating that programs specifically designed to help students in developmental math or underprepared students have a positive impact on student success. This is important to consider with the new co-requisite model, which is designed to help students succeed in entry-level college math courses.

Vasquez et al. (2011) also found that other learning strategies such as how the course is designed, how the tests are designed, and time-management skills help students. Yet, they also stated that the benefits of SI do not seem to stay with students after they have taken their math courses. Students tend to go back to their previous behavior of bad study habits. Despite this finding, the literature supports the fact that learning support courses help students. According to Williams and Siwatu (2017), underprepared students have long benefited from developmental education programs and resources designed to provide students with both academic and professional skill needed to succeed in their developmental and entry-level college studies (p. 24). Furthermore, expertly designed developmental education programs have the potential to solve the math deficiency skills underprepared students have (Bahr, 2008, p. 442). It is hard to understand why states like Florida would make developmental education optional for all its underprepared university students (Park et al., 2018) and not re-require them to enroll in a co-requisite like program.

According to Wheeler and Bray (2017), students who were placed in developmental math performed in their entry-level college math courses at the same level as those students who did not need to take developmental math. This finding implied that if students who were placed in developmental math had not taken the developmental math course, they would not have succeeded in their entry-level college math course. Thus, at least for the institution where this study took place, this means that developmental math works and helps students succeed in their college math course. Wheeler and Bray (2017) also found that students who took a developmental math course were more likely to graduate from two-year colleges compared to those who were not placed.

Conversely, Bonham and Boylan (2012) stated that many students who enrolled in developmental math courses do not finish the recommend sequence of math courses. They found that only about 33% do. However, their study is seven years old and some of their data were even older. Some of their data were from back in the late 80's and early 90's. Since then, many changes have happened to developmental math curriculums. For example, many states and universities are now using the either the co-requisite model or learning labs to help underprepared students succeed both in developmental math and in their entry-level college math course. This finding was supported by the recommendation made by Bailey (2009), who stated that one way to help students who need developmental education was by removing the developmental sequences and to let students take entry-level college courses along with supporting resources such as a co-requisite courses, tutoring, or supporting labs (para. 20). In a similar way Fong et al. (2015) stated that colleges and universities need to modify their current developmental education programs to provide students with more opportunities for attempting both developmental and entry-level college courses (p. 719).

The researcher's experience with this topic comes from the work he has done at his university. The researcher's university has developed a developmental education system that requires students who score at the lower end of the placement cut off scores to take a learning lab along with their learning support course or entry-level college course. Specific ranges for appropriate placement were created to determine who is required to take the supporting lab and who is not. His university has removed the three sequences of developmental math courses and instead they have created one developmental math course which, along with the co-requisite supporting lab, is helping students in both the developmental math course and in the college-level course. Bonham and Boylan (2012) also found that colleges that are using different "teaching strategies" (p. 15), like the one the researcher of this study's college is using, have significantly increased the passing rate. They found that there was a 20% increase in students' passing rates of entry-level college courses (p. 15).

Colleges and universities are working hard to restructure developmental math in ways that will remove the many exit points and introduce diverse "teaching strategies" (Bonham & Boylan, 2012, p. 15) that would help students succeed. Xu and Dadgar (2018) suggested a similar approach to the model being used at the researcher's university where developmental courses are combined to reduce the number of exit points (para. 35). The number of exit points has a huge impact on student success. Xu and Dadgar (2018) found that it is less likely that students will succeed in their developmental studies if there are more exit points in their developmental education program (para. 34).

Fong et al. (2015) found that students placed at the lowest level of developmental math had the highest level of attrition compared to other levels of developmental math. According to Fong et al. (2015), of the 15,106 students who were placed at the lowest level, "arithmetic" (p. 732), only 61% attempted it and only 64% passed the course. From the same group, 72% attempted the next math level, "pre-algebra" (p. 732), and only 79% passed the course, then 83% attempted the next level, "elementary algebra" (p. 732), which is the college level for anyone seeking an associate degree, and 75% (2127 students) passed the course. So, from 15,106 students only 2,217 succeeded in reaching and passing the math course needed to get an associate degree, and even fewer (1004 students) moved on to pass the next level which is required for those students considering to get a four-year degree or for transfer credit (Fong et al., 2015). Even though there are experts who suggest developmental education helps students, the results stated above show that changes to the current traditional systems must take place to better serve this large group of underprepared students (Xu & Dadgar, 2018, para. 3). The help students currently receive from taking developmental math courses is not enough to overcome the students' poor academic skills (Bailey, 2009. para. 2).

Similarly, Quarles and Davis (2017) findings stated that one of the reasons that could explain why developmental math does not help students succeed in their first entry-level college math course is because most developmental math courses only teach students to memorize steps to solve problems. They go on to say that their findings are corroborated by the large number of students, who previously had taken a developmental course after failing entry-level college math courses. According to Bailey (2009), only about a third of students enrolled in developmental math successfully pass their courses to reach college-level math courses and "degree completion for remedial students is rare" (para. 8). He went on to say that many students who took developmental math courses at two-year colleges performed the same as students who did not take learning support courses (Bailey, 2009).

On the other hand, Fong et al. (2015) found that even though there are a small number of students who make it to the "highest levels" (p, 732), these students are "'catching up' and even exceeding their peers who were initially placed into higher courses" (p. 739). Therefore, reducing the number of exit points could help students succeed in developmental math. Developmental math is beneficial for those who need it, and when colleges properly place students according to their skill levels, developmental education will be of benefit to those students (Fong et al., 2015).

Similarly, Xu and Dadgar (2018) conducted a study to measure the success of developmental education in colleges that have students with poor math proficiency skills (para. 3). Their study compared two sequences: one where students had to take three developmental math courses and one where students had to take two developmental math courses. They found that students who took the longer path did not benefit more from the extra course and their chances of a four-year degree completion were also diminished. Thus, this study supports other research that indicates the more exit points there are in developmental math programs, the less likely the chance that students will benefit from them and even progress through the sequence of courses to earn college level math credits. Research findings like this should be used to help those proposing and making changes to developmental education programs across the nation (Xu & Dadgar, 2018). Hence, the need for reforming developmental math with new models like the co-requisite model, which reduces the number of exit points or required developmental math courses, allowing students to have a better change of earning college level math credits.

Co-Requisite Model

Weisburst et al. (2017) found that changes to the current structure of the developmental math curriculum could help to increase the passing rate of students taking developmental math courses, and also to increase persistence in continuing with their college careers. They studied two models, one where students took shorter-term courses and one where students received support at the same time they took their courses, similar to the co-requisite model and similar to the model used at the researcher's university. Weisburst et al. (2017) found that:

> Students in shorter courses were 12% more likely to pass (DE) math and 2% more likely to pass a first college-level (FCL) math course within a year. Likewise, students also enrolled in a study skills course were 4% more likely to pass DE math, 1% more likely to pass FCL math within a year, and 4% more likely to persist to the next college year. These findings suggest that emerging reforms to DE show promise and deserve further study. (p. 183)

Vandal (2016) conducted a literature review of the current state of co-requisite models in the United States, and his literature review found that the co-requisite model is working and helping students pass entry-level courses. This is corroborated by Scott-Clayton (2012), who found that if better cutoff score measures are used and more students are given the opportunity to take college-level courses, then their chances of successfully passing those courses is about 50% (p.22). The co-requisite model will allow more students to take entry-level college math courses who otherwise would be required to take developmental courses, thus increasing their chances of passing their entry-level college courses. This is corroborated by the findings of a co-requisite pilot study conducted by the Tennessee Board of Regents (2015). Their findings proved that when students were placed in co-requisite math courses, students' passing rates in mathematics went from 12.3 percent to 63.3 percent adding to the research that is showing that co-requisite models are working and helping students succeed in their college-level math courses in states that are implementing this new model.

Developmental Math in Georgia

In Georgia, the conversation of reforming developmental education has been taking place for many years. In 2011, the state governor, Nathan Deal, indicated that the state was going to be part of the Complete College America (CCA) initiative to increase college graduation rates ("Deal Announces," 2011). The need to increase passing and graduation rates among college students in the state of Georgia is very important; according to Delaney and Beaudette (2013). By 2020 more than half of the available jobs in the state will require a college degree or some form of postsecondary education (para. 2) and at the moment "only 42%" of working adults have those qualifications (para. 2). Therefore, in 2013 the University System of Georgia (USG) created a task force to address this issue (University System of Georgia Mathematics, 2013). A new model has emerged as the model that will replace the existing sequential developmental education system.

This model is known as the co-requisite model. In this model students who otherwise would been placed in a developmental math course now will be placed in an entry-level college course while taking a co-requisite support course to help them succeed in their entry-level college course. Studying this new model is of great importance, especially in mathematics due to the large number of students who fail to progress through the multiple developmental math courses, which they have to take in a traditional developmental program, as cited by the research above. In Georgia about 20% of students have to take a developmental course and about three percent earn a college degree in a range of six years (University System of Georgia Mathematics, 2013).

However, this percentage is a little lower than what Delaney and Beaudette' (2013) findings showed, they stated that about 50% of the USG freshman students and "26% of TCSG first-time students" (para. 3) were underprepared to succeed in entry-level college courses. Additional research needs to be done to identify which of the previous two studies had the most accurate data. Important changes are being made and it is important that the correct data are used to make those decisions.

The report conducted by the USG task force found that mathematics is particularly a difficult subject to pass, and it poses a barrier for many students taking developmental math courses. The task force found that for some students passing mathematics is almost impossible, thus creating an extreme obstacle to overcome to earn a college degree. This is evident in developmental math courses, but also outside of developmental math courses where the percentages of students getting a grade lower than a C is a little above 40% (University System of Georgia Mathematics, 2013). Knowing mathematics is very important, as it is an important factor for any individual's economic and social prosperity (University System of Georgia Mathematics, 2013, p. 3). The report listed eight recommendations for improvement to be implemented in the entire USG. The recommendations are as follows:

1. Focus on supporting success in college credit-bearing, gateway mathematics courses for *all* students.
2. Align gateway mathematics course sequences with academic programs of study. In particular, College Algebra should not be the default class for non-STEM majors.
3. Implement a co-requisite approach to support student success in gateway mathematics courses.
4. Develop year-long mathematics pathways for students with significant gaps in preparation.
5. Use multiple measures to place students in gateway courses and appropriate support.
6. Terminate use of COMPASS as an exit examination.
7. Align the outcomes of gateway mathematics courses with the Common Core Georgia Performance Standards (CCGPS) for Mathematics.
8. Develop advising systems and protocols for placing students in gateway mathematics courses and co-requisite supports that align with their intended programs of study (University System of Georgia Mathematics, 2013, p. 4).

Traditionally, many students who enrolled in college either at a two-year college or at a four-year college had to take developmental math courses; and many of them did not progress to get a college degree. This trend has been more impactful in community colleges than in four-year colleges, where about 93% of students who took a developmental course never got a degree within three years compared to only 75% of students, who enrolled in a four-year college and who also took a developmental math course, never earned a degree within six years (Transforming Remediation in Georgia, n.d.).

The state of Georgia's goal is to reduce the percentage of students taking developmental courses and in turn helping these students earn a college degree (Transforming Remediation in Georgia, n.d.). So, the USG has been working to restructure its developmental programs, as noted by University System of Georgia Mathematics (2013). Work was conducted with the intent to fully administer the eight recommendations by 2015. In addition to the report mentioned above, the USG conducted many pilot programs across the state to show that restructuring developmental education has the potential of improving the low passing rates of students in entry-level and college math courses, without affecting the rigor of their curriculum (Transforming Remediation in Georgia, n.d.). Based on the results produced by the report in 2013 and the pilot studies, the USG decided to "adopt corequisite remediation as the default method of remediation" (Transforming Remediation in Georgia, n.d.) by fall 2015 with the intent of achieving significant increases in students' passing rates for all those students enrolled in or benefiting from the new co-requisite model (Transforming Remediation in Georgia, n.d.).

Private Universities vs Public Universities

Before a review of the literature about the CIPP model and its benefits for program improvement is presented, it is important to present an overview of how small private universities differ from public universities. This is important to note, since the co-requisite model being studied is in a small private liberal arts university and most of the data about the benefits of the co-requisite model are coming from large public university systems. The main difference between a private and a public university in the U.S.A. is their source of funding. Public universities are funded by their state governments, using taxpayer's money. As a result, public universities are also overseen by a board or trustees appointed by the state government and often have lower tuition fees than private universities (Public University vs. Private College, 2017). On the other hand, private universities are privately own or non-for-profit (Comparing Public vs Private Colleges, n.d.), and funding comes mainly from tuition fees, matriculation fees, and private donations (Public University vs. Private College, 2017).

Another difference is the size, most private universities tend to be small in size compared to most public universities which are much larger in terms of their student body population. Private universities tend to have small class sizes compared to public universities where classes tend to be larger (Comparing Public vs Private Colleges, n.d.; Public University vs. Private College, 2017). Another difference is the range of programs of study each type offers. Public universities tend to offer a brother range of majors since they are more well-funded, are larger in size, and have a larger student population interested in a broader range of subjects. On the other hand, private universities have a smaller range of degree offerings and may have a "particular academic focus. Some private colleges may emphasize the liberal arts or the fine arts . . . while others focus on engineering and computer science" (Public University vs. Private College, 2017, para. 5). Regardless of the type, both private and public universities main goal is to educate their constituents or student body.

The CIPP Model

The researcher will conduct an evaluation to measure the level of impact that a new co-requisite model implemented in the state of Georgia is having on students' success in their first year entry-level college math courses. The researcher will try to produce more data, which could support or reject this new approach to developmental math, through the use of the CIPP model or "Context, Input, Process, Product approach" (The CIPP Evaluation Model, 2003). This model was "developed by Stufflebeam (1983)" (The CIPP Evaluation Model, 2003, para. 1). This model fits the researcher's study perfectly because its main purpose is to provide a structure to evaluate curriculum or programs such as the new co-requisite model, the evaluation of which could serve as a way to aid participants to improve such programs where needed (Stufflebeam, 2003).

This model is particularly useful when evaluating new programs such as the new co-requisite model (Frye & Hemmer, 2012) because its four components are designed to obtain a broader idea of what is affecting the program and what is needed in the given program in order to produce achievable outcomes, the methodology to achieve such outcomes, evaluation of the execution of the program, and evaluating the results of the program to decide whether the program must continue, be modified, or end (Taşçioğullari, Kiyak, & Çiçek, 2011). Similarly Cook and Ellaway (2015) indicated that the CIPP model is appropriate when it is used to evaluate a new program or programs undergoing modifications. Evaluations serve a very important role in determining whether or not a program has achieved its goals and outcomes. In addition, evolutions allow evaluators, program administrators, and institutions to identify the program's "effectiveness, strengths, weaknesses, or the failures" (Irambona & Kumaidi, 2015, p. 116). According to Zhang et al. (2011), the CIPP model is the best model for this research study's purpose due to its "utility, feasibility, propriety, and accuracy" (p. 58). The authors arrived at that conclusion after they conducted an extensive and exhaustive research of the literature of the 26 evaluation models that exits to evaluate programs.

The CIPP model is divided into four mini evaluations that are conducted in a linear way with the exception of the Context evaluation, which is happening simultaneously as the other three are taking place. Since the research design is a quantitative descriptive design, the CIPP model and the research design will merge perfectly since both use quantitative data. For a conceptual map of the CIPP model refer to Figure 1.

According to The CIPP Evaluation Model (2003) the first evaluation in The CIPP model is the Context valuation. Even though it is the first evaluation in the model, the Context evaluation takes place throughout the entire evaluation, addressing issues that range from whether or not students' performance in other courses have an impact on their performance in the entry-level math course and co-requisite course to what external factors play a significant role on or affect students' performance (such as family, work, playing a sport for the university, etc.). Basically, the evaluation addresses what other factors have contributed to students not completing the entry-level math course other than those related to academics or to the aforementioned factors. These considerations may be outside of the control or purview of the institution, instructor, curriculum, and/or students. The evaluation may also account for students questioning if "there is a need for the course?" or "is the course relevant to job needs?" (para. 2). In other words, are the students' needs being met by the new co-requisite model? (Irambona & Kumaidi, 2015).

The second evaluation is Input evaluation where the researcher/evaluator asks questions such as: "what are the math skills of students entering into the co-requisite course?" and "what are the learning skills of students?" (The CIPP Evaluation Model, 2003, para. 3) . This section can also be used to identify the ways in which instructors plan their instruction (Irambona & Kumaidi, 2015).

Then is Process evaluation, which encompasses questions such as “Is there any training provided to instructors teaching the co-requite courses?” and “If there is not, how the lack of training could affect their teaching of the learning labs?” or “Are there any problems related to learning?” (The CIPP Evaluation Model, 2003, para. 4), or Is there a teacher training protocol for teaching the developmental labs?

The fourth element of the CIPP model is Product evaluation where questions such as: “What are the different forms of assessing students’ performance after students have taken the co-requisite course that the university uses to measure this performance?” (The CIPP Evaluation Model, 2003, para. 5) or “What are the students’ abilities after taking the course?” are asked.

The methodology to conduct this type of evaluation is diverse. Data collection can be done through “individual student interviews” and “performance tests” (The CIPP Evaluation Model, 2003, para. 6). This methodology will merge perfectly with the quantitative descriptive design of the study. Given the type of quantitative data that will be collected to address the Research Questions of the study.

This study will follow the CIPP model as stated by the creator of this model, Stufflebeam (2003), but the study will also incorporate the guidelines for the CIPP model outlined by Frye and Hemmer (2012) in their paper *Program Evaluation Models And Related Theories: AMEE Guide No. 67*. Frye and Hemmer (2012) stated that their guide is for anyone who wants to learn more about theories related to program evaluation; their guidelines are also helpful in becoming “more creative and effective evaluators” (p. 288).

A good reason to use the CIPP model in a new program is that it does not have to be strictly linear. The model is flexible enough to allow for the four components to interact with each other, as stated by Frye and Hemmer (2012):

> The CIPP model is not hampered by the assumption of linear relationships . . . CIPP components accommodate the ever-changing nature of educational programs as well as educator's appetite for program improvement data . . . the CIPP model addresses all phases of an educational program: planning, implementation, and a summative or final retrospective assessment if desired. (p. 296)

Zhang et al. (2011) indicated that the CIPP model is perfect to evaluate educational programs such as the new co-requisite model because it provides evaluators with results for program improvement during and after the evaluation (p. 62).

Benefits of the Use of the CIPP Model for Program Evaluation

Additional benefits of using the CIPP model are exemplified in the following research of the literature. Yowono (2017) conducted a study to evaluate an elementary school program that lacked the necessary resources to provide a quality education for students with especial needs. The study looked at the available resources of the program and the needs of its students, educators, curriculum, infrastructure, and financing. The CIPP model was selected as the methodology for the study, and qualitative data were collected and analyzed. Yowono (2017) found through the context evaluation that the elementary school, students, parents, teachers, and community would feel proud of having an effective "inclusive school" (p. 127) that provides quality education to students with special needs. Through the input evaluation, Yowono (2017) found that recruiting students for this type of school was affected by the socioeconomic status of the students, lack of knowledge of what students with special needs need, lack of adequate infrastructure, and adequate funding.

Through the process evaluation, Yowono (2017) found that teachers were actually competent in "curriculum differentiation, curriculum modification, individual learning, cooperative learning, motivating to learn and flexible assessment" (p.128). The product evaluation found that the new inclusive school lacked effective standards but had good outcomes with national scores increasing and students with special needs having no negative effect on these scores at inclusive schools. Thus, the CIPP model did a great job at evaluating the effectiveness of this inclusive elementary school program for students with disabilities. In a similar way, the CIPP model can be used to measure the impact of the new co-requisite model.

Another study illustrating the usefulness of the CIPP model to evaluate the "practice and effectiveness" (Kim, 2015, p. 423) of educational programs involves the research conducted by Kim (2015) about satellite secondary education in Ethiopia. Kim's (2015) study consisted of 291 participants from two different secondary schools, grades 9-12. Sixty-three participants were teachers and the rest were students. The CIPP model was used to create Likert-scale surveys to collect data in order for the researcher to identify the participants' needs. The CIPP model was used to address different factors of the program. For example, the context phase was used to examine the level of participation and perception of the program, the input was used to examine content and classrooms, the process was used to address the implementation of the program paying special attention to human resources and classroom management, and the product phase was used to examine the students' and teachers' satisfaction, effectiveness, and areas that could be improved.

Kim (2015) used an equal number of participants from each school, and participants were about equally divided in terms of gender among students. The gender gap was significantly greater for teachers than students, with more male teachers and more teachers from one location. Existing data and the CIPP model were used to create two surveys, and the quantitative data collected were analyzed using SPSS. Different data analyses were performed such as an ANOVA, descriptive analysis, and a multiple regression analysis (Kim, 2017).

Kim (2017) found that students liked learning through the satellite instruction, but that they did not like the fact that they could not communicate with the teacher. The one-way communication was the downside of satellite instruction. Suggestions for improvement are the use of TV and “two-way audio” (p. 430) communication. Kim (2017) also found that about 1/3 of students indicated that teachers are not using the TV instructional programs to teach like they should. The reasons they had for not using the satellite instruction were lack of interest and lack of technology proficiency with the satellite program. Kim (2017) indicated that this is an obstacle that teachers need to overcome. The CIPP model helped the researcher to identify areas where the program could improve to increase satisfaction from both students and teachers. Also, areas for improvement in terms of resources such as more TVs, better satellite and internet connections, teacher training, interactive communication, and more interesting content.

Cook and Ellaway (2015) conducted a study with the intent of creating a comprehensive approach for evaluating technology-enhanced learning in medical education; the CIPP model was used as one of many evaluation methods to produce such approach. The approach was designed to help teachers and administrators working in evaluating technology-enhanced learning in medical education programs. The CIPP model was used to create a map that could help the evaluator answer questions such as “‘What information should be collected to help answer my guiding questions?’ (i.e. description, justification, or clarification), followed by, ‘How can I collect this information?’” (p. 964). The map consisted of the guiding questions and the four phases of the CIPP model to “conduct a needs analysis and environmental scan” (p. 965). The context phase consisted of multiple factors such as “vision, goals, objectives, assets and opportunities" and "existing programs needs and gaps" (p. 964), the input phase consisted of four factors including "alternative vision, . . . anticipated costs" (p. 964) etc., the input phase consisted of items such as "development and implementation . . . learner experience" (p. 964), and the product phase included items such as the implementation of the program, the cost of the program and the sustainability, and unforeseen events.

Another example of the use of the CIPP model to evaluate the strengths and weakness of a program's curriculum is illustrated by the research conducted by Akpur et al. (2016). They used the CIPP model to evaluate a university's English curriculum. The evaluators used the CIPP model because the model "serves as a guide for a comprehensive as well as for a practical evaluation and it gives way to improve the curriculum" (p. 467). They also stated that the CIPP model is used for curriculum improvement and not to prove whether the program works or not. They go on to say that the model is used to provide data for decision-making about implementation of changes to the program being studied; and to determine its "merit and worth" (p. 467). Akpur et al. (2016) collected quantitative data, and they used the CIPP model to help them created the research question. They also created a Likert-scale instrument that contained 46 items. These items were distributed across the four phases of the CIPP model to address the needs of the English curriculum at the university. The survey was given to both students and teachers, and the CIPP model allowed Akpur et al. (2016) to identify the areas where students' and teachers' opinions about the program disagreed with one another as well as highlighting areas of consensus.

Akpur et al. (2016) findings produced seven areas for improvement. Students and teachers agreed that more needed to be done to create better curriculum objectives, so a needs analysis was suggested. Another suggestion involved the use of audio visual-aids in the classroom to promote in-class group activities, and to create learning activities that incorporated real-life situations into the curriculum so students could practice their English skills. This study illustrates how the CIPP model is an ideal model for the evaluation of the new co-requisite model.

Gandomark and Sandars (2018) used the CIPP model to study medical education programs. Specifically, they used the CIPP model to address the needs of an undergraduate medical education program under renewal. They emphasized the importance of understanding the context of any program when conducting an evaluation. Ho et al. (2011) conducted a research to study a suicide prevention program in Taiwan's second largest city. They used the CIPP model to conduct their evaluation. Their reasoning for using the CIPP model was due to its usefulness when evaluating educational or administrative programs. The model was used to measure the effectiveness of the Kaohsiung Suicide Prevention Center or KSPC. According to Ho et al. (2011), the CIPP model can be used as a "self-assessment tool that can be employed to make improvements within an organization over time" (p. 543). They selected participants from two different groups, one group came from people in the system, people who had attempted suicide at some point in their lives and have been registered in their suicide system. The second group came from people who called the help line. The purpose of the evaluation was to improve KSPC through better judgement and assessment.

Using the context phase of the CIPP model Ho et al. (2011) found that Kaohsiung had a significant higher suicide rate than Taiwan's average suicide rate, especially in the elderly population in need of healthcare. They emphasized the importance of collecting the correct data to address the needs of the program. In their case, the evaluators needed to monitor suicide trends to identify future groups of people in whom these trends could occur. For the input evaluation, they stated the importance of knowing how to properly distribute resources within the organization and the availability of funds. In their case, KSPC was underfunded at first, but they found additional resources through a medical fund. The input evaluation allowed them to see where they were underfunded. Ho et al. (2011) found through the process evaluation that providing suicide prevention information in multiple outlets helped KSPC achieve the goal of suicide prevention awareness. The product evaluation showed them that KSPC is constantly improving and achieving its goals given its limited funds. Thus, the CIPP model was an effective model to evaluate KSPC and in a similar way, it can be used to evaluate the new co-requisite model for entry-level math courses.

Thurab-Nkhosi (2019) used the CIPP model to conduct an evaluation about “the impact of the course CUTL 5106 Advancing Teaching with Technology” (para. 9) on a hybrid (face-to-face and online) course’s implementation. The course was one in a series of courses designed to help faculty members increase their professional development in the area of learning how to design and implement hybrid curricula. Thurab-Nkhosi (2019) stated that in order for these type of hybrid courses to be developed and implemented by faculty, faculty must be supported by their universities. The CIPP model was used to assess the effectiveness and implementation of the hybrid course mentioned above. This model was the most appropriate for this evaluation because it is flexible, seeks to improve programs, courses etc., and it can be used to correct or control current or past issues in the organization, course, program, etc. (Thurab-Nkhosi, 2019).

CUTL 5106 was a three-credit graduate course designed to teach faculty the skills of teaching using technology in the areas of design and delivery of hybrid courses. Thurab-Nkhosi (2019) used both quantitative and qualitative data. Data were collected through the use of questionnaires, Likert-scale surveys, and interviews. Thurab-Nkhosi (2019) found in the area of context that most participants who took the CUTL 5106 course agreed that the course helped them design and implement a hybrid course. Through the input evaluation, Thurab-Nkhosi (2019) found that faculty were properly supported by administrators when they were taking CUTL 5106, but once the course had concluded, the support vanished. This was because it was no longer a priority for administrators to motivate faculty to promote the implementation of hybrid courses. The course CUTL 5106 was a course that faculty had to take as part of their contracts to receive a university certificate, indicating they were proficient in teaching using technology.

The process evaluation found that most participants agreed that the CUTL 5106's curriculum was appropriate, but not everyone indicated that they have continued using what they learned in their current courses (Thurab-Nkhosi, 2019). Overall, the product evaluation found that most faculty members who took the CUTL course had positive experiences and were more confident in using technology in their courses. But faculty also stated that they needed more support from administrators when developing hybrid courses (Thurab-Nkhosi, 2019). Thus, the CIPP model produced the results necessary to address the needs and issues of the program.

Hurmaini and Abdillah (2015) conducted a study using the CIPP model to evaluate the strengths and weaknesses of a social internship program called Kukerta that used the research system called Participatory Action Research system or (PAR). The Kukerta program focused on three aspects of the university's philosophy, which included education, research, and social work. Hurmaini and Abdillah (2015) conducted the study due to the lack of evaluation data about the implementation of the program Kukerta; they wanted to make the program more "meaningful for both students and the society" (p. 56). Hurmaini and Abdillah (2015) stated that the reason for using the CIPP model was because they wanted to identify barriers during the implantation of the program to suggest or produce solutions for program improvement. They went on to say that "a program without evaluation is an incompetent thing since the effect would not be able to be measured" (p. 56). In other words, a program evaluation is conducted to see if the program achieved its outcomes, hence the evaluation must be conducted through a systematical approach of collecting, processing, and analyzing data (Hurmaini & Abdillah, 2015).

Hurmaini and Abdillah (2015) used different forms of collecting data, they conducted observations, interviews, and administered surveys. Each data collection technique served a purpose. For instance, the comparison of how the Kukerta using PAR met the needs of students and its implementation was done through the surveys. Additionally, interviews were conducted to get a better picture of the program, and observations were conducted to see what students were able to achieve or produce during the implementation of the program (Hurmaini & Abdillah, 2015). During the context evaluation, the findings suggested that the program needed to be improved significantly to meet the purpose of the program and the needs of the students. Similarly, the input evaluation found that the program needed to do a better job at training students and supervisors. For the process evaluation, Hurmaini and Abdillah (2015) found that the activities needed to be relevant to the local population. Finally, through the product evaluation, they found that the overall program needed to be improved as it lacked any significant data that suggested it was working. Thus, the programs implementation must be revised and improved (Hurmaini & Abdillah, 2015).

Another study that used the CIPP model was conducted by Azmy (2019). The author used the CIPP model to evaluate a program designed for recruiting lecturers at a university in Indonesia. Azmy (2019) collected data by observing the recruitment process, interviewing participants, and administering surveys to students. The purpose of the recruiting program was to recruit qualified lecturers who would provide quality education while achieving the university's mission. This study analyzed the program's process for recruiting lecturers who had applied to the university and met the requirements set by the university's human resources office.

Azmy (2019) used a three-level scale (low = less than 50%, moderate = more than 50%, but less than 100%, and high = very close to 100%) to measure the success of the program in accordance with the university's criteria. The CIPP model was used to measure "process and formulation of program objectives" (p. 357); for context, how each department handled the recruitment of lecturers, "budget, plans' for lecturer's needs, stages of selection, and standards for assessment of recruitment process" (p. 358); for the input phase, the process phased addressed the implementation of the program's stages, and the product phase of the CIPP model addressed the placement of lecturers in academic programs and students' satisfaction with the quality of teaching done by lecturers.

Azmy (2019) found that in the criteria being measured by the context phased, the program received a high rating, the criteria in the input and process received a medium rating, and the criteria in the product received a high rating. Overall, the CIPP model helped Azmy (2019) to show that the university's recruitment program is working well and that it just needed minor adjustments. For example, an increase in the university's budget would help the process run smoothly, as it would increase participation from human resources and improvement to the university's facilities. Thus, this study provided another example of the benefits of using the CIPP model to conduct a program evaluation at the university level.

Harrell and Reglin (2018) conducted a study using the CIPP model to evaluate the effects of a faculty advising program (FAP) on students' satisfaction and retention at a two-year college's nursing program implemented after 2013. The reason for conducting this evaluation was due to a constant decline in student retention in the nursing program between 2009-2012. This study could be related to the poor success rate of students in developmental math sequences and first-year entry-level college math courses and the need to measure how the new co-requisite model for entry-level math college courses is addressing this issue. Harrell and Reglin (2018) used only two of the four factors of the CIPP model. They called their evaluation “decision-oriented” (p. 33) evaluation; and they used only the process and product factors of the CIPP model to conduct their evaluation to provide administrators and decision makers the data needed to make informed decisions about the FAP. The process factor was used to evaluate the students’ satisfaction with the FAP. The product factor addressed the effectiveness of the FAP in increasing student retention during and after its implementation between 2013-2016.

Harrell and Reglin (2018) stated that the CIPP model is an “effective model for researchers who have the opportunity to work closely with staff members who manage programs” (p. 38) in the same site where the study is taking place. Overall, the data showed that for the process phase students were satisfied with the FAP. The product evolution showed that the implementation of the FAP had a huge positive impact on students’ retention, the percentages ranged between 72%-96%. Similarly, this researcher will conduct an evaluation of the new co-requisite model for entry-level math college courses at an institution he is familiar with, thus the CIPP model is the best model to conduct the new co-requite model’s evaluation.

Irambona and Kumaidi (2015) conducted a mixed-method study to evaluate the effectiveness of a high school English teaching program in Indonesia. They used the CIPP model for their evaluation. Irambona and Kumaidi (2015) stated that evaluations can be used to evaluate the organization’s goals and objectives with the purpose of making decisions about maintaining the current curriculum or making modifications to it. Irambona and Kumaidi (2015) stated that the reason their country was conducting evaluations to measure the success or failure of its academic curriculum was because it was trying to bring its education level up to the same level of bordering countries and the rest of the world. In a similar way, colleges and universities in the U.S. are changing to the new co-requisite model to reform their underperforming developmental education curriculum. Irambona and Kumaidi (2015) found that, overall, the English program had qualified teachers and facilities to meet the needs of the students. The Irambona and Kumaidi (2015) evaluation strongly reflects what this researcher is trying to accomplish with his study of the new co-requisite model.

Bishop and Mabry (2016) conducted a study using the CIPP model to evaluate a credit-bearing literacy course called LIB 301for nontraditional learners. They stated that the reason for using the CIPP model to evaluate the LIB 301 course was because it is a "cyclical design . . . [that] fosters continual program improvement through assessment of outcomes in context to stakeholders needs, environment, resources, and overall program impact" (p. 68). Bishop and Mabry (2016) stated that the reason for conducting the evolution was because they wanted to measure students' ability to find useful resources that students could use for their course's project. Bishop and Mabry (2016) collected both quantitative and qualitative data based on students' assessments of their ability to retain and to transfer knowledge and based on students' feedback and instructors' observations, respectively. The data were used to identify challenges that students had while looking for resources. These data were intended to provide suggestions for curriculum improvements, which would help both students and instructors teaching LIB 301, to reduce teacher burnout. The CIPP model allowed instructors to make improvements to the curriculum and instruction during the data collection period between 2012-2015. The data showed that students lacked the skills to correctly locate resources, but after changes to the curriculum were made, students' outcomes improved and there was less teacher burnout (Bishop & Mabry, 2016).

Zhang et al. (2011) conducted a study using the CIPP model to produce a "framework for service-learning projects" (p. 62). They found that the CIPP model is very useful for "guiding the planning, implementation, and assessment of service-learning projects" (p. 78). They stated that this model is a reliable model to use because it has a variety of approaches, over time it has been totally assessed, and it is widely approved by the literature. The CIPP model is extremely useful in educational settings such as the new co-requisite model for entry-level math college courses because it allows evaluators to create goals or objectives to best meet the students' needs, it informs the program's implementation, assesses its outcomes, and provides suggestions to improve the program (Zhang et al., 2011). The evaluators found that when participants are allowed to be part of the decision-making process, the needs of both the program's providers and its participants are met. Zhang et al. (2011) concluded by stating that service-learning providers can use the CIPP model as a tool to collect data throughout the multiple phases of the program with the intend of using the assessment results to make informed decisions about whether to keep the program as it is or to make changes for program improvement.

Haji, Morin, and Parker (2013) conducted a study of evaluation theories to produce a holistic guide for program evaluation in the health profession. They stated that the CIPP model was and is intended for program improvement evaluations. They go on to say that the environment in which the evolution is taking place plays a huge role on the development of the evaluation's questions, the methodology of the evolution, and how the findings are interpreted (p. 345). The CIPP model can also help evaluators to determine if the program is correctly doing what it is supposed to do in terms of goals, objectives, and outcomes (Haji et al., 2013).

According to Rojas et al. (2018) evaluators should select the evaluation model that best fits their needs considering the purpose of the evaluation, the time available for the evaluation, the available resources, and the expectation outcomes of the evaluation (p. 371). For the reasons stated above by the cited research, the CIPP model will be used as the theoretical framework for this study. Below is a conceptual map of the CIPP model that will be used to guide the process of this study, but not in a sequential manner.

Conceptual Map of The CIPP Mode

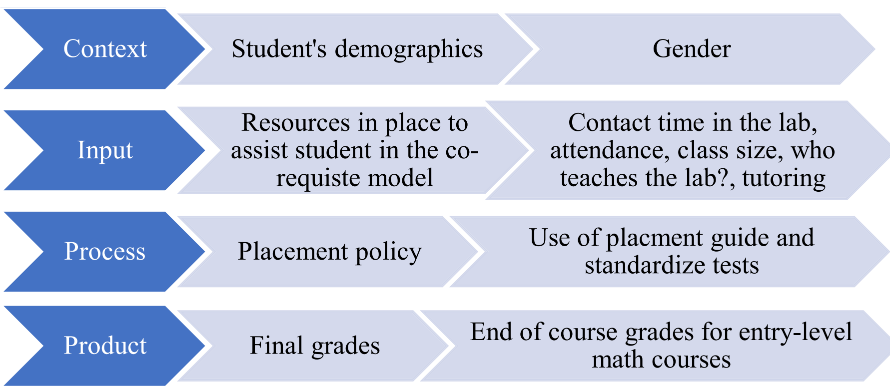

Figure 1. The CIPP model is not necessarily linear in nature and data for its factors could be collected throughout the entire process of the evaluation/study. This conceptual model was designed to guide the collection of data for the different factors of the CIPP model. The CIPP model's four factors were incorporated into the Quantitative Descriptive Design process.

Summary

This chapter provided a comprehensive review of the literature about developmental education and changes to its traditional sequence. A review of the literature about the importance of placement practices and their impact on student success in college math courses was conducted. The literature showed that placing students correctly is very important, but unfortunately the people making this decision might not be well trained to do so (Melguizo et al., 2014).

The literature showed how different states have approached the issue of reforming developmental education. Some states have eliminated it from their curriculums, and others have redirected it to community colleges. The literature showed that community colleges are doing an effective job of picking up the responsibility of helping students who need developmental education. The literature showed that in some states, students taking developmental courses in community colleges had a 20% better probability of successfully passing their entry-level college math course compared to students who completed their developmental sequence at a four-year university (Williams & Siwatu, 2017).

The literature also showed that students placed in developmental courses faced multiple barriers and challenges, such as the high cost and time of successfully exiting developmental math sequences to earn college credit. The literature showed that different models and teaching strategies in developmental education have the potential for improving students' success rate. These different teaching strategies include supporting labs like the co-requisite model, additional tutoring, small class sizes, or concentrating in more basic and indispensable topics rather than trying to cover large amount of content. The literature also showed that factors like how the course is designed, how the tests are designed, and acquisition of time-management skills help students and have been proven beneficial to students' success (Vasquez et al., 2011).

The co-requisite model is one learning strategy that is working and helping students to successfully pass entry-level college math courses, as shown by the literature. Many states have implemented a version of the co-requisite model in the public universities and community colleges. Georgia is one of those states where the co-requisite model was implemented in 2015 with the intent to significantly increase the passing rates of students entering college. Since the co-requisite model was just implemented in the state of Georgia a few years ago, there are still not enough data-especially about how this new model is impacting students' success in small private universities. The CIPP model was selected as the theoretical framework for this study. An extensive literature reviewed was conducted in this chapter that showed the benefits of using the CIPP model for program evaluation in educational settings.

Chapter III

METHODOLOGY

In this chapter a description of the study's design, population, sampling procedures, data collection procedures, and data analysis will be discussed. This study used a quantitative descriptive research design to evaluate the efficacy of a mathematics co-requisite course model. This study blended the four factors of The CIPP model with the sequence and format of the quantitative descriptive design to address four quantitative research questions.

Research Questions

Context:

1. What are the current demographics of college students enrolled in entry-level college math?

Input:

2. What resources are in place to support the delivery of entry-level college math?

Process:

3. What methods are used to place students in the entry-level math courses and co-requisite math course?

Product:

4. Are there statistically significant differences in passing rates between men and women college students who took an entry-level college math course using the new co-requisite model compared to those students who did not?

Research Design

This study used a quantitative descriptive design. This research design was used to study a segment in time of the co-requisite model, and it was measured as it naturally occurred to describe the relation between variables (Waugh, 2018). The design used secondary archived data and a 2 x 2 Factorial ANOVA to look for differences between IVs and interaction effects between the two independent variables on the DV (Vannatta Reinhart & Mertler, 2016). The data came from multiple sections of two entry-level mathematics courses and co-requisite mathematics labs or supporting mathematics lab courses. For the purpose of this study and to keep the courses anonymous since they are made public in the university's catalog, the courses are referred to as MTH 1 and MTH 2. MTH 1 was required for non-science majors and MTH 2 was required for science majors. The corresponding co-requisite math labs or supporting math labs are referred to as MTHL 1 and MTHL 2 accordingly. The labs provided academic assistance to students who according to their placement scores (ACT, SAT or ACCUPLACER- see Table 3) needed extra help to succeed in their entry-level math course. The co-requisite courses were structured as a lab rather than a lecture-based course to provide more instructor-student and peer-to-peer interactions. Quantitative data were collected as soon as the researcher obtained IRB approval. The university's Office of the Registrar provided end of course grades of all of the students who took the entry-level courses MTH 1 and MTH1 and co-requisite courses MTHL 1 and MTHL 2 from the inception of the co-requisite course model in Fall 2014 through Fall 2019 but not including summer terms in between. The researcher obtained secondary de-identified data in a coded list with students' IDs instead of names, this way the researcher did not know the participants identity and the university protocol to ensure the privacy and anonymity of participants was followed. The end of course grades for entry-level courses

MTH 1 and MTH 1 and co-requisite courses MTHL 1 and MTHL 2 were secondary data archived in a university's data based. In addition, the researcher obtained demographics data such as gender.

Once the de-identified data set was received, a new key code was created in Microsoft Excel using a P-Code that ranged between P1-P537 to be able to connect and identify the participants' student ID. Once the key was created this new key was shared with the university's Office of the Registrar and the researcher deleted the students' IDs from his data set leaving only the new P-Code to connect and identify students' records.

For the CIPP model, the researcher collected quantitative data for the following CIPP model factors: Context, Input, and Process. These quantitative data were collected from the university's website, catalog, and the university's Director of Mathematics. The university's website and catalog are open to the public and the Director of Mathematics is the researcher of this study, thus no additional permission or consent was needed to obtain these data. The data collected were resources available to support students in the co-requisite model, general information about the math labs, and placement process.

SPSS 26.0 was used to test the 2 x 2 Factorial ANOVA assumptions, and to obtain tables with results such as significant values for the main effects and interaction effect, histograms, Levene's Test, post-hoc tests, and descriptive statistics. The study had two independent variables (IV) and one dependent variable (DV). The independent variables were: (a) the comparison between students who took the entry-level courses (MTH 1 and MTH 2) with the co-requisite support lab (MTHL 1 and MTHL 2) respectively with those students who did not (meaning Lab vs No Lab) and (b) the comparison between men and women (Gender). The DV was the end of the course scores for students who took the entry-level course with the co-requisite support lab and those students who did not (final grade of the entry-level course). The two independent variables were measured as a categorical scale and the dependent variable was measure as an ordinal scale.

The two main effects and interaction effect analyzed by the 2 x 2 Factorial ANOVA were:

1. Main Effect 1: Was there a statistically significant difference in the DV between those who took the entry-level course with the co-requisite course MTHL1 and MTHL 2 compared to those who did not?
2. Main Effect 2: Was there a statistically significant difference in the DV between men and women?
3. The Interaction Effect: Was there a statistically significant interaction in the DV based on taking the entry-level course with the co-requisite course and gender?

Additional tests were conducted to test assumptions such as normality and homogeneity of variance. Skewness values, kurtosis values, histograms, and Z-test were used to test for normality. Levene's Test was used to test for homogeneity of variance. The data set was also split to test for normality for all four levels of the IVs. The feature of data analysis of frequencies was used in SPSS 26.0 to calculate the normality of each group which produced histograms and a table with skewness and kurtosis values for each level (See Table 4 and Figures 3-6).

In addition, data collected through the CIPP model's factors Context, Input, and Process were also used to understand the quantitative results produced by the 2 x 2 Factorial ANOVA.

Validity

According to Waugh (2018) internal validity is when the researcher manipulates the independent variable to measure if there is a true change in the dependent variable. External validity is when the manipulation of the independent variable has a true effect of the dependent variable and the results can be generalized. Ary et al. (2014) report that a quantitative descriptive study suffers from both internal and external validity threats because the researcher did not: (a) manipulate or control the independent variable(s), (b) did not assign participants to each group (those who received the treatment and those who did not) and (c) could not control other external factors that could have impacted the DV.

The groups being compared were selected because they "already possess[ed] the variable of interest" (Ary et al., 2014, p. 360); example, co-requisite lab vs not lab. Thus, because of the lack of control of the IVs this type of study has "less internal validity" (Ary et al., 2014, p. 361). If the results show a change in the DV, causality (that the changed occurred because of the IVs) cannot be assumed; alternative explanations must be considered for the change in the DV. Creswell (2014) concludes that a great concern with threats to validity is that it could be hard to conclude if the treatment applied, in the case of this study the co-requisite support lab, had any effect on the DV and not other factors.

To reduce the threats to the internal validity of the study the researcher used stratified random sampling to select participants' records for the sample size (See Table 2 and sampling section in Chapter 3). To reduce the threat to external validity reliable testing tools were used such as SPSS 26.0 (Creswell & Plano Clark, 2018) and a 2 x 2 Factorial ANOVA. In SPSS 26.0 F tests were calculated to determine where the difference occurred in the main effects and interaction effect (Ary et al., 2014). In addition, a Pairwise Comparisons test was conducted to pinpoint where that difference occurred within the levels of the group. Also, the presence of two IVs helped reduce the threats to external validity. Ary et al. (2014) recommended that increasing the number of external IVs reduces the threat to external validity because when more external IVs that have the potential to affect the DV are considered, the chances of other external factors affecting the change in the DV are reduced.

Site Selection and Sampling Procedures

Site Selection

The researcher selected one small private liberal arts university's co-requisite math program in southwest Georgia to examine the research questions under investigation. The site was selected because the researcher is the director of mathematics at the site selected and was familiar with the program. The university is a non-profit university that offers undergraduate and graduate degrees. Eighty-three percent of its funding comes from tuition and fees and the rest comes from government grants, private donations, and investment returns. The university has a student enrollment of about 1300 students; about one third are student athletes. In 2019, 97% of its students received a form of financial aid ("Integrated Postsecondary Education Data System," 2019). The majority of the students who took the entry level math courses MTH 1 and MTH 2 on the campus-based co-requisite program were student athletes. Sixty percent of the university's undergraduate population is under 24 years of age and 95% of the graduate student population is 24 years of age or older. In 2018 about seventy eight percent of the undergraduate and graduate student population were distant learners ("Integrated Postsecondary Education Data System," 2019). In academic year 2018-2019 the annual average cost of attendance for an in-state or out-of-state full-time student was $16,940 a year compared to University System of Georgia institutions which raged between $2,780-$10,008 for instate tuition and $10,526-$30,604 for out-of-state tuition in 2019 for full-time students (University System of Georgia Tuition Rate, 2019). Therefore, this institution differs significantly from large public universities in the University System of Georgia which in 2019 had an overall enrollment of 333,507 students in its 26 colleges and universities (University System of Georgia Enrollment, 2019). In 2018 the university had an overall graduation rate of 47% with a graduation rate of 45% for men and 50% for women (Integrated Postsecondary Education Data System, 2019).

The university placed students in MTH 1 or MTH 2 based on their major and based on their placement scores (ACT, SAT, or ACCUPLACER). Non-science majors were placed in MTH 1 and science majors were placed in MTH 2. As a result, not every student was required to take the co-requisite support math lab MTHL 1 or MTHL 2 (See Table 3). The research proposal along with IRB forms and required documents were submitted to both the site selected and the university from which the researcher is attaining his Ed.D.. Once permission was obtained from IRB (See Appendix), the data collection and sample selection began. The researcher contacted the selected university's Office of The Registrar and requested the desired data.

Sampling

Sampling size was very important for each part of this study. To ensure that the sample size met all of the requirements of the "statistical test[s]" (Creswell & Plano Clark, 2018, p. 177) a power analysis was conducted. The power analysis allowed the researcher to make an informed decision about the appropriate minimum sample size for this study. The researcher used the software G*Power 3.1 version to conduct the power analysis. The results from this power analysis produced a minimum sample size of 152 participants that could allow the researcher to achieve a statistically significant result for the Factorial ANOVA (Faul, Erdfelder, Lang, &

Buchner, 2007). Therefore, to enhance confidence the researcher used the university secondary quantitative data from 300 students, almost double what the power analysis recommended. Hence, the sample size being much larger than the minimum sample size recommended by the results from the power analysis allowed the researcher to be confident that the results produced by the Factorial ANOVA would produce a significant statistical result.

There were 537 students who took the entry-level math course MTH 1 or MTH 2 from Fall 2014 through Fall 2019 (See Table 1). This study focused solely on the program's traditional campus-based instructional model. For the study's quantitative data stratified random sampling was used because this sampling strategy allowed the researcher to select a proportional number of participants from different groups of the population (men and women, and students who took the entry-level college math course with the co-requisite lab and those who took the same course without a co-requisite lab) to have a sample size proportionally representative of the overall population (Creswell & Plano Clark, 2018). See Table 1 that contains the breakdown of the population.

Table 1

Population of Students Who Took an Entry-Level Math Course with or without a Supporting Math Lab

	With Lab	Without Lab	Total by Gender
Gender	n (%)	n (%)	n (%)
Men	90 (17)	229 (43)	319 (60)
Women	70 (13)	148 (27)	218 (40)
Total by Category	160 (30)	377 (70)	537 (100)

The study's sample size is divided into four groups:

Group 1 are men who took the entry-level math course MTH 1 or MTH 2 with the corresponding support math lab MTHL 1 or MTHL 2.

Group 2 are women who took the entry-level math course MTH 1 or MTH 2 with the corresponding support math lab MTHL 1 or MTHL 2.

Group 3 are men who took the entry-level math course MTH 1 or MTH 2 without the corresponding support math lab.

Group 4 are women who took the entry-level math course MTH 1 or MTH 2 without the corresponding support math lab.

The following formular was used to select each group for the sample size: Group = (Overall Segment of the Population/ Overall Number of the Population) * (Study's Desired Sample Size).

(1) Group 1 = (90/537) * (300) = 50; which represents 17% of the study's sample size

(2) Group 2 = (70/537) * (300) = 39; which represents 13% of the study's sample size

(3) Group 3 = (229/537) * (300) = 128; which represents 43% of the study's sample size

(4) Group 4 = (148/537) * (300) = 83; which represents 27% of the study's sample size

The overall sample size was n = 300. As it can be seen in Table 2, each group in the sample size proportionally represented its corresponding segment in the population. Once the number for each group was known the population's data were filtered by group and using a random number generator website the corresponding sample size was obtained.

Table 2

Sample Sizes for Students Who Took an Entry-Level Math Course with or without a Supporting Math Lab

	With Lab	Without Lab	Total by Gender
Gender	n (%)	n (%)	n (%)
Men	50 (17)	128 (43)	178 (60)
Women	39 (13)	83 (27)	122 (40)
Total by Category	89 (30)	211 (70)	300 (100)

Data Collection

The research proposal along with IRB forms and required documents were submitted to both the site selected and the university from which the researcher is attaining his Ed.D. Once the site's IRB granted permission to obtain the desired secondary archived data, the researcher contacted the Office of the Registrar and requested the students' end of the course grades for the campus-based sections of MTH 1 and MTH 2 taken from Fall 2014 through Fall 2019, whether or not the students took the co-requisite support lab, semester the class was taken, section, and gender. The data obtained were secondary archived data owned by the university, therefore it was not needed to ask for students' consent to use these data. The Office of the Registrar pulled the data and sent it to the researcher in a Microsoft Excel spreadsheet in a de-identified format with students' IDs instead of names. The Excel spreadsheet had the following columns: semester, students' ID, course name (MTH1 or MTH 2), final grade in MTH 1 or MTH 2, supporting math lab taken (yes or no), and gender. The study focused only on the campus-based co-requisite program.

Once the data were received, a new key code was created, and an additional column was added in the same Excel spreadsheet using a P-Code with Ps ranging from P1-P537 to assign to each student ID. Once the new key code was shared the column in the researcher's Excel spreadsheet copy with students' IDs was deleted leaving only the new P-code to connect to students' records. This was done to follow IRB and university's protocol of keeping students' identity private and anonymous.

The CIPP Model Data Collection

The placement guide with ACT, SAT, and ACCUPLACER scores and resources available to students in the co-requisite program, general information about the program, and resources put in place to assist students in the co-requisite model were obtained from the university's Director of Mathematics and 2020-2021university catalog.

Data Analysis

Once the de-identified data set was received in a Microsoft Excel spreadsheet from the Office of the Registrar, a new key code was created in Excel using a P-Code that ranged between P1-P537 to be able to connect to student IDs. On the researcher's Excel spreadsheet copy students' IDs were deleted. Using stratified random sampling as it was stated in the sampling section above the records of 300 students were selected. Once these records were selected, the data set was divided into four groups (See Table 2), a check was done to make sure that each group proportionally represented its corresponding category in the population (See Tables 1 and 2). Once this check was done, the data were coded to be entered in the software SPSS 26.0 ("SPSS Statistics," n.d.) for its analysis. There were two independent variables and one dependent variable.

The data were coded as follows: the dependent variable's values, final grades in MTH 1 and MTH 2 (A, B, C, D, & F) were given the following code in SPSS 26.0. A = 4, B = 3, C = 2, D = 1, and F = 0. This variable was run as an ordinal variable. The first independent variable (the co-requisite support math lab MTHL 1 or MTHL 2) was coded using Lab = 1 and No Lab = 2. This variable was run as a nominal or categorical measure. Finally, for the second independent variable (gender) the following code was used, Men = 1 and Women = 2. This variable was also run as a nominal measure.

Once the data were entered in SPSS 26.0 tests for the assumptions of normality and homogeneity of variance were run. These tests were crucial and were tested to determine whether the Factorial ANOVA could be conducted to analyze the quantitative data.

Testing of Assumptions

To test the data for normality two main steps were conducted:

Step 1. A test of normality was conducted to test the normality of the DV (final grades in the entry-level math courses MTH 1 and MTH 2) for the entire sample size. During step 1 a histogram and skewness values and kurtosis values were used to determine if the normality assumption was met; please see explanation of results and Figure 2 in Chapter 4. Step 2. The data were split to test for normality of each individual group 1- 4 (see the sampling section in this chapter for a reference of each group). In step 2 the data were split and the normality assumption for each of the four groups mentioned in the sampling section was tested.

Once the data were split a normality test using frequencies was run in SPSS 26.0 that produced four histograms with skewness and kurtosis values for each group. After the histograms were analyzed it was determined that an additional test was needed to further determine if the normality assumption was met. A z-test was used to make this determination (Mishra et al., 2019). The z-test produced z-scores for each group and each group's normality was calculated using its corresponding skewness and kurtosis values and their standard error values. Each z-score was calculated by "dividing the skewness or kurtosis value by their [respective] standard error" (Mishra et al., 2019, p. 70) (See Figures 3-6 and a detailed explanation of this process in Chapter 4).

To test the assumption of homogeneity of variance a homogeneity test was run in SPSS 26.0 and a Levene's test was conducted. The results of the Levene's test produced a nonsignificant result which meant that this assumption was met. In addition, descriptive statistics were also calculated to help explain the results produced by the 2 x 2 Factorial ANOVA, to "determine the general trends in the data" (Creswell & Plano Clark, 2018, p. 213), and to go from a descriptive to an inferential data analysis (Creswell & Plano Clark, 2018).

Null Hypotheses

After the testing of assumptions was conducted and descriptive statistics were calculated it was determined that it was appropriate to conduct the 2 x 2 Factorial ANOVA to analyze the data. The Factorial ANOVA was used to look for differences between IVs and interaction effects between the two independent variables on the DV (Vannatta Reinhart & Mertler, 2016). Since there were two IVs and one DV, there were two main effects and one interaction effect as stated at the beginning of Chapter 3. Therefore, the following three hypotheses were tested:

The first hypotheses tested the statistically significant difference between students who took the entry-level college math course MTH 1 or MTH 2 without the lab compared with those who took the math lab MTHL 1 or MTHL 2 respectively (IV-1). The null hypothesis for this hypothesis was:

1. Ho: There is no statistically significant difference in the end of course grades between students who took the entry-level course MTH 1 or MTH 2 with the support lab MTHL 1 or MTHL 2 respectively and those who did not.

The second hypotheses tested the statistically significant difference between men and women (IV-2). The null hypothesis was:

2. Ho: There is no statistically significant difference in the end of course grades between men and women.

Finally, the third hypotheses tested the statistical significance of the "interaction of the levels" (Vannatta Reinhart & Mertler, 2016, p. 74) between the two independent variables. The null hypothesis was:

3. Ho: There is no statistically significant difference in end of course grades between students who took the entry-level math courses MTH 1 or MTH 2 with the support lab MTHL 1 or MTHL 2, respectively, and gender.

In addition, three F ratios were calculated, one for each null hypothesis. The F ratio's were calculated using SPSS 26.0 to measure the level of variances or ratio of variance "*between-groups variability* . . . [and the] *within-groups variability*" (Vannatta Reinhart & Mertler, 2016, p. 72-73). Also, an interaction effect was calculated to determine how IV-1 and IV-2 could have explained the differences. To indicate where exactly the difference occurred for the main effect gender on the DV the additional Pairwise Comparisons test (Vannatta Reinhart & Mertler, 2016) was conducted in SPSS 26.0 using estimated marginal means. This was done by comparing main effects and selecting a confidence interval adjustment Bonferroni in SPSS 26.0 to identify where the difference occurred for the main effect gender on the DV.

Another data analysis that was performed using SPSS 26.0 as part of the 2 x 2 Factorial ANOVA was effect size or eta squared, which could be indicated by η^2 . The effect size was calculated for every IV, and their interaction. The objective of the η^2 was to use it to explain the overall "variance that [was] explained by the IVs." (Vannatta Reinhart & Mertler, 2016, p. 77). To interpret it, the effect size value needs to be multiplied by 100% to obtain the effect size value as a percentage. Once it is in percentage form, it is used to explain the percentage of the "variability" (Ary et al., 2014, p. 197) of the DV that is determined by the IVs. For example, an effect size of .38 explains 38% of the "the variance in the dependent variable [because] of the presence of the independent variable" (Ary et al., 2014, p. 197). Another way of interpreting this effect size is by indicating that 62% of the variance in the DV is not explained by the IV; other factors must be considered as the reason for the variance in the DV. According to Ary et al. (2014) there are three levels of effect size to consider; an effect size of .01 is considered a small effect size, .06 is considered a medium effect size, and an effect size of .14 or above is considered a large effect. All the Eta Square values produced by the data analysis were very small (additional explanation provided in Chapter 4).

The CIPP Model

The data collected for three factors of the CIPP model (Context, Input, Process) cannot be analyzed using any known quantitative statistical methods. These data were collected and used to provide potential explanations for the quantitative results of the study.

Summary

This chapter contained the research design, research questions, sampling procedures, site selection, null hypotheses tested, and procedures used to collect and to analyze the data. The following Research Questions were used: Context: What are the current demographics of college students enrolled in entry-level college math? Input: What resources are in place to support the delivery of entry-level college math? Process: What methods are used to place students in the entry-level math courses and co-requisite math course? Product: Are there statistically significant differences in passing rates between men and women college students who took an entry-level college math course using the new co-requisite model compared to those students who did not?

The following two independent variables were stated, IV-1 = The comparison between students who took the entry-level courses (MTH 1 and MTH 2) with the co-requisite support lab (MTHL 1 and MTHL 2) respectively with those students who did not (meaning Lab vs No Lab) and IV-2 = The comparison between men and women (gender). The dependent variable was; DV = the end of the course scores for students who took the entry-level course with the co-requisite support lab and those students who did not (final grade of the entry-level course). The two IVs were measured on a categorical scale and the DV was measured on an ordinal scale.

The data came from two entry-level mathematics courses and co-requisite mathematics supporting labs. The researcher contacted the Office of the Registrar after receiving approval from IRB to conduct the study. The data obtained were secondary, de-identified archived data for all the students who took the entry level-math courses MTH 1 and MTH 2 from Fall 2014 through Fall 2019. The researcher received 537 student records (end of course grades, semester course was taken, course section, whether student took the lab or not, and gender). From this population a sample of 300 students' records was selected using stratified random sampling. Then the data were coded and entered in SPSS 26.0 for analysis. Before a Factorial ANOVA was conducted in SPSS 26.0 the assumptions of normality and homogeneity of variance were tested using histograms, skewness and kurtosis values, Z-test, and a Levene's Test accordingly. The results showed that the data were approximately normal, and the assumption of homogeneity was met. The data for the CIPP model (placement policy and resources in place to help students in the co-requisite program) came from the university's Director of Mathematics, the university 2020-2021 catalog, and website.

Once the data were collected, coded, and assumptions tested, a 2 x 2 Factorial ANOVA was conducted to analyze the data and to test two main effects and an interaction effect. Additional tests such as F ratios, effect size, and pairwise comparisons were also calculated in SPSS 26.0. The data obtained for the factors (Context, Input, Process) of the CIPP model did not required a statistical data analysis. The results from the data analysis and tests are presented in the following chapter (Chapter 4).

Chapter IV

RESULTS

Introduction

The purpose of this quantitative descriptive study was to use a 2 x 2 Factorial ANOVA and the CIPP model to determine if the co-requisite model implemented in a small private liberal arts university had an impact on students' end of course grades for their entry-level math course. The co-requisite model used a supporting math lab that students had to take simultaneously with their entry-level math course based on their placement scores. The intent was to evaluate the campus-based co-requisite program's success and how it affected students' success rate by comparing passing rates of students who took the co-requisite support lab with students who did not and gender. Success in the entry-level math courses was defined as passing the class with a grade of C or better. The data came from multiple sections of two entry-level math courses and two co-requisite supporting math labs. For the purposes of this study, the entry-level courses are referred to as MTH 1 and MTH 2. MTH 1 was the entry-level math course that non-science majors were required to take, and MTH 2 was the entry-level math course that science majors were required to take. The corresponding co-requisite supporting math labs are referred to as MTHL 1 and MTHL 2 accordingly. The labs provided academic assistance to students who according to their placement scores (ACT, SAT or ACCUPLACER- see Table 3) needed extra help to succeed in their entry-level math course. The co-requisite courses were structured as a lab rather than a lecture-based course to provide more instructor-student and peer-to-peer interactions.

To collect the data the researcher contacted the selected university's Office of the Registrar and requested the desired data. The Office of the Registrar pulled the data and sent it to the researcher in a Microsoft Excel spreadsheet in a de-identified format with students' identification numbers (IDs) instead of names. The Excel spreadsheet had the following columns: semester, students' IDs, course name MTH1 or MTH 2, final grade in MTH 1 or MTH 2, supporting math lab taken (yes or no), and gender. The data set contained the records of N = 537 students and from these set n = 300 were selected for the study using stratified random sampling (See the sampling section in Chapter 3).

The study focused only on the campus-based co-requisite program. The data obtained were secondary archived data. The data came from the records of students who took the entry-level math courses MTH 1 and MTH 2 from Fall 2014 through Fall 2019. SPSS 26.0 was used to analyze the data. The following research questions were used to determine if the co-requisite program had an impact on students' success in the entry-level math course.

Context:

1. What are the current demographics of college students enrolled in entry-level college math?

Input:

2. What resources are in place to support the delivery of entry-level college math?

Process:

3. What methods are used to place students in the entry-level math courses and co-requisite math course?

Product:

4. Are there statistically significant differences in passing rates between men and women college students who took an entry-level college math course using the new co-requisite model compared to those students who did not?

This chapter will present the results obtained from the data analysis and from the data collection for the four factors of the CIPP model (Context, Input, Process, and Product). It will start with the demographic data (Context), the resources put in place to help students in the co-requisite program (Input), the university's placement policy to place students in the entry-level math course (Process), the results from the testing of assumptions of normality and homogeneity of variance, the descriptive statistics results, and the results from the 2 x 2 Factorial ANOVA (Product).

Demographic Data

There were 537 students who took the entry-level math course MTH 1 or MTH 2 from Fall 2014 through Fall 2019 (See Table 1 in Chapter 3). This study focused on the program's traditional campus-based instructional co-requisite model. There were no missing data, the 537 students' records included every student who took the entry-level math course from Fall 2014 through Fall 2019. From the 537 student's records, 300 were selected. The only demographic data obtained were gender. These data answered Research Question 1 and the Context factor of the CIPP model. There were 178 (60%) men and 122 (40%) women, of whom 89 (30%) took the supporting math lab and 211 (70%) who did not. The breakdown follows and can be seen in Table 2 in Chapter 3. Fifty (17%) men took the supporting lab and 128 (43%) did not compared to 39 (13%) women who took the supporting lab and 83 (27%) women who did not.

Resources Put in Place to Help Students in the Co-requisite Program

The data obtained for the Input factor of the CIPP model and to answer Research Question 2 were collected by contacting the Director of Mathematics at the selected site and the university's website, but no statistical analysis could have been performed on these data. The data obtained were: (a) the supporting math labs were offered once a week for 1 hr. and 15 minutes. (b) They counted as one credit hour courses where attendance was required, and each supporting math lab had a maximum capacity of 18 students per section. (c) The supporting labs were often taught by adjuncts and not by the same instructor who taught the entry-level math section of MTH 1 or MTH 2, but often the same faculty (adjunct or full-time) member taught both supporting math labs MTHL 1 and MTHL 2. (d) The entry-level courses enrollments were mixed, combining students who were required to take the co-requisite support lab and those who did not. In addition to the support students got from the supporting math lab, the university offered tutoring services (face-to-face and online virtually) through its tutoring center located at the library. Full-time instructors offered 10 hours of office hours per week while adjuncts offered one office hour per week so that students could receive additional help with their courses.

A description of the labs (MTHL 1 and MTHL 2) and what happened in the labs was also provided by the director of mathematics, the labs provided academic assistance to students who according to their placement scores (ACT, SAT or ACCUPLACER- see table 3) needed extra help to succeed in their entry-level math course. The co-requisite courses were structured as a lab rather than a lecture-based course to provide more instructor-student and peer-to-peer interactions. The instructors provided instruction over content students had already covered in the entry-level course's lecture to reinform the content, followed by in-class exercises. The faculty walked throughout the classroom assisting students with their in-class exercises. Peer interaction was allowed and encouraged. Students were not required to take tests in the lab. They were graded based on their class participation and weekly reflections where they reflected on what they had learned that week and what they still needed help with. Small additional assignments were given, such as completing practice tests for the entry-level math course, creating a formula sheet for their test, and showing proof that they had completed their homework/assignments for the entry-level math course.

University's Placement Policy for Entry-Level Math Courses

The data obtained for the Process factor of the CIPP model and to answer Research Question 3 were obtained by contacting the Director of Mathematics and looking at 2020-2021 university catalog which is posted on the university's website and open to the public. The university used three standardized placement tests scores (ACT, SAT, and ACCUPLACER) and a placement guide to place students in the entry-level math courses with or without a supporting math lab. The university placed students in MTH 1 or MTH 2 based on their major and based on their placement scores (ACT, SAT, or ACCUPLACER). MTH 1 was required for non-science majors and MTH 2 was required for science majors. Not every student was required to take the co-requisite support math lab MTHL 1 or MTHL 2 this was determined by their placement scores (ACT, SAT, or ACCUPLACER). Table 3 shows the placement guide used by the university to determine who was required to take the supporting math lab MTHL 1 or MTHL 2 and who was not. No quantitative data analysis was or could have been performed on these data. These data were collected and used to provide potential explanations for the quantitative results of the study, to answer the Research Question 3, and the CIPP model factor Process.

Table 3

Placement Guide for Entry-Leve Math courses MTH 1 and MTH 2

Placement Test	Score	Course	Co-requisite Lab
SAT	510 & Above	MTH 1 or MTH 2	None
	450-500	MTH 1 or MTH 2	MTHL 1 or MTHL 2
ACT	20 & Above	MTH 1 or MTH 2	None
	18-19	MTH 1 or MTH 2	MTHL 1 or MTHL 2
ACCUPLACER	258 & Above	MTH 1	None
	250-257	MTH 1	MTHL 1
	266 & Above	MTH 2	None
	259-265	MTH 2	MTHL 2

Testing of Assumptions: Normality and Homogeneity of Variance

To test the data for normality two main steps were conducted:

Step 1. A test of normality was conducted to test the normality of the DV (final grades in the entry-level math courses MTH 1 and MTH 2) for the entire sample size. During step 1 a histogram and skewness values and kurtosis values were produced and used to determine if the normality assumption was met (See Table 4 for skewness and kurtosis values and refer to Figure 2 for histogram).

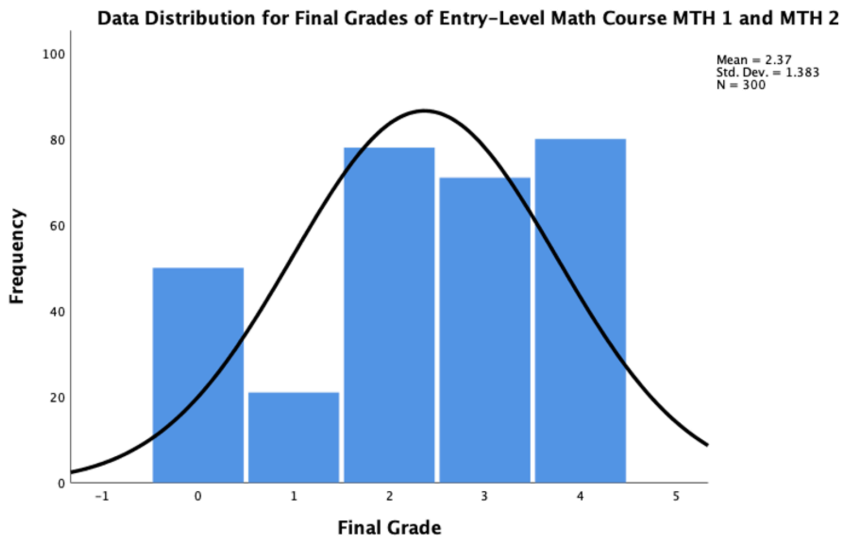

Figure 2. Final grade distribution for the sample size. A = 4, B = 3, C = 2, D = 1, and F = 0.

The skewness value was -0.45 and the kurtosis value was -0.954. Thus, based on the skewness and kurtosis values and the histogram in Figure 2, the data did not seem perfectly normally distributed. However, according to Vannatta Reinhart and Mertler (2016) “generally speaking, analysis of variance is robust to violations of the normality assumption” (p. 74). Since the histogram showed that the data were not perfectly symmetric, but the data were not completely abnormal, further analysis was conducted. For example, if the skewness and kurtosis values are within -1 and + 1 the data are “approximately normal” (GoodData, n.d., para. 4; Mishra et al, 2019, p. 70) and the skewness values then can be divided into two intervals; those which are on the two tail ends and within (-1, -.5) and (+.5, +1) are “moderately skewed” and those which are in the center within (-.5, .+.5) are “approximately symmetric” (para. 4). The data were approximately normal with a skewness value that is “approximately symmetric” (para. 4). Thus, even though the data were not perfectly normally distributed, it was approximately normal.

Step 2. The data were split to test for normality of each individual group 1- 4 (see the sampling section in Chapter 3 for a reference of each group), including the DV. Once the data were split in SPSS 26.0 a normality test was run in SPSS 26.0 that produced four histograms with skewness and kurtosis values for each group (See Figures 3 – 6 and Table 4).

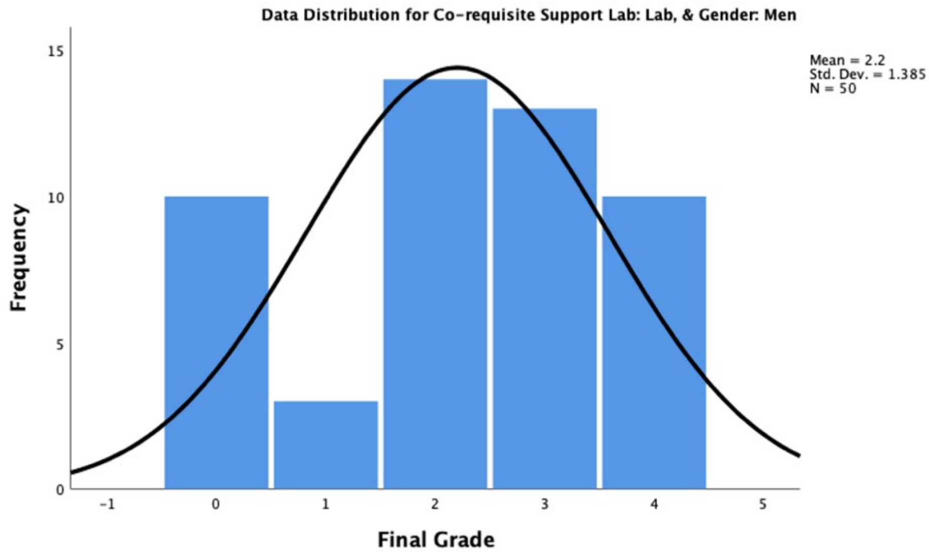

Figure 3. Data distribution for Group 1: Men who took the co-requisite support lab with the entry-level math course MTH 1 or MTH 2. A = 4, B = 3, C = 2, D = 1, and F = 0.

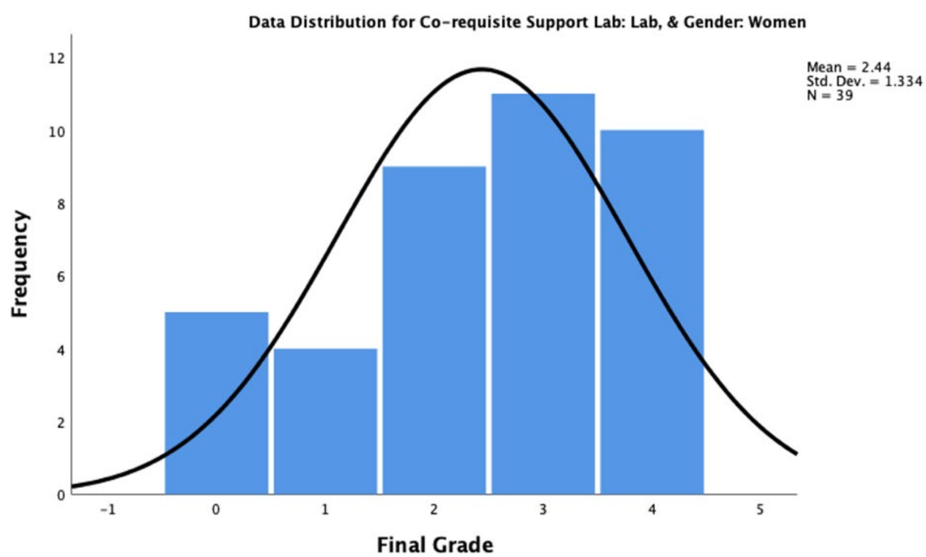

Figure 4. Data distribution for Group 2: Women who took the co-requisite support lab with the entry-level math course MTH 1 or MTH 2. A = 4, B = 3, C = 2, D = 1, and F = 0.

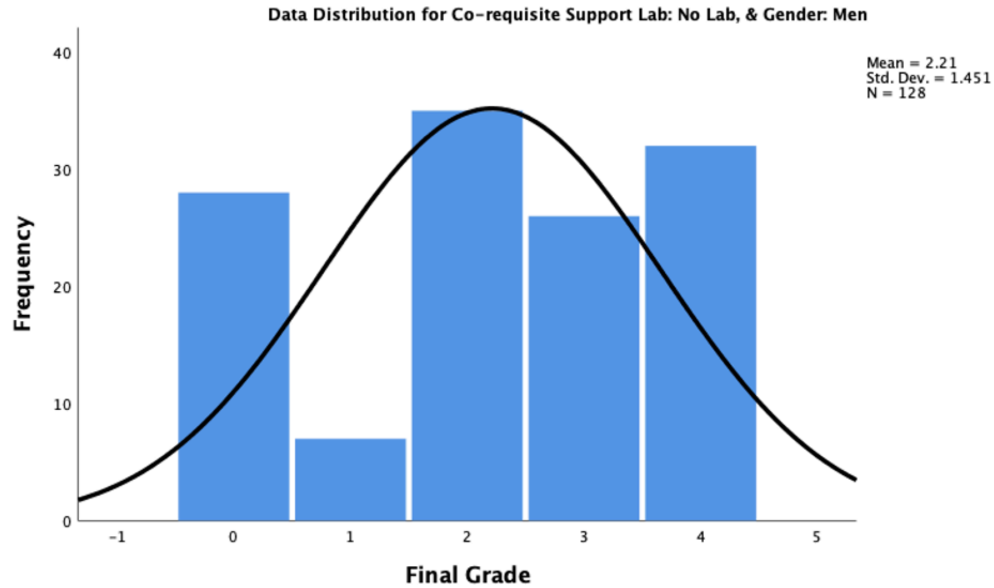

Figure 5. Data distribution for Group 3: Men who did not take the co-requisite support lab with the entry-level math course MTH 1 or MTH 2. A = 4, B = 3, C = 2, D = 1, and F = 0.

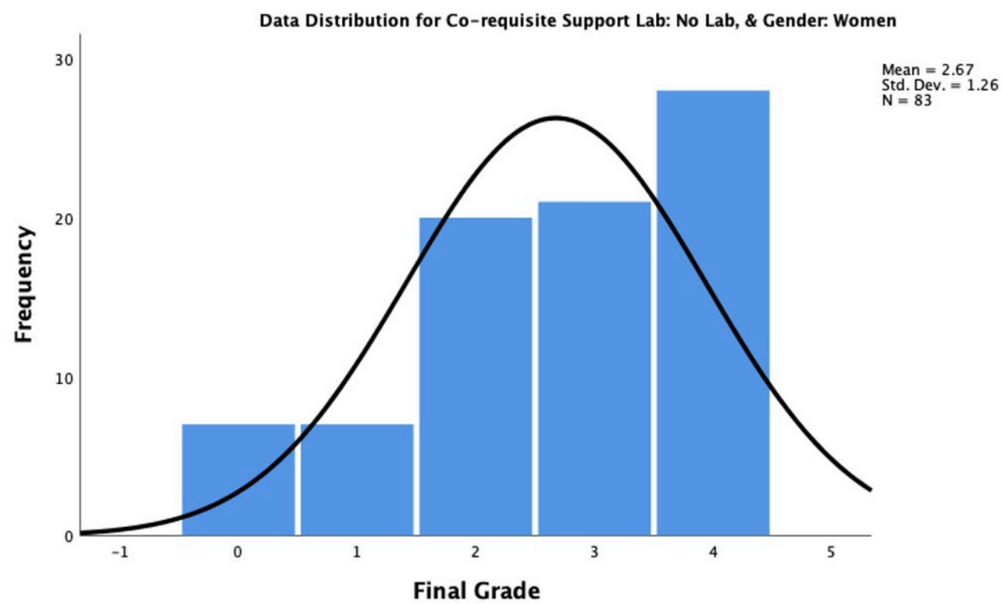

Figure 6. Data distribution for Group 4: Women who did not take the co-requisite support lab with the entry-level math course MTH 1 or MTH 2. A = 4, B = 3, C = 2, D = 1, and F = 0.

By looking at each histogram the data distribution seemed not to be normally distributed. After the histograms were analyzed it was determined that an additional test was needed to further determine if the normality assumption was met. Mishra et al. (2019), indicated that if a histogram does not show a perfect normal distribution of the data, there is another test that can be conducted using skewness and kurtosis values and their standard error values to determine if the data were normally distributed.

Since each group has a different sample size (see Table 2 in Chapter 3), a new test was used to test for normality. According to Mishra et al. (2019), "a z-test is applied for normality test using skewness and kurtosis…For small sample size (n < 50), z value ± 1.96 are sufficient to establish normality of the data [and] for medium-sized samples (50 ≤ n < 300)" (p. 70) a z-value within ± 3.29 is sufficient to stablish normality. Z-scores are the quotient of the skewness or kurtosis values and their standard error values. The results of this test can be seen in Table 4.

Table 4

Testing the Normality Assumption Using Skewness, Kurtosis, and Z-test

Group	Skewness	Std. Error of Skewness	Z-Score = Skewness/Std. Error of Skewness	Kurtosis	Std. Error of Kurtosis	Z-Score = Kurtosis/Std. Error of Kurtosis	n	Acceptable z-score: Within ± 3.29 Normal	Acceptable z-score: Within ± 1.96 Normal
DV	-0.45	.141	-3.191	-0.954	.281	-3.395	300	Skewness is within and Kurtosis is not	
Group 1	-0.374	.337	-1.109	-0.994	.662	-1.501	50	Both Acceptable	
Group 2	-0.522	.378	-1.380	-0.775	.741	-1.045	39		Both Acceptable
Group 3	-0.313	.214	-1.462	-1.168	.425	-2.748	128	Both Acceptable	
Group 4	-0.669	.264	-2.534	-0.49	.523	-0.936	83	Both Acceptable	

Note: DV = Dependent variable for entire sample size. n = Sample Size for each group. Green font was used to indicate acceptable and red font for unacceptable for all z-scores.

The results shown in Table 4 produced by the Z-test indicated that the assumption of normality was met for all four groups individually and is approximately normal for the DV, which in step 1 was also shown to be the case. But as it has been stated above, Factorial ANOVAS are “robust to violations of the normality assumption” (Vannatta Reinhart & Mertler, 2016, p. 74). Overall, it can be concluded that the data were not perfectly symmetric, but that the data were approximately normal.

To test the assumption of homogeneity of variance, a homogeneity test was run in SPSS 26.0 and a Levene’s test was conducted. The results of the Levene’s test produced a non-significant result (F (3, 296) = .768, p = .513), the significance level was measured on an alpha level of .05. Since the significance level was greater than .05, it meant that this assumption was met (See Table 5).

Table 5

Levene's Test of Equality of Error Variances[a,b]

		F	df1	df2	Sig.
Final Grade	Based on Mean	.768	3	296	.513

Note. Tests the null hypothesis that the error variance of the dependent variable is equal across groups. a. DV= final grade, b. Intercept + Learning_Support + Gender + Learning_Support * Gender

Descriptive Statistics

Descriptive statistics were calculated to help make sense of the results produced by the 2 x 2 Factorial ANOVA, adding to the data that could answer the last Research Question 4. They were also used to “determine the general trends in the data” (Creswell & Plano Clark, 2018, p. 213) and to go from a descriptive to an inferential data analysis (Creswell & Plano Clark, 2018). The data showed that women M = 2.6 (SD =1.28) had a higher mean than men M = 2.21 (SD = 1.43) on both groups those who took the supporting lab and those who did not. Overall, in every level, women had a higher mean and lower standard deviation than men. The overall mean for those who took the supporting lab was $M = 2.3$ ($SD = 1.36$), for those who did not take the supporting lab was $M = 2.39$ ($SD = 1.39$), and the overall mean for the sample size was $M = 2.37$ ($SD = 1.38$) (See Table 6).

Table 6

Descriptive Statistics of Means and Standard Devastations of the *Dependent Variable: Final Grade by Category Lab vs No Lab and Gender*

Co-requisite Support Lab	Gender	Mean	Std. Deviation	N
Lab	Men	2.20	1.385	50
	Women	2.44	1.334	39
	Total	2.30	1.360	89
No Lab	Men	2.21	1.451	128
	Women	2.67	1.260	83
	Total	2.39	1.394	211
Total	Men	2.21	1.429	178
	Women	2.60	1.283	122
	Total	2.37	1.383	300

Additionally, two frequency tables were included in this section to help inform the number or percentage of students who scored at a C or better in the entry-level math course (See Table 7).

Table 7

Final Grade Frequency Distribution

Letter Grade	Frequency	Percent	Cumulative Percent
F	50	16.7	16.7
D	21	7.0	23.7

Table 7 (Cont'd)

Final Grade Frequency Distribution

Letter Grade	Frequency	Percent	Cumulative Percent
C	78	26.0	49.7
B	71	23.7	73.3
A	80	26.7	100.0
Total	300	100.0	

Table 7 shows that 229 passed their entry level course with a grade of C or better. This was a 76.3% success rate.

Table 8

Final Grade Frequency Distribution by Group Lab vs No Lab and Gender

Co-requisite Support Lab	Gender	Letter Grade	Frequency	Percent	Cumulative Percent
Lab	Men	F	10	20.0	20.0
		D	3	6.0	26.0
		C	14	28.0	54.0
		B	13	26.0	80.0
		A	10	20.0	100.0
		Total	50	100.0	
	Women	F	5	12.8	12.8
		D	4	10.3	23.1
		C	9	23.1	46.2
		B	11	28.2	74.4
		A	10	25.6	100.0
		Total	39	100.0	
No Lab	Men	F	28	21.9	21.9
		D	7	5.5	27.3
		C	35	27.3	54.7
		B	26	20.3	75.0
		A	32	25.0	100.0
		Total	128	100.0	

Table 8 (Cont'd)

Final Grade Frequency Distribution by Group Lab vs No Lab and Gender

Co-requisite Support Lab	Gender	Letter Grade	Frequency	Percent	Cumulative Percent
No Lab	Women	F	7	8.4	8.4
		D	7	8.4	16.9
		C	20	24.1	41.0
		B	21	25.3	66.3
		A	28	33.7	100.0
		Total	83	100.0	

Table 8 shows the frequency distribution for each of the four groups:

In Group 1, 37 men who took the entry-level math course with the supporting math lab passed the course with a grade of C or better; their success rate was 74%. In Group 2, 30 women who took the supporting math lab with their entry-level math course passed the course with a grade of C or better; their success rate was 76.9%. In Group 3, 93 men who took the entry-level math course without the supporting math lab passed the course with a grade of C or better; their success rate was 72.6%. In Group 4, 69 women who took the entry-level math course without the supporting math lab passed the course with a grade of C or better with a success rate of 83.1%. When divided by groups, both women who took the supporting math lab and those who did not had a higher success rate than their men counterparts. Table 9 shows a complete summary of the means, SDs, and passing rates by category produced by the descriptive analysis and frequency tables.

Table 9

Comprehensive Summary of Mean, SDs and Passing Rates by Category

Gender	Co-requisite Support	*M*	*SD*	Passing Rate %
Men	Lab	2.2	1.39	74

Table 9 (Cont'd)

Comprehensive Summary of Mean, SDs and Passing Rates by Category

Gender	Co-requisite Support	*M*	*SD*	Passing Rate %
Women	Lab	2.44	1.33	76.9
Men	No Lab	2.21	1.45	72.6
Women	No Lab	2.67	1.26	83.1
Men	Lab & No Lab	2.21	1.43	73
Women	Lab & No Lab	2.6	1.28	81.15
Men & Women	Lab	2.30	1.36	75.3
Men & Women	No Lab	2.39	1.39	76.8
Men & Women	Lab & No Lab	2.37	1.38	76.3

ANOVA Results

A 2 x 2 Factorial ANOVA was conducted to measure the means difference between the learning support math lab and gender with regards to the DV = final grades. These results addressed the Research Question 4 and the Product factor of the CIPP model.

Significance of Main Effects

A 2 x 2 Factorial ANOVA was conducted to compare the two main effects, learning support math lab and gender (See Table 10). The significance of each main effect was investigated because the interaction effect was nonsignificant. The results of the first main effect (co-requisite support math lab) produced a nonsignificant result, (F (1, 296) = .504, p = .478, partial $\eta^2 = .002$). The results for the second main effect (gender) produced a significant result (F (1, 296) = 3.96, p = .048, partial $\eta^2 = .013$). These results from the main effects were also used to answer the following two null hypotheses:

1. Ho: There is no statistically significant difference in the end of course grades between students who took the entry-level course MTH 1 or MTH 2 with the support lab MTHL 1 or MTHL 2 respectively and those who did not.

2. Ho: There is no statistically significant difference in the end of course grades between men and women.

Table 10

2 x 2 Factorial ANOVA Tests of Between-Subjects Learning Support and Gender Effects

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	12.555[a]	3	4.185	2.216	.086	.022
Intercept	1384.080	1	1384.080	732.748	.000	.712
Co-requisite_Support	.952	1	.952	.504	.478	.002
Gender	7.473	1	7.473	3.957	.048	.013
Co-requisite_Support * Gender	.793	1	.793	.420	.518	.001
Error	559.111	296	1.889			
Total	2252.000	300				
Corrected Total	571.667	299				

Interaction Effect

The ANOVA's table showed that there was not a significant interaction between the two IV's, (F (1, 296) = .42, p = .52, partial $\eta^2 = .001$) for details refer to Table 10. These results were also used to answer the last null hypotheses.

3. Ho: There is no statistically significant difference in end of course grades between students who took the entry-level math courses MTH 1 or MTH 2 with the support lab MTHL 1 or MTHL 2 respectively and gender.

A linear plot was also used to visually identify any interaction effect between groups, within groups, and between levels of each group and to determine if the interaction was significant (See Figure 7). The result of this calculation indicated that there was an "ordinal"

(Vannatta Reinhart & Mertler, 2016, p. 72) interaction between the two IVs; however, the interaction between factors was non-significant. The linear plot showed that there was a difference between the distance between the levels Women-No Lab and Men- No Lab and the distance between the levels Women- Lab and Men-Lab. There was also a difference between women who took the lab and those who did not.

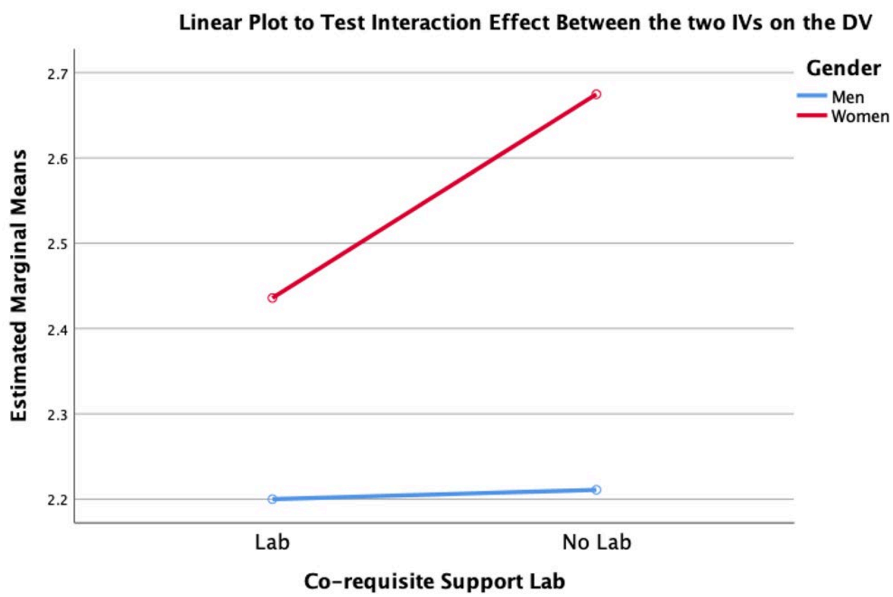

Figure 7. Linear plot for the interaction of the two IVs on the DV.

Additional Test: Pairwise Comparison and Bonferroni

After a 2 x 2 Factorial ANOVA was conducted to calculate the main effects an additional test was conducted to indicate where exactly the difference occurred for the main effect of gender on the DV. The Pairwise Comparisons test (Vannatta Reinhart & Mertler, 2016) was conducted in SPSS 26.0 using estimated marginal means. This was done by comparing the main effects and selecting a confidence interval adjustment Bonferroni in SPSS 26.0 to identify where the difference occurred for the main effect gender on the DV. The results showed that the significant difference occurred in gender for those who did not take the co-requisite supporting lab (p = .017) at an alpha level of .05 (See Table 11).

Table 11

Pairwise Comparisons on Dependent Variable by Gender and Co-Requisite Support Lab

Co-requisite Support Lab	(I) Gender	(J) Gender	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
						Lower Bound	Upper Bound
Lab	Men	Women	-.236	.294	.422	-.814	.342
	Women	Men	.236	.294	.422	-.342	.814
No Lab	Men	Women	-.464*	.194	.017	-.845	-.083
	Women	Men	.464*	.194	.017	.083	.845

Note. Based on estimated marginal means
*. The mean difference is significant at the .05 level.
b. Adjustment for multiple comparisons: Bonferroni.

Summary

This chapter presented the results from the quantitative descriptive study conducted in a small private liberal arts university located in Southwest Georgia. The study was conducted to study the impact the co-requisite model implemented at the university had on students' success (getting a grade of C or higher) in their entry-level math courses MTH 1 or MTH 2. The study used secondary archived data from Fall 2014 through Fall 2019 and focused solely on the campus-based program. This study used a 2 x 2 Factorial ANOVA and the four factors (Context, Input, Process, and Product) of the CIPP model to conduct the analysis.

The sample size contained 300 students' records that included: (a) end of course grades for entry-level math courses MTH 1 and MTH 2, (b) semester the class was taken, (c) whether or not the lab was taken, and (d) gender.

The results were presented in the following order: (a) demographics, (b) resources put in place to help students in the co-requisite program, (c) university's placement policy for entry-level math courses, (d) testing of assumptions: normality and homogeneity of variance, (e) descriptive statistics, and (f) ANOVA results.

The findings of the study indicated that the data were not perfectly symmetric and that the data were approximately normal. Three tests were conducted to reach this result. The first test used histograms, which indicated that the data did not look perfectly symmetric. Then additional tests were conducted to determine if the assumption was met, including the z-test. This z-test produced z-scores that indicated that the overall data were within acceptable ranges and thus approximately normal. The results from the descriptive statistics indicated that women had higher mean scores and lower standard deviation scores than men as a group and at the individual level between groups. The results of the 2 x 2 Factorial ANOVA indicated that the main effect learning support lab was not significant, the main effect for gender was significant, and the interaction effect was not significant at an alpha level of .05. To identify where exactly the significant difference occurred on the second main effect (gender) on the DV, a Pairwise Comparisons test was conducted, which produced a significant result for women who did not take the co-requisite support math lab. This result indicated that a significant difference occurred between women who did not take the support lab and men who did not take the support lab. The significant value for women who did not take the support lab was $p = .017$ at an alpha level of .05.

Chapter V

SUMMARY AND DISCUSSION

The subject of mathematics is a subject that most students have to take in college to earn a degree. Taking at least one mathematics course is part of almost any undergraduate program's requirement to graduate with a college degree. Knowing mathematics has become more important as society has become a more technological society where knowing mathematics is very important. Students need to know "basic mathematics and how to apply it in unfamiliar settings" (University System of Georgia Mathematics, 2013, p. 3). At the moment, around 60% of students entering college in the United States of America need learning support in mathematics (Park et al., 2018). Therefore, understanding what students need to succeed in college math courses is very important. A new model, the co-requisite model, has emerged as the new way of offering developmental math assistance to students who lack the necessary math skills to succeed in the entry-level math courses (Bailey, 2009; Howard & Whitaker, 2011).

The purpose of this quantitative descriptive study was to use a 2 x 2 Factorial ANOVA and the CIPP model (Context, Input, Process, Product) to determine if the co-requisite model implemented in a small private liberal arts university located in Southwest Georgia had an impact on students' passing rates between students who took an entry-level college math course with a supporting math lab and those who did not. The co-requisite model used a supporting math lab that students had to take with their entry-level math course based on their placement scores. The purpose was to evaluate the program's success and how it affected students' success rates defined as passing the class with a grade of C or better. To accomplish this task secondary archived data from Fall 2014 through Fall 2019, demographics data, resources put in place to help students in the co-requisite model, and placement policies were collected and analyzed. The following research questions were used to guide this quantitative descriptive study.

Research Questions

Context:

1. What are the current demographics of college students enrolled in entry-level college math?

Input:

2. What resources are in place to support the delivery of entry-level college math?

Process:

3. What methods are used to place students in the entry-level math courses and co-requisite math course?

Product:

4. Are there statistically significant differences in passing rates between men and women college students who took an entry-level college math course using the new co-requisite model compared to those students who did not?

This chapter connects relevant literature to current study findings. It starts with a summary of the methodology of the study and a discussion of the findings that includes limitations and forecasts suggestions for future research. The chapter ends with a discussion of the conclusions and recommendations for program improvement.

Methodology

This study used a quantitative descriptive design. This research design is used to study a segment in time of a phenomenon that is still currently happening, and the phenomenon is measured as it naturally occurs to describe the relation between variables (Waugh, 2018).

Archived data are used to compare the interaction between variables. Therefore, secondary archived data and a 2 x 2 Factorial ANOVA were used to look for differences between IVs and interaction effect between the two independent variables on the DV (Vannatta Reinhart & Mertler, 2016). The data came from multiple sections of two entry-level math courses and co-requisite math labs. The two entry-level math courses were labeled MTH 1 and MTH 2. MTH 1 was required for non-science majors and MTH 2 was required for science majors. The corresponding co-requisite math labs were referred to as MTHL 1 and MTHL 2 accordingly. The labs provided academic assistance to students who according to their placement scores (ACT, SAT or ACCUPLACER- see Table 3) needed extra help to succeed in their entry-level math course. The co-requisite courses were structured as a lab rather than a lecture-based course to provide more instructor-student and peer-to-peer interactions.

Once IRB approval was obtained to conduct the study (See Appendix), the researcher contacted the selected site's Office of the Registrar who provided the desired archived data. These data included all of the students who took the entry-level courses MTH 1 and MTH 2 and co-requisite courses MTHL 1 and MTHL 2 from the inception of the co-requisite course model in Fall 2014 through Fall 2019. The study focused only on the university's campus-based co-requisite program. The researcher obtained secondary de-identified data in a coded list with students' IDs instead of names; this way the researcher did not know the participants identity and the university protocol to ensure the privacy and anonymity of participants was followed.

Once the data were received it were recoded, removing the students' IDs and replacing them with a new P-Code that ranged from P1-P537. The data set contained 537 students' records from which 300 records were selected using stratified random sampling. In addition, data for the CIPP model were also collected. Finally, the quantitative data were coded in order to be entered into SPSS 26.0 and several tests were performed. The data for the CIPP model were used to provide potential explanations for the quantitative results of the study.

Validity

According to Waugh (2018) internal validity is when the researcher manipulates the independent variable to measure if there is a true change in the dependent variable. External validity is when the manipulation of the independent variable has a true effect on the dependent variable and the results can be generalized. Ary et al. (2014) indicate that a quantitative descriptive study suffers from both internal and external validity threats because the researcher did not: (a) manipulate or control the independent variable(s), (b) did not assign participants to each group (those who received the treatment and those who did not) and (c) could not control other external factors that could have impacted the DV.

To reduce the threats to the internal validity of the study the researcher used stratified random sampling to select students' records for the sample size (See Table 2 in Chapter 3). To reduce the threat to external validity reliable testing tools were used such as SPSS 26.0 (Creswell & Plano Clark, 2018) and a 2 x 2 Factorial ANOVA. In SPSS 26.0 F tests were calculated to determine where the difference occurred in the main effects and interaction effect (Ary et al., 2014). In addition, a Pairwise Comparisons test was conducted to pinpoint where the difference occurred within the levels of the group. Also, the presence of two IVs helped reduce the threats to external validity. Ary et al. (2014) recommended that increasing the number of external IVs reduces the threat to external validity because when more external IVs that have the potential to affect the DV are considered, the chances of other external factors affecting the change in the DV are reduced.

Participants

The site selected for the study was a small private liberal arts university in Southwest Georgia. The site was selected because the researcher is the director of mathematics at the site selected and was familiar with the university's co-requisite course model. Sampling selection is crucial for any study, to ensure that the study's sample met the requirements of the quantitative data analysis tests a power analysis was conducted. This power analysis allowed the researcher to make an informed decision about the appropriate minimum sample size for this study. The software G*Power 3.1 version was used to conduct the power analysis. The results from the power analysis indicated that a minimum sample size of 152 participants was required to achieve a statistically significant result for the Factorial ANOVA. Therefore, to enhance confidence the quantitative data of n = 300 (178 men and 122 women) students were selected from the N = 537 using stratified random sampling to ensure that the sample size proportionally represented each group in the population (See Tables 1 and 2). Hence, the sample size being much larger than the minimum sample size recommended by the results from the power analysis allowed the researcher to be confident that the results produced by the Factorial ANOVA would produce a significant statistical result. The sample size was divided into four groups (See Table 2), producing two levels for each main effect or IV.

Data Collection and Analysis

The data came from multiple sections of two entry-level math courses. Once IRB approval was received, the researcher contacted the university's Office of the Registrar and requested (a) students end of course grades for the campus-based sections of MTH 1 and MTH 2 taken from Fall 2014 through Fall 2019, (b) whether or not the co-requisite support lab was taken, (c) semester the course was taken, and (d) gender. Gender were also data collected for the CIPP model factor Context. The study focused only on the campus-based co-requisite program.

The data obtained were secondary archived data owned by the university, therefore it was not needed to ask for students' consent to use these data. Once the data were received in an Excel spreadsheet, a new key code was created and an additional column was added in the same Excel spreadsheet using a P-Code with Ps ranging from P1-P537 to assign to each student ID. Then, the students' IDs were deleted for the researcher's data set. This was done to follow IRB and university protocol of keeping students' identity private and anonymous.

Data for the CIPP model factors (Input, Process, and Product) were a placement guide (See Table 3). This guide had a breakdown of placement scores (ACT, SAT, and ACCUPLACER) and who was required to take the co-requisite support math lab and who was not. General information about the co-requisite labs was also obtained such as: (a) duration of the lab, (b) how many times it was offered during the week, (c) number of credits it was worth and class size, (d) who taught the labs, and (e) attendance requirements. An additional support offered by the university was tutoring services (face-to-face and online virtually) provided through the university's tutoring center located at the Library.

For the data analysis, the following process was conducted. After receipt of the data from the Office of the Registrar, a stratified random sampling was used to select the records of 300 students. The sample size was further divided into four groups (See Table 2). The reason for dividing the sample into four groups was to ensure that the sample size n = 300 proportionally represented the population, N = 537. Once this check was conducted. The data were coded to be entered into SPSS 26.0. For the dependent variable final grades (ordinal variable) the following codes were given A = 4, B = 3, C = 2, D = 1, and F = 0 in SPSS 26.0. For the first IV (co-requisite support math lab MTHL 1 or MTHL 2) the following code was given Lab = 1 and No Lab = 2 in SPSS 26.0. And lastly, for the second IV gender, the following code was used in SPPS 26.0, Men = 1 and Women = 2. Both IVs were run as categorical measures. The assumptions of normality and homogeneity of variance were tested using histograms, skewness values, kurtosis values, z-test, and Levene's Test accordingly.

A 2 x 2 Factorial ANOVA was run in SPSS 26.0. The Factorial ANOVA was used to look for differences between IVs and interaction effects between the two independent variables on the DV (Vannatta Reinhart & Mertler, 2016). Since there were two IVs and one DV, there were two main effects and one interaction effect as stated at the beginning of Chapter 3. Therefore, the following three hypotheses were tested using three F ratios:

1. Ho: There is no statistically significant difference in the end of course grades between students who took the entry-level course MTH 1 or MTH 2 with the support lab MTHL 1 or MTHL 2 respectively and those who did not.
2. Ho: There is no statistically significant difference in the end of course grades between men and women.
3. Ho: There is no statistically significant difference in the end of course grades between students who took the entry-level math courses MTH 1 or MTH 2 with the support lab MTHL 1 or MTHL 2 respectively and gender.

In addition, the F rations and interaction effect were calculated using F and *p* values and a linear plot (See Figure 7). Because the interaction effect was non-significant and there was one main effect (gender) that was significant additional tests were conducted to identify where the difference occurred. A Pairwise Comparisons test was conducted, using estimated marginal means and comparing main effects. Effect sizes were also calculated to determine the percentage that explained the variation of the DV by the main effects.

The data collected for three factors of the CIPP model (Context, Input, Process) could not be analyzed using any known quantitative statistical methods. These data were collected and used to provide potential explanations for the quantitative results of the study.

Summary of Findings

The findings for the CIPP model factors (Context, Input, and Process) can be summarized into three categories: (a) demographics, (b) placement policy (See Table 3), and (c) general information about the co-requisite lab and practices. For (a) (See Table 1 – 2 in Chapter 3) which contain the population and sample size. There were 178 (60%) men and 122 (40%) women of whom 89 (30%) took the lab and 211 (70%) who did not. Fifty (17%) men took the supporting lab and 128 (43%) did not compared to 39 (13%) women who took the supporting lab and 83 (27%) women who did not. For (b) (See Table 3 in Chapter 4). For (c) the results were the following: co-requisite supporting math lab MTHL 1 or MTHL 2 was offered once a week for 1:15 hours, the lab counted as one credit hour course, attendance was required, the support lab had a max capacity of 18 students per class, and labs were taught by adjuncts and not by the same instructor who taught the entry-level math section MTH 1 or MTH 2. The entry-level classes MTH 1 and MTH 2 had both students, those who were required to take the lab and those who did not. In addition to the math support students got from the co-requisite math lab, the university offered tutoring services (face-to-face and online virtually) through its tutoring center located at the library where students could have received additional help.

The 2 x 2 Factorial ANOVA was conducted to determine if there was any statistically significant difference in passing rates between students who took the entry-level math course

MTH 1 or MTH 2 with the co-requisite support lab and those who did not. For complete ANOVA results refer to Table 10. The results showed a non-significant result for the co-requisite support lab (F (1, 296) = .504, p = .478, partial $\eta^2 = .002$). The results for the second main effect (gender) were significant, (F (1, 296) = 3.96, p = .048, partial $\eta^2 = .013$). The interaction effect was non-significant, (F (1, 296) = .42, p = .52, partial $\eta^2 = .001$). A linear plot was also used to determine if the interaction was significant (See Figure 7). A pairwise comparisons test was conducted which produced a significant result for gender for those who did not take the support lab (p = .017) at an alpha level of .05.

The results of the descriptive statistics were: (a) for men who took the co-requisite support lab M = 2.2 (SD = 1.39), (b) for women who took the co-requisite support lab M = 2.44 (SD = 1.33), (c) men who did not take the lab M = 2.21 (SD = 1.45), and (d) women who did not take the support lab M = 2.67 (SD = 1.26). For students who took the co-requisite support lab M = 2.30 (SD = 1.36), for all students who did not take the lab M = 2.39 (SD = 1.39) and for gender: men M = 2.21 (SD = 1.43), women M = 2.60 (SD = 1.28). The entire sample size (n = 300) had a M = 2.37 (SD = 1.38).

In addition, Tables 7 and 8 have frequency distributions of the DV with percentages. Overall, 229 passed their entry-level course with a grade of C or better, this was a 76.3% success rate. When the data were divided into the four groups (See Table 8) the passing success rates with a grade of C or better were: (a) 74% for men who took the co-requisite support lab, (b) 76.9% for women who took the co-requisite support lab, (c) 72.6% for men who did not take the support lab, and (d) finally 83.1% for women who did not take the support lab. For a complete summary of means, SDs, and of passing rates (See Table 9 in Chapter 4).

Discussion of Findings and Related Literature

The CIPP Model Factors: Context, Input, and Process

Context. The findings for the demographics answered the Research Question 1: What are the current demographics of college students enrolled in entry-level college math? There were 178 (60%) men and 122 (40%) women of whom 89 (30%) took the supporting math lab and 211 (70%) who did not. This fact contradicts the national demographics in terms of gender for students taking entry-level math courses where there are more women than men "51.1% female and 48.9% males" (Ndum, Allen, Way, & Casillas, 2018, p. 64). This is also corroborated by Lopez and Gonzalez-Barrera (2014) who found that women enrolled in college at 71% compared to men at 61%. Thus, the university is unique in this category with a smaller women population taking entry-level math courses.

Input. The findings for the Input factor of the CIPP model revealed that the university used different practices that according to the literature help students enrolled in the co-requisite model. These data answered Research Question 2: What resources are in place to support the delivery of entry-level college math? The information obtained from the Director of Mathematics indicated that the university's program engaged in the following practices.

The co-requisite labs were 1 credit courses and offered once a week for a contact time of 1hour and 15 minutes, the USG Ad Hoc Steering Committee (2014) recommended at least "1 credit - 2 contact hours/week" (p. 7). So, in this practice the university did what other schools are doing in terms of credit assignment for the co-requisite lab, the contact time was less and that is something that could be recommended for program improvement. Another best practice implemented by the university's co-requisite program, according to the literature, was the use of small class sizes; the labs were cap at a max of 18 students. According to Fong et al. (2015), when class sizes are small, students in developmental math courses performed better. Thus, in this regard the university's co-requisite program is doing the right thing by keeping the class size small.

Another practice was that attendance was required for the co-requisite labs. According to the literature mandatory attendance is a best practice for students in the co-requisite model (Abbott, 2019; Becker, 2017). The university also offered tutoring services to students in the co-requisite model, tutoring is a best practice, Abbott (2019) found that students who attended tutoring services earned higher grades in the entry-level math classes than those who did not. Bailey (2009) also recommended that tutoring be offered as an additional assistance to students in a co-requisite model.

Another practice used by the university's co-requisite model was mixing students in the entry-level math courses, these courses had both types of students. This is a practice supported by one of the recommendations made by the USG Ad Hoc Steering Committee (2014) that indicated that is preferable to have "students participating in the co-requisite support component…mixed with non-co-requisite students" (p. 9). In addition, mixing students could be beneficial for students because having students of different levels in the same class could allow peer tutoring to take place. Peer tutoring has been shown to help the student (Kling, & Salomone, 2015). Separating these groups into two classes would only reproduce the structure of what the old model of the developmental education had. One higher level and one lower level in terms of mathematics skills. The content taught in these entry-level courses has not changed for centuries, but the way and the pace at which they are taught needs to change to accommodate the mathematic needs of students. According to Buckles, Haydel, Thompson-Sanchez, and Page (2019) faculty teaching co-requisite model courses need to make "learning more interactive by incorporating technology . . . [and shifting] to a more collaborative effort in teaching and learning, focusing more on faculty-student and student-student interaction in the classroom" (p. 44). According to Saxon and Martirosyan (2017) students who need math support need to be taught at a slower pace than those who do not, so perhaps having a mixed class creates a balance in the pace of the course. Perhaps this is why the mean of those students who took the lab $M = 2.30$ ($SD = 1.36$) was very similar to the mean of those who did not $M = 2.39$ ($SD = 1.39$).

The last practice that the co-requisite model used was not always having the same faculty teaching the entry-level course and the support lab. This practice goes contrary to what the literature recommends. The USG Ad Hoc Steering Committee (2014) recommended that the same faculty teach both the entry-level course and the lab. In addition, according to Saxon and Martirosyan (2017) not having the same faculty teaching both courses was not a best practice because it could have affected attendance in the co-requisite support lab. They found that when different faculty teach the course and the support lab students tend to miss the lab more often. Edgecombe (2011) indicated that having the same faculty teaching both courses, entry-level and math lab, "maximize[s] the potential of the model" (p. 12). During a webinar Dr. Tristan Denley provided a review of the data up to 2019 about the co-requisite model in the USG which indicated that when the same faculty teaches both courses this model produces the best results (Complete College Georgia, 2020). According to Abbott (2019), the USG has mandated that the same faculty teach both courses. The university where the study was conducted is a private university. Therefore, it does not have to follow the mandate from the USG, but given the support from the literature about this best practice it is a recommendation that will be passed along to the program's director for consideration and adaptation in the institution. Perhaps this practice will increase the passing rate.

Process. The data obtained through the CIPP model factor Process answered Research Question 3: What methods are used to place students in the entry-level math courses and co-requisite math course? This result produced a placement guide that the university used and is still using to place students in the co-requisite program (See Table 3). The guide used scores from three standardize test ACT, SAT, and ACCUPLACER, but did not include multiple measures. The USG Ad Hoc Steering Committee (2014) recommended to all its intuitions to use multiple measures. The recommendation was to use a "Mathematics Placement Index (MPI)" (p. 20) model which considers the placement scores from ACT, SAT, or COMPASS and the student's high school GPA. Using the correct placement process is crucial as it will have an effect on students' college progress, "the correct placement of incoming . . . college students into their first college-level mathematics course is . . . both critical and pivotal . . . to succeed in reaching their goal" (University of North Carolina System Math Pathways Task Force, 2019, p. 2) of passing the entry-level course. This is another area for program improvement to incorporate a new placement policy which includes multiple measures.

Descriptive Statistic

The following findings of the descriptive statistics and the 2 x 2 Factorial ANOVA addressed the last factor of the CIPP model (Product) and answered the last Research Question 4: Are there statistically significant differences in passing rates between men and women college students who took an entry-level college math course using the new co-requisite model compared to those students who did not? In addition, the three null hypotheses produced by the two main effects and interaction effect were tested and answered.

Starting with a discussion of the descriptive statistics, these data showed that the passing rate (final grade of C or better) for the overall sample size (N = 300) who took the entry-level math course MTH 1 or MTH 2 was 76.3% (n = 229) and the overall mean was $M = 2.37$ (SD = 1.38). The passing rate of those students who took the lab was 75.3% (n = 67) and their mean was $M = 2.3$ ($SD = 1.36$). When the data were separated and looked at by gender, women outperformed their counterparts for both groups those who took the lab and those who did not. The passing rate of women who took the lab was 76.9% (n = 30), and women who did not take the support lab had a passing rate of 83.2% (69) compared to their counterparts' passing rates which were 74% (n = 37) and 72.6% (n = 93) accordingly.

These passing rates are comparable to what is found in the literature. And in the case of women who did not take the lab, their passing rate exceeded what most university systems that have implemented the co-requisite model are getting. According to Denley (2017), the passing rate for the entire USG was 63% between 2015-2017 and 68% in 2018 (Complete College Georgia, 2020), which was more than three times what the passing rate was in 2013 at 20% for all USG institutions with the traditional developmental model. These passing rates are also comparable to what the Tennessee Board of Regents (TBR) obtained after its implementation of the co-requisite model, the passing rate was 75% between 2015-2016 (Denley, 2016). Based on the results women performed better than men, especially women who did not take the lab, but even women who took the lab performed slightly better than men who took the lab and those who did not. This was corroborated by Wheeler and Bray (2017) who found that women who received math support "had higher odds of passing" (p. 12) the entry-level math course than men (Moeining, 2016).

When the means and standard deviations were compared, the comparison also provided a clear indication that women who did not take the lab had higher mean $M = 2.67$ ($SD = 1.26$) and smaller SD than the other three groups; see Table 6 for a complete breakdown of the means and

*SD*s. The data showed that women had higher means and smaller *SD*s than their counterparts and that of the sample size. Having a smaller *SD* meant that women's scores for the entry-level math course were closes together, their scores were more consistent than those of men especially between men and women who did not take the lab. On the other hand, the group that took the support lab performed more closely to each other, their means and *SD* were very similar; M = 2.44 (SD = 1.33) for women, and M = 2.2 (SD = 1.38) for men. This could have happened because the support they received from the lab brought their academic differences closer together. Even though there were differences in passing rates, means, and SDs for all groups, these differences were very small which meant that students who received the co-requisite support lab performed relatively the same as those students who did not. The findings of this study support the work of Wheeler and Bray (2017). They found that students who received additional math assistance performed in their entry-level math courses at the same level as students who did not need developmental math. Their finding implied that if students who were placed in developmental math had not received the additional math assistance, they would not have succeeded in their entry-level math course. Thus, the results of this study indicate that developmental math works and helps students succeed in their entry-level math courses.

2 x 2 Factorial ANOVA Results and the CIPP Model Factor Product

The results of the 2 x 2 Factorial ANOVA and the factor Product of the CIPP model answered the Research Question 4: Are there statistically significant differences in passing rates between men and women college students who took an entry-level college math course using the new co-requisite model compared to those students who did not? In addition, the three null hypotheses produced by the two main effects and interaction effect were tested and answered.

The results of the 2 x 2 Factorial ANOVA produced a non-significant result (F (1, 296) = .504, p = .478, partial $\eta^2 = .002$), for the first main effect (co-requisite support lab). The following null hypothesis was tested. Ho: There is no statistically significant difference in the end of course grades between students who took the entry-level course MTH 1 or MTH 2 with the support lab MTHL 1 or MTHL 2 respectively and those who did not. Based on the non-significant result from the first main effect there was not enough evidence to reject this hypothesis.

The effect size was very small (Ary et al., 2014) and explained only .2% of the variance on the DV or better said 99.8% of the variance in the DV was not explained by this main effect, given the small effect size there were perhaps other factors that could have affected the variance in the DV (Ary et al., 2014). However, the non-significant result from the first main effect of the 2 x 2 Factorial ANOVA showed that there was not a difference in end of course grades between students who took the co-requisite support math lab and those who did not. This finding that both groups of students performed equally in the entry-level math course was corroborated by the descriptive statistics which showed the two groups of students to have very similar means, SDs, and passing rates in the entry-level math courses MTH 1 and MTH 2.

The results for the second main effect (gender) were significant, (F (1, 296) = 3.96, p = .048, partial $\eta^2 = .013$). The following null hypothesis was tested. Ho: There is no statistically significant difference in the end of course grades between men and women. Based on the significant result from the second main effect there was enough evidence to reject this hypothesis. However, even though the result was significant, and the hypothesis was rejected it was important to look at the effect size. The effect size was very small (Ary et al., 2014) and indicated that only 1.3% of the variance in the DV was explained by gender, or 98.7% of the variance in the DV was not explained by gender but by other unknown factors. Because of the effect size, it cannot be assumed that the variance on the DV solely depends on gender.

The interaction effect was non-significant, (F (1, 296) = .42, p = .52, partial $\eta^2 = .001$). The following null hypothesis was tested. Ho: There is no statistically significant difference in the end of course grades between students who took the entry-level math courses MTH 1 or MTH 2 with the support lab MTHL 1 or MTHL 2 respectively and gender. Based on the non-significant result from the interaction effect there was not enough evidence to reject this hypothesis. The very small effect size (Ary et al., 2014) almost zero and smaller than for the two main effects, indicated that only .1% of the variance in the DV was explained by the interaction between the co-requisite support lab and gender. Thus, it cannot be concluded that the variance in the final grades in the entry-level math course were solely determined by the co-requisite lab and gender.

A linear plot was also used to visually identify any interaction effect between groups, within groups, and between levels of each group and to determine if the interaction was significant (See Figure 7). According to Vannatta Reinhart and Mertler (2016), there are two types of interactions that could be observed on a linear plot "ordinal and disordinal" (p. 72). The linear plot shown in Figure 7 shows an ordinal interaction since the two lines do not cross, but they are not perfectly parallel to each other either. Since the two lines did not intersect then there was not a significant interaction effect between groups (Vannatta Reinhart & Mertler, 2016), corroborating the findings of the 2 x 2 Factorial ANOVA. The linear plot clearly shows that there was a significant difference in gender between those who took the lab and those who did not. Since the interaction was not significant the next step was to further evaluate the main effects. This was done separately for each factor through the use of a Pairwise Comparisons test (Vannatta Reinhart & Mertler, 2016).

Given the significant result obtained for the second main effect and the non-significant result for the interaction effect an additional test was conducted to determine where the significant difference occurred for the main effect of gender. A pairwise comparisons test was conducted which produced a significant result for gender for students who did not take the support lab (p = .017) at an alpha level of .05. Knowing this, the table of descriptive statistics was used to narrow down where this difference occurred. The difference occurred in women who did not take the co-requisite support lab, they performed significantly higher than their counterpart with a M = 2.67 (SD = 1.26). Their mean and SD were higher and lower respectively than the rest of the means and *SD*s respectively (See Table 6).

These findings from the 2 x 2 Factorial ANOVA were similar to what Moening (2016) found in a similar study that looked at archived data of a co-requisite model in a community college in Indiana. The data were collected from five semesters and the results indicated that women had a passing rate of 64.7% compared to men with only 52.5%, this corroborated the findings of this study which indicated that women also performed better than men who took co-requisite support lab and those who did not. Overall, it seemed that women performed better than men.

Limitations of the Study

This study had a few limitations. The first limitation was that the researcher used archived data, did not have control over the independent variables, and as a consequence, the result cannot be generalized outside the institution. Because of the limitations caution must be used when making conclusions about significant results produced by the data analysis. Other factors such as: attendance, mix courses, additional tutoring received, small class sizes, different teacher for entry-level course and lab, etc. would have to be considered too for the explanation of the variance in the DV (Ary et al., 2014).

Another limitation was the researcher works for the university where the co-requisite model was being studied. The researcher's conclusion could be bias in favor of indicating that the results indicate a positive impact of the co-requisite model, therefore further research by an independent party needs to be conducted to see if the findings are similar.

Another limitation was that this study only used two independent variables, and there could have been many other factors that affected the variance in students' passing rates.

Delimitation of the Study

The study had one delimitation; this study is limited to one small private university in Southwest Georgia. The university is a non-profit university that offers undergraduate and graduate degrees with a student enrollment of about 1300 students from which about two thirds are student athletes ("Integrated Postsecondary Education Data System," 2019). The majority of the students who took the entry level math courses (MTH 1 and MTH 2) on the campus-based co-requisite program were student athletes. Sixty percent of the university's undergraduate population is under 24 years old and 95% of the graduate student population is 24 years old or older. In 2018 seventy eight percent of its undergraduate and graduate population were distant learners ("Integrated Postsecondary Education Data System," 2019). This study is also limited to the university's on campus population. Therefore, this institution differs significantly from large public universities in the University System of Georgia. Consequently, the results of the study cannot be generalized beyond the university's co-requisite program.

Suggestions for Future Research

There are several recommendations for future research. The first one is to replicate this study at the same institution or at a similar institution using the same research design, but including archived quantitative data from more semesters. This research should use a multiple regression instead of an ANOVA for its data analysis. It should also include more independent variables such: (a) attendance, (b) age, (b) ethnicity, (c) students status (traditional vs nontraditional), (d) time the class was taken (morning, afternoon, evening), (e) years of teaching experience, (f) students' attitudes towards the co-requisite lab, and (g) teachers attitudes towards teaching the co-requisite lab. Having more IVs would make the study more robust; adding more IVs will also minimize the threats to external validity (Ary et al., 2014) allowing the researcher to identify which IV had a significant effect on the DV and allowing the result to be generalized.

Another recommendation would be to conduct a Sequential Mixed Methods Design at the same institution with the purpose to determine if the co-requisite support lab had a significant impact on students passing rates in the entry-level math course. This research should use the same archived data, but it should include more than two IVs. It should use interviews with students and faculty to gather students' and teachers' experiences with the co-requisite lab. Having qualitative data that could support or reject the findings from the quantitative phase. It would be very important to determine what parts of the program are working and which need to be improved or modified or removed.

Another study would be one that uses a quantitative approach and archived data to compare the passing rates between the old model of developmental math and the new co-requisite model at the same university to better identify the percentage increase in students' passing rates allowing the researcher to better determine the impact of the co-requisite model.

Finally, another research that should be conducted is a quantitative research that compares the passing rates of students in entry-level math courses on a campus-based co-requisite model with its counterpart for online entry-level courses. There is growing literature about the positive impact that campus-based co-requisite models are having on students' passing, but there is a gap in the literature about how the co-requisite model is being implemented and/or affecting students' passing rates for online students.

Conclusions and Recommendations

Understanding what factors have the most impact on students' passing rates who are enrolled in the co-requisite model at the institution is crucial for program improvement. Knowing what needs to be corrected and what needs to continue is crucial to help students achieve their goal of successfully passing the entry-level math course. Passing the entry-level math course increases the students' odds of earning a college degree (Bailey, Jaggars, & Jenkins, 2015; Edgecombe, 2011). Based on the study's results two conclusions can be made about the success of the co-requisite model in helping students' pass the entry-level math course MTH 1 or MTH 2.

Conclusions

The first conclusion, based on the results from the 2 x 2 Factorial ANOVA, indicated that the co-requisite model is working. The results from the 2 x 2 Factorial ANOVA produced a nonsignificant result for the first main effect. This finding indicated that the group of students who needed the lab as determined by the placement scores from the standardized tests (ACT, SAT, or ACCUPLACER), performed as well as students who were determined by their placement scores to not need the additional math assistance. This indicated that the Ho: There is no statistically significant difference in the end of course grades between students who took the entry-level course MTH 1 or MTH 2 with the support lab MTHL 1 or MTHL 2 respectively and those who did not, was true. Obtaining a non-significant result for the first main effect in conjunction with the results from the descriptive statistics clearly indicated that the lab helped students who were determined to need additional assistance to perform as well as students who did not. Therefore, the co-requisite lab worked as intended and had an impact on students' passing rates in the entry-level math class.

In addition, the significant result obtained for the second main effect of gender combined with the results from the descriptive statistics showed that women performed better than men and support the findings of the 2 x 2 Factorial ANOVA that rejected the second Ho. There was clearly a difference in passing rates between men and women in the two groups (see Table 9 in Chapter 3).

Given the limitations and delimitations of the study caution must be used when making generalizations about the results outside the university where the study took place. The effects sizes for the two main effects and interaction effect were very small, therefore, the majority of the variance in the DV could have also been explained by many other factors not considered for the study. Such factors as the tutoring service students received, tutoring has been proven to help students in the co-requisite model (Abbott, 2019; Bailey, 2009; Becker, 2017), or the small class sizes of the labs, or being in a mixed class, or the fact that attendance was required. The fact that women performed better than men corroborates what other research has shown (Moeining, 2016; Wheeler & Bray, 2017).

It is evident that these results along with the results from the descriptive statistics and the CIPP model factors Input and Process add to the body of the literature in general and corroborate what it has been found by other research about the benefits of the co-requisite model. These results formed a bigger positive picture of the co-requisite model being studied, indicating that it is working as intended. This conclusion was reached and supported by the positive results from the descriptive statistics and 2 x 2 Factorial ANOVA. In addition, this conclusion also supports the findings of Wheeler and Bray (2017) and what the USG has found regarding the benefits of the co-requisite model.

The second conclusion is based on the combination of the results obtained from the CIPP model four factors, the results from the descriptive statistics, and the significant result from the 2 x 2 Factorial ANOVA. If these results are analyzed as a whole unit rather than discretely, it is clear that the co-requisite program is showing working and producing positive results. These results do not pinpoint what factors are affecting the students' passing rates, but they do show positive results. The passing rates for all four levels (women-lab (76.9%), women-no lab (83.2%), men-lab (74%), & men-no lab (72.6%)) are comparable and in some cases better than those being obtained by the USG's co-requisite model which is in the mid 70% (Complete College Georgia, 2020) and other university systems that have implemented the co-requisite model like the Tennessee University System with a passing rate in the mid 70s% (Denley, 2016). The co-requisite model also implemented practices that match some of the best practices recommended by the USG such as small class sizes, mix classes, mandatory attendance, and tutoring services.

Therefore, it is evident based on the study's results and the literature that the university's co-requisite program has and is producing similar or even better passing rates than other universities that have implemented the co-requisite model. The USG has documented that the co-requisite model does help students succeed in the entry-level math course and the study's findings add to the body of the literature that corroborates it. The growing body of research supports the finding that the co-requisite model is working.

The results of this study along with the results produced by the literature have significant implications for practice in the field of developmental education. As a consequence, more states are now adopting the co-requisite model as the only model for remediation in mathematics. The state of Virginia seeing the great results that the co-requisite model has had on other states across the nation, decided to implement its version of the co-requisite model in Fall 2020 (Beamer, 2020). Dillard University located in New Orleans conducted a pilot study to measure its impact of the co-requisite model on students' passing rates, this was decided based on the positive results shown in Georgia and Tennessee co-requisite model. Its findings show that the co-requisite worked, all the students in the pilot program passed the class with a C or better. Therefore, in Fall 2018 the university decided to fully adopt and implement the co-requisite model for its entry-level math courses (Buckles, et al., 2019). Kashyap and Mathew (2017) conducted a study where they placed freshman students (155) into three courses (developmental course, entry-level math alone, co-requisite model) their findings indicated that the co-requite model was the best model with a success rate of 79.42% and in Fall 2015 the model was fully implemented. Therefore, based on the literature and the results from this study the co-requisite model is working and having a positive impact on students' passing rates in the entry-level math courses MTH 1 and MTH 2.

Recommendations

The following recommendations are intended for the institution's program improvement and for consideration for other institutions of higher education implementing the co-requisite model. The first recommendation is to increase the contact time from 1 hour and 15 minutes to at least 2 hours per week. Other institutions should consider adding or increasing their contact time for the co-requisite lab as well. According to results produced by the USG Ad Hoc Steering Committee (2014) having more contact hours improves students passing rates in the co-requisite program. The second recommendation is to use multiple measures when placing students into the co-requisite model. Properly placing students improves the odds of students passing the entry-level courses (University of North Carolina System Math Pathways Task Force, 2019). This recommendation is one that institutions of higher education should seriously consider because the literature and the results of this study has shown that most states and institutions do not use it or do not know how to appropriately use multiple measures to properly place students. The last recommendation, to use the same faculty for both the entry-level math course and the co-requisite support lab, has been shown to increase students' passing rates in the co-requisite model (Complete College Georgia, 2020).

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APPENDIX:

Institutional Review Board Protocol Except Report

Institutional Review Board (IRB)
For the Protection of Human Research Participants

PROTOCOL EXEMPTION REPORT

Protocol Number: 04025-2020 **Responsible Researcher:** Remigio Padilla-Hernandez

Supervising Faculty: Dr. Christopher Waugh

Project Title: *The Impact that A New Co-Requisite Model for Entry-Level College Courses is Having on Students' Success in Mathematics.*

INSTITUTIONAL REVIEW BOARD DETERMINATION:

This research protocol is **Exempt** from Institutional Review Board (IRB) oversight under Exemption **Categories 2 & 4**. Your research study may begin immediately. If the nature of the research project changes such that exemption criteria may no longer apply, please consult with the IRB Administrator (irb@valdosta.edu) before continuing your research.

ADDITIONAL COMMENTS:

- *Upon completion of this research study all data (email correspondence, survey data, participant lists, etc.) must be securely maintained (locked file cabinet, password protected computer, etc.) and accessible only by the researcher for a minimum of 3 years.*
- *Pseudonyms and the corresponding student ID number list each must be kept in separate files.*
- *The researcher must read aloud the submitted and approved Interview Research Statement to each participant at the start of each interview session.*
- *Interview recordings must be deleted immediately upon creating the interview transcript.*

☒ ***If this box is checked, please submit any documents you revise to the IRB Administrator at irb@valdosta.edu to ensure an updated record of your exemption.***

Elizabeth Ann Olphie *04.03.2020*
Elizabeth Ann Olphie, IRB Administrator

Thank you for submitting an IRB application.
Please direct questions to irb@valdosta.edu or 229-253-2947.

Revised: 06.02.16