THE RELATIONSHIP BETWEEN FAST-TRACKING STUDENTS INTO CURRICULUM MATH USING MULTIPLE MEASURES AND THEIR SUBSEQUENT SUCCESS RATES: A QUANTITATIVE STUDY OF SELF-DIRECTED LEARNING IN DEVELOPMENTAL MATHEMATICS

A Dissertation
by
CHANDRA NOËL LEHNER

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APPROVED BY:

____
Dr. Lisa Poling
Chairperson, Dissertation Committee

____
Dr. Les Bolt
Member, Dissertation Committee

____
Dr. Hunter Boylan
Member, Dissertation Committee

____
Dr. Audrey Dentith
Director, Educational Leadership Doctoral Program

____
Max C. Poole, Ph.D.
Dean, Cratis D. Williams School of Graduate Studies

Abstract

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CHANDRA NOËL LEHNER
B.A., Florida Gulf Coast University
M.A.T., Florida Gulf Coast University
Ed.D., Appalachian State University

Dissertation Committee Chairperson: Dr. Lisa Poling

Why do people do what they do? Motivation is essential when it comes to self-directed learning. This study examined the relationship between fast-tracking students into college-level math using multiple measures and their subsequent success rates, while simultaneously looking at the success rates of students (with a comparable high school GPA) who were required to progress through a self-directed developmental math course sequence initially before taking the same college-level math class. The ability to set goals has a major impact on how much learning can be achieved in a self-directed environment. The theory of self-directed learning will be critically analyzed, along with its goals and effectiveness in a computer lab setting.

Developmental math – It is the same concept educators have been debating for decades now, just different rhetoric. The fundamental issue behind this concept comes down to cost savings (Epper & Baker, 2009; Humphreys, 2012; Pretlow III & Wathington, 2011; Walters, 2012). Multiple Measures for Placement is the latest North Carolina state policy that should help increase college graduation rates as well as reduce the cost for instruction by eliminating the

need for so many developmental math courses. The history of developmental math was explored in this study, along with the responsibility of high schools as well as educators and administrators in their roles of increasing the success rates of college graduates nationwide. The question remains: Will students who are fast tracked using the Multiple Measures for Placement Policy into curriculum math do just as well or better than their counterparts who were required to progress through a self-directed, developmental math course sequence initially before taking the same college-level math class? In addition to this question, the researcher also aimed to find out whether placement into developmental mathematics is predicted by gender, race (Caucasian vs. Non-Caucasian), and/or socio-economic status as defined by the Free Application for Federal Student Aid (FAFSA and non-FAFSA)? These are the questions the research intended to resolve with its findings.

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Dedication

This dissertation is dedicated to my one and only son – Joshua John Allen-St. John. When I was pregnant with you twenty years ago, I was still an undergraduate taking Calculus classes. As you grew, you watched me continue my educational journey along with starting your own. I am SO PROUD of the man you have become. Know I will always love you. Know everything I have ever done in my adult life, including every test taken, every paper written, every weekend given up to study, even this 166-page dissertation has all been for *YOU*. More than anything, I have always wanted to make you proud to have me as your mother. I know until the day I die, I will continue to strive to be the best 'momma' I can be for you. I love you dearly. I can never say that enough. You need to remember to do the same to yours.

One more thing Josh – TAG, you're IT!

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Chapter 1 Introduction

For years, the United States has been the leader in business, industry, technology, and even educational attainment ("Best countries for education," 2018; Yanushevsky, 2011). It is no secret that the United States has been losing its foothold as the greatest nation in the world for some time now based partly on its standing in educational attainment (Rice, 2015). Countries such as China, the United Kingdom, Germany, and Japan have all stepped up their pursuit aiming to take that number one ranking as world leader away from the United States (Hall, 2017; Human Rights Advocate, 2017). For this reason, the United States is searching for answers; trying to maintain its number one status as a world leader. One of the first places our leaders are looking for answers to improve the future direction of our country is to the young people currently enrolled in K-12 schools and in colleges and universities. Leaders are looking to the educational institutions on which our country has always relied upon for solutions (Berger & Fisher, 2013). If the United States plans to maintain its status as being number one in world power, innovation, and leadership, then it needs to start investing more time and energy in the youth of its future (Yanushevsky, 2011). Simply put, the United States needs to start investing more in the education of today if they want the best leaders of tomorrow. Maybe the answer is not to spend more money on education, but for the money to be spent on education more wisely.

Problem Statement

The literature suggests that the United States needs to do a great deal of catching up with its rival countries when it comes to educating the best and brightest of tomorrow's world leaders. One beneficial way to compete in today's global economy is through investing in innovative ways to improve education in all areas of science, technology, engineering, and mathematics (Yanushevsky, 2011). Spellings, President of the University of North Carolina System and former US Secretary of Education, was cited as saying, “We live in a world where technological innovation and global competition are increasing at a pace never before seen. Now is the time to invest in our children to make sure they are prepared to succeed in the 21^{st} century” (Yanushevsky, 2011, p. 12). Improving our educational system will allow more students to graduate from high school and then complete college (Humphreys, 2012). Graduating more students from college with degrees will give the United States a chance when competing with rival countries in the emerging fields of today: science, technology, engineering, and mathematics.

On February 24, 2009, President Barack Obama spoke to Congress in his first joint address where he laid out his plan to have the United States rank number one in the percentage of college graduates. The President assured the nation that by 2020, the United States would again have the highest percentage of college graduates in the world (Committee on Measures of Student Success, 2011; Humphreys, 2012; Obama, 2009). The President stated, “In a global economy where the most valuable skill you can sell is your knowledge, a good education is no longer just a pathway to opportunity—it is a prerequisite;” emphasizing “every American will need to get more than a high school diploma” (Obama, 2009, p. 15). In order to reach this goal, the U.S. Department of Education projects that the U.S. will need to increase the number of college graduates by 50%. To put that number into perspective, this translates into eight million more students who will need to graduate with 2- and 4- year degrees by the year 2020 (Boggs, 2015; Obama, 2009; U.S. Department of Education, 2011).

One might wonder where these eight million more students are going to originate from. A large percentage of students are going to come from the 25- to 34- year old age group who have already graduated from high school and taken time off school. Sixty percent of this group need to graduate with an Associate's degree by 2020 in order to meet President Obama's goal (Fry, 2017). Since 25- to 34- year olds are not the focus of our population for this study, they will not be discussed in this paper. The population of the study deals with the younger student who strained to make it through high school.

These struggling students will need to graduate from high school first and then graduate from college, both in record numbers in order to meet Obama's goal (Bailey, Jeong, & Cho, 2009; Scrivener & Coghlan, 2014). Because of the goal set forth by our government, our nation's community colleges are going through drastic changes to their admission standards in order to meet the 2020 deadline (Attewell, Lavin, Domina, & Levey, 2014; Boggs, 2015; Bracco, Austin, Bugler, & Finkelstein, 2015; Walters, 2012). Since the President's speech to Congress in 2009, four detailed initiatives have been put in place to help with the goal of reaching 50% more college graduates by the year 2020.

Initiatives in action – achieving the dream (2004 – 2009). Achieving the Dream (AtD) is a 5-year initiative with the same objective of graduating more college students. Established in 2004 by the Lumina Foundation, its main objective was to "…be a catalyst for providing ways for colleges to strengthen … their capacity to ensure that more students complete their college education" ("Helping more community college," 2017, p. 1). With a budget of $15 million, 26 colleges were challenged to examine evidence, policy, knowledge, and engagement surrounding student completion in developmental education (Bowling, 2017; Pretlow III & Wathington, 2011). The AtD initiative marked the first time that community colleges had begun to intentionally look at their data to make formal decisions about college processes. What many colleges realized was that students were getting trapped in developmental classes and never progressing (Bowling, 2017). With this knowledge, community colleges then began to turn to their neighboring community colleges to see what they could learn from their best practices and began to mitigate some of the challenges students and colleges were encountering. Through AtD, a framework was created to help support students academically (Bowling, 2017). One of the products of Achieving the Dream was learning communities – support for students in their academic courses through cohort learning while incorporating campus and community connections (“Learning communities,” 2017).

Initiatives in action - the developmental education initiative (2009 – 2012). In 2009, the North Carolina Community College System (NCCCS) devised a strategy to reduce the number of students entering developmental education, as well as, increase the number of college graduates (The Hunt Institute, 2015). The plan was entitled, DEI – the Developmental Education Initiative and encompassed goals and transformations that needed to take place in order for the reform to be successful: “reduce unnecessary enrollment in developmental education courses; accelerate student completion; and increase the number of students who complete the developmental-course sequence and enroll in curriculum-level classes” (The Hunt Institute, 2015, p. 1). Key transformations that needed to take place in order for these goals to be reached were: “redesign the North Carolina Community College System curriculum (see A New State Redesign); implement appropriate placement measures (see Multiple Measures Alternative); and establish a new diagnostic test aligned to the developmental curriculum (see Placement Test Quandary)” (The Hunt Institute, 2015, p. 2). DEI looked specifically at developmental education strategies necessary to help students. Fifteen colleges across six states took part in DEI. Only one community college from North Carolina was chosen to be in the Developmental Education Initiative. A budget of $732,000 was allotted per college ($244,000 a year for three years) to fund these developmental education strategies (Bowling, 2017). Through DEI, Learning Communities on campuses continued to flourish. Supplemental Instruction (SI) was another support put in place to help students with their developmental coursework. SI targets historically difficult classes by offering non-remedial help to students in a welcoming, peer-led support fashion. SI has been known to increase student success rates and retention ("Supplemental instruction," 2017).

Initiatives in action - completion by design (2012 – 2017). Stemming from the work DEI had already undertaken, Completion by Design (CBD) was another initiative implemented in 2012. Funded by the Bill and Melinda Gates Foundation (2017), this initiative was a 5-year strategy to help "community colleges boost completion rates for most students, by focusing on comprehensive institutional transformation at scale" ("Completion by design," 2017, p. 1). It was also the biggest investment ever in higher education with $9.7 million being invested in a cadre of five community colleges in North Carolina alone (Bowling, 2017). Other states participating in the initiative include Ohio and Florida. Completion by Design identified specific Guided Pathways for students to take in order to complete a credential. These pathways focused on the first-year college student experience, the realignment of programs to make them more streamlined, and finally how to get students to complete the credential ("Completion by design," 2017). This pathway is meant to get students focused on the job or degree they want and then back track [their education] from there; what do students need to complete that goal? CBD saw more personal advising on campus to help make sure students were on track to graduate and did not veer too far off of their program of study.

With all of these initiatives, came great improvements in numbers. According to the U.S. Department of Education's National Center for Educational Statistics (2017), the high school graduation rate for the nation as a whole hit 81% in 2012 – 2013; 82.3% the following year and 83% in the 2014 – 2015 school year (U.S. Department of Education, 2015). This was the highest percent ever recorded since the states adopted a new way of calculating these statistics in 2010. With record high school graduates, came record incoming college freshmen (IES: Institute of Education Sciences, 2016). The issue many colleges faced now was that these new students were being placed into colleges' developmental courses more so than into the college – level, credit bearing classes (Duffy, Schott, Beaver, & Park, 2014). Policymakers also recognized this trend based on the following initiative put in place in 2015.

Initiatives in action - multiple measures for placement policy (2015 - current). Multiple measures is a policy set in place to enhance the number of graduates from college. This policy is fulfilling the transformation effort made by the Developmental Education Initiative to "implement appropriate placement measures" (The Hunt Institute, 2015, p. 2). The Multiple Measures for Placement Policy, a Gates-funded initiative, was originally piloted in three states in 2015: California, North Carolina, and Wisconsin (Duffy et al., 2014). Today, Multiple Measures for Placement Policy is being implemented across nine states. Multiple measures allows colleges and universities to assess incoming freshmen using more than one measure, like the college's placement test, which is often flawed, to lessen the number of students being placed into developmental classes. It is the hope of colleges and universities that this new policy could potentially increase the number of college graduates in the United States (Ngo & Kwon, 2014). In turn, the increase in college graduates could be seen as the solution to securing the nation's position at its top spot with world powers (Berger & Fisher, 2013; Yanushevsky, 2011). Keep in mind, multiple measures is a policy put in place with minimal effort and minimal cost – it looks at measures already in place to determine placement, such as Grade Point Average (GPA) or standardized test scores (Bracco, Dadgar, Austin, Klarin, Broek, & Finkelstein, 2014). In order to increase graduation rates, colleges are looking to move a majority of the students out of developmental education and into curriculum classes (with no prerequisite classes required), whether they are prepared or not. This policy can be lumped in with all the other ineffective solutions policymakers have devised over the years to increase success numbers. It is a cynical way of looking at education and is a mostly politically-driven policy because administrators seem to benefit more so than the students the policy is supposed to benefit (Rabovsky, 2014; Thornton & Friedel, 2015).

"If colleges allow more students to bypass remediation and go directly into college level math, it is likely that more students will pass. It is also likely that more students will fail. Except now, you have more students with Fs on their record affecting their GPA and financial aid" (H. Boylan, personal communication, November 18, 2017). This is a conundrum that has yet to be explored. There are definite consequences for over placing and under placing students in college-level mathematics (Ariovich & Walker, 2014). If students are under placed, which has historically been true, the students may get discouraged in the barrage of developmental courses and may never complete college (Bracco et al., 2015). The other side of this debate happens when a student is placed in mathematics classes beyond their ability, like we are beginning to see with multiple measures (Belfield & Crosta, 2012). The issue then becomes how to educate a student who is completely unprepared for the mathematics that lie ahead of them when they are placed into a classroom that is above their ability level? The student gets discouraged in class, and often times, tends to bring down the achievement scores of their more academically-prepared classmates (Scott-Clayton, Crosta, & Belfield, 2013). This behavior will undoubtedly lead to higher failure rates in college-level math classes. There needs to be more of a balance at the cut score for when students are able to bypass developmental coursework and go straight into curriculum. The results of this research will add to the literature on this topic.

Research Questions

As a result of this research, the following two questions are anticipated to be answered:

1. Does a self-directed, developmental math course sequence have an impact on student achievement (final course grade) in the subsequent curriculum math course MAT 143 – Quantitative Literacy?
2. Is placement into developmental mathematics predicted by gender, race (Caucasian vs Non-Caucasian), and/or socio-economic status (FAFSA and non FAFSA)?

Hypotheses. Question #1 - $\boldsymbol{H_0}$: $\boldsymbol{\beta_1 = 0}$; Students who engage in a self-directed developmental math course sequence prior to entering the curriculum math class, Quantitative Literacy – MAT 143, perform no better on final course grades than those who were able to bypass developmental math and go straight into the curriculum math via multiple measures.

$\boldsymbol{H_1}$: $\boldsymbol{\beta_1 \neq 0}$; Students who engage in a self-directed developmental math course sequence prior to entering the curriculum math class, Quantitative Literacy – MAT 143, perform better on final course grades than those who were able to bypass developmental math and go straight into the curriculum math via multiple measures.

Question #1-a. – $\boldsymbol{H_0: \beta_1 = 0}$; Placement into developmental mathematics is not predicted by gender, race (Caucasian vs Non-Caucasian), and/or socio-economic status (FAFSA and non FAFSA)?

$\boldsymbol{H_1: \beta_1 \neq 0}$; Placement into developmental mathematics can be predicted by gender, race (Caucasian vs Non-Caucasian), and/or socio-economic status (FAFSA and non FAFSA)?

Level of significance p = .05.

Significance of Issue

The need for remediation has been around as long as education has been present in modern day society (Boylan & Bonham, 2014; Boylan & White, 1986; Breneman, Costrell, Haarlow, Ponitz, & Steinberg, 1998). In 1636, it was found that students at Harvard College, the nation’s first public institution, needed tutoring because they had forgotten ancient languages such as Latin and Greek (Boylan & Bonham, 2014; Breneman, et al., 1998). Because of this need, much research has been performed on developmental mathematics to determine the best way of assisting students in mastering course material. Topics such as placement into developmental mathematics (Belfield & Crosta, 2012; Melguizo, Kosiewicz, Prather, & Bos, 2014; Ngo & Kwon, 2014), student motivation in developmental mathematics (Guy, Cornick, & Beckford, 2015), persistence in curriculum math after developmental math exposure (Bontrager, 2016), and developmental education reform (Bracco et al., 2015) are just a few of the many topics that have been thoroughly examined by researchers over the years.

There is some research on the Multiple Measures for Placement Policy, but the policy is currently active in only a handful of states including Florida, North Carolina, Hawaii, Wisconsin, and California (Duffy et al., 2014). California was the first to enact the policy in 1986, preceding MALDEF, the Mexican American Legal Defense and Educational Fund discrimination lawsuit of 1991 (Duffy et al., 2014). Since the Multiple Measures for Placement Policy did not go into effect in North Carolina until the fall of 2015, little research exists for the state. Likewise, there is currently no research on the effects of multiple measures in the curriculum mathematics classroom. This study evaluated the final course grades of two groups of students for the college-level math class, Quantitative Literacy – MAT 143: those who were allowed to bypass developmental mathematics and enroll in a college-level math class by way of multiple measures (MM group). The other group consisted of students who were required to take the developmental mathematics course first (the treatment) and then proceed to the same college-level mathematics course (Dev group). The final grades were then compared to see if there was any difference between the students who took the self-directed developmental math course sequence and those who were placed directly into the college-level math class using multiple measures.

A Brief History of Developmental Education

Historically speaking, some students have come through the doors unprepared for college-level work. A supplementary tutoring program was first created at Harvard College to bring those trailing students up to college-level curricula. Since then, the need for developmental coursework has never waned. Furthermore, the best way to remediate students continues to be a topic of debate. Even as recently as November 2017, there is discourse in how to best remediate developmental students.

In 1795, the University of North Carolina opened the doors to its first incoming freshman, Hinton James, who, according to folklore, trekked all the way to the university's campus (approximately 90 miles) from Wilmington, NC on foot (Foust, 2017; Graham, 2017; Trawick, 1988). After James, the university gradually noticed an influx of ill-prepared students and had to make modifications to accommodate these students (Boylan & Bonham, 2014). A special prep school was constructed to assist these students with their academic deficiencies. Deficiencies in mathematics, reading, and writing were all part of the prep school's developmental curricula. Once students were deemed college-ready by the school instructors, only then would they be allowed to register in college-level courses.

The university system did not want to continually deal with the arrival of underprepared students, so admission policies were put into effect limiting access of college-level courses only to those who were deemed college-ready (Breneman et al., 1998; Pretlow III & Wathington, 2011). Consequently, this led to the creation of the College Entrance Examination Board in 1900 (Schudson, 1972). This organization was to restore "…order to the chaos of college entrance requirements" by standardizing the entrance exams (Schudson, 1972, p. 36). An unintended consequence of this standardization process was that it led to an inconsistency in diverse populations on university campuses (Schudson, 1972). The two-year community college, however, welcomed the overabundance of students with learning deficits; seeing it more as an institutional goal and means of continual state funding (Arendale, 2002; Boylan, 1988; Cohen, Brawer, & Kisker, 2014; Pretlow III & Wathington, 2011). Since the expansion of community colleges, developmental education has become a major sector of every community college's mission (Breneman et al., 1998; Kee, 2013). Known as the Father of the North Carolina Community College System, Dr. William Dallas Herring (n.d.) said it best, "We must take people where they are and carry them as far as they can go within the assigned function of the system" (para. 1). This statement really does speak to the effect community colleges have on its students, and not just the academically prepared students, but the students who come to us ill-equipped as well.

Definition of Terms

Cut Score – Minimum score used by colleges to determine placement into developmental courses.

Developmental Education Initiative (DEI) – A strategy devised by the North Carolina Community College System (NCCCS) to reduce the number of students entering developmental education and increase the number of college graduates (The Hunt Institute, 2015).

Developmental Math Redesign - A Pew-funded effort by the National Center for Academic Transformation (NCAT) that established how colleges and universities can redesign instructional methodologies in the classroom using innovative technology to attain cost savings in addition to quality enhancements of their programs. Many redesign projects concentrate on large-enrollment, introductory courses that have the potential of impacting a considerable number of students and generating substantial cost savings to the college (Epper & Baker, 2009; Pretlow III & Wathington, 2011; The National Center for Academic Transformation, 2005).

Emancipatory Learning – Third goal of self-directed learning; more related to social change than it is to individual change.

MALDEF – The Mexican American Legal Defense and Educational Fund (National headquarters, 2009).

Multiple Measures - The use of more than one indicator of college readiness to determine student placement into college-level coursework (Bracco et al., 2014).

NC DAP – Known as the North Carolina Diagnostic Assessment and Placement; a placement test used in North Carolina by all community college beginning Fall 2016.

Pearson – A for-profit corporation who "…uses Adaptive Learning tools to assess student performance and activity in real time" (Pearson, 2017, para. 1). Pearson also claims that by using data and analytics, they can personalize content to reinforce concepts that target each student's strengths and weaknesses.

Readily Accessible Resources - First assumption that needs to be met if one wants to become a self-directed learner. This includes access to resources such as books, technology, faculty, etc. Anything that would allow students to have as much control as possible over their own learning (Brockett & Hiemstra, 1985; Brookfield, 1985).

Reading Lexile Level – A scientific approach to measuring reading ability and the text demand of reading materials. Like a thermometer, except rather than measuring temperature, the Lexile Framework measures a text's complexity and a reader's skill level (MetaMetrics, 2017).

Self-directed Learning (SDL) - Self-actuated adult learners taking responsibility for their own learning; the highest degree of learning one can achieve; teacher plays the role of facilitator (Brockett & Hiemstra, 1985; Knowles, 1975; Knowles, Holton III, and Swanson, 2005).

Transformational Learning – Second goal of self-directed learning; described as an internal change in consciousness (Brookfield, 1986).

* Appendix A contains a Definition of Terms section specific to Chapter 3 – Methodology.

Organization of the Study

This research is organized across five distinct chapters. Chapter One contains the introduction to the issue, the problem statement, the research questions, a brief description of the methodology section, significance of the issue, and a detailed list of definitions. Chapter Two describes a comprehensive review of the literature as it relates to developmental education, mathematics specifically, and self-directed learning in both the classical sense, as well as building a case for why this study is being proposed. A theoretical framework is also offered as a rationale for the lens through which the data collected will be analyzed. Chapter Three presents an overview of the methodological approach to the proposed research study. A detailed description of the research design is offered to help the reader understand the elements of the study. Design rationale will be discussed in addition to the role of the researcher. Any ethical issues related to the research will be examined, including how these issues will be addressed to insure integrity throughout the research design. IRB procedures will be mentioned. Finally, data analysis and trustworthiness of the findings will conclude the chapter examination. Chapter Four involves a brief introduction to the research, method, and elements presented in this part of the study. It will also include a section of results, where appropriate data will be presented. Chapter Five deals with the conclusions of the study: a short introduction, analysis with links to the literature, gaps in the literature are addressed, limitations are discussed, and a revisiting of the conceptual framework, along with implications of the study are linked with data and findings. Finally, recommendations for future research are offered in this chapter.

Chapter 2 Theoretical Framework and Literature Review

Introduction

Why do people do what they do? Motivation is one clear way of explaining this inner drive. Similarly, self-directing one's own learning entails taking responsibility for the material at hand, as well as, for the driving factors that initially led one to become self-directed in the first place. In fact, each one of us has a unique reason for doing the things we do. This is why learning and motivation are inseparable, one does not happen without the other. Motivation is an essential piece when it comes to being a self-directed learner (Knowles, 1975). Motivation is too broad of a topic to be discussed within this paper, therefore, for the purposes of this study, the term 'motivation' will be defined as an individuals need to attain personal happiness through participation in some action of choice (Damasio, 2003).

For this study, it also needs to be noted that the developmental math courses discussed in this paper are being taught using a self-directed (self-paced) learning model. Students use computers to watch videos of instructors teaching pre-designed lessons, which is optional. Students are then required to complete hand written classwork, in addition to online homework. Finally, students take an assessment that is structured the same, just with values changed (with different numbers). Students are required to get a score of 80% mastery on the online assessment before moving on to the next developmental math course in the sequence. All of this work must be completed in a five-week time frame or else the student must repeat the course (Bickerstaff, Fay, & Trimble, 2016). Bickerstaff, Fay, and Trimble (2016) conducted a study on modularization in developmental mathematics in Virginia and North Carolina for the Community College Research Center (CCRC) whereby they found 'the dark side' of self-paced learning, depending on the student's prior knowledge of mathematical concepts and motivation, may take an enormously long time for learning to occur. Five weeks may not be enough time to allow for optimal student success in this self-directed learning model. On the other hand, not all developmental math programs in North Carolina are taught using the same self-directed learning model (Bracco et al., 2015). Since the state allowed each of its 58 community colleges autonomy in setting up their developmental redesign, there are 58 iterations of the self-directed learning model. Those models will not be discussed for the purpose of this research paper.

This chapter will focus primarily on self-directed learning as it pertains to the learner. An extensive history of self-directed learning will be reviewed, examining its major authors and their contributions to the theory. There will be an explanation of the key principles of self-directed learning, specifically looking at how these principles influence the theory in the classroom. A critique of the theory will be offered in relation to the Multiple Measures for Placement Policy, where students and instructors are concerned. Finally, implications for self-directed learning will be discussed in terms of serving as a framework for understanding the Multiple Measures for Placement Policy and its effect in the mathematics classroom. Self-directed learning is a major contributor to the theoretical foundation of this study. The Developmental Education Initiative will be analyzed, along with its essential goals and transformations required.

A Framework for Understanding – Self Direction and the Developmental Student

It has been stated that if a student is able to self-direct their own education, answering and assessing questions on their own, the highest level of learning has been realized (Brookfield, 1985; Hewitt-Taylor, 2001; Kleden & Adisucipto, 2015; Knowles, 1980). This level of learning cannot be reached without some understanding of one's ability to self- direct in certain learning situations. This system of thinking has to be a conscious decision made on behalf of the student.

There is a kind of mindfulness about learning that needs to take place. It is also imperative for one to have an understanding of their own personal transformational and emancipatory learning processes as well. Students need to understand how their learning affects them and the world around them. If all of these levels are in place, as well as having readily accessible resources, then self-directed learning may be achieved. This level of learning in developmental mathematics, coupled with one's motivation to learn is what provides the theoretical framework for a developmental math student to be successful in today's post-multiple measures classroom. Without incentive to learn (Baumgartner, 2003; Gilbert, Musu-Gillette, Woolley, Karabenick, Strutchens, & Martin, 2014; Knowles et al., 2005), it is difficult to reach the goal of being an authentic self-directed learner. Knowles et al., (2005) believed there are internal factors that motivate a student to learn (personal attainment) as well as external factors (grades). How important these factors are to the learner will greatly determine how much knowledge is retained and transferred to other learning situations.

Speaking from a developmental content standpoint, mathematics requires higher-order thinking that an SDL classroom is ideal for when mastering the demanding material in the timeframe that suites the individual learner. Self-directed learning also enables the student to retain the most information versus other learning strategies (Ariovich & Walker, 2014; Fain, 2015). This is because self-directed learning requires the student to take on a much more active role in their learning versus the traditional, passive classroom setting.

Mathematics requires students to analyze, synthesize, formulate and solve problems (Sumantri & Satriani, 2016). Distinct from the other sciences, you do this over and over and over in order to understand and remember the concepts. Math is also a subject that builds upon itself (Caffarella, 2014). Students learn best when they are able to visualize the concepts and connect it to prior knowledge. Mathematics is known for being formulated after patterns and similarities (Stigler, Givvin, & Thompson, 2013). When one is able to connect these patterns, mathematical reasoning and understanding can take place (Henningsen, & Stein, 1997; Rivera, n.d.). One of the principles of Mathematical Learning Theory is that given sufficient time, any student can achieve mastery of a concept (Culatta, 2015). In a self-directed classroom, students have extra time to grasp the concepts needed to master the subject. Multiple measures, by way of GPA, is placing students out of these self-directed, developmental classes and straight into college-level math classes where the self-direction (in mathematics) and perseverance (in attitude) being acquired may be imperative to students' success in the college-level class.

Upon successful navigation of self-directed learning in the ever-changing, sometimes isolating world of developmental mathematics, a student should enter a college-level math class more prepared to handle the rigor that is often required. This is opposed to a student who gets to bypass developmental math class because of multiple measures and is placed directly into a credit-bearing math class. Failure to reach these two essential components of learning, which are central to self-directed learning, motivation or the ability to self-direct, gravely puts the developmental student at risk of failing the class. Self-directed learning without motivation is like trying to sail a sailboat without any wind. Motivation without being a self-directed learner is like running a maze blindfolded. One cannot exist without the other in today's self-directed developmental mathematics classes.

History of Self-Directed Learning

Self-directed learning (SDL) goes by many monikers. *Individualized instruction, self-regulated learning, self-planned learning, prescriptive learning, programmed learning,* and *computer-mediated instruction* are just a few labels (Hiemstra, 1994; Pintrich, 2004;

Wlodkowski & Ginsberg, 1995). Self-Directed Learning theory has been around for decades, but the concept has stayed fundamentally the same (Baumgartner, 2003; Heimstra, 1994; Merisotis & Phipps, 2014). Piskurich (1993) describes the learning theory as involving "self-actuated adult learners taking responsibility for the education that moves them from where they are to the place they want to be" (p. 1). Brookfield (1985) illustrates the perfect type of self-directed learning as happening when "….process and reflection are married in the adult's pursuit of meaning" (p. 15). Even though students have a tendency to be dependent on their instructors, more than they should (Hewitt-Taylor, 2001; Kleden & Adisucipto, 2015; Merriam, 2001), self-directed learning is a skill they still need to develop for future success in life. Self-directed learning is being endorsed as one of the most critical skills necessary in today's 21st century workforce (Kleden & Adisucipto, 2015; Ramnarayan & Hande, 2005; Rashid & Asghar, 2016; Trilling & Fadel, 2009). Knowles (1975) believes self-directed learning has become essential for being successful in today's society. Being self-directed in one's own learning gives them the skills to take initiative in projects, work through them with independence and persistence, and to be self- disciplined at the same time. What employer would not want their employees to be able to evaluate, synthesize, organize, problem solve, all the while managing their time successfully?

Self-directed learning can be traced back as far as ancient Greece – to Socrates and Alexander the Great (Hiemstra, 1994). Both Benjamin Franklin and Harry Truman were also well versed as self-directed learners (Brockett & Hiemstra, 1985). The 1950s saw the first attempt at systematizing self-directed learning. Teaching machines were touted as the wave of education's future, but were quickly replaced because of their inhumane qualities, such as lack of compassion and empathy. In the 1970s, audiotape programs became popular. Creative lectures with pictures, sound effects, and numerous voices were adopted as authentic self-directed learning practices. These were replaced by the ever-changing technology of VHS videotapes. According to Piskurich (1993), the use of videotapes in learning situations put self-directed learning back three decades. Video made it feasible to distribute the same boring lectures that had been putting students to sleep in lectures halls for years, to thousands of college students at one single time (Piskurich, 1993).

The age of the computer. Needless to say, self-directed learning slipped back into obscurity until sometime in the mid-1980s when the birth of the personal computer brought the learning theory back (Knowles, 1980). Self-directed learning had begun to again take on a life of its own in the field of learning theory. Studies have shown (Fonesca, Martí, Redondo, Navarro, & Sanchez, 2014; Hegeman, 2015; Ramnarayan & Hande, 2005; Rashid & Asghar, 2016) that the use of technology in the classroom is associated with higher levels of student achievement. With the advantages self-directed learning offers, from individual flexibility and cost reduction to time effectiveness, it is no wonder colleges and universities are looking to SDL as a solution to their budget constraint crisis (Epper & Baker, 2009; Hegeman, 2015; Humphreys, 2012; Walters, 2012). Wang (2009) asserts that when technology is integrated into the learning environment correctly, it can benefit students in two ways: it turns the student from a passive learner into an active learner, and when students are engaged, they are more likely to become accountable for their own learning (Chu, Fulton, & Keller, n.d.; Fain, 2011). Based on the literature, it is apparent students can become more self-directed as learners through the use of current technology.

Pioneers of SDL. Carl Rogers is credited, along with Abraham Maslow, among others, with initiating the human potential movement in the 1940s and 1950s (Burgan & Congos, 2008). This movement was recognized for stressing self-understanding, self-actualization, and personal growth of an individual (Burgan & Congos, 2008). Known as the father of client-centered therapy, Rogers took a more humanistic approach with his clients (Greening, 1987). He believed his clients were empowered to take responsibility for their own learning in all facets of their life, including academia, in opposition to being reliant on someone else for their learning (Burgan & Congos, 2008). This new approach to psychotherapy of being more client-centered versus therapist centered became known as the Rogerian approach (Heim, 2012).

The non-directive approach Rogers advocated was also evident in the student / teacher relationships. He believed the teacher should be like a facilitator in learning, serving the group, rather than leading the group (Rogers, 1983). Rogers used a quote by the ancient Chinese philosopher, Lao Tse, to depict his idea of the perfect teacher. As translated in Tao Te Ching:

> A leader is best
> When people barely know he exists,
> Not so good when people obey and proclaim him
> Worst when they despise him.
> But of a good leader, who talks little,
> When his work is done, his aim fulfilled,
> They will say ‘We did this ourselves’ (Lao Tse, trans. 1995, XVII).

This way of thinking reinforces Freire’s approach to teaching. The Brazilian educator and philosopher believed that the teacher should resist the traditional role of being omniscient and unyielding with students (Freire, 1992). Instead the teacher should take on a more compassionate role that creates an atmosphere where students become more self-empowered and can see that they too can effect change (Freire, 1992). This type of learning can only take place in an environment prone for being transformative, emancipatory, and self-directing.

In the 1960s, Skinner furthered the work on the individualized instruction movement. This led to the development of modularized instruction, specifically in psychology. Skinner is considered one of the creators of self-directed learning after his introductory text enabled students to work at their own pace (Holland & Skinner, 1961). Skinner touted in his book, "The Analysis of Behavior: A Program for Self-Instruction," that machines offered many advantages over other teaching techniques by allowing students to advance at their own rate, to advance only after mastering the material, and to be consistently active in their learning and continually receiving feedback (Holland & Skinner, 1961).

Skinner's work preceded the Keller (1968) article entitled, "Goodbye, Teacher… ." This article set influential groundwork for the individualized instruction movement of the 1970s. Keller (1968) described how during World War II, he had the opportunity to observe military training sessions from an interesting vantage point. He noticed the training was highly individualized and even though many students began at the same place, all were given the opportunity to progress at their own speed, often advancing far beyond the rest of the class. This experience gave Keller the idea for his first General Psychology course using programmed instruction at Arizona State University – the specification of skills, the demand for perfection at each level, previous students acting as classroom facilitators, and the minimizing of lectures and maximizing of practice (Keller, 1968).

Tough (1967) and Houle (1988) furthered the work in this field, seen as the future of education, based on the numerous advantages it offered to students, their instructors and the colleges themselves (Baumgartner, 2003; Pearson, 2016; Piskurich, 1993; Ramnarayan & Hande, 2005). These advantages included characteristics such as time efficiency, cost reduction and one-on-one instruction. Various research studies have been conducted using the work of Tough from the 1970s and 1980s. He was the first to devise a term describing self-directed learning, coined ‘self-planning’ (Tough, 1967). This is purportedly the highest degree of learning one can achieve and teaches one how to be a lifelong learner, if desired (Ramnarayan & Hande, 2005). Tough’s dissertation was devised to study how students get help from other students in self-directed learning situations. In the beginning stages of the learning theory, there was a difference in opinion between Tough and Houle as to the purpose of studying someone who is self-directed (Donaghy, 2005). In fact, Tough (1967) found that the steps educators carry out in planning for their classes – setting goals (for learning), finding good resources, choosing the correct (teaching) process and assessing (student) progress (Baumgartner, 2003; Donaghy, 2005; Khiat, 2015; Knowles, Holton III & Swanson, 2005) – were the same steps a self-directed learner goes through when learning something new. It is said that the best way to learn something is to teach it. Since the steps for self-directed learning are the same steps teachers encounter when preparing to teach their students, it is no wonder self-directed learning is the highest level of learning one can achieve.

Knowles is another theorist in the field of Adult Learning Theory. He believed self-directed learning occurred when an adult takes responsibility for their own person, becoming self-sufficient and independent in all things (Knowles, 1975). His definition of learning is geared towards how adults acquire knowledge versus children (Knowles, 1975). It is this examination of the adult learner that leads Knowles (1975) to speculate that an adult’s learning will be at its finest when the student is empowered to self-direct their own learning, using past experiences as a resource for learning, researching in fields they consider important to real-life applications, and where the learning process is problem-based as opposed to subject-based. The instructor’s role in all of this is seen as a facilitator of learning (Brockett & Hiemstra, 1985;

Kleden & Adisucipto, 2015; Knowles, 1975; Knowles et al., 2005); someone who participates in the examination process with students versus standing at the front of the classroom, communicating topics. Based on a review of the literature, it is apparent that researchers such as Rogers, Maslow, Skinner, Tough, Houle, and Knowles are considered some of the major innovators of the Self-Directed Learning Theory.

Key Principles and Assumptions of Self-Directed Learning

Speaking from the humanistic philosophy for which self-directed learning has been defined by Brockett and Hiemstra (1985), Knowles (1980), and Tough (1967), there are three principle goals of self-directed learning, along with two underpinning assumptions (Merriam, 2001). The three goals of self-directed learning are the ability to self-direct oneself in a learning situation, transformational learning, and emancipatory learning. Brookfield (1985) contends that one can achieve self-directed learning through these three goals only if the following two assumptions are in place: having readily accessible resources and control over one's own learning. Figure 1 shows the hierarchy of how all these principles and assumptions are related.

Assumptions. The first inference that has to be made when one wants to become a self-directed learner is that there exists an overabundance of resources readily available to the learner (Brockett & Hiemstra, 1985; Brookfield, 1985). Brookfield (1985) theorized that there is a specific population of students who are being underserved when it comes to the current technological resources in use, such as personal computers. Without sufficient resources, one cannot adequately direct their own learning, thereby defeating the purpose of becoming self-directed.

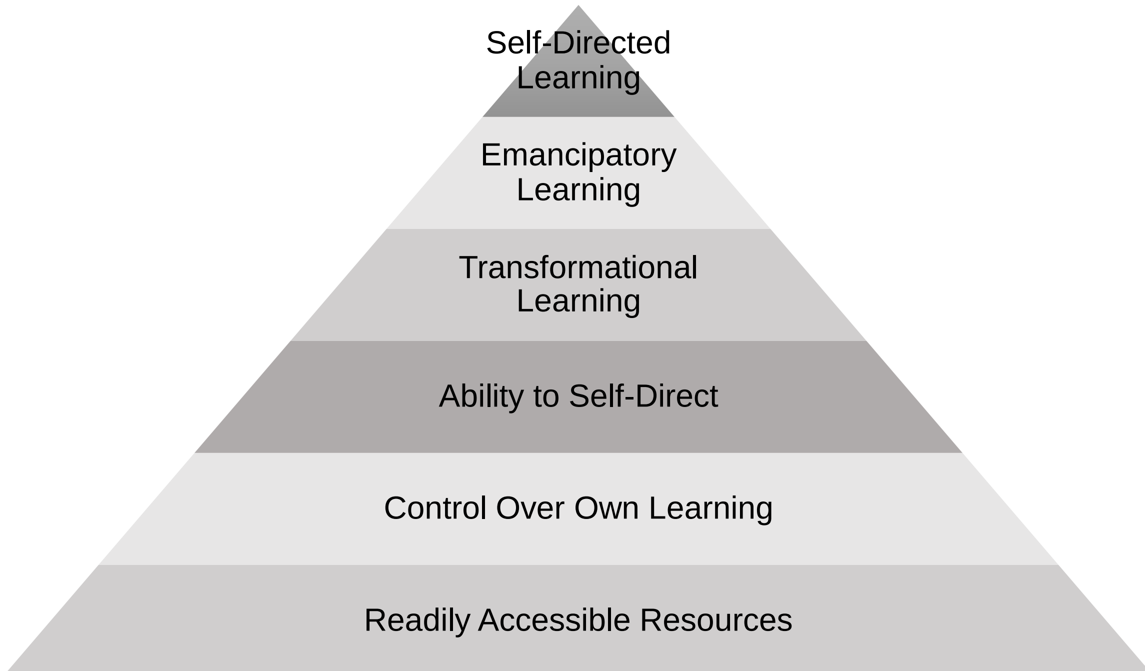


Figure 1. Hierarchy of Self-Directed Learning. This figure shows the hierarchy of how Self-Directed Learning is achieved in relation to all other principles and assumptions.

From Figure 1, it is clear to see that having resources available is the basis of all self-directed learning. From there, having control over one's own learning is imperative to the beginning stages of being a self-directed learner. Once a student has control of their own learning, they will undoubtedly be able to self-direct themselves in a learning environment. From this point, transformational and emancipatory learning needs to materialize. When all those stages are in place, self-directed learning has been achieved.

The second inference that has to be made when thinking of self-directing one's own learning is that one has to have control over their learning process. More specifically, "…having learners exercise control over all educational decisions needs to be a consistent element of self-directed learning" (Merriam, Caffarella, & Baumgartner, 2007, p. 109). In addition to these two assumptions, three key goals to self-directed learning are one's ability to self-direct, transformational learning and emancipatory learning.

Ability to self-direct. The first goal of self-directed learning is to increase the ability of students to self-direct their own education. Having control over learning is the first step beyond readily available resources for any self-directing learner as depicted in Figure 1. French philosopher Rancière (1991) went to the extent of pronouncing his own definition of equality, he believed people are qualified in directing their own intelligence toward the shaping of beliefs. Whether they live up to this capacity is another story entirely. It was Rancière's opinion that "… man is a will served by an intelligence" (Rancière, 1991, p. 51). The degree to which one's intelligence performs depends entirely on one's ability to act on this will. The less one acts on their will, the more they are giving in to a type of 'intellectual weakening' (Galloway, 2012; Rancière, 1991). It is this intellectual weakening that may account for the difference in intelligences among societies (Galloway, 2012; Rancière, 1991). One may also perceive this ability to act on his will as another meaning for motivation.

In terms of education, Khiat (2015) examined the works of Cleary, Platten, and Nelson (2008) and found that a student's level of self-direction was positively correlated to academic performance, motivation, and persistence in school. When a student becomes vested in the learning process, the learning process becomes personal. The student is able to take ownership of the learning, thereby being more aware of knowing what it takes to be successful in the classroom. Tough (1967) believed learners were already self-aware in their own learning process, often impressed with how knowledgeable students were in constructing their own learning. It was his belief that students want more assistance in becoming better self-directed learners (Tough, 1967). Pintrich (2004) contends "…students have to become aware of and monitor their progress toward their goals, monitor their learning and comprehension, in order to be able to make any adaptive changes in their learning" (p. 392). These adaptive changes are what allow students to gain cognitive control over their own learning thereby progressing them further towards their eventual educational goal. Having cognitive control allows one to resist past behaviors that have proven inappropriate and choose certain behaviors that will lead to long term goals (Quist, 2017). It is a conscious way of thinking about the choices we make. The cognitive control is what leads one to become a true self-directed learner in life.

Transformational learning. The second goal of self-directed learning is in regards to transformational learning (Brookfield, 1985; Merriam, 2001; Mezirow, 1991). Adults need to take time out for significant reflection and understanding in learning before they can ever attempt to master self-directed learning. According to Brookfield (1986), adult learners need to be able to "…distinguish clearly between the techniques of self-directed learning and the internal change in consciousness" (p. 38). Transformational learning happens with this internal change in consciousness. It has been compared to a metamorphosis of sorts; like a caterpillar transforming into a butterfly. Whereas informational learning changes what we know, transformational learning changes how we know (Baumgartner, 2003). Mezirow (1991) believes when we can understand 'why' we assign specific meanings to our relationships in real life, only then are we true adult learners. Transformational learning has been described by Baumgartner (2003) as the alteration of consciousness that radically modifies our way of existence in the world forever. Transformational learning is an important component of self-directed learning because when one becomes self-governing in their thinking processes, only then can one become a self-directed learner (Baumgartner, 2003; Hassi & Laursen, 2015; Knowles et al., 2005; Merriam, 2001;

Mezirow, 1991). As a result of this transformational change in thinking, one can achieve a true self-directed learning stage.

Emancipatory learning. Finally, the third and final goal to becoming a self-directed learner is to promote emancipatory learning. This is defined as the "process of freeing ourselves from forces that limit our options and our control over our lives, forces that have been taken for granted or seen as beyond our control" (Florida State University, n.d., p. 1). Emancipatory learning is more about revolutionary change than it is about the individual pursuit of knowledge as indicated in transformational learning. It is learning in the pursuit of social justice (Rhoads, 2009). Emancipatory learning concerns itself with a specific group of individuals: the marginalized and the powerless. Thompson (2000) describes the pedagogy as scholarship that "…can be used to assist individuals and groups to overcome educational disadvantage, combat social exclusion and discrimination, and challenge economic and political inequalities" (p. 1). Emancipatory learning is more related to social change than it is to individual change. Unlike transformational change, emancipatory change may not be an individual choice. It is more of a collective movement and it is not something that can happen overnight. This type of change is important to self-directed learning because when one realizes how the pursuit of learning can affect their overall position in life (transformational learning), only then can the individual strive to change the environment around them, thereby affecting change in the lives of others (emancipatory learning). Rancière describes emancipatory learning as progress towards personal scholarly freedom (Rancière, 1991).

It is clear to see how all three goals for self-directed learning are linked. One cannot become a master at reflection and understanding until they are self-directed. Also, one cannot participate in emancipatory learning until they take the time to properly reflect on their learning and their reasoning for doing so.

Models of Self-Directed Learning

Self-directed learning is based upon three key principle goals for learning: the ability to self-direct oneself in a learning situation, transformational learning, and emancipatory learning. These goals subdivide the theory into different models. The resulting models fall into the categories of sequential SDL, interwoven SDL, and instructional SDL. These models were designed by some of the leading experts in the field of adult learning, among them Tough, Brockett and Hiemstra, and Grow. Following is a detailed description of each model.

Sequential SDL. The sequential model was designed by Tough (1967) and describes guidelines for deciding the what, where, and how to study. Tough recommended the best way to sequentially self-direct one's learning was to set appropriate deadlines, find good resources, carve out the necessary time to learn, and then increase one's motivation to learn, if it was deemed necessary to the learner (Tough, 1967). This model characterizes the prototypical definition of self-directed learning. Designed by Tough (1967) and Knowles (1975), sequential SDL is a more straightforward, linear model of learning that follows the humanistic philosophy on which the definition was constructed (Baumgartner, 2003; Knowles, 1975; Tough 1967). The definition moves the learner from identifying needs, to locating resources and uncovering instructional strategies, to assessing proper outcomes. Sequential SDL is important to the learning theory because it represents the original design of self-directed learning. Figure 2 shows the linear relationship between the different stages of sequential SDL.

Step 1: Need → Decide what to learn → **Step 2: Create** → Create a plan; map out means to finish → **Step 3: Execute** → Carry out system to employ plan → **Step 4: Assess** → Assess what has been learned; Re-assess need

Figure 2. A Linear Model of Self-Directed Learning. This figure shows how Self-Directed Learning takes on a linear model for learning. Source: Knowles, M. S., Holton III, E. F., & Swanson, R. A. (2005). *The Adult Learner* (6th ed., pp. 21-281). Amsterdam, Holland: Elsevier.

Interwoven SDL. Brockett and Hiemstra (1985) designed a Personal Responsibility Orientation (PRO) model, referred to as the interwoven model. There are four components to their PRO model. First, Brockett and Hiemstra (1985) believed that learners must take responsibility for their learning. The second component deals with the notion of self-directed learning as an instructional strategy. This involves the student organizing, applying, and then assessing their own learning. Third, is the component of learner self-direction. Maslow (1968) believed self-directed learners might be more motivated to want to achieve their greatest promise in life. He also thought self- directed learners to be more tolerant of others, extremely honorable, able to manage uncertain conditions better, and to be especially imaginative. The final component of the model is the connection that happens between self-directed learning and learner self-direction. The interwoven model takes the sequential model up another level by requiring the learner to take responsibility. It still incorporates the same fundamental concepts of sequential learning, but then seems to take the learning idea further. Brockett and Hiemstra (1985) agree that the best learning happens when the students' *need* for self-direction is tied to their opportunities to be self-directed in their learning.

Instructional SDL. The third model of self-directed learning is Grow's (1991) instructional model. This is the most appealing of the three self-directed learning models because it allows the instructor to remain as a fixture in the classroom throughout three of the four stages. In stage one, where the students are dependent and the teacher acts as an authority or coach, students are considered low on the self-direction scale (Baumgartner, 2003; Galloway, 2012; Knowles et al., 2005). The instructor is needed for guidance and coaching. Students in this stage enjoy lectures, skills and drills practice, and tutoring sessions. Stage one of Instructional SDL is the model that most closely resembles the typical (traditional) classroom. Stage two finds students on a more moderate scale of self-direction. Students are interested in learning at this stage (Baumgartner, 2003; Knowles et al., 2005). Teachers act as motivators, giving praise and encouragement as students excel towards self-direction. Stage three is the intermediate stage of Grow's instructional model. Students have become active learners and involved at this stage, but need a guide through the learning process (Baumgartner, 2003; Knowles et al., 2005). Teachers are seen more as facilitators in their learning by suggesting resources and different methods of obtaining knowledge (Baumgartner, 2003; Knowles et al., 2005). Stage four is the highest level of self-direction in Grow's model. In this stage, Grow (1991) believes students "…consult experts but are both able and willing to take responsibility for their learning, direction, and productivity" (p. 134). Students are expected to design a timetable to accomplish their learning goals. Examples of stage four self-directed learners are those involved in internships, independent studies, and writing dissertations in graduate programs.

Grow's instructional model is the key component missing from a majority of colleges' self-directed learning packages. Again, his model of self-directed learning allows the instructor to stay in the classroom, helping students along in their learning, until they reach stage four of the model. Only then are students able to circumnavigate learning on their own. It is hard for students to be self-directed without some sort of formal training (Hewitt-Taylor, 2001; Knowles et al., 2005). Colleges are taking students, some fresh out of high school, others who have not been in school for decades, and assuming they are stage four self-directed learners. If educators do not teach students how to become self-directed learners, corresponding to Grow's stage four of learning, then how can we expect students to walk into the classroom, and a math classroom at that, on day one, and be self-directed?

Personalized system of instruction. As an additional note, Keller's Personalized System of Instruction (PSI) (1968) should be mentioned in this section. Keller's answer to self-directed learning governed the world of psychology instruction back in the 1970s and 1980s (Keller, 1985). First described in his 1968 paper, "Goodbye Teacher…," Keller's PSI was strictly governed by five essential principles: course mastery, use of tutors, self-pacing, stress of the written word, and use of lectures for motivational purposes only (Eyre, 2007; Keller, 1968; Kulik, Kulik, & Cohen, 1979). Just like in self-directed learning, a typical PSI course would consist of content being broken down into smaller units. Students would then take a test at the end of the material to see if mastery had been achieved. One difference with Keller's PSI was in how students would achieve this mastery. Keller was a big believer in the idea that if students were not able to master a certain topic, then they should be allotted the opportunity to restudy the material and test again. This process could continue as many times as necessary until the student passed. In essence, students could take the test as many times as they wanted. There is fault in this philosophy since it was determined that many students would simply not study between test attempts. This led to an endless cycle of test and retest until they finally got something correct, not necessary the definition of mastery – the student's demonstrated readiness to move onto new content (Eyre, 2007).

Self-directed learning designs expect the student to take responsibility for his or her own learning, unlike what most students are accustomed to from high school. Self-directed learning techniques should be taught to students at a younger age; taught to students in their primary years of schooling. This is difficult to do when those years are set up with benchmarks of testing that have to be met every year in order for students to progress to the next grade level. With all the high stakes testing happening in schools today (Kern, 2013; Minarechová, 2012; Mora, 2011; Thibodeaux, Labat, Lee, & Labat, 2015), self-directed learning is something that typically does not get broached until the college years, if then. By then, many students are set in their ways, set in their roles of teacher and student (Galloway, 2012; Knowles, 1980). They know what is required of them – take notes, sit at the desk, and take the test when needed (Galloway, 2012). They know what is required of the teacher – teach at the board, give the test on test days and grade it. No more, no less. The assumption that students are already self-directed in their learning is a deficiency in the theory of self-directed learning. Self-directed learning is a major shift in thinking for both factions involved and it doesn't happen without practice and effort.

Critique of Self-Directed Learning

As with any learning theory, there are advantages and disadvantages that must be considered. Of course, not every learning theory fits every student's learning style. Self-directed learning is a model whereby students become proficient at sections of preset material, while working at their own pace, without the help of an instructor. Piskurich (1993) asserts this is not the only definition of self-directed learning, nor is it all-inclusive. Self-directed learning was never designed to be a one-size-fits-all design for every student (Brockett & Hiemstra, 1985;

Flores, 2014; Hewitt-Taylor, 2001; Knowles et al., 2005). The issue with colleges and their self-directed learning packages today is that many are intended as a one-size-fits-all design. The cost saving component of self-directed learning is so substantial that it overrides all other learning strategies, thereby leaving students and instructors no choice in their learning approaches. In the following section, the advantages and disadvantages of self-directed learning will be discussed as it pertains to the student, the instructor, and the college.

Advantages. One of the advantages of self-directed learning is that it allows for a large number of students in the mathematics classroom at one time (Ariovich & Walker, 2014; Piskurich, 1993; Pretlow III & Wathington, 2011). Whereas a traditional classroom might have a target number of students for classroom enrollment, a self-directed classroom can fit as many students as it has computers or seats. The higher student/teacher ratio in a self-directed classroom quite often leaves the teacher and tutor stretched beyond compare.

Another advantage of self-directed learning is its non-reliance on the instructor (Brockett & Hiemstra, 1985; Hewitt-Taylor, 2001; Kleden & Adisucipto, 2015; Knowles, 1975). Not having to wait for an instructor to ‘teach’ a class not only increases the availability of the material being offered, but also makes it cheaper to offer. This byproduct of self-directed learning is what has made the instructional strategy so appealing to colleges and universities looking to save on faculty costs, which happens to be the largest expenditure for all colleges (The National Center for Academic Transformation, 2005; Trout & Vela, 2016).

Consistency of presentation is yet a third advantage of self-directed learning (Piskurich, 1993). With a majority of presentation materials being offered to students in the same delivery mode, there is no room for confusion or error. This is not true when you have a faculty of twenty instructors all having autonomy in the classroom teaching the same subject twenty different ways. Some may use the online homework application, some may not. Students can come out of the same class having numerous interpretations on the same math topic. With self-directed learning, there is a standardization to the learning material being presented.

Another strength of self-directed learning is the ‘Just in Time’ training approach (Pearson, 2016; Piskurich, 1993). This is described as training that is ready when the student is ready. In a traditional classroom, students may need an extra week on fractions before moving into solving equations, but they normally would not get that extra time. Those students would have to move with the pace of the class and the instructor. In self-directed learning, the student can take the extra time he or she needs to learn that concept before moving onto the next module.

A final advantage of self-directed learning is that content is not repeated over and over. In a traditional classroom, students may fail a test due to family situations, work issues, or merely by needing more time on the material. This may cause them to have to repeat the course – over and over. In the self-directed learning design, the material is broken in “chunks” or “bites” (Bracco et al., 2015; Hegeman, 2015; Seccombe & Stewart, 2014). Every school has its own verbiage on this, but the point is, students will complete each bite or module and never have to repeat it again.

One of the original selling points of self-directed learning was that is allowed students to work at their own pace (Baumgartner, 2003; Seccombe & Stewart, 2014). The design initially looked at learning as a function of time required to master material (H. Boylan, personal communication, September 27, 2017). Weaker students could take longer time to master the material, while stronger students could finish course material faster. This aspect may still be found in certain self-directed learning designs today, but it is no longer the main selling point. During the Gates’ funded, Changing the Equation (CTE) program, it was found that even though a majority of instructors thought their students would quickly place out of individual modules, in reality, only one or two actually did (Twigg, 2013). In fact, a majority of students needed the entire semester to complete the module, while some students needed to slow down even more to ensure mastery before moving on (Twigg, 2013). A big reason behind this was due to the fact that when pacing is left to the developmental student, often the pacing slows to nothing. Developmental students need structure and guidelines (Caffarella, 2014). They need due dates. If not, the work will never get done. Twigg (2013) admits that mastery learning implies students do more and learn more, but often times, this learning will take longer than traditional courses.

Disadvantages. SDL does not prohibit personalized instruction, but in practical terms, when an instructor has too many students, they are not able to provide personalized instruction to all of their students. Because of the nature of self-directed learning, one could potentially have every student working on a different math topic. SDL leaves little time for the individual instructor or tutor to work one-on-one with students, like the learning style was originally designed to focus on (Bickerstaff et al., 2016). In addition to this, students miss the instruction piece altogether. Hewitt-Taylor (2001) reported on a study by James and Clarke (1996) where it was suggested that students like the independence that came with self-directed learning, they just did not like the added responsibility and effort required on their part to learn in that manner. Knowles (1975) was shocked to find his students did not want to become self-directed learners. By contrast, the students wanted Knowles to teach them the content. It is true, self-directed learning puts the onus on the students and allows the instructor to portray more of a facilitator role in the classroom. The students theoretically become more active in their learning with self-directed learning than they are in the traditional classroom (Bickerstaff et al., 2016; Ramnarayan & Hande, 2005).

One cannot discuss the disadvantages in the classroom without discussing the role of the instructor and the giving up of power in the classroom (Hewitt-Taylor, 2001). A self-directed learning package done effectively is designed to lessen the role of the instructor in the classroom. Piskurich (1993) asserts, "An instructor, as disseminator of knowledge, is neither needed nor desirable for a well-done SDL package to be effective" (p. 6). This is considered a disadvantage to both the instructor, as well as, to the student. The instructor loses his or her control over what is being taught in the classroom. Since all students are now self- directed, the instructor merely wanders around the room, answering questions repetitiously. There is no longer a daily planning of lessons, a transfusion of knowledge from instructor at the front of the board to the students sitting anxiously awaiting data delivery in the classroom. Socialization between students and teacher are minimal. Piskurich (1993) argues "As you will see, there is often the need for a facilitator, …and at times a special evaluator, but the instructor is not in the cast of SDL" (p. 6). Both students and instructors disagree with this notion (Hegeman, 2015; Hewitt-Taylor, 2001). In a study conducted by Hewitt-Taylor (2001), looking at the viewpoints of both students and teachers concerning self-directed learning, it was found that SDL can be of some value, but only when it is paired with teacher-led instruction. Self-directed learning can be a good idea, but if you take the instructor completely out of the equation, this will eventually lead to a disconnect somewhere between the content and the students (Hegeman, 2015). This disconnect cannot be good for students' overall achievement levels.

Another disadvantage to self-directed learning is the lack of due dates. Piskurich (1993) believes the aspect of one's control is essential to self-directed learning, and the lack thereof can be a major, almost impossible drawback to using the instructional strategy. Though the capacity to self-direct one's own learning is imperative to becoming a self-directed learner, studies have shown students tend to procrastinate more than is necessary (Ng, 2016; Wäschle, Allgaier, Lachner, Fink, & Nückles, 2014). Ng (2016) defines procrastination as a motivational strategy where self-handicapping ensues and assignments are put off or effort is withdrawn in order to delay the obligation. This procrastination time can reach even longer interludes when the material pertains to mathematics content. Students have a habit of regulating their effort level when it comes to class and homework assignments (Zimmerman, 2002). Without ever knowing it, students are already self-directing their own learning when they procrastinate on assignments.

Researchers go as far as even categorizing procrastinators into two groups: active and passive procrastinators (Ng 2016). An active procrastinator is one who can put off assignments until the eleventh hour and then be successful with the task at hand. Ng (2016) purports that "active procrastination could be viewed as educationally productive postponement [when] it involves effective effort at the last minute" (p. 49). A passive procrastinator is one who will put off the assignments until the last minute and then just quit. Overall, procrastination is an important aspect of self-directed learning and in some instances, can lead to effective learning. For students who are active procrastinators, this can still lead to a workable timeline. For the passive procrastinators, who always put off doing their assignments until tomorrow, tomorrow never comes. Having no due dates is seen as an advantage in self-directed learning, but students really need to know how to manage this, otherwise it can turn into a crippling disadvantage.

Since it takes a great deal of time and effort to put together a true self-directed learning platform, development costs can be quite high. Piskurich (1993) affirms "SDL packages must stand on their own, because no instructor will be available for filling in the gaps" (p. 18). In a traditional classroom, you have the instructor there to answer questions, and guide students in the right direction if they veer too far off course. In self-directed learning classrooms, there is less instructional support for the students because of the sheer size of the class. For any college planning to put together their own SDL program, Piskurich (1993) asserts if a college cannot design the program correctly, they should not design it at all.

Another disadvantage to using a self-directed learning program is the loss of community in the classroom (Knowles, 1980; Knowles et al., 2005). Students are left working on their own, since each are working at their own pace. This dynamic leaves no room for class discussion, group work, partner sharing, etc. In a traditional classroom, students have the opportunity of working together, building relationships with each other, and with their instructor. In a self-directed learning classroom, those relationships are strained at best.

A final drawback of self-directed learning is that it is unfamiliar to the masses (Ariovich & Walker, 2014; Hewitt-Taylor, 2001). Knowles (1980) concluded that students are not used to being self-directed in their studies and may find this method awkward and challenging at first. Students come into a math class already with preconceived notions of what they are going to be encountering. To walk into a classroom where there are no whiteboards, no teacher, nothing but a bunch of computer screens staring back at them can be extremely intimidating for some "computer-phobic" students, especially to those in the older populations, who may have been out of school for decades (Ariovich & Walker, 2014). To walk into the classroom only to find it is now all taught online when they know not the first thing about computers is almost too much for some to handle.

What Does the Literature Say about Policy?

In this section, the broader political context of multiple measures will be discussed, looking specifically at how policy shapes the classroom organization from a teaching and learning perspective. All efforts will be made to synthesize the major trends, findings, and debates in the historical and contemporary contexts surrounding the Multiple Measures for Placement policy. Critiques of the strengths, weakness, and gaps in the body of literature will be examined in relation to the policy and how it affects education today. An analyzation of how multiple measures frames and shapes this issue for educational practitioners, with a particular concern for social justice in the classroom, will be examined.

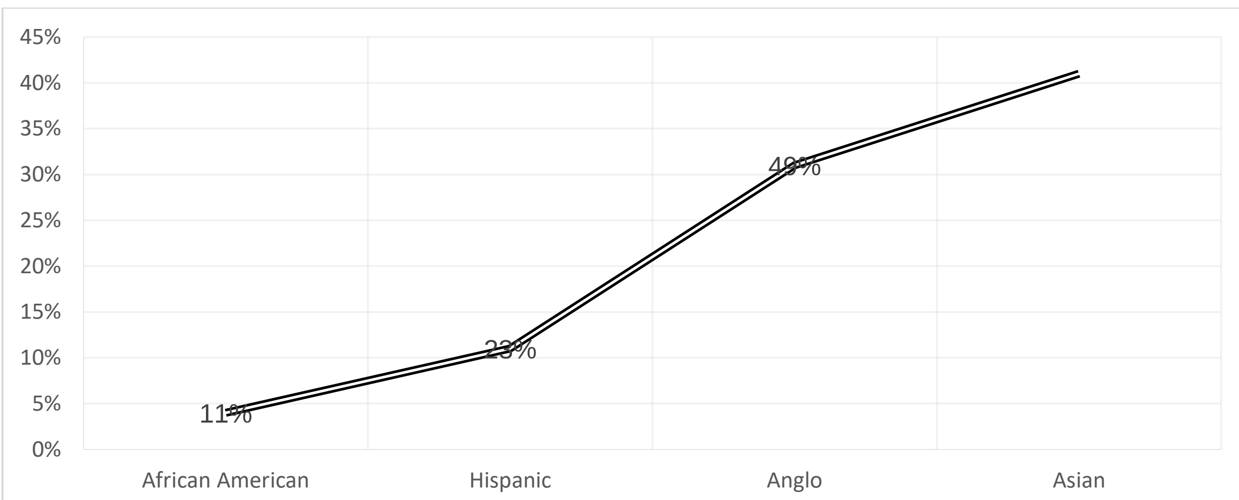
Major Trends, Findings, and Debates Regarding Multiple Measures

Multiple Measures for Placement is another way of looking at how students are deemed college-ready. It also goes against what is regarded as best practices in the field of developmental education (Illinois Mathematics Association of Community Colleges, n.d.; Mathematics Special Professional Interest Network, 2002). Historically, according to the National Center for Development Education, it was recommended that all students entering a community college for the first time be required to take the college's placement test to determine the proper sequence of courses for their program (Boylan, 2002; Bracco et al., 2015). Even as recently as 2011, the national movement was towards a standardization in placement testing for all community colleges, policymakers thought these tests played a vital role in student success (Hughes & Scott-Clayton, 2011; Ngo & Kwon, 2014).

Policy makers and educators agree that the current model for remediating students in developmental education, mathematics specifically, is not working (Boylan & Bonham, 2014; Bracco et al., 2015; Hughes & Scott-Clayton, 2011; Melguizo et al., 2014). There seems to be a turning point in our higher education system today and the best way our leaders have found to deal with this reality is to go from one policy extreme to another. If developmental mathematics is not effective for students, then find more approaches to putting students straight into curriculum classes (using multiple measures). This will not change the fact that these students may not be ready to face the challenges that lay ahead of them in these more rigorous college-level math courses.

Historical perspective. At a meeting in August 2013 for the National Assessment Governing Board (NAGB), who oversees the National Assessment of Educational Progress (NAEP) test, language was adopted to define college preparedness scores for reading and math on the NAEP exam. It was determined that students who scored 163 out of 300 possible points on the 12th grade assessment would be reasonable estimates for the percentage of students who hold the skills and knowledge necessary (in those subjects) to designate them academically equipped for college (Fields, 2013). In 2009, only 26% of these students reached the ‘proficient’ level in mathematics. Finn Jr. (as cited in Sparks, 2013), chairman of the NAGB when the NAEP achievement levels were first authorized 23 years ago, was quoted at a symposium in Washington declaring, “the ‘proficient’ level was always intended to be aspirational, while ‘basic’ was supposed to show you were literate and could make your way through the subway system” (p. 2). Now that having students college-ready is the current initiative in K – 12 schools today, NAEP’s proficient level is as close to demonstrating college-readiness as a test can exhibit.

According to the American College Test (ACT) exam, which is another test that students can take to assess college readiness (also considered a multiple measure), 62% of 2016 graduates who took the ACT test fail to meet ACT’s definition of what it means to be college-ready in English, reading, math and science (Kerr, 2016; Melguizo et al., 2014). This news is not encouraging; those numbers are down 2 percentage points from 2015. However, the numbers look even more disheartening for minority students (see Figure 3). Breaking down the 62% who fail to meet passing criteria by ethnicity, only 11% of African-American students met the ACT’s definition of college-readiness in all four subjects. This is also true for 23% of Hispanics, and 49% of Anglo students (Kerr, 2016). Numerous studies point to the fact that minorities and people of color are disappointingly the face of developmental education today (Attewell et al., 2014; Bailey et al., 2009; Harrington, Lloyd, Smolinski, & Shahin, 2016; Ngo & Kwon, 2014). Looking at the ACT results specifically from a mathematics standpoint, more than 50% of the students who took the ACT exam failed to meet the college-ready criteria. Both the ACT and the 12th grade assessment are indicating that our students are graduating from high school in record numbers not ready to face the challenges of college-level work. Yet, students are coming to colleges, under multiple measures, and being placed directly into curriculum classes.



African American Hispanics Anglo-Americans

Figure 3. Percentage of Students – College Ready. This figure shows the percentage of students by ethnicity who met the ACT's definition of college-readiness in all four subjects. Source: Kerr, J. C. (2016, August 24). ACT Scores Show Many Grads Not Ready for College-level Work. *U.S. News & World Report*. Retrieved from http://www.usnews.com/news/politics/articles/2016-08-24/bigger-numbers-of-high-school-grads-taking-act-college-test

High school effect. High schools appear to be doing their job of graduating more students than ever before. According to the National Center for Education Statistics, the 2006 – 2007 school year saw the number of students graduating from high school within four years of starting their ninth grade year hit a record high (Resmovits, 2013). Nearly 4 million students began their high school careers in the 2006 – 2007 academic school year. Four years later, 78.2% of those students graduated with a high school diploma. This has been the highest observed graduation rate since 1968. Figure 4 shows the average freshman graduation rate for high school students from the years 1990 – 1991 through 2009 – 2010 as reported by the U.S. Department of Education and the National Center for Education Statistics (NCES).

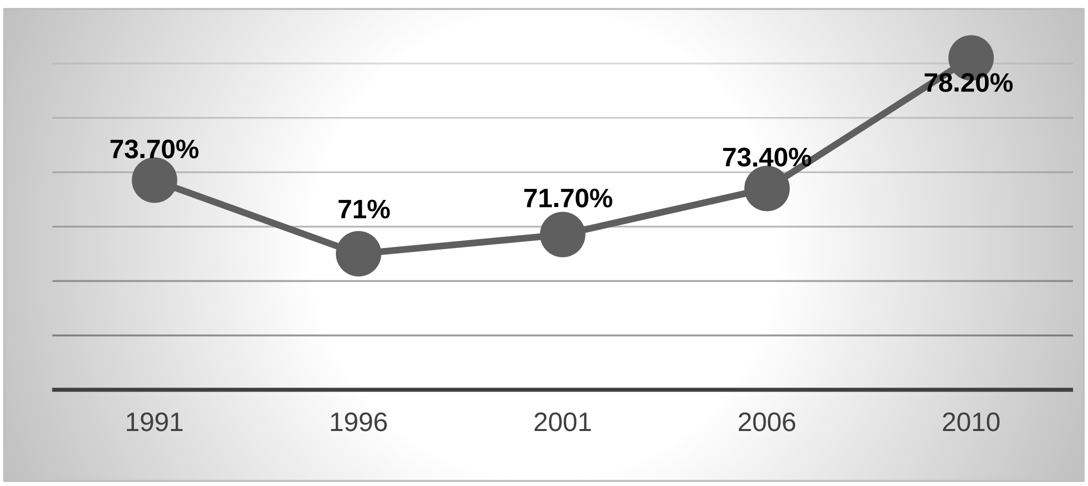


Figure 4. Graduation Rate: Selected Years. This figure shows the average freshman graduation rate for U.S. public high school students. Source: Resmovits, J. (2013, January 22). Graduation Rate Hits Record High For High School Students: Government Report. In *Huffington Post*. Retrieved from http://www.huffingtonpost.com/2013/01/22/graduation-rate-record-high-school-students_n_2522128.html

Although, according to a study published in Community College Week, the widening gap among graduation rates between those who took developmental courses and those who did not, "…reflected differences in learning skills carried over from high school, rather than the impact of remedial classes themselves" (Lu, 2013, p. 13). This study indicates to researchers that the deficits seen at the college level are not the responsibility of developmental coursework, but rather it is the cumulative effects from years of deficits from students' high school careers (Attewell et al., 2014; Harrington et al., 2016; Jenkins, Lahr, & Fink, 2017; Merisotis & Phipps, 2014). Devine (1996), for his book *Maximum Security,* conducted an ethnographic study of New York City Schools. In it, he describes how many high school students age out of a grade and are just passed along without ever learning the content that is deemed necessary to move on to the next grade level. According to Devine (1996), students are fully aware of the fact that " …in September of their eighth-grade year that they have already aged out and …will be passed on to a senior high school, so they do nothing but play around, if they bother to come to school at all" (p. 33). Devine reported that the major issue with these schools is that 88% of students entering the ninth grade will need a developmental math class in order to catch up with their peers. This implies math teachers will have to spend the entire ninth grade, and sometimes ninth and tenth grades, teaching students how to do junior-high mathematics. Only when a student enters the eleventh grade are they up to par with high school (9^{th} grade) math content.

The foremost concern with this issue are the graduation requirements and the core courses of study that are required by all high schools in order for students to earn a high school diploma. It is plausible that this age-out process is also happening all across the United States (Advocates for Children of New York, 2015; Kee, 2013; Rossiter, 2012; Yanushevsky, 2011). Looking specifically at North Carolina's mathematics core courses, for example, if 88% of students who were passed along and came into an Algebra I class lacking the knowledge to complete its requirements, then teachers would spend the entire first year or two teaching junior high math to high school students. One has to wonder, "What credits do the students earn for those first two years the teacher is teaching seventh and eighth grade math?" Algebra I and II credits are the most likely the answers to that question. Rossiter (2012) reported a majority of his seniors entering PreCalculus in D.C. schools did so with a fourth grade-level math equivalency. This is exactly the reason why there is an entire culture of students graduating from high school lacking the skills in math necessary to enter the college arena.

Filling the gap. Students are graduating from high school in record numbers, yet lacking the skills necessary to be successful in college are costing themselves and the taxpayers enormously – and not just in dollars (Bailey et al., 2009; Harrington et al., 2016; Melguizo et al., 2014; Merisotis & Phipps, 2014). Developmental course credits taken every year are exceedingly large. An appraisal by Breneman et al., (1998) estimated the national cost of developmental education in 1998 as high as $1 billion dollars - $911 million to be exact (Pretlow III & Wathington, 2011). At that time, state appropriations to public higher education institutions were approximately $40.5 billion dollars (Pretlow III & Wathington, 2011). Putting those numbers into perspective places developmental education at just 2.25% of the total annual operating budget for higher education. This percentage is nowhere near significant when you consider developmental courses and the access it offers to college-level courses to be the cornerstone of allowing underserved students a chance at making a better life for themselves and their families (Palmadessa, 2017). Fast forward to the 2000 – 2001 academic year. Some now estimate the economic cost of developmental courses taken to be as vast as three billion per year (Heidi, Perin, & Miller, 2013; Merisotis & Phipps, 2014; Pretlow III & Wathington, 2011). Again, for that period of time, state funding for higher education was $108.7 billion dollars (Pretlow III & Wathington, 2011). This still leaves spending for developmental courses at just above 2.75% of the total annual operating budget for the nation as a whole. In a study by

Pretlow and Wathington (2011), it was estimated that the cost of developmental education is declining. This is based on data from the 2004 – 2005 academic year (Pretlow III & Wathington, 2011). Reasons given for the decline were colleges' ability to deliver developmental courses more effectively using technology and by limiting the number of times a developmental course could be taken – and paid for with federal dollars (Pretlow III & Wathington, 2011).

In addition to the monetary value of developmental mathematics courses, it is also costing the students' valuable time. Furthermore, with developmental mathematics courses comes the loss of momentum toward completing degree requirements. This is where the disconnect comes between record numbers of high school graduates and the lack of college graduates (Harrington et al., 2016). Students are so motivated graduating from high school, only to come to college to be put back into high school level courses for remediation. This has been very discouraging for students and has often led to an endless cycle of withdrawals and repeat courses (Ariovich & Walker, 2014; Bonham & Boylan, 2011). People on all sides of the debate, from policy makers, college administrators, to instructors, researchers, and best practices reformers have been devising strategies that lead to institutional and instructional reform to increase student completion rates in college (Ariovich & Walker, 2014; Boylan & Bonham, 2014; Bracco et al., 2015; Heidi et al., 2013). This in turn, will help colleges reach President Obama's goal of having the highest percentage of college graduates by the year 2020 (Boggs, 2015; Humphreys, 2012; Palmadessa, 2017; Pickard, 2014).

There is no easy answer to the question of how to properly place students in college. The students are the ones who are getting lost in this process. Students get passed along without having the prerequisite skills for the next level (Devine, 1996; Mirel, 2006; Rossiter, 2012). Moving students hastily through curriculum courses could be effective, but the method undoubtedly will not work for those students with the weakest content knowledge (Mangan, 2013). This approach frequently does not work because students continue to graduate from high schools all across the U.S. and end up in developmental courses. The solution to the problem has not been to push students ahead in high school, continuing to push these students ahead in college will certainly not be the solution to the problem either.

Placement test quandary. College placement tests, including ACT's Compass and The College Board's Accuplacer, have been the best tools previously available to gauge college-readiness for entering freshmen in community colleges. As of 2013, the North Carolina Diagnostic Assessment and Placement test (NC DAP) was NCCCS' best effort at establishing new diagnostic assessments, specially aligned to the developmental mathematics curricula (Bracco et al., 2015; Ngo & Kwon, 2014; The Hunt Institute, 2015). This was one of the three transformations needed in order to meet the specific goals of the Developmental Education Initiative. By establishing the NC DAP, a criterion-referenced instrument, specifically aligned to the curricula, it was the hope that this endeavor would reduce a student's time spent in developmental mathematics. These tests are much cheaper to produce than standardized tests such as the Scholastic Aptitude Test (SAT) or ACT and can be easier to access for the student population entering community colleges today (Bostian, 2012). Typically, students who perform well on the placement tests are put into higher-level classes. Students who score poorly will end up in developmental classes and have less than a 30% chance of ever reaching curriculum-level courses (Bostian, 2012; Harrington et al., 2016; Melguizo et al., 2014; Stigler et al., 2013).

The issues with students taking these tests upon their arrival to campus are long and complicated. Placement tests are suitable at testing content knowledge at that particular point in time, but that is not always the entire substance of a student's knowledge base. These tests do not take into account a student's family and socio-economic background, as well as his or her emotional, intellectual, or motivational factors for attending school (Bostian, 2012; Jenkins et al., 2017). Frequently, students do not properly prepare before they take these tests, not realizing the high stakes' consequences these tests can have on their college career. As a result, they are blindsided by the more difficult questions in mathematics they have had little to no exposure to. This causes poor passing rates and in turn, places students directly into developmental mathematics courses. This lack of preparation for the placement test can cost the student a semester or more of non-credit bearing courses (Stigler et al., 2010). From the students' standpoint, being placed in one or more developmental classes can be incredibly discouraging (Ngo & Kwon, 2014).

Implications to State Law

The poor success rates in developmental mathematics courses have had many people questioning the validity of college placement tests. People were starting to wonder just how accurate they were in placing students in the proper sequence of courses (Ngo & Kwon, 2014). It was exactly these types of concerns over the impartiality of placement testing that caused the Mexican American Legal Defense Fund to file a lawsuit against a California college claiming discrimination in its placement testing practices (Armstrong, 1995). In this lawsuit, it was alleged that Fullerton College forced students to take developmental classes based on the scores from the students' placement tests. This action kept students from earning college credit and delayed registration into curriculum courses, further stunting their college career. Nineteen other colleges in California also joined the suit stating Fullerton violated the Matriculation Law and due-process guarantees by the state's constitution (Armstrong, 1995). Ultimately, the lawsuit ended up being dropped. The California community college system chancellor vowed to make placement tests less linguistically and ethnically biased. He also vowed to use more multiple measures when it came to student placement (Hughes & Scott-Clayton, 2011). The lawsuit filed by MALDEF did not exactly change policy, but what it did do was force the system to make changes in the way it looked at placement for all students. It also pushed California to go against what is believed to be best practices in placement for students in developmental mathematics courses by not strictly adhering to placement testing guidelines.

Down the Rabbit Hole

Developmental coursework, mathematics specifically, is one of the major reasons why a majority of college students do not go on to complete their Associate's degree or transfer to a four-year institution (Breneman et al., 1998; Fain, 2011; Pretlow III & Wathington, 2011). According to Lu (2013), only 28% of community college students who took at least one developmental mathematics course in their career earned a degree or certificate within 8 ½ years of beginning school. This is compared to 43% of non-developmental students who graduated. According to the Community College Research Center at Columbia University's Teachers College, approximately 60% of two-year college students register for at least one developmental course, mathematics or English (Bracco et al., 2015; Humphreys, 2012; Lu, 2013; Melguizo et al., 2014). Observing these numbers from a distance, the conclusion might indeed be that developmental mathematics courses appear to be the gateway courses holding students back from succeeding to reach their college goals. The question remains, Do students perform poorly in developmental math because of poor placement? Did they walk in the door inadequately prepared to take the placement test? Is their failure the burden of the developmental instructors, the high school teachers or both? Can blame be placed on the student for not putting enough emphasis on the developmental classes and taking them seriously enough to earn a passing grade? Do decision-makers think all of these issues will just disappear once students are able to simply bypass developmental math courses and enter straight into curriculum math courses? The next few years of data will only begin to start answering these questions (Bracco et al., 2015).

Multiple Measures Alternative

High-stakes placement tests were the reason why many states were looking for an alternative on how to properly place students in college courses. This is why multiple measures has become popular again with states such as California, Florida, and North Carolina fueled by the perceived failure of the placement tests and the high number of students entering into developmental classes. It is approximated that less than one in ten students who begin their career in developmental coursework at a community college actually make it to graduation within three years of enrolling (Mangan, 2013; Walker, 2015). One ideal solution to this issue may lie in the concept of Corequisite Remediation – where students take college-level courses and developmental courses simultaneously. This program will move a majority of academically ill-equipped students into curriculum-level classes with '…mandatory, just-in-time instructional support' ("Corequisite remediation," 2013, para. 1). Math programs could be organized to match the mathematics curricula with a student's real-life career goals.

It is approximated that only about 15% of students who place into developmental classes actually need to be there. The other 85% of students could be successful in credit-bearing courses if the college were to contemplate a wider range of criteria in placing them (Bracco et al., 2015; Mangan, 2013; Ngo & Kwon, 2014). This broader set of criteria has become known as the Multiple Measures for Placement Policy and fulfills *DEI's* goal of reducing unnecessary enrollment in developmental education courses. Liston (2012) argues there is no doubt that many students have deficiencies in their learning, but that national research indicates these students would be successful in credit-bearing courses if given the opportunity to enroll in them. The fast lane into curriculum via multiple measures could potentially keep countless students out of the endless cycle known as developmental coursework and could possibly save them in both time and money (Ngo & Kwon, 2014). This cycle realizes *DEI's* third goal which is to increase the number of students who complete the developmental-course sequence and enroll in college-level classes. It is hopeful that the Multiple Measures for Placement Policy change will spearhead placing more students in curriculum classes and hopefully more students leaving college with a credential, as Obama hopes versus just leaving college.

In 2011, SuccessNC, a Community College Initiative started by Community College Presidents and Trustees, began working alongside CCRC. CCRC was conducting research on how to better assign students to curriculum or developmental courses using multiple measures. According to Research for Action (RFA), who prides itself as being the bridge to the "…worlds of research and educational policy and practice," they estimate that between 24% and 33% of students are being incorrectly misplaced lower than they should be (using these placement tests) into developmental coursework (Research for Action, 2018, para. 1). This can be compared to almost 40% of community college students who never had to take a developmental course that were able to graduate within that same eight-year period (Committee on Measures of Student Success, 2011). In another study released in early 2012 by CRCC, 20,000 NC community college students' high school transcripts were analyzed and linked to their general success in college. It was determined that a student's high school GPA was a better overall predictor of college success than that of the college's standardized placement test. This GPA correlation supports success in both college-level math and English courses. The study predicted that when using high school GPA as a means of placing students in curriculum classes as opposed to the college's placement test would reduce the number of students being misdirected into developmental classes by 50% (Morrissey & Liston, 2012).

In February 2013, North Carolina released its Multiple Measures for Placement Policy to all its 58 NC Community Colleges and to The University of North Carolina College System. This was in conjunction with California and Wisconsin, who were also in the process of adopting the same Multiple Measures for Placement Policy in order to increase college completion rates for students (Duffy et al., 2014). North Carolina fell in the middle of these two states regarding demographics. Even though each of these three states had implemented the Multiple Measures for Placement policy, not every state saw fit to do so in exactly the same way. For North Carolina, the state chose to go with the following system definition for multiple measures:

> In North Carolina, the policy refers to a hierarchy of measures that institutions use when determining placement. First, students may be placed directly into college-level courses if they have an un-weighted high school GPA of 2.6 or above. Students who do not meet the GPA cutoff can submit their ACT/SAT scores to demonstrate readiness for college-level courses. Students unable to be placed in college level coursework based on those measures or who graduated from high school more than five years ago must take a placement test. Therefore, although multiple measures of ability are included in the policy, it is possible that many students will place out of developmental education classes with only one measure (Duffy et al., 2014, p. 6).

A caveat to this policy examines the GPA cut score more closely. College placement advisors will take into account prior math courses taken in high school as well as the student's respective grades (Ngo & Kwon, 2014).

It should be noted that even though the policy takes into consideration multiple measures of a student's math ability, only one measure is needed to place out of the developmental math course sequence. For instance, if a student comes to the community college with a high school GPA of 3.2, by means of multiple measures, this student would get to bypass the developmental math course sequence and go straight into a college-level math class. Likewise, if a student had a low GPA, but had high ACT or SAT scores, that standardized test score would be sufficient to place the student into college-level math. Even though there are multiple measures the colleges' admissions office will take into consideration, it only takes one of those measures to allow the student to bypass developmental math and go straight into a curriculum math course.

The Multiple Measures for Placement Policy was written with good intentions. There is no denying that developmental mathematics courses can be a mine field waiting for unsuspecting students trying to navigate the motivation and perseverance needed of being a first-year college student. According to Liston (2012), Associate Vice President for Policy Research and Special Projects at NCCCS, in her three-year study of a math cohort, students who began in the developmental math course sequence, only 10% went on to complete the curriculum-level math class. These numbers are shown in Figure 5.

The new Multiple Measures for Placement Model currently proposed in North Carolina allows all post-2007 high school graduates who have an unweighted GPA greater than 2.6 to enter directly into curriculum classes, including college-level English and mathematics courses (State Board of Community Colleges, 2013). There are enormous implications for implementing such measures across a college campus. Both policy makers and educators have their own ideas of what these implications imply. Perhaps the biggest investor in this policy change, the student, will have no idea what those implications will mean until it is too late. Only time will tell what making these types of significant modifications to community colleges' enrollment standards will do to future student success (Bracco et al., 2015). It may be years before the full effects of multiple measures are understood.

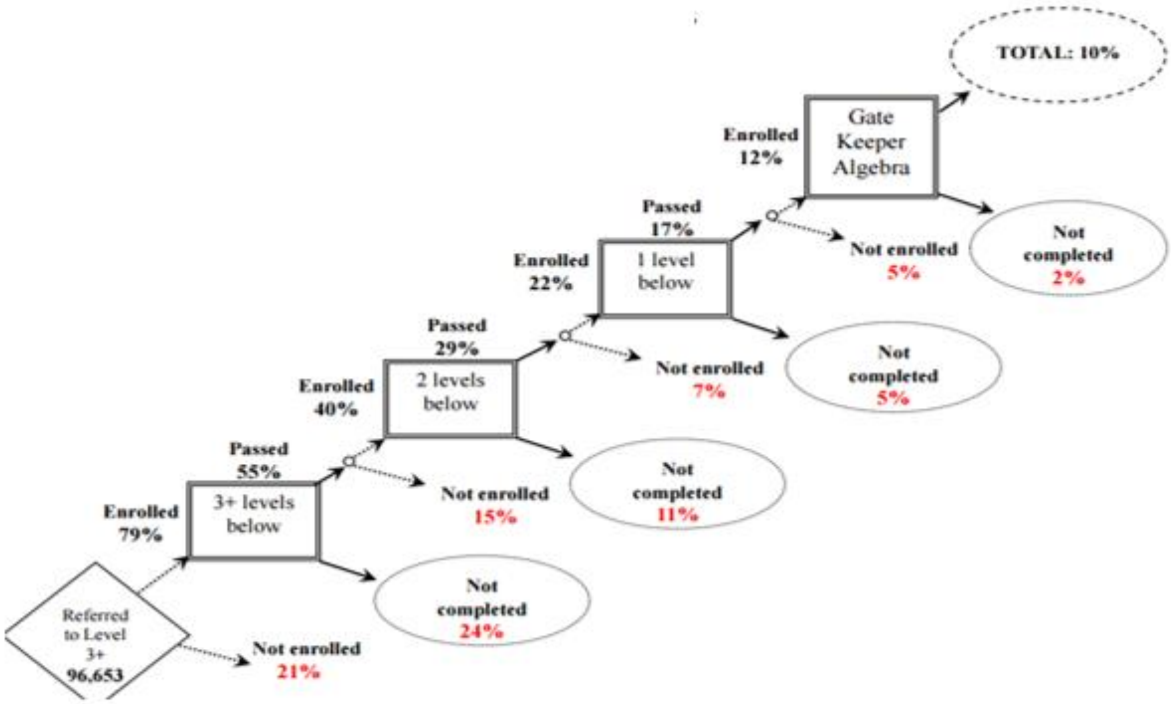


Figure 5: Achieving the Dream Math In-Order Course Completion & Enrollment of Students Referred to Lowest Level Developmental Math. This figure shows how a cohort of student can begin at the lowest level of developmental mathematics and only approximately 10% will persevere through to the Gate Keeper course. Source: Community College Research Center. (2010, October). Achieving the Dream Math In-Order Course Completion & Enrollment of Students Referred to Lowest Level Developmental Math. Retrieved from http://c.ymcdn.com/sites/www.ncgrantmakers.org/resource/resmgr/2010_annual_meeting/atd_math_level_3_progression.pdf

What Other States Are Organizing

Recommendations using multiple measures for placement are what lawmakers have voted into policy in Florida. Beginning in 2014, current high-school graduates and all activeduty military students will have the choice of whether to take the developmental courses or even the placement tests designed to determine their readiness for college-level work (Chu et al., n.d.; Mangan, 2013). This new policy has sent a ripple of fear (in faculty) all across Florida's 28 state and community colleges, and for good reason. Instructors are concerned "…an influx of unprepared students could destabilize introductory courses and set up those who will struggle for failure" (Mangan, 2013, p. 1). If colleges opt for an absolute open door policy to credit bearing classes, more students will be enrolled in the courses who cannot master them. Florida is not the only state making these types of laws either. Connecticut, Tennessee, and now North Carolina all have made decisions funneling students straight into curriculum classes based on research that developmental courses are not working. Looking at it from another perspective. Some critics argue that colleges should be "…left to determine why students shouldn't start in college-level courses instead of why they should be blocked from them" ("Corequisite remediation," 2013, para. 1). It is true that the system for remediating students is broken, but the alternative may be just as devastating to the educational success of students and of the colleges.

Weakness of the Policy

Because of the soaring costs of developmental mathematics courses, many states are looking to minimize or even do away with mathematics remediation altogether. Why should they, the taxpayers, pay for the students to be educated twice in the same curriculum; first in K – 12 and then again in developmental mathematics courses? The problem with loosening the requirements for college entrance by using multiple measures is that policies like this will affect how mathematics is taught in subsequent curriculum math courses (Attewell et al., 2014; Mirel, 2006). This will also have huge implications on students' success rates in mathematics and not necessarily for the better. The GPA for which students are placed in curriculum classes is based on the overall GPA in high school, not the GPA of their math courses alone (Duffy et al., 2014). Everyone wants students to graduate, but they must graduate with the measurable abilities and skills to be successful in today's 21st century global market. This lowering of standards is already occurring in community colleges across the state of North Carolina with massive implications to the math programs and its students (Attewell et al., 2014; Bickerstaff et al., 2016).

A New State ReDesign

In combination with multiple measures, North Carolina has also gone through an evolutionary change to the way it teaches developmental math (Bracco et al., 2015; Epper & Baker, 2009; Pretlow III & Wathington, 2011). This new state redesign satisfies *DEI's* goal of accelerating student completion in developmental mathematics courses by redesigning the developmental mathematics curricula. Pew Charitable Trusts funded a grant in 1999, called the Program in Course ReDesign, where colleges were charged with redesigning the way they teach developmental mathematics (Bickerstaff et al., 2016; Epper & Baker, 2009; Pretlow III & Wathington, 2011). Technology was fused into the course design to allow for optimal integration of active learning, mastery learning, use of technology, and 'Just in Time' support (Epper & Baker, 2009). The program succeeded in its mission – it reduced instructional costs to the college, which is often, the most substantial cost, while simultaneously, improved student learning (Epper & Baker, 2009). In today's busy classrooms, there is not enough time to teach the course without the use of technology (Epper & Baker, 2009). Time spent in developmental mathematics is consistently being criticized for being too time-consuming already. It is doubtful more time will be allowed for this coursework to be taught. Utilizing technology in the developmental mathematics classroom can be viewed as a triumph from all perspectives.

Recently, questions have arisen about the appropriateness of using technology in the role of facilitating developmental mathematics learning. Ariovich and Walker (2014) reported on a study of course redesign at a large community college in the suburbs of a diverse, metropolitan district. The study looked at modularization success rates as it pertained to developmental mathematics specifically. The results were not favorable for the design. When any college switches from a traditional design (A, B, C grade to pass), to a course redesign in modularization (80% - 85% grade for mastery), unquestionably, success rates will decline. This is what the data showed at this large community college being studied. Immediately, skeptics are going to argue the design is a failure and isn't appropriate for student learning. This is just simply not the case. Perhaps the only statistics being examined were the 68% pass rate for traditional courses (A, B, C grade) versus the redesign courses' pass rate of 37% (A and B only to pass). Developmental mathematics is undeniably the course with the highest failure rate in colleges nationwide (Fain, 2011). Nothing has changed in the curriculum with modularization. It has simply raised the standards in evaluating students of developmental mathematics – as it should. It was found that even though initially students who took the redesigned course did not fare as well as students in the traditional course; there was a 37% pass rate in traditional versus a 28% pass rate for the redesign (Ariovich & Walker, 2014). It should be noted that of the students who were successful in the redesign, 54% of them were successful in their subsequent math course, as compared to 34% of the students who were initially successful in the traditional math course (Ariovich & Walker, 2014). Those numbers should speak volumes about the success of the self-directed developmental course redesign.

The redesigned program currently in place in North Carolina encompasses all three previous traditional developmental math classes: Essential Mathematics (MAT 060), Introductory Algebra (MAT 070), and Intermediate Algebra (MAT 080). Students registered in these newly redesigned classes are required to do almost all work using the online math component, MyMathLab.com, a product of Pearson Education, Inc. This design has been set up as a self-directed learning system using appropriate technology. The model being employed is known as an emporium model where all students utilize computers and the Internet to self-direct their developmental mathematics learning. Instructors and tutors act as facilitators in the classroom. Students watch the optional online videos (also designed by Pearson) for each section and then do homework and take quizzes – all online. Theoretically, only when students have definitively mastered the material, do they take the final test for that module. For North Carolina, the curriculum is broken into eight modules. Each module is required of a student if they place into developmental mathematics. Appendix D gives a description of the topics contained within each individual module, as well as individual Student Learning Outcomes for each module (Guilford Technical Community College, 2016).

Upon completion of modules 010 – 050, students are then deemed ready for the curriculum math course MAT 143 – Quantitative Literacy. Each student in the course is required to meet pre-designed Student Learning Outcomes for that course as well. These outcomes were designed by the curriculum faculty and outline exactly what is required to be taught in each curriculum MAT 143 course. The Student Learning Outcomes for the MAT 143 course are outlined in Appendix B.

Barbitta (2010), one of the original members of the redesign team for the state of North Carolina, who is now the Associate Director of Special Projects for the North Carolina Community College System Office, described the program as self-directed learning. This program allows students to be "…more active and engaged learners, receive immediate feedback about their work, focus on what they do not know, and move quickly through what they do know. This is a combination of guided content learning, acceleration and remediation as needed" (personal communication). In this new state redesign, it is the hopes of both administrators and legislators that students will be more responsible for their own learning in developmental mathematics and will do so in a timelier manner.

Previous studies have hinted at the increase in student success in curriculum courses due to the modularization of developmental mathematics (Ariovich & Walker, 2014; Fain, 2015). Boylan, Director of the National Center for Developmental Education (NCDE) believes the emporium model, when executed correctly, should work (Fain, 2011). However, he echoes that in a time of budgetary crises …colleges will eliminate its people. They (colleges) will not eliminate the students (Boylan, 2011; Fain, 2011). In the emporium model, the connection between student and instructor is key for student success.

Conclusion

It has yet to be seen how the multiple measures mandate will affect the community college graduation rates of North Carolina's students. Will college math instructors continue to lower their standards to meet the students where they are and still allow them to pass the college-level class or will we see an increased number of drop outs in curriculum math repeatedly? It was observed in the 1960s that by "allowing students to take and fail college level courses and retake those classes did not increase completion rates" (Lu, 2013, p. 13). In reality, this action lead to higher student withdrawals and reduced money for students. In the 1970's, community colleges decided to relax their standards on placement testing, orientation and prerequisite requirements. This led to the 'student's right to fail philosophy' (Hughes & Scott-Clayton, 2011; Rounds & Andersen, 1985; Zeitlin & Markus, 1996), where it was believed that these students were adults and they should know best as to whether they could master the course material or not. Only after a decade of attempting this inadequate policy did lawmakers go back to mandatory placement and prerequisites because of the overwhelming cost of student failure and withdrawal rates (Hughes & Scott-Clayton, 2011). Santayana in his work, “The Life of Reason: Reason in Common Sense,” once proclaimed those who don’t learn from history are doomed to repeat it because history here seems to again be repeating itself (trans. 1905). Many states have used multiple measures as a means to place students only to see the policy fail. North Carolina has legislated the developmental mathematics course redesign before, only to have students demand in-class instruction from teachers (S. Duff, personal communication, February 10, 2014). It will be exciting to see just what the future holds for the state of North Carolina and its educational policies over the next decade or so. With any luck, decision-makers in charge learn from the mistakes made in the past with regard to multiple measures and will not sentence our educational system to repeat the failures seen so many times before.

As stated in Aristotle’s Metaphysics, “Men do not think they know a thing until they have grasped the ‘why’ of it” (trans. 2000, I). Many have been left asking these type of questions. Why are we implementing this policy? Why is it having all these unintended effects? Why did we not know this was going to happen? The goal of employing multiple measures was to increase student access to curriculum-level courses and to improve students’ completion rates – plain and simple. The policy has increased student access to curriculum-level courses. This is evident in the near elimination of the developmental mathematics department and the new math redesign that was so innovative in North Carolina only six years ago. This evidence is also seen in the funding budget for developmental education in North Carolina. According to Grovenstein, Vice President and Chief Financial Officer of the North Carolina Community College System

Office, developmental education costs hit peak spending in the state in 2011 with approximately $143,750,000 being allocated to the program (personal communication, April 17, 2017). Since multiple measures and the redesign have been in place, that spending has dropped to an astonishing $36,778,848 in 2016 (E. Grovenstein, personal communication, April 17, 2017). That drop equates to a 74.4% decrease in spending for developmental education. It has yet to be seen whether multiple measures will improve students' completion rates in curriculum classes. This indicator of success is what this study hopes to reveal.

Chapter 3 Methodology

Introduction

Within this chapter, the foundation for the research design will be laid out for the reader. Data was collected over a period of five semesters in a Quantitative Literacy course – MAT 143. The final course grades were compared between two groups of students - those who were placed into a developmental math course sequence prior to entering the curriculum math course and those who were able to bypass the developmental course sequence by means of multiple measures. The final course grades were then compared to see if students who had been exposed to the developmental course sequence had performed any better than those who were placed using multiple measures. Logistic regression was used to analyze the data.

Methodology

The research in this study was quantitatively grounded. The statistical test used to analyze the data was the General Linear Model, which compares how certain independent variables affect specific dependent ones (Glen, 2016). The General Linear Model, or GLM, is an umbrella term used in statistics for analyzing the more specific regression analysis, analysis of variance (ANOVA), and analysis of covariance (ANCOVA), among others (Theory: The General Linear Model, n.d.). The GLM behaves much like a typical linear function in that it contains both a dependent variable, Y, and an independent variable, X_i, where i denotes the i^{th} independent variable. The fundamental equation used to express the General Linear Model is given by $Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + E$, where β_i represents the weight of each independent variable (its coefficient), E represents the prediction error, and α represents the intercept (Theory: The General Linear Model, n.d.). All of these concepts will be explained in more detail in the Research Rationale.

In order to use the General Linear Model in any statistical testing situation, four major assumptions need to be agreed upon. First, there is an assumption of linearity between the dependent and independent variables. The second assumption is that there is a degree of normality which exists within the residuals or the prediction error. Thirdly, there is an equality that must be maintained within residual variances. Finally, fixed independent variables must be measured without error (Goebel, 2014; Jeon, 2015; Lund & Lund, 2013a; Theory: The General Linear Model, n.d.). Once these assumptions were met, certain statistical tests were administered to determine if the data was a good fit for the model. The General Linear Model used in this research study depended on the available *N* in this study as well as the nature of the variables, which were both categorical in nature.

Research Design

The research design for this project consisted of a quantitative secondary analysis. The data had already been collected by the community college being examined. Some advantages to using secondary analysis of a data set were that it allowed for trends in the data be analyzed for meaningful interpretation (Winch, Todd, Baker, Blain & Smith, n.d.). This type of study also allowed for comparisons to be made in the data set over time (Winch, et al., n.d.). The sample collected from the data set should be representative of the population as a whole, since data was collected through a random sampling process. The institution being studied serves an estimated 3.3% of the total 735,000 student population attending all 58 community colleges in the state of North Carolina (Guilford Technical Community College, 2014) These students are made up of both city and rural students, male and female, as well as exhibiting differing characteristics of race (“Institutional Research, Effectiveness, and Reaffirmation,” 2016). Figures 6 and 7 show the characteristics of the students both by gender and race (Guilford Technical Community College, 2014).

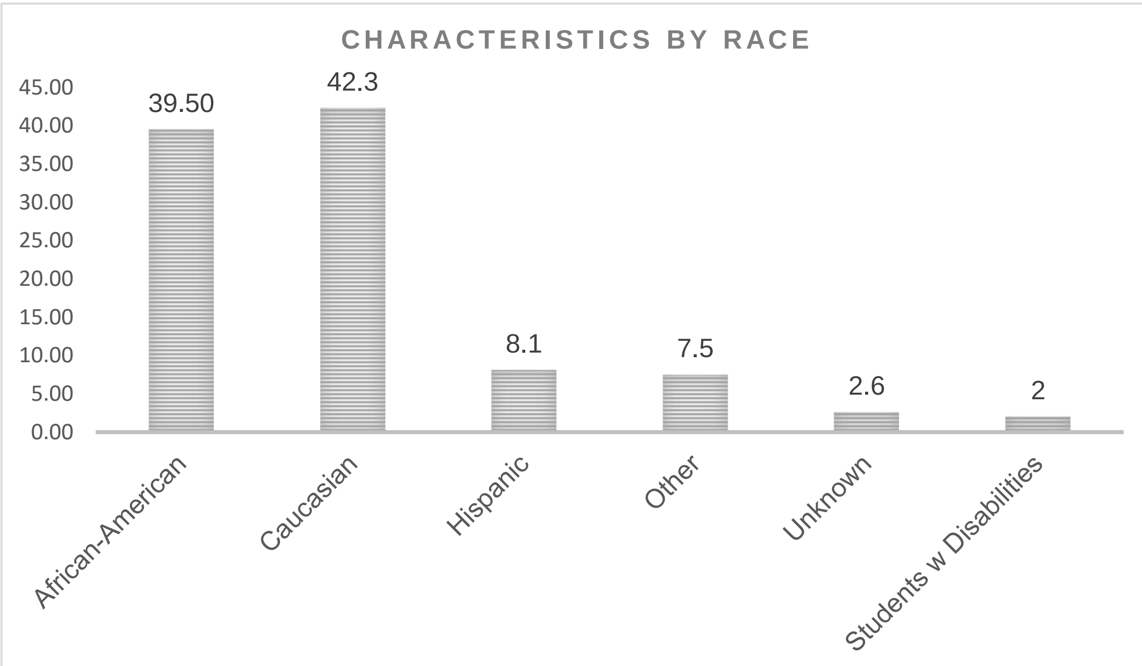


Figure 6. Curriculum Student Body Characteristics (Fall 2015). This figure depicts the student body characteristics of curriculum students being studied by race at the selected institution.

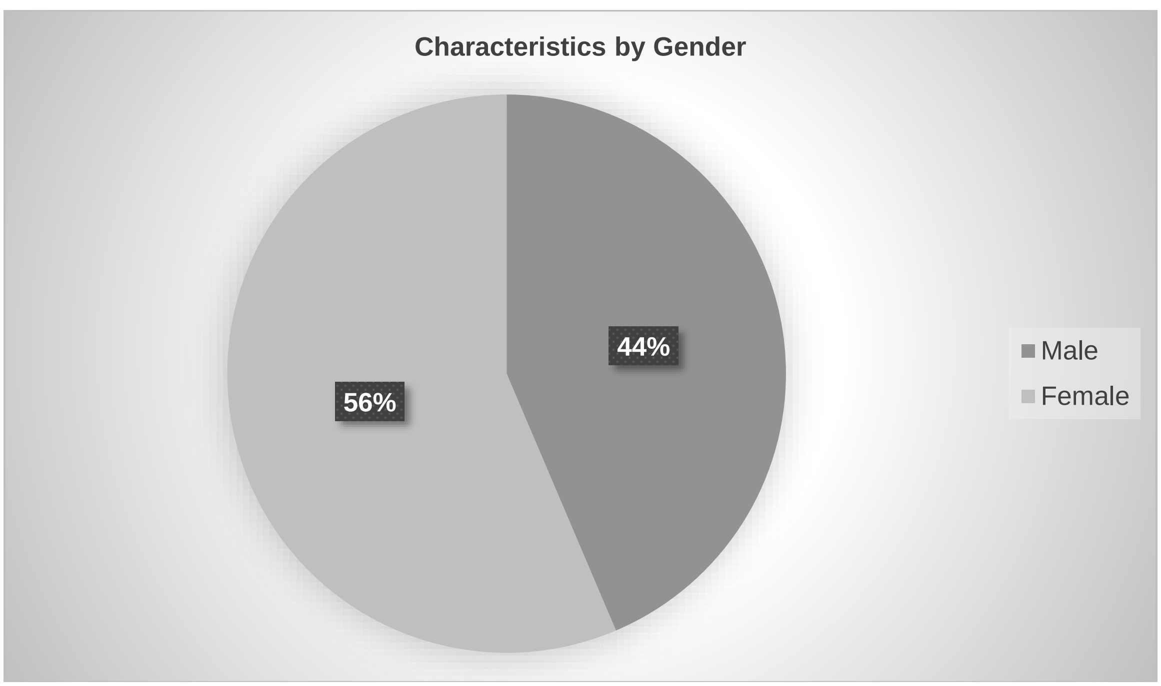


Figure 7. Curriculum Student Body Characteristics (Fall 2015). This figure depicts the student body characteristics of curriculum students being studied by gender at the selected institution.

Approximately 24,250 students were enrolled in the particular community college being studied at the time, with 51.5% of those students being enrolled in curriculum classes, 34.6% enrolled in continuing education programs and 13.9% enrolled in basic skills (Guilford Technical Community College, 2014). This large population allowed any results and conclusions from the research to be made generalizable to the population as a whole. Assuming N was a large enough sample size (greater than 30), this allowed for the Central Limit Theorem to be used in approximating a normal distribution with mean, μ and standard deviation $\frac{\sigma}{\sqrt{n}}$ (Triola, 2015).

The dependent variable for this research design was the final course grade for the curriculum math class, Quantitative Literacy – MAT 143. This variable was defined as categorical and discrete in nature. The independent variable (or predictor variable) for the research design consisted of whether or not a student had to complete the developmental math coursework sequence before being placed into curriculum math. Subpopulations of the predictor variable were examined pertaining to a student's gender, race, and/or socio-economic status. All predictor variables in this study were categorical as well as discrete in nature.

Administrative social science data was the data collection tool for this research. This type of data is derived from any public sector's day-to-day operations, like that of the two-year community college being evaluated (Connelly, Playford, Gayle, & Dibben, 2016). The data was not collected for any specific research purposes, but rather as an observational tool for placement, registration, and enrollment purposes of its student body. Advantages to using administrative social science data include access to larger data sets, less expensive (to non-existent) data collection costs, and its relevance in the evaluation of specific policies (Connelly et al., 2016).

Research Rationale

The purpose of this study was to see whether there was a relationship that existed between the dependent variable, final course grades in the curriculum math class, Quantitative Literacy – MAT 143, and the independent variable, participation in the developmental math course sequence. The researcher wanted to determine if the developmental course sequence had a positive impact on student success once they completed their curriculum math course. It would also be examined to determine if a student's gender, race, and/or socio-economic status as defined by participation in FASFA predicted whether that student would participate in the developmental math course sequence.

The General Linear Model (GLM), mentioned earlier, was also used to analyze the data. This model encompasses an array of statistical analyses including ANOVA, regression analysis and logistic regression. Logistic regression was the chosen model used to explore the relationship between the dependent variable and the predictor variables including gender, race, and/or socio-economic status. Logistic regression is often used in cases where the relationship needs to be explained between these types of variables in a quantitative study (Hosmer, Lemeshow & Sturdivant, 2013; Mood, 2010). In this study, the dependent variable being studied was the student grades in the curriculum math class – MAT 143. Ultimately, we can reduce the question down to whether the students passed the curriculum class or not. All A – C grades were grouped together as a 'pass' grade or 'yes.' All D, F, W grades were grouped together as a 'fail' grade or 'no,' for the purposes of this study. Logistic regression enabled the researcher to investigate whether the predictor variable had any impact relationship on the categorical variable of interest (Lund & Lund, 2013a). In this study, we were trying to see if the developmental course sequence students had taken had an impact on their subsequent success on the curriculum math course grade in MAT 143? It was questioned whether any of the predictor variables including gender, race, and/or socio-economic status could predict students' placement into the developmental math course sequence using logistic regression.

The four major assumptions that had to be met with logistic regression were not as restricting to the major assumptions that had to be met for the General Linear Model. Using logistic regression required the following assumptions be met: dependent variable should be measured at the nominal level – dichotomous; any independent variables should be measured at either the continuous, ordinal, or nominal level; no multicollinearity amongst the independent variables; and no outliers should exist in the data (Kovaz, 2018).

Logistic regression allowed for this prediction by discovering the equation that best predicted the dependent variable, Y, based on all independent variables, X_i. The independent predictor variables in this research are described as:

$X_1 = Demographics\ by\ Sex,$

$X_2 = Demographics\ by\ Race,$

$X_3 = Demographics\ by\ FAFSA\ Participation.$

Logistic regression was used to help predict relationships that were found between any of the potential predictors and participation in the developmental math course sequence. It was also used to answer the question if participation in the developmental math course sequence yielded higher success in the curriculum course grades in MAT 143. Logistic regression was the best regression tool available considering the nature of the variables in this study.

Just like with any other tool available, logistic regression does not come without some limitations. One of the major limitations that logistic regression posed to the research lay in what was unobserved (Mood, 2010). That is, when logistic regression was performed, not all variables in the equation were accounted for. This affected the outcome of the coefficients, thereby affecting the overall General Linear Model. This result is referred to as Unobserved Heterogeneity, or unobserved differences. The issue with the unobserved heterogeneity arises in the interpretation of the odds ratios at the analysis stage; when one compares the model across samples or across groups of samples (Mood, 2010). Since this research aimed at really answering only one major dichotomous question with no other samples to compare, the effect of the unobserved heterogeneity was hopefully kept to a minimum. When we aimed to answer the second question, "Is placement into developmental mathematics predicted by gender, race (Caucasian vs Non-Caucasian), and/or socio-economic status (FAFSA and non FAFSA)?" this may have led to some unobserved variables having an effect, since we were comparing among numerous groups. This needed to be factored into the analysis portion of the research.

Unobserved heterogeneity is certainly something that could be controlled for by using a continuous dependent variable (Mood, 2010). It was just not that simple to do in this study. The issue arose with the curriculum math course, Quantitative Literacy – MAT 143. At the particular community college being studied, the curriculum math instructors have autonomy in their classrooms. Granted, they are all given a similar syllabus at the beginning of the semester, with identical Student Learning Outcomes (SLOs) to be achieved; they are still left to teach and test as they feel inclined. For this reason, the pass/fail dichotomous dependent variable was thought to be the best fit for the logistic regression model.

Research Questions

As a result of this research, the following two questions are anticipated to be answered:

1. Does a self-directed, developmental math course sequence have an impact on student achievement (final course grade) in the subsequent curriculum math course MAT 143 – Quantitative Literacy?
2. Is placement into developmental mathematics predicted by gender, race (Caucasian vs Non-Caucasian), and/or socio-economic status (FAFSA and non FAFSA)?

Hypotheses. Question #1 - $\boldsymbol{H_0}: \boldsymbol{\beta_1 = 0}$; Students who engage in a self-directed developmental math course sequence prior to entering the curriculum math class, Quantitative Literacy – MAT 143, perform no better on final course grades than those who were able to bypass developmental math and go straight into the curriculum math via multiple measures.

$\boldsymbol{H_1}$: $\boldsymbol{\beta_1 \neq 0}$; Students who engage in a self-directed developmental math course sequence prior to entering the curriculum math class, Quantitative Literacy – MAT 143, perform better on final course grades than those who were able to bypass developmental math and go straight into the curriculum math via multiple measures.

Question #2. – $\boldsymbol{H_0}: \boldsymbol{\beta_1 = 0}$; Placement into developmental mathematics is not predicted by gender, race (Caucasian vs Non-Caucasian), and/or socio-economic status (FAFSA and non FAFSA).

$\boldsymbol{H_1}$: $\boldsymbol{\beta_1 \neq 0}$; Placement into developmental mathematics can be predicted by gender, race (Caucasian vs Non-Caucasian), and/or socio-economic status (FAFSA and non FAFSA).

Level of significance p = .05. The level of significance was defined as the likelihood of a false positive or Type I error. Just because all threats to validity had been met does not necessarily mean the result will be accurate (Michael, n.d.). Researchers had to decide what level of risk they were willing to take with the study. A *p* value of .05 means there is a chance that 5 out of the 100 results will be incorrect due to random error. The level of significance, α, can differ in each study based on the number of incorrect results the researcher is willing to accept. The gold standard of alpha testing, α, in statistical models sets the level of significance equal to .05.

Role of the Researcher

As with any quantitative research design, the role of the researcher was in the background, completely impartial to any of the data collection processes or conclusions drawn from that data. This study was taken from data that had already been collected. There were no surveys conducted, no focus groups. There were no interactions between the participants and the researcher whatsoever. As mentioned before, the only identifying characteristic of the participants were Student ID numbers, similar to Banner IDs.

Ethical Issues

There are two ethical issues the researcher believes needed to be addressed in this study. First, the researcher was examining the final course grades of students who completed Quantitative Literacy – MAT 143. It may be likely that the researcher was the math professor of record for some of the classes included in the data set. Again, it should be reiterated that students were identified only by their Student ID numbers. The researcher was also not looking at students in any particular professor's course, only by section number (i.e., MAT 143 – MJT07). Therefore, the researcher was not able to distinguish between students who were taught by herself and students who were taught by another professor.

A second ethical issue that needed to be brought to light was the fact that the researcher was one of the original four members of the Redesign Team for Developmental Math at this community college. The researcher was in the math classes from day one to see all of the progress that has happened in the redesign. Many of the instrumental decisions that were reached to help make the program the success that it is today were done in the researcher's presence. This study was looking into whether students who go through the self-directed developmental math redesign are more successful in a curriculum math class than those who were just bypassed along according to the Multiple Measures for Placement Policy mandated by the state. Any bias on the researcher's part had to be put aside in thinking that the self-directed developmental math course sequence is making a difference in students' success when it came to evaluating the data at the conclusion of this research.

Data Sources

Data for this research was drawn from the community college's fully-integrated student records management system database - Colleague® by Ellucian. The company was designed with features specifically made for applications in higher education. Colleague® advertises a product where assimilated data delivers a holistic view in an easily accessible, understandable, and applicable format to allow for fact-based decisions to be reached (Ellucian, 2013). One of the company's core values is to Dare: "Fight to be the undisputed leader in higher education technology and solutions" (Ellucian, 2013, p. 1). The company proudly delivers its product to more than 2,300 institutions in over 40 countries world-wide ("Datatel and sungard higher education," 2012).

Data Collection

For the purposes of this study, data in Colleague® was confined to just Student ID numbers, course placement, course grades, courses taken, gender, ethnicity, financial aid and eligibility. Restrictions were entered into Colleague®, then pulled out with Informer queries into CSV Excel files for data analysis. No other identifying markers were recorded within the data set. Since data security is of the utmost importance in any kind of research, every attempt was made to protect the identities of participants. The data used in this research was identified as Internal Data, requiring only a minimal security data classification level since it posed minimal risk to participants (Appalachian State University, 2015). This type of data contained information produced only for use by university members with a legitimate purpose to access said data (Appalachian State University, 2015). No names were used in identifying participants; only student IDs. All data was stored on password-protected Excel files.

Participants

The participants in this research study consisted of community college students enrolled in both developmental mathematics courses, as well as the curriculum math class, Quantitative Literacy – MAT 143, though not necessarily at the same time. The time frame for participant selection was Summer 2015 to Spring 2017.

Participant Selection

This research study aimed to compare two different groups of students to see if developmental mathematics (the treatment) had an effect on final course grades for a curriculum class compared to students who were able to bypass developmental mathematics and go straight into a curriculum math course via the Multiple Measures for Placement Policy mandated by the state. Because the two groups needed to be similar in math ability, there was a need to keep GPA close in proximity. GPA restrictions for students bypassing developmental math using the Multiple Measures for Placement Policy would be $2.60 \leq x \leq 2.69$. GPA cut scores for students being placed into developmental math would be $2.50 \leq x \leq 2.59$. This GPA exception otherwise excluded additional acceptable subjects. Any student placed in the curriculum math class via multiple measures using either SAT/ACT scores or NC DAP scores was also excluded from the sample.

Age was also an exclusion factor for this study. Both populations had to be within one year of high school graduation. Because of this restriction, all participants should have been comparatively close in age (approximately between the ages of 18 and 21 years of age). Similarly, developmental math students were only considered for study inclusion if they progressed from developmental math to the curriculum MAT 143 course within 3 semesters (one calendar year) from developmental math course completion. This allowed for minimal gap in mathematics course knowledge.

Other minor exclusions that should be noted were:

1. Students who took MAT 143 online were not counted in the data set. The researcher was only looking at face-to-face class data. Online students are a different type of student and often times, the data reflects this difference.
2. There may be a small number of students who did not get placed into a curriculum class by way of multiple measures, but rather took the college's NC DAP test and was

able to place into curriculum math by this means. The number of students in this group was thought to be minimal, so these students were excluded from the study as well.

IRB Procedures

Institutional Research Board (IRB) approval for this dissertation research was requested from and approved by both the community college being examined in this project as well as through Appalachian State University; the University conferring the degree. Approval for the IRB through Appalachian State University has been included at the end of this chapter for reference. The researcher also had to renew their Collaborative Institutional Training Initiative (CITI) certificate in order to conduct this research. Similarly, those results have been included at the conclusion of this chapter for review.

Data Analysis

Since there is a limited range of probabilities available if the equation were used directly in regression analysis, the odds ratio, Ψ, of the probabilities was the focus of logistic regression in this research (McDonald, 2014). In taking the natural log, *ln*, of the odds ratio, this makes the equation more appropriate for running a regression model. Therefore, the equation for multiple logistic regression was given by:

$$\ln\left[\frac{Y}{1-Y}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i, \quad \textbf{\#1}$$

$where$

$X_1 = Demographics\ by\ Sex,$

$X_2 = Demographics\ by\ Race,$

$X_3 = Demographics\ by\ FAFSA\ Participation$ (McDonald, 2014).

This equation behaves much like a typical linear function in that it contains both a dependent variable, Y, and an independent variable, X_i, where *i* denotes the *i*th independent variable. There are four weights, β_i, or coefficients of X_i, since there are four independent variables in the equation. Each weight was determined individually upon fitting the data to the specific logistic regression model (Box, Hunter, & Hunter, 2005; Theory: The General Linear Model, n.d.). The y-intercept for the model was given by β_0.

In any regression equation, a key value is known as the conditional mean, denoted by *E*(y|x), which is the mean value of the outcome variable given the independent variable (Hosmer, Lemeshow & Sturdivant, 2013).

$Given\ E(y|x) -$ "the Expected value of y, given x."

$E(y|x) = \beta_0 + \beta_1 x + \beta_2 x + \beta_3 x + \cdots$, for all x's $(-\infty, \infty)$

Let $\pi = E(y|x)$

$$\therefore \pi(x) = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}} \qquad \textbf{\#2,}$$

where $\pi(x) = ln \frac{\pi(x)}{1 - \pi(x)}$.

Notice how the last equation mirrors equation #1 from the previous page

$$\ln\left[\frac{Y}{1 - Y}\right] = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_i X_i$$

In essence, these are the same equations with different variables. If the dependent variable, Y, is coded as 0 or 1, then $\pi(x)$ provides that Y = 1|x, which is expressed $\pi(x)$. It follows that (1 - $\pi(x)$) gives the conditional probability Y = 0|x. Therefore, for(x_i, y_i), where $y_i = 1$, the contribution to the likelihood function is $\pi(x_i)$. For ordered pairs when $y_i = 0$, the contribution of the likelihood function is (1 - $\pi(x_i)$), where $\pi(x_i)$ expresses the value of $\pi(x)$ computed at x_i

(Hosmer, Lemeshow & Sturdivant, 2013). An appropriate way of expressing the likelihood function takes on the following form:

$$\pi(x_i)^{y_i}[1-\ \pi(x_i)]^{1-y_i} \ \textbf{\#3}$$

From here, assuming independence of observations, we get the product of terms:

$$l(\beta) = \prod_{i=1}^{n} \pi(x_i)^{y_i}[1-\ \pi(x_i)]^{1-y_i} \quad \textbf{\#4}$$

In order to apply the maximum likelihood method, differentiation can be used with formula #4. For this example, it will be easier to work with the log of the equation. Therefore, the log-likelihood is given by:

$$L(\beta) = ln[l(\beta)] = \sum_{i=1}^{n}\{y_i \ln[\pi(x_i)] + (1-y_i)\ln[1-\pi(x_i)]\} \ \textbf{\#5}$$

In order to see if the coefficients of the logistic regression equation are significant, the following question must be asked, "Does the model that includes the variable in question tell us more about the outcome (or response) variable than a model that does not include that variable" (Hosmer, Lemeshow & Sturdivant, 2013, p. 11)? To achieve this, we compared the observed values of the dependent variable to the predicated values attained by the model; once with the variable in question and once without (Hosmer, Lemeshow & Sturdivant, 2013). These observations will become important further on in Chapter Four. For now, an easier equation to view what is happening in #5 can be stated by the following:

$$D = -2\ln\left[\frac{likelihood\ of\ the\ fitted\ model}{likelihood\ of\ the\ saturated\ model}\right]$$

where a saturated model is defined as having as many parameters as it does data points. *D*, known as the deviance in a logistic regression equation, is comparable to the residual sum-of-squares in linear regression (Hosmer, Lemeshow & Sturdivant, 2013). A majority of this mathematics is what goes on behind the scenes when SPSS was used to analyze the data in Chapter Four.

Trustworthiness

Methods for establishing trustworthiness differ when dealing with a quantitative study as opposed to a qualitative study. While qualitative studies use credibility, dependability, transferability, and confirmability to establish trustworthiness, quantitative studies focus mainly on validity, reliability, and objectivity (“Quantitative vs. qualitative methods,” 2012).

Validity can be broken into two parts: internal and external. Internal validity is used to evaluate trustworthiness by ensuring threats to internal validity have been controlled for by the researcher. Possible threats to internal validity for this research include selection, instrumentation, treatment replications, statistical regression, and subject attrition (“Quantitative vs. qualitative methods,” 2012). Internal validity also concerns itself with the validity of instruments used in the research design, as well as measurements used in the study (“Quantitative vs. qualitative methods,” 2012).

External validity is quantitative research’s answer to transferability, a method used for establishing trustworthiness in qualitative research. External validity uses the results from the research to generalize them to a larger population. Factors that could affect the external validity of research might include subjects, time, intervention, and measures used in the study (“Quantitative vs. qualitative methods,” 2012). This method of trustworthiness relies heavily on the sampling technique used in the study. Researchers most often use confidence intervals to convey precise external validity limits of the study.

Reliability is a second method used by quantitative researchers for establishing transferability in a research study. In this research study, stability estimate was used to prove reliability. This method required a treatment be administered to one group of students and then waiting a certain amount of time before administering the same treatment to the same group of students ("Quantitative vs. qualitative methods," 2012). In the developmental math course sequence, students were administered a diagnostic test at the beginning of their module. Students were then exposed to the same homework, quiz, and testing procedures where the same exact test was administered at the conclusion of their module. It is important to note that reliability is important to quantitative studies because it forms the foundation for validity. It also measures a sense of dependability in the study – will the research produce the same results every time it is duplicated?

Finally, objectivity is the third method researchers use for proving the trustworthiness of a study. Objectivity is the quantitative equivalent of confirmability in qualitative research. Objectivity uses the practice of measurements, data collection and analysis to prove objectivity ("Quantitative vs. qualitative methods," 2012). This method is imperative to the research design because it offers a basis for which reliability and validity are formed. Objectivity also speaks to the distance the researcher must keep from the participants in order to not be influenced ("Quantitative vs. qualitative methods," 2012). As researchers of this quantitative design, we focused only on the facts of this study and what it revealed to us.

Considering the variables in this research are all categorical, the researcher was limited in the types of statistical analyses which could be performed with the data. It should also be noted that a great deal of trustworthiness in this study depended on the size of N, the data set. Assuming N was of a sufficient size, every measure was taken by the researcher to ensure accurate, believable, reliable, and valid results. All assumptions required to use logistic regression was met by the data, so any resulting conclusion should be considered valid. SPSS was used to analyze the data set for logistic regression in addition to the chi-square statistic test for independence. This allowed for minimal to zero calculation errors.

Chapter 4 Results

Introduction

This research aimed to compare the final course grades of select MAT 143 Quantitative Literacy students who bypassed developmental mathematics using the Multiple Measures for Placement Policy with those who took the developmental mathematics courses based on GPA. The GPA of students in this study ranged from 2.50 to 2.69, with those students in the 2.50 to 2.59 range being from the Developmental Group (Dev group) and those students in the 2.60 to 2.69 range being from the Multiple Measures Group (MM group). The GPA was restricted in a way to keep the math ability of students close in proximity to each other. This allowed the research to be valid when comparing the results. The population of students in the MAT 143 Quantitative Literary courses were taken from a large, urban community college in the southeastern United States.

Quantitative secondary analysis was utilized in this study to examine the data. Since all the variables were categorical in nature, logistic regression was the model used to determine if the response variable (grades) was related to the explanatory or predictor variable (developmental course sequence). A tributary study was also conducted to determine if placement into developmental mathematics was predicted by gender, race, and/or socio-economic status. IBM's SPSS was the statistical software package used to run the regression analyses. The results of running a logistics regression in SPSS displayed, among others, four main tables: a Classification Table, an Omnibus Tests of Model Coefficients Table, a Hosmer and Lemeshow Test with Contingency Tables and the Variables in the Equation table. With these four tables, the researcher could accurately report the results from running a logistics regression test in SPSS.

Participants

The participants in this research study consisted of community college students enrolled in both the developmental mathematics courses, as well as the curriculum math class, Quantitative Literacy – MAT 143, though not necessarily at the same time. The time frame for participant selection was for Summer 2015 to Spring 2017. Because the two groups needed to be similar in math ability, there was a need to keep the GPA of students close in proximity. GPA restrictions for students bypassing developmental math using the Multiple Measures for Placement Policy was held at $2.60 \leq x \leq 2.69$. GPA cut scores for students placed into developmental math was held at $2.50 \leq x \leq 2.59$. This GPA exception otherwise excluded a majority of acceptable subjects. Similarly, any student placed in the curriculum math class via multiple measures using either SAT/ACT scores or NC DAP scores was also excluded from the sample.

Age was also an exclusion factor for this study. Both populations had to be within one year of high school graduation. Because of this restriction, all participants should have been comparatively close in age (approximately between the ages of 18 and 21 years of age). Likewise, developmental math students were only considered for study inclusion if they progressed from developmental math to the curriculum MAT 143 course within 3 semesters (one calendar year) from developmental math course completion. This allowed for minimal gap in their mathematics course knowledge.

Other minor exclusions that should be noted here include:

1. Students who took MAT 143 online were not counted in the data set. The researcher was only looking at face-to-face class data. Online students are a different type of student and often times, the data reflects this difference.
2. There may be a small number of students who did not get placed into a curriculum class by way of multiple measures, but rather took the college's NC DAP test and was able to place into curriculum math by this means. The number of students in this group was thought to be minimal, so these students were excluded from the study as well.

As much as I tried to keep parameters for the study and its participants as similar as possible, it must be acknowledged that the exclusion factors stated may critically decrease the amount of overall variability in the sample. Thus making the analysis of the findings less powerful for small effects. I accepted this risk and was willing to proceed with the study anyway. In total, these restrictions allotted 99 subjects in the data pool for analysis out of a total of over 1,200 students who took the courses in the time span of Summer 2015 to Spring 2017.

Results

After performing binary logistic regression on the 99 subjects in this research design, the following results were discovered.

In the Classification Table (Table 1) of the Baseline Model, which included only the intercept in its calculations, it was found that, given the base rates of two decision options, 58 / 99 or 58.6% passed the college-level math class, MAT 143. Therefore, having no other information available (SPSS calls this holding the constant equal to 0), the best strategy every time is to predict that the student will successfully complete MAT 143 (Kremelberg, 2011;

Minitab, Inc., 2016; Wuensch, 2014). Using this approach, one would be correct approximately 59% of the time.

Table 1

Classification Table from SPSS Output which Details Pass Rate

Classification Table[a,b]

Observed			Predicted: A,B,C Pass / D,F,W Fail: Fail	Predicted: A,B,C Pass / D,F,W Fail: Pass	Percentage Correct
Step 0	A,B,C Pass / D,F,W Fail	Fail	0	41	.0
		Pass	0	58	100.0
	Overall Percentage				58.6

a. Constant is included in the model.

b. The cut value is .500

The key output of Binomial Logistic Regression is the meaning of the p-value. This will allow one to see if there is any significance between the response variable and the prediction equation (Kremelberg, 2011; Minitab, Inc, 2016; Wuensch, 2014). The significance level for this research was originally set at $\alpha = .05$. If $p \leq \alpha$, one can determine there is a statistically significant association between terms. If $p \geq \alpha$, one cannot determine there is a statistically significant association between terms. As noted in the Variables in the Equation table (Table 2), each p-value outlined in yellow is well above the significance level, alpha = .05. Therefore, this tells us that it cannot be determined statistically if there is a significant association between the response variable and the predictor variables.

Table 2

Variables in the Equation Table from SPSS Output which Details the P-value

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	DevEd Taken(1)	-.430	.454	.896	1	.344	.651
	Gender(1)	.291	.444	.428	1	.513	1.337
	Financial Aid			1.659	2	.436	
	Financial Aid(1)	.873	.725	1.450	1	.228	2.394
	Financial Aid(2)	.824	.688	1.436	1	.231	2.279
	Student Ethnicity			.641	4	.958	
	Student Ethnicity(1)	.590	1.091	.292	1	.589	1.804
	Student Ethnicity(2)	.873	1.198	.532	1	.466	2.395
	Student Ethnicity(3)	.465	1.075	.187	1	.665	1.591
	Student Ethnicity(4)	-21.156	40192.970	.000	1	1.000	.000
	Constant	-.731	1.322	.306	1	.580	.481

Another interesting statistic in the Variables in the Equation table are the odds ratios. This statistic allows us to better understand the affects our predictor variables have on our response variable (Kremelberg, 2011; Minitab, Inc, 2016; Wuensch, 2014). Odds ratios can be difficult to understand for many people. One first has to understand the odds of an event happening. When we speak of odds, we are speaking of the odds in favor of an event happening. There is also a mathematical definition for the odds against an event happening. For this example, we will deal with only with the odds of an event happening. Odds is defined by taking the probability that event, *E,* will occur and dividing it by the probability that *E* will not occur (Blitzer, 2015). Mathematically speaking, it is defined as

$$\text{Odds } (E) = \frac{P\ (E)}{P(not\ E)}$$

Taking odds a step further, odds ratios are defined as the odds of the event in one group occurring divided by the odds of the event in a separate group occurring (Grimes & Schulz, 2008). The formula for finding an odds ratio is given as such

$$Odds\ ratio = \frac{\frac{p_1}{1 - p_1}}{\frac{p_2}{1 - p_2}}$$

$$where\ p_1\ \&\ p_2 = Probability\ of\ Group\ 1\ and\ Group\ 2's\ Outcomes$$

(Grimes & Schulz, 2008)

Since the independent and dependent variables are categorical in nature, the relation between them approaches a chi-squares distribution where the expected outcomes are compared to the observed outcomes. A simpler way of thinking about odds ratios is comparing the proportion of the observed frequency with the frequency expected by chance. No variance is shared between variables because each specific variable is only part of the regression equation. For this reason, an odds ratio greater than one indicates that the treatment is more likely to occur than predicted by chance by the amount of ratio above one. Likewise, an odds ratio less than one indicates that the treatment is less likely to occur than predicted by chance by the amount between the ratio and one. An odds ratio equal to one indicates no linear relationship exists between the independent and dependent variables (“Binary logistic regression,” n.d.). By examining the odds ratios, any confounding bias that may have occurred in the research design or analysis should be controlled for here. Confounding bias results when extra variables that were not accounted for in the original research design make their way into your model and affect your research data (Glen, 2017).

Odds ratios are complicated and are not always reliable. Relative risk is similar to odds ratio and easier to understand. Relative risk (RR) applies the probability of an event occurring in one group and compares it to the probability of an event occurring in another group (Relative Risk, 2017). Whereas odds ratios are calculated by using the ratio of odds, relative risk employs percentages to calculate its probabilities. Odds ratios and relative risks mirror each other when the outcome of the event is rare. It is only when the outcomes become usual that the odds ratio greatly exaggerates the effect size of the relative risk, making both measures a poor approximation of the statistics (Grimes & Schulz, 2008). Since odds ratios are among the output data in logistic regression, it is an appropriate, but limited measure of correlation.

In Table 3, the last column yields the exponentiation of the B Coefficient. This is known as the odds ratio in logistic regression. Odds ratios that are greater than one indicate an event that is more likely to occur; that there is a positive relationship between the independent variable and the dependent variable. While an odds ratio that is less than one indicates an event that is less likely to occur. In other words, there is a negative relationship between the independent variable and the dependent variable ("Binary logistic regression," n.d.; Kremelberg, 2011; Minitab, Inc., 2016; Wuensch, 2014). As evident in Table 3, the effect developmental mathematics had on our response variable – course grade in class – was an odds ratio less than one. This indicates that the event is less likely to occur. Whereas the odds ratios for all of the other predictor variables were greater than one, indicating these events were more likely to occur. To be more specific, the odds ratio for gender was 1.337. According to the Categorical Variables Codings chart, males were coded as a 1 for this variable in SPSS. Therefore, the odds that a male student passed the curriculum math course, MAT 143, was 1.3 times higher than one would have expected by chance.

The odds ratios for the financial aid predictor were almost equal. The odds that a student passed the curriculum math course, MAT 143, was 2.4 times higher than one would have expected by chance for students who are not receiving financial aid versus being 2.3 times higher than expected by chance for students who are receiving financial aid. At least for this predictor variable, it did not seem that money, or the financial burden it placed in students, was the motivating factor in whether or not a student was successful in the curriculum class. It is often the opinion of some instructors that students are in class for the money. At least with this sample, the data does not show money as being a significant factor.

Lastly, when looking at the odds ratios for the student ethnicity predictor, some interesting facts were uncovered. The odds that a student passed the curriculum math course, MAT 143, was 1.8 times higher than expected by chance for students of Black, non-Hispanic descent; 2.4 times higher than expected for students of Hispanic descent; and 1.6 times higher than expected for students of White, non-Hispanic descent. This ratio was non-existent for students of Asian, Pacific Islander descent or who came from the Indian sub-continent, Other category.

Table 3

Variables in the Equation Table from SPSS Output which Details Odds Ratios

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	DevEd Taken(1)	-.430	.454	.896	1	.344	.651
	Gender(1)	.291	.444	.428	1	.513	1.337
	Financial Aid			1.659	2	.436	
	Financial Aid(1)	.873	.725	1.450	1	.228	2.394
	Financial Aid(2)	.824	.688	1.436	1	.231	2.279
	Student Ethnicity			.641	4	.958	
	Student Ethnicity(1)	.590	1.091	.292	1	.589	1.804
	Student Ethnicity(2)	.873	1.198	.532	1	.466	2.395
	Student Ethnicity(3)	.465	1.075	.187	1	.665	1.591
	Student Ethnicity(4)	-21.156	40192.970	.000	1	1.000	.000
	Constant	-.731	1.322	.306	1	.580	.481

The third table to analyze when performing a binomial logistic regression on data is located in Table 4 – the Omnibus Tests of Model Coefficients. This test will indicate how well the current model is outperforming the null model (Kremelberg, 2011; Minitab, Inc., 2016; Wuensch, 2014). The value in the significance column (the p-value), which in this case is the same for all, is .699, is the probability of obtaining the chi-square statistic given the null hypothesis is true (Kremelberg, 2011; Minitab, Inc., 2016; Wuensch, 2014). Another way of saying this is it is the probability of obtaining the chi-square statistic, 5.540, if there is no effect of the predictor variables, occurring simultaneously, on the response variable (Kremelberg, 2011; Minitab, Inc., 2016; Wuensch, 2014). In order for the data to be statistically significant, the p-value would have to be less than the alpha or critical value in this research study, set at $\alpha = .05$. Since $.699 \geq .05$, the model is determined to be not statistically significant.

Table 4

Omnibus Tests of Model Coefficients Table from SPSS Output which Details Chi-square

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	5.540	8	.699
	Block	5.540	8	.699
	Model	5.540	8	.699

Finally, in order to tell whether the model was a good fit for the data, the Hosmer and Lemeshow Test (Tables 5 and 6) will be analyzed. If it is determined that the p-value for the goodness-of-fit test is lower than the critical value of $\alpha = .05$, then the predicted probabilities deviate from the observed probabilities (Kremelberg, 2011; Minitab, Inc., 2016; Wuensch, 2014). Hence, the binomial logistic regression function cannot predict the outcome. In this case, the p-value for the Hosmer and Lemeshow Test is $p = .410$. This value was greater than $\alpha = .05$.

Therefore indicating the model fit the data well. There was just no significance in the prediction model.

Table 5

Hosmer and Lemeshow Table from SPSS Output which Details How Well the Model Fit the Data

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	8.244	8	.410

Table 6

Contingency Table for Hosmer and Lemeshow Test from SPSS Output which Details How Well the Model Fit the Data

Contingency Table for Hosmer and Lemeshow Test

		A,B,C Pass / D,F,W Fail = Fail		A,B,C Pass / D,F,W Fail = Pass		
		Observed	Expected	Observed	Expected	Total
Step 1	1	7	6.558	3	3.442	10
	2	3	2.643	2	2.357	5
	3	4	5.150	7	5.850	11
	4	7	6.652	8	8.348	15
	5	4	3.237	4	4.763	8
	6	2	3.419	7	5.581	9
	7	5	4.029	6	6.971	11
	8	5	4.794	9	9.206	14
	9	1	3.321	10	7.679	11
	10	3	1.195	2	3.805	5

Based on the evidence, the model had been shown to fit the data, yet the data had shown not to support the null hypothesis. There was no other conclusion left than to fail to reject the null hypothesis.

Question #1 - $\boldsymbol{H_0}$: $\beta_1 = 0$; FAIL TO REJECT. Students who engage in a self-directed developmental math course sequence prior to entering the curriculum math class, Quantitative Literacy – MAT 143, perform no better on final course grades than those who were able to bypass developmental math and go straight into the curriculum math via multiple measures.

Question two deals with how placement into developmental mathematics is predicted by different variables such as gender, race, and/or socio-economic status of the students. Again, binary logistic regression was performed on the 99 subjects in this research design. What follows is the analysis of the data.

In the Classification Table (Table 7) of the Baseline Model, which included only the intercept in its calculations, it was found that, given the base rates of two decision options, 66 / 99 or 66.7% of students were able to bypass developmental mathematics by means of the Multiple Measures for Placement Policy . Therefore, having no other information available (SPSS calls this holding the constant equal to 0), the best strategy every time was to predict that the student would be able to bypass developmental mathematics and go straight into a curriculum math course (Kremelberg, 2011; Minitab, Inc., 2016; Wuensch, 2014). Using this approach, one would be correct approximately 67% of the time.

Table 7

Classification Table from SPSS Output which Details Percent of Students Bypassing Developmental Mathematics

Classification Table[a,b]

Observed			Predicted: DevEd Taken No	Predicted: DevEd Taken Yes	Percentage Correct
Step 0	DevEd Taken	No	66	0	100.0
		Yes	33	0	.0
	Overall Percentage				66.7

a. Constant is included in the model.

b. The cut value is .500

The key output of Binomial Logistic Regression is, again, the meaning of the p-value. This allowed us to see if there was any significance between the response variable and the predictor variable (Kremelberg, 2011; Minitab Inc., 2016; Wuensch, 2014). The significance level set at $\alpha = .05$ can determine if there was a statistically significant association between terms. If $p \geq \alpha$, one cannot determine if there was a statistically significant association between terms. As noted in the Variables in the Equation table (Table 8), each p-value outlined in yellow was well above the significance level, alpha = .05. Therefore, this tells us that it cannot be determined if there was a statistically significant association between the response variable and the function containing the predictor variables.

Table 8

Variables in the Equation Table from SPSS Output which Details Significance between Variables

Variables in the Equation

		B	S.E.	Wald	df	Sig.
Step 1[a]	Student Ethnicity			.712	4	.950
	Student Ethnicity(1)	19.980	40192.802	.000	1	1.000
	Student Ethnicity(2)	20.653	40192.802	.000	1	1.000
	Student Ethnicity(3)	20.469	40192.802	.000	1	1.000
	Student Ethnicity(4)	20.275	40192.802	.000	1	1.000
	Financial Aid			1.207	2	.547
	Financial Aid(1)	.702	.780	.809	1	.368
	Financial Aid(2)	.233	.758	.094	1	.759
	Gender(1)	.013	.455	.001	1	.977
	Constant	-21.449	40192.802	.000	1	1.000

The third table to analyze when performing a binomial logistic regression on data is located in Table 9 – the Omnibus Tests of Model Coefficients. This test indicates how well the current model was outperforming the null model (Kremelberg, 2011; Minitab, Inc., 2016; Wuensch, 2014). The value in the significance column (the p-value), which in this case is the same for all, was .918, is the probability of obtaining the chi-square statistic given the null hypothesis is true (Kremelberg, 2011; Minitab, Inc., 2016; Wuensch, 2014). Another way of saying this is it is the probability of obtaining the chi-square statistic, 2.617, if there is no effect of the predictor variables, occurring simultaneously, on the response variable (Kremelberg, 2011; Minitab Inc., 2016; Wuensch, 2014). In order for the data to be statistically significant, the p-value would have to be less than the alpha or critical value in this research study, set at $\alpha = .05$. Since $.918 \geq .05$, the model was determined to be not statistically significant.

Table 9

Omnibus Tests of Model Coefficients from SPSS Output which Details How Well the Current Model Outperforms the Null Model

Omnibus Tests of Model Coefficients

		Chi-square	df	Sig.
Step 1	Step	2.617	7	.918
	Block	2.617	7	.918
	Model	2.617	7	.918

Finally, in order to tell whether the model was a good fit for the data, the Hosmer and Lemeshow Test (Tables 10 and 11) was analyzed. If it was determined that the p-value for the goodness-of-fit test was lower than the critical value of $\alpha = .05$, then the predicted probabilities deviate from the observed probabilities (Kremelberg, 2011; Minitab, Inc., 2016; Wuensch, 2014). Hence, the binomial logistic regression function cannot predict the outcome. In this case, the p-value for the Hosmer and Lemeshow Test was $p = .786$. This value was $> \alpha = .05$. Therefore indicating there was not enough evidence to conclude that the model does not fit the data.

Table 10

Hosmer and Lemeshow Test from SPSS Output which Details How Well the Model Fit the Data

Hosmer and Lemeshow Test

Step	Chi-square	df	Sig.
1	3.946	7	.786

Table 11

Contingency Table for Hosmer and Lemeshow Test from SPSS Output which Details How Well the Model Fit the Data

Contingency Table for Hosmer and Lemeshow Test

		DevEd Taken = No		DevEd Taken = Yes		
		Observed	Expected	Observed	Expected	Total
Step 1	1	10	10.180	3	2.820	13
	2	12	12.240	5	4.760	17
	3	9	7.704	2	3.296	11
	4	3	3.378	2	1.622	5
	5	10	12.105	9	6.895	19
	6	7	5.072	1	2.928	8
	7	5	4.926	3	3.074	8
	8	6	6.126	4	3.874	10
	9	4	4.268	4	3.732	8

Based on the evidence, the model had been shown to fit the data, yet the data had shown not to support the null hypothesis. There is no other conclusion left than to fail to reject the null hypothesis.

Question #1-a. – $\boldsymbol{H_0}$: $\beta_1 = 0$; ***FAIL TO REJECT.*** Placement into developmental mathematics is not predicted by gender, race (Caucasian vs Non-Caucasian), and/or socio-economic status (FAFSA and non FAFSA)?

Even though it looks like we fail to reject our null hypothesis, this conclusion does not mean our research was for naught. There are some interpretations that can be read into the data and its conclusion. Clearly, students who took a developmental course sequence did not perform better in the curriculum math course, as it was hypothesized, but they did perform just the same.

These interpretations will be examined in the next chapter dealing with the conclusions.

Chapter 5 Conclusions

Introduction

This chapter draws together the preceding sections; connecting the historical research to the present findings. Any gaps in the rationale and their significance will be discussed. Limitations of the study will also be examined. For future reference, the Theoretical Framework will be revisited to determine its usefulness in the study. If any changes are suggested based on the findings, they will be provided here. Implications of the research will be presented, as well as how these implications may be addressed by educators and administrators. Finally, recommendations for future research will be identified and encouraged.

Analysis – Literature Links

This research aimed to answer the question, “Does a self-directed, developmental math course sequence have an impact on student achievement (final course grade) in the subsequent curriculum math course MAT 143 – Quantitative Literacy?” Students who were randomly selected to be in the Developmental (Dev) group based on their GPA cut scores coming out of high school were one GPA point academically below their Multiple Measures (MM) group peers. Results from the study concluded the null hypothesis be rejected. There was no clear evidence of mathematical advances amongst final course grades of the MM group and the Dev group. However, considering that the Dev group came into college academically deficient, and upon arrival were required to enroll in the self-directed developmental mathematics course sequence before entering curriculum math, this does not mean the developmental course sequence did not do its job. The Dev group was able to perform academically at the same level in the MAT 143 – Quantitative Literacy course as their higher- performing peer group.

The conclusion supports the literature reported earlier in the study. One of the big questions with developmental coursework and the role multiple measures plays in alleviating its participation is the idea of where the cut score should be held for GPA. In this research, our GPA for the Dev group was set at 2.50 – 2.59. It seems as if the 2.50 GPA is a good cut score for placing students into developmental courses. What needs to be studied further is how many of the students who were at the lower end of the multiple measure cut score for GPA (2.60) did not pass the curriculum course.

This is the challenge that has yet to be explored with multiple measures - Where is the appropriate cut score for GPA on both ends? If colleges put more students into curriculum courses, hoping they will pass, is it not also true more students will go into curriculum math (who could have benefitted from developmental courses) and fail? Ariovich and Walker (2014) believe there are consequences for over placing and under placing students in college-level mathematics. There needs to be more of a balance at the cut score for when students are able to bypass developmental coursework and go straight into college-ready courses.

In addition to blurring the lines surrounding cut scores, this research seemed to reinforce the idea that self-directed learning served students in their college-ready math course. Self-directed learning in developmental mathematics coupled with one's motivation to learn provided for the theoretical framework for this research. Ariovich and Walker (2014) affirm self-directed learning enables students to retain more information versus other learning strategies (Fain, 2015). It was proposed that upon the successful navigation of self-directed learning in developmental mathematics, a student should enter a curriculum math class more prepared to handle the rigor that is often required of them. Although no differences were seen between the Dev group and the MM group in this study, according to Boylan, "The purpose of developmental education is to level the playing field for poorly prepared students. If poorly prepared students did as well as better prepared students in [the] study, then developmental education was successful" (personal communication, September 27, 2017).

As mentioned in the rationale for this study, much research has been performed on developmental mathematics over the past few decades to try to determine the best way of assisting students to be more successful in their coursework. From placement, to motivation and persistence, and finally reform, developmental mathematics has been studied thoroughly for decades. This study determined that whatever gaps in knowledge existed between students' math ability upon entering college disappeared once the Dev group of students were exposed to the developmental math course sequence. This exposure allowed the Dev group to compete at the same level mathematically upon entering a curriculum math course. The developmental math course sequence evened the playing field for students in the college classroom academically.

The significance of this study was to reveal what effects, if any, multiple measures had upon students in curriculum math courses. Since the policy went into effect in North Carolina in the fall of 2015, little to no research exists on the effects of multiple measures on student success in the curriculum mathematics classroom. It is well known that a percentage of students were being misplaced into developmental coursework using colleges' placement tests (Jenkins et al., 2017). It is approximated that only about 15% of students who place into developmental classes actually need to be there. The other 85% of students could be successful in credit-bearing courses if the college were to contemplate a wider range of criteria in placing them (Bracco et al., 2015; Mangan, 2013; Ngo & Kwon, 2014). What is not known is the success rates of these students once the curriculum course is finished. It has yet to be seen whether multiple measures will improve students' completion rates in curriculum classes. How well did they perform? What were their grades in subsequent math courses? These are questions that need to be studied more carefully when it comes to the Multiple Measures for Placement policy. It may takes years to see the effects this new multiple measures policy has had on our students and their foundational knowledge base in mathematics. Many of these effects will be evident decades from now in the United States' ability to continue to compete globally in a more advanced technological, STEM-focused society.

Limitations

The limitations in this study are vast. It was not an easy task to try to measure the success rates of this particular group of students with all the variables that come into focus. The first limitation of the study is the college-level class that was chosen, Quantitative Literacy – MAT 143. A majority of students who matriculate through developmental mathematics only take the first five modules. This allows them to register for one of two transferable curriculum math courses, Quantitative Literacy or Statistics. More students register for the Quantitative Literacy class, so that was the reason MAT 143 was chosen as the curriculum class for this research.

The length of the study is the second limitation of this research. The data collection took place from Summer 2015 to Spring 2017. This was mainly due to the massive changes the developmental mathematics department had undergone since its inception. The two-year time period chosen for the study was the most consistent time in developmental mathematics since the redesign was put into place in Spring 2011. Appendix C shows a document designed by the Emporium Lab Coordinator, which outlines all the major changes the program had experienced since it began. This document should give a sense of the sheer volume of changes students and faculty were having to endure to get the redesign program where it is today.

A third limitation to this study was the fact that only one community college in the state was evaluated for its data. According to the North Carolina Community College System's Developmental Math Modular Curriculum Guide (2011), one of its core Redesign Principles states that each college has the authority to implement the modularized curriculum in a fashion that is suitable given the resources of the college. This principle allowed each community college in the state to implement the redesign any way the college chose. Some colleges chose to keep the modular design in the traditional format, with instructors in the classroom, teaching students face-to-face. Other colleges chose a completely online format, where students were only required to come in for the proctored exam at the end of the course. Finally, others chose the emporium-style lab setting, like in this study, where students are required to be in the lab setting on campus, doing their work online, while getting help from instructors and tutors on demand. Since it was up to each community college to implement the program how they thought best, only one community college was chosen to be in this study.

A fourth limitation of the study involves participant selection. There was a need to keep the ability, skill level, and time out of math courses similar. For these reasons, only students who were placed into the curriculum math class via Multiple Measures for Placement within one calendar year (fall, spring, summer) of entering the community college were included in the study. The same rule applied for developmental mathematics students. Those who completed the developmental mathematics course sequence and entered the curriculum math course within one calendar year were included in the study. Often times, instructors will see students take their developmental course sequence at the beginning of their college journey and then not attempt their curriculum math class until the very last semester before graduation. Students have forgotten all the math content and good study habits for being successful at math. These students were just not included in the study. Similarly, students who graduated from a high school more than a year ago (Summer 2014) would not be included in the study as well. Someone being out of high school for four years, even though by the Multiple Measures for Placement standards is deemed college-ready, was not considered a viable participant to compare to someone just coming out of developmental mathematics, having had that recent exposure to the math. It just would not have been a fair comparison in skill level.

Because the time frame of how long a student could be out of high school was placed on the study participants, age became an inadvertent limitation of the study. Clearly, if a student cannot be out of high school longer than one year, the age of that student participating in this research is less than 22. One could not compare the course grades of an 18-year-old college freshman with that of someone who has been out of school for 20 plus years. Age had to be controlled for in this situation, therefore both groups (MM group and Dev group) consisted of students who were only out of high school for one year or less.

In addition to age, GPA was also considered an variable that needed to be addressed. How can one compare a student who was placed into a curriculum math class via Multiple Measures for Placement with a 4.0 GPA with a student who had to complete the developmental mathematics course sequence and earned a 2.0 in high school? These students do not have the same math ability. Hence, GPA was restricted to 2.50 to 2.59 for the developmental group and 2.60 to 2.69 for the Multiple Measure for Placement group. Hopefully, this would allow any association discernible at the end of the study to be as close in approximation as possible.

One side effect of limiting age and GPA to such extent could be the restrictions this may have caused on the other variables in the study forcing them to yield false or inaccurate data. These limitations could have affected the variance in the sample to the point that one would not have expected to find any reliable data. Age and GPA may have had collinear effects on the other variables. Thus when removed, those effects on the other variables may have also been limited. It was deemed necessary to control for GPA and age in this study, otherwise, one would be comparing two different types of math students and math abilities.

Repeaters in the curriculum class were not included in the study. If someone had taken the curriculum math class more than one time, they were excluded from the study results. There wasn't really a concern with this being an exclusion on the developmental side. Developmental students, by this point, had only five weeks to complete a module. In reality, some did have to repeat in order to complete the module. If these students were excluded on this end as well, based on all other restrictions, this would have left few participants to study. Therefore, it was determined that developmental students were not to be excluded, but anyone who took the curriculum math course more than one time would be excluded from the results. These students would have had the opportunity to go through the material more than one time, giving that student a better chance at success. It just didn't seem appropriate to compare this student to others in the study.

Other minor limitations of the study included students who were placed into the curriculum classes by means of their SAT scores or the college's NC DAP test. The research was only looking at students who were placed by means of Multiple Measures. Online students were excluded from the study. An online student is in a different environment and reacts differently than a face-to-face student. Teaching styles of curriculum instructors were not controlled for in the study. This is another variable that could differ greatly from class to class and affect the outcome.

One final limitation that should be noted is the statistical method used in this study to analyze the results. Logistic regression was the preferred method chosen given the nature of the variables in this study. From the limitations, one will notice all the variables in this study are categorical in nature. This does not lend itself to the most comprehensive mathematical analysis of any research data.

Revisiting the Theoretical Framework

The theoretical framework for this study blended self-directed learning with one's motivation to learn. Since motivation was deemed too broad of a topic to be discussed within this research paper, it was simply narrowly defined as an individual's need to attain personal happiness through participation in some action of choice (Damasio, 2003). The motivations of students were never measured or recorded. Looking at the theoretical framework for this research design, it is the belief that the framework worked relatively well for what was being investigated, given the variables at hand. This research was quantitative in nature and never intended to take into consideration any qualitative, motivational factors of the students being analyzed. However, the researcher realizes that the motivational factors of students can contribute greatly to or limit a student's ability to succeed in mathematics.

Based on the study's findings, the model was shown to be a good fit for the data, yet the data failed to reject the null hypothesis. It was determined that students who engage in a self-directed developmental math course sequence prior to entering the curriculum math class, Quantitative Literacy – MAT 143, perform no better on final course grades than those who were able to bypass developmental math and go straight into the college-level math via multiple measures. It could also be interpreted as students who engaged in a self-directed developmental math course sequence prior to entering the college-level math class were empowered enough to perform at the same level mathematically as those who were able to bypass developmental math and go straight into the curriculum math via multiple measures. If the developmental students had never received the treatment of the developmental math course sequence prior to entering the curriculum math class, the developmental group of students may have performed much worse. This research study helped to confirm that the two student groups (MM v. Dev) attained equal ground at the end of the semester in terms of course grade success in curriculum math.

Future research dealing with developmental mathematics and its effect on students' success rates as compared to those who get to bypass developmental math and go straight into curriculum may want to include a qualitative component on motivation. The motivation piece was a key component of self-directed learning, but was not studied with any complexity in this research. Other designs might want to look at the specific reasons as to a student's motivations for learning mathematics. This could also incorporate not only the developmental math student, but the curriculum math student as well. It is important to reiterate that influential motivational factors to the learner will greatly determine how much knowledge is retained and transferred to other learning situations.

Implications

Even though it was proven that based on the data, we fail to reject the null hypothesis, the implications in this study are considerable. This does not imply our study was for naught. According to the Hosmer and Lemeshow Test, the model was confirmed to be a good fit for the data. Our p-value for the test was $p = .410$. This value was greater than $\alpha = .05$, indicating there was insufficient evidence to conclude that the model does not fit the data. The data fit the model, but the implications were not necessarily profound. This is based on the variables in the equation table where the p-value calculated was well above the significance level, alpha = .05. This told us that it cannot be determined if there was a statistically significant association between students who took the developmental math course sequence and their curriculum course grade.

Do these findings translate as developmental mathematics making absolutely no difference in the students' overall success in college-level mathematics? It is a concern that many who read this may translate the data as such. It should be taken into consideration that the students were close in GPA range when they were examined for this study. The correct way to view the data would be that the thirty-three students who persisted through the developmental course sequence, entered the curriculum class on a more even playing field, mathematically speaking, as compared to the rest of the students who were placed via multiple measures. The students in the Dev Group were able to compete with the students in the MM Group to the point where no difference could be seen between test scores at the end of the curriculum class. Developmental coursework brought the students up to the level where they needed to be in order to compete equally in a curriculum classroom. Without the developmental math course sequence, there is no proof that these students would have persevered and been successful in a curriculum math class.

Policymakers and administrators alike need to look at the data and results of this research as more of a 'glass half full' scenario. Just because the test grades at the end of the curriculum class came out as equal does not imply that developmental mathematics makes no difference to a student's success in future math courses. It has been mentioned in earlier chapters that developmental courses can be an expense for a college. With enrollment numbers declining since recovery from the Great Recession of 2007, colleges are looking for more creative ways to save money. Reading this research incorrectly would be the perfect justification to try to eliminate developmental courses from a college setting.

If policymakers and administrators were to make the mistake of getting rid of developmental courses, especially in mathematics, there would be a huge knowledge gap at the core of the classroom. If students are coming to college unprepared from high school, and with developmental math courses out of the equation, there is nowhere for students to go but out the front door. It is just not possible for students who are so far behind to catch up in the subject. If anything, this research proves there needs to be more studies done in this area to affirm the encouraging aspects of developmental coursework in its role of truly preparing students for curriculum course rigor.

Recommendations for Future Research

As this dissertation was in progress, Senate Bill 561 was being written into law in the state of North Carolina. This bill essentially states that all North Carolina high school seniors will be evaluated their senior year before graduating based on ACT scores, GPA, and other college-readiness indicators yet to be determined by the State Board of Community Colleges (S. 561, 2015). If students are not deemed college-ready by these indicators, the students will be required to take remedial math and/or English class their senior year before graduating to get them prepared for college-level courses (S. 561, 2015). The state of North Carolina will be moving developmental coursework back to the high schools for a majority of students beginning with the 2018 – 2019 academic school year. These developmental classes will be taught by high school faculty, with college instructors overseeing the implementation and content delivery of the courses (S. 561, 2015).

The research in this study looked at a younger population of students (18- to 21- years of age). As of next academic school year, all high school seniors graduating are supposed to be academically prepared to enter college and therefore, should not be enrolling in a developmental mathematics course. Developmental mathematics will still exist though. As long as there are students, there will always be a need for developmental education. Students will always require the need to refresh their academic skills. Students will always face barriers beyond the classroom environment.

Future research dealing with developmental mathematics and its effect on students' success rates as compared to those who get to bypass developmental math and go straight into curriculum will still be limited by age. A student can only use the Multiple Measures policy as a means to bypass developmental courses for five years upon graduation. After this point, the student is required to take the college's placement test to see if they are eligible for curriculum math or place into developmental math. With most high school students deemed 'college-ready' coming straight out of high school in 2019 (taking developmental math their senior year in high school), the majority of those students will enter straight into a curriculum math class. If the student waits more than five years before beginning college, they will lose the 'college-ready' status and will be forced to take the placement test at that point. For a majority of students, five years is a long time to take a break from math concepts. In this scenario, either all students are in the curriculum class (directly after high school) or all are in developmental education (five years later). This will lead to the face of developmental courses having a much older student body population.

Future research comparing developmental students with curriculum students may be nearly impossible in the state of North Carolina because of Senate Bill 561, but this will not stop research at additional institutions with similar designs in other states such as Virginia and Tennessee. Furthermore, a more longitudinal study comparing the success rates between developmental and curriculum students would be of benefit to the greater research community. The current study only looked at a 2-year period from 2015 to 2017. All the design changes that occurred within the developmental program inhibited extending the study timeline any further. Once states decide to keep developmental coursework steady beyond just a few years, a more longitudinal study with a larger population of students (maybe an entire state or region) would yield some important data for researchers, policy makers, and administrators alike.

In addition to selecting cohorts in different states, researchers may also want to look at different types of platforms in which the math content is being delivered. In this research study, MyMathLab was utilized as the delivery source for the math content. This is not the only platform for learning math employing self-directed learning. Other platforms such as MathXL (a subsidiary of Pearson), WebAssign, and ALEKS are often used in replace of MyMathLab. These platforms could be investigated as to their role in helping students self-direct their learning in mathematics. WebAssign is an online, fully-customizable instructional tool for use by STEM instructors with their students. WebAssign began as a learning project at NC State University in 1997. Purchased by Cengage Learning in 2016, today, WebAssign has more than one million students using it as their preferred mathematics learning platform in more than 2,600 institutions worldwide (Cengage Learning, 2017). ALEKS was designed by researchers (software engineers, mathematicians, and cognitive scientists) as a collaboration between the University of California and New York University, and features Artificial Intelligence (AI) at the center of its design

(McGraw-Hill, 2017). Students work through math concepts, while ALEKS assesses their ability to understand the topic at hand. If ALEKS' AI estimates the student requires more remedial work in order to master the concepts, the coursework will change to reflect the remediation. Students continue working until all math concepts in that section have been mastered. ALEKS is considered a revolutionary way of learning math online, combining student confidence with learning momentum (McGraw-Hill, 2017). Future research could compare if the use of these platforms are of any more benefit to student success in curriculum math versus the platform used in this research design, MyMathLab.

The latest move by some states concerning their developmental coursework policy has been to remove the barrier completely from students trying to get a college degree. Florida headed the trend back in 2014, when they made it optional for students to register for developmental coursework (Chu et al., n.d.; Mangan, 2013). Now California is steering the way by dropping the typically required placement test and subsequent remedial coursework in math and English at Cal State. Students no longer have to take these standardized, entry-level exams and can thus, enroll straight into curriculum classes. According to Executive Order 1110, "Assessment of Academic Preparation and Placement in First-Year General Education Written Communication and Mathematics/Quantitative Reasoning Courses," the "…broadest utilization of multiple measures in assessing academic readiness and determining course placement for first-year students" will be implemented (2017). By using the most broadest definition of Multiple Measures in order to place its students, Cal State is hoping to raise its graduation rate from 19% to 40% by 2025 (Xia, 2017). Critics argue this is just another example of watering down the curriculum in the United States, thereby, dumbing down our society as a whole (Hamilton, 2017). Future studies could look at the success rates of students in curriculum math where states like Florida and California have made developmental coursework optional or even removed the program altogether.

Finally, it would be highly recommended to research the cut scores at which students were deemed college-ready and fast tracked into curriculum math. According to the results of this study, it seems reasonable to assume that students with a 2.50 to 2.59 GPA were performing well in curriculum courses once they have been exposed to the developmental math course sequence. What needs to be studied further is how many of the students who were at the lower end of the multiple measure cut score for the GPA of 2.60 did not pass the curriculum course?

Conclusion

Drastic changes in curriculum like GPA cut scores, and making developmental curriculum optional, will continue to deny the United States the opportunity to compete at higher levels of science, technology, engineering, and mathematics on the world stage (Bennett, 2009; Engler, 2012). The question remains, "Are our students getting any better or stronger in math because of these curriculum changes?" We need stronger college graduates in science, technology, engineering, and mathematics, not weaker students with a General Education degree in order to continue to compete on a global level.

Since the university system was developed, there has been a need for developmental coursework to prepare students for college-level work. When community colleges expanded, developmental coursework became a major sector of every community college's mission (Breneman et al., 1998; Kee, 2013). Herring (2017) was sincere when he spoke, "We must take people where they are and carry them as far as they can go within the assigned function of the system" ("Dr. Dallas Herring," 2017). This statement really does speak to the effect community colleges have on its students, and not just the academically prepared students, but the students who come to us unprepared as well. The results of this research hopefully adds to the literature on this issue in confirming that whatever gaps in knowledge existed between students' math ability upon entering college ceased to exist once the Dev group of students were exposed to the developmental math course sequence.

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Appendix A

Definition of Terms

Specific to Chapter 3 - Methodology

Categorical Variables – Variables that are assigned a label; fit into categories. No hierarchy amongst categories (i.e. male, female).

Central Limit Theorem – For all samples of the same size *n* with *n* > 30, the sampling distribution of $\bar{x}$ can be approximated by a normal distribution with mean μ and standard deviation $\frac{\sigma}{\sqrt{n}}$ (Triola, 2015).

Cross-Tabulation – Describes the relationship between two categorical variables in table form.

Dependent Variable – X; The variable that is being predicted by Y, the independent variable.

Expected Frequency – Product of the *i*th row and *j*th column totals, divided by total sample size. Value should be less than 5. Given by the formula:

$$E_{ij} = \sum \frac{T_i \times T_j}{N}$$

Discrete Variable – Countable in nature; not continuous (infinite).

Independent Variable – Y; The variable that is being used to predict the X, the dependent variable. Also referred to as predictor variables.

Inferential Statistics - Techniques that allow researchers to use samples of a population to make generalizations about the populations from which the samples were drawn (Lund & Lund, 2013a).

Level of Significance - The chance of making an incorrect decision based on the hypothesis testing result (Michael, n.d.). Denoted by either p or alpha, α.

Logistic Regression – A predictive analysis used to describe data and explain the relationship between one dependent categorical variable and one or more categorical independent variables (Kovak, 2018).

Measures of Central Tendency – A way of describing the central position of a frequency distribution for a given set of data. Relevant statistics include mean, median, mode, and midrange (Lund & Lund, 2013a).

Measures of Variation – A way of describing the spread of the data in relation to its mean. Relevant statistics include range, quartiles, variance, and standard deviation (Lund & Lund, 2013a).

Natural Log – Denoted by $ln(x)$; It is defined as the inverse of the exponential function, e^x. In other words, it is a function of time needed to get to a specific level of growth ("Demystifying the natural", n.d.).

Odds Ratio – Ψ (psi); Measures the association between an outcome (dependent variable) and a treatment (independent variable). Speaking in terms of odds, it is a comparison of two odds: the odds of the outcome occurring given the treatment compared to the odds of the outcome occurring without the treatment (Kovak, 2018).

Pearson's Chi-Square Test for Independence - χ^2; Developed by Karl Pearson, it is a process of measuring the joint frequency distribution to determine whether the variables are statistically independent or related (Michael, n.d.).

Post hoc test – Termed *a posteriori*, meaning test is performed after an outcome; test that shows there is a statistically significant difference between two groups given that one has already proven there is a difference in group means using inferential statistics (Lund & Lund, 2013b).

Prediction error - Difference between the observed value of the dependent variable for a given observation and the value of the dependent variable predicted for that observation from the linear model; denoted by *E* (Theory, n.d.).

Type 1 Error – The mistake of rejecting a true null hypothesis (Triola, 2015).

Unobserved Heterogeneity – Variation in the dependent variable that is caused by variables not observed (Mood, 2010).

Appendix B

Student Learning Outcomes for MAT 143 – Quantitative Literacy

At the completion of the course, the students should be able to do the following:

1. Judge the reasonableness of results using estimation, logical processes, and a proper understanding of quantity.
2. Utilize proportional reasoning to solve contextual problems and make conversions involving various units of measurement.
3. Identify, interpret, and compare linear and exponential rates of growth to make predictions and informed decisions based on data and graphs.
4. Differentiate between simple and compound interest and analyze the long-term effects of saving, investing, and borrowing.
5. Describe, analyze, and interpret statistical information such as graphs, tables, and summarized data to draw appropriate conclusions when presented with actual statistical studies.
6. Determine probabilities and expected values and use them to assess risk and make informed decisions.
7. Analyze civic and/or societal issues and critique decisions using relevant mathematics (Lynch, 2016).

Appendix C

Summary of Challenges with Developmental Education Math Data

Process Changed as Follows:

Before 2011SP:

- 4-credit, 16-week courses: MAT 050 (moved to basic skills in 2009), MAT 060, MAT 070, MAT 080

2011SP:

- Pilot of 13 math modules serving as curriculum for approximately 10 sections of MAT 060-080 courses
- All other courses continued with traditional MAT 060-080 curriculum

2011SU:

- Same as 2011SP, except all students in traditional curriculum sequence warned to finish in summer because in 2011FA, all courses taught with new design

2011FA - 2012SU:

- MAT 060-080 taught with 13 module curriculum
- Campus #1 and Campus #2 taught through Emporium Lab
- Campus #3 taught face-to-face

2012FA - 2013SU:

- MAT 060-080 revised into 8 module curriculum per state guidelines
- All courses taught through Emporium Lab

2013FA - 2014SP:

- Courses now called DMA 010-080
- 3, 2 and 1 credit shells
- Placement determined by COMPASS placement test – if student tested out of MAT 060 placement, they got credit for DMA 020-030; out of MAT 070 got credit for DMA 010-050; out of MAT 080 got credit for all DMAs
- Students in multi-credit shells could 1) pass or fail one or more of the DMAs in the shell 2) pass or fail the shell 3) receive an "NR" grade by not beginning one or more DMAs in a shell. For example, in a 3 credit shell, a student could get course credit (CC) for DMA 010; get a grade of "R" (repeat) for DMA 020; and a grade of "NR" (never reached) for DMA 030; and an "R" for the shell. Four grades.
- NC DAP launched in March 2014. Students taking NC DAP are assessed on skills in each DMA **[Cherry-picking].** A score of 7 for any DMA 010-050 allows student to skip that DMA. Scoring 7 on all DMA 010-050

allows student to enroll in MAT 152 or lower. Scoring 7 on all DMA 010-060 allows student to enroll in MAT-171.

- Multiple Measure policy implemented at college, allowing students with HS unweighted GPAs >2.6, a fourth HS math that requires Algebra II as a pre-requisite, and graduation in the last 5 years to bypass placement testing and enroll directly into curriculum math.

2014SU:

- 3, 2, and 1 credit shells
- Placement determined by Multiple Measures policy or NC-DAP

2014FA - 2015SP:

- Same as 2014SU, except 4-credit shells added
- NCCCS re-launched NC DAP

2015SU - 2015FA:*

- 3, 2, and 1 credit shells only
- Score of 7 or higher required on NC DAP for **all** DMA 010-050 to enroll in MAT-143 or 152
- Score of 7 or higher required on NC DAP for **all** DMA 010-060 to enroll in MAT-171
- Any score below 7 on NC DAP for any DMA results in student being referred to DevEd and beginning math sequence in DMA 010 **[No longer Cherry-picking]**
- Students referred to DevEd take a diagnostic at the start of each DMA. A score of 80 on that diagnostic results in a course credit (CC) for that DMA. Scores below 80 mean the student must complete the course work for the DMA and then take a test after the coursework is completed. A score of 80 on the test results in CC.
- Once a student receives a CC for a DMA, she moves on to the next DMA.

2016SP – 2017FA:*

- All shells are one credit
- Each shell is 5 weeks long
- Students can complete one DMA and then begin and even complete additional DMAs during the same 5-week period (**Hunt, 2017).

**Name changed to protect identity *Includes time interval for study data

Appendix D

Student Learning Outcomes for DMA 010 – DMA080

DMA010 Operations With Integers	**Class Hrs: 0.75**	**Lab Hrs: 0.5**	**Credits: 1**
This DMA provides a conceptual study of integers and integer operations. Topics include integers, absolute value, exponents, square roots, perimeter and area of basic geometric figures, Pythagorean theorem, and use of the correct order of operations. Upon completion, students should be able to demonstrate an understanding of pertinent concepts and principles and apply this knowledge in the evaluation of expressions.			
In order to successfully complete this module, the student will: 1. Apply operations on integers using appropriate technology. 2. Apply order of operations on rational numbers, using appropriate technology. 3. Calculate the perimeter and area of basic geometric figures, using appropriate technology. 4. Evaluate exponents on integers. 5. Solve real world problems involving the operations with integers.			
DMA020 Fractions and Decimals	**Class Hrs: 0.75**	**Lab Hrs: 0.5**	**Credits: 1**
This DMA provides a conceptual study of the relationship between fractions and decimals and covers related problems. Topics include application of operations and solving contextual application problems, including determining the circumference and area of circles with the concept of pi. Upon completion, students should be able to demonstrate an understanding of the connections between fractions and decimals. Prerequisite: **DMA 010.**			
In order to successfully complete this module, the student will: 1. Apply the operations on fractions, using appropriate technology 2. Apply the operations on decimals, using appropriate technology. 3. Solve problems involving the circumference and area of a circle. 4. Evaluate the negative exponents in scientific notation. 5. Convert between standard notation and scientific notation. 6. Solve real world problems involving fractions and decimals.			
DMA030 Proportion/Ratio/Rate/Percent	**Class Hrs: 0.75**	**Lab Hrs: 0.5**	**Credits: 1**
This DMA provides a conceptual study of the problems that are represented by rates, ratios, percent, and proportions. Topics include rates, ratios, percent, proportion, conversion of English and metric units, and applications of the geometry of similar triangles. Upon completion, students should be able to use their understanding to solve conceptual application problems. Prerequisite: (**DMA 010 and DMA 020.)**			
In order to successfully complete this module, the student will: 1. Solve problems using proportions, using appropriate technology. 2. Solve percent problems, using appropriate technology. 3. Convert measurements within and between the U.S. customary and metric system using unit analysis 4. Solve real world problems involving ratios, rates, proportions and percents.			
DMA040 Expressions/Linear Equations/Inequalities	**Class Hrs: 0.75**	**Lab Hrs: 0.5**	**Credits: 1**
This DMA provides a conceptual study of problems involving linear expressions, equations, and inequalities. Emphasis is placed on solving contextual application problems. Upon completion, students should be able to distinguish between simplifying expressions and solving equations and apply this knowledge to problems involving linear expressions, equations, and inequalities. Prerequisite: (**DMA 010, DMA +020, DMA 030.)**			
In order to successfully complete this module, the student will: 1. Evaluate algebraic expressions, using appropriate technology. 2. Perform operations on algebraic expressions, using appropriate technology. 3. Solve linear equations in one variable algebraically, analytically, and graphically, using appropriate technology. 4. Solve inequalities in one variable algebraically, analytically, and graphically, using appropriate technology. 5. Solve real world problems involving linear equations and inequalities in one variable.			
DMA050 Graphs/Equations of Lines	**Class Hrs: 0.75**	**Lab Hrs: 0.5**	**Credits: 1**
This DMA provides a conceptual study of problems involving graphic and algebraic representations of lines. Topics include slope, equations of lines, interpretation of basic graphs, and linear modeling. Upon completion, students should be able to solve contextual application problems and represent real-world situations as linear equations in two variables. Prerequisite: (**DMA 010, DMA 020, DMA 030 and DMA 040.)**			
In order to successfully complete this module, the student will:			

1.	Graph linear equations in two variables, using appropriate technology.
2.	Determine the equation of a line, using appropriate technology.
3.	Solve linear equations in two variables.
4.	Solve real world problems involving graphs of linear equations in two variables.

Appendix D: Student Learning Outcomes for DMA 010 – DMA080. A DMS-001 Course requires completion of one of these DMA Modules. This figure depicts the individual module Student Learning Outcomes.

Appendix E

IRB Approval Letter & CITI Training Transcripts

Appalachian STATE UNIVERSITY

INSTITUTIONAL REVIEW BOARD

Office of Research Protections
ASU Box 32068
Boone, NC 28608
828.262.2692
Web site: http://researchprotections.appstate.edu
Email: irb@appstate.edu
Federalwide Assurance (FWA) #00001076

To: Chandra Lehner
Leadership & Educational Studies, LES
CAMPUS EMAIL

From: Monica Molina, IRB Associate Administrator
Date: 3/13/2017
RE: Notice of IRB Exemption

STUDY #: 17-0234
STUDY TITLE: The Relationship between Fast-Tracking Students into Curriculum Math Using
Multiple Measures and Their Subsequent Success Rates: A Quantitative Study of Self-Directed Learning in Developmental Mathematics

Exemption Category: (1) Normal Educational Practices and
Settings

This study involves minimal risk and meets the exemption category cited above. In accordance with 45 CFR 46.101(b) and University policy and procedures, the research activities described in the study materials are exempt from further IRB review.

All approved documents for this study, including consent forms, can be accessed by logging into IRBIS. Use the following directions to access approved study documents.

1. Log into IRBIS
2. Click "Home" on the top toolbar

3. Click "My Studies" under the heading "All My Studies"
4. Click on the IRB number for the study you wish to access
5. Click on the reference ID for your submission
6. Click "Attachments" on the left-hand side toolbar
7. Click on the appropriate documents you wish to download

Study Change: Proposed changes to the study require further IRB review when the change involves:

- an external funding
- source, the potential for a
- conflict of interest,
- a change in location of the research (i.e., country, school system, off site
- location), the contact information for the Principal Investigator,
- the addition of non-Appalachian State University faculty, staff, or students to the research team, or the basis for the determination of exemption. Standard Operating Procedure #9 cites examples of changes which affect the basis of the determination of exemption on page 3.

Investigator Responsibilities: All individuals engaged in research with human participants are responsible for compliance with University policies and procedures, and IRB determinations. The Principal Investigator (PI), or Faculty Advisor if the PI is a student, is ultimately responsible for ensuring the protection of research participants; conducting sound ethical research that complies with federal regulations, University policy and procedures; and maintaining study records. The PI should review the IRB's list of PI responsibilities.

To Close the Study: When research procedures with human participants are completed, please send the Request for Closure of IRB Review form to irb@appstate.edu. If you have any questions, please contact the Research Protections Office at (828) 262-2692 (Robin). Best wishes with your research.

Websites for Information Cited Above Note: If the link does not work, please copy and paste into your browser, or visit https://researchprotections.appstate.edu/human-subjects.

CC:
Lisa Poling, Curriculum & Instruction

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COMPLETION REPORT - PART 1 OF 2
COURSEWORK REQUIREMENTS*

* NOTE: Scores on this Requirements Report reflect quiz completions at the time all requirements for the course were met. See list below for details. See separate Transcript Report for more recent quiz scores, including those on optional (supplemental) course elements.

- **Name:** Chandra Allen (ID: 3725236)
- **Institution Affiliation:** Appalachian State University (ID: 1265)
- **Institution Email:** allencn1@email.appstate.edu
- **Phone:** 3363344822

- **Curriculum Group:** Basic/Refresher Course - Human Subjects Research
- **Course Learner Group:** Social/Behavioral Research Course
- **Stage:** Stage 2 - Refresher Course

- **Record ID:** 11210459
- **Completion Date:** 21-Feb-2017
- **Expiration Date:** 21-Feb-2020
- **Minimum Passing:** 80
- **Reported Score*:** 100

REQUIRED AND ELECTIVE MODULES ONLY	DATE COMPLETED	SCORE
Appalachian State University (ID: 12694)	21-Feb-2017	No Quiz
SBE Refresher 1 – Defining Research with Human Subjects (ID: 15029)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Privacy and Confidentiality (ID: 15035)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Assessing Risk (ID: 15034)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Research with Children (ID: 15036)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – International Research (ID: 15028)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – History and Ethical Principles (ID: 936)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Federal Regulations for Protecting Research Subjects (ID: 937)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Informed Consent (ID: 938)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Research with Prisoners (ID: 939)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Research in Educational Settings (ID: 940)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Instructions (ID: 943)	21-Feb-2017	No Quiz

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

Verify at: www.citiprogram.org/verify/?k5cfa3734-3f2f-44e4-b8ed-3b88b041f666-11210459

Collaborative Institutional Training Initiative (CITI Program)
Email: support@citiprogram.org
Phone: 888-529-5929
Web: https://www.citiprogram.org

COLLABORATIVE INSTITUTIONAL TRAINING INITIATIVE (CITI PROGRAM)

COMPLETION REPORT - PART 2 OF 2
COURSEWORK TRANSCRIPT**

** NOTE: Scores on this Transcript Report reflect the most current quiz completions, including quizzes on optional (supplemental) elements of the course. See list below for details. See separate Requirements Report for the reported scores at the time all requirements for the course were met.

- **Name:** Chandra Allen (ID: 3725236)
- **Institution Affiliation:** Appalachian State University (ID: 1265)
- **Institution Email:** allencn1@email.appstate.edu
- **Phone:** 3363344822

- **Curriculum Group:** Basic/Refresher Course - Human Subjects Research
- **Course Learner Group:** Social/Behavioral Research Course
- **Stage:** Stage 2 - Refresher Course

- **Record ID:** 11210459
- **Report Date:** 07-Mar-2017
- **Current Score**:** 100

REQUIRED, ELECTIVE, AND SUPPLEMENTAL MODULES	MOST RECENT	SCORE
SBE Refresher 1 – History and Ethical Principles (ID: 936)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Federal Regulations for Protecting Research Subjects (ID: 937)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Informed Consent (ID: 938)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Research with Prisoners (ID: 939)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Research in Educational Settings (ID: 940)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Instructions (ID: 943)	21-Feb-2017	No Quiz
SBE Refresher 1 – International Research (ID: 15028)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Defining Research with Human Subjects (ID: 15029)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Assessing Risk (ID: 15034)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Privacy and Confidentiality (ID: 15035)	21-Feb-2017	2/2 (100%)
SBE Refresher 1 – Research with Children (ID: 15036)	21-Feb-2017	2/2 (100%)
Appalachian State University (ID: 12694)	21-Feb-2017	No Quiz

For this Report to be valid, the learner identified above must have had a valid affiliation with the CITI Program subscribing institution identified above or have been a paid Independent Learner.

Verify at www.citiprogram.org/verify/?k5cfa3734-3f2f-44e4-b8ed-3b88b041f666-11210459

Collaborative Institutional Training Initiative (CITI Program)
Email: support@citiprogram.org
Phone: 888-529-5929
Web: https://www.citiprogram.org

Vita

Chandra Noël Lehner was born in Portsmouth, Virginia to Norm and Linda Allen. She graduated from Emmanuel Christian School in Ft. Myers, FL in 1993. Noël began pursuit of her mathematics education at Guilford Technical Community College before finishing her B.A. in mathematics at Florida Gulf Coast University in Ft. Myers, FL. It was here that she went on to pursue a Master's degree, earning an M.A. in Teaching with a concentration in mathematics. During this time, Noël taught mathematics at both the middle and high school levels in Florida's public classrooms. In 2006, she moved with her family back to North Carolina where she began her career as an Associate Professor of mathematics at Guilford Technical Community College, her alma matter. Since teaching in the community college setting, Noël has sought to further her education by earning an Ed.S. degree in Higher Education with a concentration in adult and developmental education from Appalachian State University. Upon successful completion of this program, Noël enrolled in the Ed.D. program at Appalachian State University, pursuing a degree in Educational Leadership.

Alongside her educational journey, Noël is very proud to say that she has raised a very bright and caring human being herself, Mr. Joshua John Allen-St.John. He was always her focus first and foremost in life, and continues to be so. Noël is also proud to say that she is the new wife to the love of her life, marrying for the first time in March of 2016 – Tod Patrick Lehner. Recently, her most precious love is her first grandson, Ryker Baylon Allen, born February 21, 2018.