University of Arkansas, Fayetteville

ScholarWorks@UARK

Graduate Theses and Dissertations

12-2022

Improving Math Placement of Non-Traditional Students in Arkansas Community Colleges Using Multiple Measures Assessments

Johnathon Edward Paape
University of Arkansas, Fayetteville

Follow this and additional works at: https://scholarworks.uark.edu/etd

Part of the Adult and Continuing Education Commons, Community College Leadership Commons, and the Science and Mathematics Education Commons

Citation

Paape, J. E. (2022). Improving Math Placement of Non-Traditional Students in Arkansas Community Colleges Using Multiple Measures Assessments. *Graduate Theses and Dissertations* Retrieved from https://scholarworks.uark.edu/etd/4777

This Dissertation is brought to you for free and open access by ScholarWorks@UARK. It has been accepted for inclusion in Graduate Theses and Dissertations by an authorized administrator of ScholarWorks@UARK. For more information, please contact scholar@uark.edu.

Improving Math Placement of Non-Traditional Students in Arkansas Community Colleges Using Multiple Measures Assessments

A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Education in Adult and Lifelong Learning

by

Johnathon Paape
University of Arkansas
Bachelor of Music in Music Theory, 2010
University of Arkansas
Master of Music in Music Composition, 2013
University of Arkansas
Master of Education in Higher Education, 2017

December 2022
University of Arkansas

This dissertation is approved for recommendation to the Graduate Council.

Michael T. Miller, Ed.D
Dissertation Chair

Kevin M. Roessger, Ph.D
Committee Member

Kit Kacirek, Ed.D
Committee Member

ABSTRACT

For decades, community colleges have relied on standardized placement tests to determine student readiness for college-level coursework. COVID-19 exposed the flaws of relying on a single measure to assess student readiness as many test sites shut down during the pandemic. Previous research has also pointed out the high rate of misplacement when using placement tests as a single factor. This is particularly important for non-traditional students as they often lack the guidance needed to successfully navigate and prepare for such tests. The result of this situation is often that non-traditional students are placed into remedial courses despite having the potential to do well in college-level coursework. With research showing extended time in college often leads to attrition coupled with other research showing math as a gatekeeper course to completion, examining more accurate measures is critical. Because of this, many community colleges have started exploring alternative ways to place students into college-level coursework using more holistic factors. A popular and effective method of placement in recent years has been multiple measures assessments (MMA). These assessments allow for the use of multiple factors to create a more accurate placement picture for students. The purpose of the study was to explore these multiple measures assessments, determine variables of interest, and test whether MMAs are suitable alternatives to placement exams. The results of the study revealed that the MMA model created was more effective overall in determining student readiness for College Algebra for Arkansas community college students.

©2022 by Johnathon Paape
All Rights Reserved

ACKNOLEDGEMENTS

I would like to acknowledge my cohort for always supporting each other, including me, through all the difficult moments in the program. I appreciate all the time we have gotten to spend together and wish each of you a momentous graduation and future career.

To my dissertation committee, I cannot thank you enough for agreeing to serve and guide me through this process. Your feedback, advice, and support have been invaluable on so many levels. I can easily say I would not be where I am now were it not for all of you.

To Dr. Michael Miller, it has been truly wonderful to have had the opportunity to study with you and get to know you for as long as I have. Your door has always been open for me and you have always been willing to share with me your knowledge and experience in higher education and life in general. I could not have asked for a better mentor in any respect. I will always appreciate the guidance and mentorship you have offered me (and hopefully will continue to offer) over the years.

Lastly, to my wife Hayley. It feels like I have been in school most of our relationship so far, which hasn't always been easy. Your support of my education throughout has always pushed me forward even when my strength to do so sometimes waned. I love you very much and am excited to see where life takes us from here.

TABLE OF CONTENTS

LIST OF TABLES

Chapter 1 - Introduction to the Study

Introduction

In the last few years, higher education has experienced many challenges that have been cause for examination of policies, procedures, and best-practices. The COVID-19 pandemic, political and social unrest, and rapidly changing demographics of college-going students have created challenges that higher education institutions have struggled to address. Among these challenges has also been the difficulty for community colleges that rely solely on placement tests as indicators of college-readiness to effectively and accurately place students into college-level courses. The disruption due to the COVID-19 pandemic caused many testing sites to postpone operation, leaving these colleges without the ability to assess student readiness. This, along with research that has shown test-only policies to be inaccurate with regards to remedial and college-level course placement, has prompted many in higher education to examine alternative options to test-only placement policies (Scott-Clayton, 2012). As such, multiple measures assessments (MMAs) have been an increasingly popular option due to their flexibility and shown increases in the accuracy of placing students.

In this chapter, I outline how multiple measures assessments are becoming an accepted placement method in the community college environment as well as how test-only placement policies impact non-traditional student success. I also discussed factors outside of standardized test scores that can signal potential success in college-level math courses for non-traditional students. I then further discussed how placement tests (i.e. ACT, SAT, Accuplacer®®, etc…) have historically been used for the purposes of placement into college-level math courses and how these methods are increasingly viewed as an obsolete measure of readiness for college-level courses.

With COVID-19 upending many placement testing sites, as well as general issues with the tests themselves, a new model is needed to assess college-level math readiness for non-traditional students that will take their unique educational needs into account. I have theoretically defined concepts related to non-traditional student success in college-level math based on previous literature and described the questions guiding the study. Using logistic regression analysis, I have also provided a new placement model for college-level math placement that Arkansas community colleges can use to guide the implementation of a multiple measures placement system of their own. I concluded this chapter with a discussion of the study's scope and limitations.

Context of the Study

Community colleges in the United States are responsible for providing training and educational opportunities to a great number of students each year. To add to this challenge, a high number of students enter college academically under-prepared to take college-level math and English courses and are instead placed into developmental coursework which decreases their chances of graduating or transferring (Bailey et al., 2015). This is of particular note for math courses as they tend to have a higher remedial placement rate, lower success rates, and lower sequence completions than their English-course counterparts (Bailey, 2009; Bailey et al., 2010). An issue complicating the discussion is that "Policies and regulations governing assessment, placement, pedagogy, staffing, completion, and eligibility for enrollment [in college-level coursework]…vary from state to state, college to college, and program to program" (Bailey et al., 2008, p. 1).

Generally, the primary method of determining student placement in college-level courses has been through the examination of standardized tests such as the ACT, SAT, Compass, or

Accuplacer®® (Hughes & Scott-Clayton, 2011; Rutschow et al., 2019). In recent years, though, these tests have faced scrutiny over their apparent lack of predictive validity and value (Scott-Clayton, 2012; Scott-Clayton et al., 2014). In response to these concerns, a placement policy renaissance has occurred throughout the US to introduce new methods of placement that provide a more accurate look at student readiness. These new methods, often referred to as multiple measures assessments (MMAs), have been increasingly used to examine multiple factors to determine college-level placement.

Traditional students, who are historically defined as any student aged 18-22 who enters college directly out of high school, have generally been used as the defining metric of college policies and culture (Hittepole, 2019). Non-traditional students, though, have a myriad of features that can define them and can be difficult to track due to the varying ways in which one can be defined as non-traditional. According to NCES (n.d.a), over the past decade non-traditional student enrollment was around 40% between 2011-2019. When looking at all students over 24 years old (a common defining metric), non-traditional undergraduates at public 2-year colleges comprised around 1.7 million (approximately 32%) of 2-year college students during the 2019-2020 academic year (Chronicle of Higher Education, 2021). As such, non-traditional students are highly represented within community colleges with needs different than that of their traditional counterparts.

Non-traditional students are historically defined as having any of the following characteristics: 24 years of age or older; delayed enrollment into college; part-time enrollment status; working part-or full-time; financially independent; having dependents; and/or having completed a GED equivalency program (Bean & Metzner, 1985; Hardin, 2008; Horn & Carroll, 1996; Radford et al., 2015; Schuetze, 2014). Although strides have been made to try and serve

this unique student population, many community colleges fall short of this goal. With offerings such as online coursework and workforce degrees for those seeking immediate job entry, community colleges have attempted to allow some flexibility for students for whom the traditional method of academic work does not suit them. Certain policies and procedures at the college-level such as placement policies, lack of flexible courses, and lack of access to student services continue to hinder non-traditional student degree attainment, retention, and course completion (Hardin; 2008; Scott-Clayton, 2012).

A main concern usually comes in determining college-readiness for this population. Traditionally, community colleges have used test placement scores as the primary factor in determining students' readiness for college-level courses. Testing challenges presented during the Covid-19 pandemic, coupled with what many scholars see as validity, accuracy, and socio-economic issues with placement tests have highlighted many of the problems with relying solely on placement tests for placement purposes (Scott-Clayton, 2012; Scott-Clayton et al., 2014). In fact, some states now have required the consideration of other factors in addition to test placement scores due to previously mentioned concerns with placement tests (Bahr et al., 2019; Barbitta & Munn, 2018; Woods et al., 2018). While many traditional students in Arkansas already have taken evaluative tests such as the ACT at least once in high school (as required by Arkansas state law) and therefore have at least one set of scores to be used by institutions, non-traditional students do not always have placement scores readily available (or, the scores are too old to be used). In turn, they are often asked to take a comparable standardized test (Accuplacer®® or Compass) in-lieu-of the ACT or SAT. Students attempting to navigate this part of the process are often underprepared to take such a test after years out of high school or may not realize the importance of the scores for placement purposes (Bailey et al., 2015). This

results in placement scores that may indicate the need for remediation when, in fact, such remediation may not be warranted, creating further barriers to this already at-risk population (Scott-Clayton, 2012).

A growing body of research has shown that students are often misplaced by policies that use placement scores as a standalone measure (Scott-Clayton, 2012; Scott-Clayton et al., 2014). This is often due to the misalignment between high school and college curriculum outcomes as well as the fact that standardized test scores are usually not indicative of the student as a whole (Rutschow et al., 2019; Shelton & Brown, 2010). In a study conducted at community colleges in New York, Barnett et al. (2018) found that students placed using measures outside of, but in many cases including, Accuplacer®® scores were placed into college-level math at a rate of 14% higher than students in the control group. These numbers indicate a gross placement error rate for students placed by test scores alone. This is concerning when coupled with the fact that not only do well over half of community college students place into at least one developmental course, many of these students do not make it through the remediation sequences they begin (Bailey, 2009; Bailey et al., 2015, Chen, 2016). With multiple measures having been shown to more accurately assess potential for student success, thus reducing placement into developmental coursework, implementing these models is a step towards reducing student attrition due to remedial sequences.

In recent years, some colleges have adopted multiple measures assessments (MMAs) to allow for use of factors outside of standardized test scores to be used in placement decisions. When examined together, these factors have been shown to correlate with student success and include background information such as high school GPA, specific coursework taken during high school related to the content of placement (e.g. English or Math), and motivational factors

such as GRIT (Barbita & Munn, 2018; Ngo & Kwon, 2015; Woods et al., 2018). MMAs are a type of placement method that examines some or all of these other factors (as opposed to only test-placement scores) to determine college-readiness for students. The issue, though, is that many community colleges, while serving a high number of non-traditional students, do not look at factors outside of test scores and often do not consider time since high school as a mitigating factor to preparedness. The problem therein lies in the documented accuracy issues of standardized test scores and higher education's reliance on these scores as sole determinants of college-course placement, specifically for non-traditional and underrepresented minority students who may not be prepared for such tests upon entry.

Need and Purpose of the Study

The study looked to address the growing need for further research into important factors used in, and the utility of, multiple measures assessments as a potential alternative to only using standardized placement scores. While existing studies have addressed specifically what factors outside of standardized test scores are useful in multiple measures models in different contexts, few have actually created scalable, dynamic models and even fewer included time since high school in their models (Barnett et al., 2018; Bahr et al., 2019; Scott-Clayton, 2012; Woods et al., 2018). There are also no studies directed at examining multiple measures models within the State of Arkansas specifically. This is unfortunate as there is the potential for multiple measures assessments to assist in providing more accurate placement, leading to reduced remedial placement, increasing students' chances of completing college-level math and a college credential. Arkansas community college three-year graduation rates have risen slightly to 19.9% as of the 2012 cohort; however, this was preceded by a steady decline for the previous cohorts (ADHE, 2015a). In addition, the remediation rate for Arkansas community college math for 2014

was 48.7% (ADHE, 2015b). Though, there are many factors that affect these numbers, a high remediation rate examined through the lens of research showing placement errors related to test-only policies indicate the need for a change in placement models. Although the Arkansas Department of Higher Education (ADHE) does encourage the use of MMAs, they are not currently required by ADHE nor is there a specific guide on how to implement such a model. There is also no specific guidance from ADHE on which recommended variables may best place students.

With non-traditional students making up a large population of the community college sector, as well as a shift in focus by constituents and stakeholders from access to completion, providing a more accurate placement model will be essential in accounting for the unique characteristics of non-traditional students. More accurately placing students into entry-level classes will better benefit students and colleges by reducing the amount of time to credit-bearing courses, getting students through gateway courses faster, reducing attrition due to length of time in remediation, and, hopefully, increasing overall student retention and graduation rates.

The study also hopefully helped bridge access, retention, and completion gaps for students in low-socioeconomic status (SES) situations as well as underrepresented minority students. Since these demographic groups have often been penalized by way of lack of access to study materials and tutors, as well as high registration fees for standardized tests, finding a suitable alternative to test-score-only placement will helped prevent already vulnerable populations from experiencing further barriers to completing their education.

The pragmatic purpose of this research was to create and evaluate an algorithmic multiple measures placement model for the State of Arkansas in hopes of improving placement rates of non-traditional into college-level math courses. The hope was to provide a blueprint for multiple

measures design and implementation for Arkansas community colleges. Since the State of Arkansas requires a "better than 75 percent likelihood of the student's ability to earn a "C" or better grade" in order to be placed into entry-level college Math and English, the threshold of success for the study was a 76% or greater chance of passing for each student (ADHE, 2016, p. 3.08.2). The main purpose of the study was to increase the number of non-traditional students placed into college-level math in community colleges. As was shown, retention and completion rates for students who test into developmental coursework were lower than for those who test out of remediation. Adding to this issue was that many students who test into developmental coursework may actually have the capacity to pass college-level math if assessed using other methods beyond test-placement scores (Scott-Clayton, 2012; Scott-Clayton et al., 2014).

First, I used a logistic regression analysis to show the predictive significance of other readiness measures to predict student success in college-level math courses. Though the State of Arkansas has two primary math pathways (College Algebra and Quantitative Reasoning), only College Algebra was examined for the scope of the study. Secondary data sets were analyzed to examine the likelihood of success when multiple factors were considered including *HS GPA*, *age* (time since HS graduation), *last HS math course* taken, *grade in last HS math course,* and *HS GPA*age* to measure students' likelihood of success in college-level math courses. Curvilinearity for *age* was also determined to see if higher-order terms needed to be added to the model.

Next, I added *Classic Accuplacer® math scores* to the model to show the predictive power of standardized test scores when added to multiple measures assessments. Prior research has shown that, when other factors are considered, the predictive capability of standardized test scores decreases, in some cases to the point of being non-significant for placement purposes

(Scott-Clayton, 2012). With this, I hoped to impress upon the reader the capability for multiple measures assessments to take the place entirely of test placement scoring as a measure of student readiness. Last, I examined the significance of the variables to determine what final factors should be used to create a practical model that can be used by community colleges in Arkansas as a guide to create their own multiple measures placement policies. The result of which was the creation of an algorithmic multiple measures model that can aid in the accurate placement of students into math courses.

Statement of the Research Problem

To address the needs listed above, the following research questions and sub-questions were examined:

1. What was the demographic profile of the subjects included in the research sample?
2. Did multiple measure assessments equally or better predict non-traditional student success in College Algebra than *Classic Accuplacer math scores*?
    a) What factors predicted non-traditional students' success in passing entry-level college math courses?
    b) Did *age* influence the relationship between HS GPA and success?
3. Did the final multiple measures model equally, or more accurately, assess underrepresented non-traditional minority placement into College Algebra?

Definitions

To clarify meanings throughout the study, the following definitions were used:

Community College: Public institutions whose highest degree offered is typically an Associate's degree. Often colloquially referred to as "2-year" colleges.

Developmental/remedial education: Education below the college level taken as a pre-requisite to access college-level courses or as co-requisites with the college-level course.

HS GPA: a cumulative measure of coursework completed in high school based on a 4.0 scale. Retrieved from high school records required to be collected by public state institutions.

Multiple measures assessment (MMA): the use of two or more student factors (e.g. HS GPA, test scores, grades in subject area, etc…) to determine student readiness for college-level Math and English

Non-traditional: as defined by previous studies, a student meeting any one of the following criteria: 24 years of age or older; married; has dependents; self-supported financially; part-time school status; obtained GED or lacks HS diploma; has at least one year between HS completion and the start of college (Radford et al., 2015; Schuetze, 2014).

Time since HS: number of years since high school completion. Utilized by calculating the difference between high school graduation date (as listed on HS transcript) and time college entry

Test placement scores/Standardized test scores: scores based off commonly used placement tests such as ACT, SAT, Accuplacer®®, or Compass. For the purposes of this research, scores used will be Accuplacer®® math scores.

Underrepresented Students: Students who come from underrepresented minority or disproportionally affected groups

Scope and Limitations

As a single-state study, generalizations outside of the state using Arkansas specific data may not be warranted. The data used were specific to Arkansas; however, the models that were created used variables based on theory from previous research and thus could be used in

conjunction with other states' specific data to create an applicable model outside of Arkansas. Another concern was that no non-cognitive factors were considered in these models. Some institutions may implement non-cognitive factors such as motivation tests (e.g. GRIT) to assist with placement. While these may be useful, since few states (including Arkansas) have such a test listed as mandatory, no data currently exist to explore the usefulness of non-cognitive factors in measuring success in college-level Math courses in Arkansas.

Next, while generally accepted by most researchers as valid, some question the integrity of HS GPA due to large differences in rigor and support in K-12 systems around the US. The limitation here is in a situation where a K-12 school district may be passing students who should not be passed, thus undermining the reliability of HS GPA to accurately depict students' success in high school and leading to contamination in the multiple measures models. However, with consensus among scholars that HS GPA is still an accurate representation of academic skill, it was still used for the purpose of the study. Though some non-traditional students enter community colleges with GEDs, I chose to only examine students who completed high school and have a high school GPA. This was to ensure a large enough sample size to be able to run the analyses and have confidence in the results.

Though the hope of the study is to create a placement model that community colleges in Arkansas can use as a guide in creating a multiple measures model, limitations from the study's sample and the model exist. The models created for the study utilize sample data containing students who achieved standardized test scores that allowed the to enroll in college-level coursework. A consequence of this is that using the models for predictions of success outside of the ranges of the examined variables may not be appropriate. Though predictive modeling can give some predictions based on potentially unavailable data, the results of the study were used to

examine theoretical ranges while leaving open the possibility of being applied to a specific community college sample to examine the practical uses.

Lastly, due to concerns with the pragmatic use of the findings, variables such as race, ethnicity, and gender will not be explored. Because I hoped for these models to be implemented in community colleges as assessments of student readiness for college-level math, using such variables in the model was not possible. To address issues with external validity, procedures as outlined by Osborne (2015) were used to determine validity of the models outside of the context of this study.

Theoretical Framework

Because non-traditional students have vastly different needs and priorities than traditional students, finding a theory specific to this population was very important. This study was guided by Bean and Metzner's (1985) Conceptual Model of Nontraditional Undergraduate Student Attrition. The theory states that there are four primary reasons nontraditional students leave higher education: academic, background, environmental, and psychological. It is expected that environmental support "compensates for low scores on the academic variables" (p. 492). It is also expected that lower levels of psychological variables such as satisfaction or goal commitment, and higher levels of stress, will offset any benefits gained by HS GPA. High school performance is also expected to influence attrition decisions by affecting college GPA. Furthermore, *background* variables such as age and enrollment status "are included as reminders that they must be controlled [for] or they would be expected to interact with other variables" (p. 492). Through the lens of this framework, as well as other relevant research, *background*, *psychological*, and *environmental* factors are examined to determine the variables used in the

model. The subsequent success rate of students is determined by these factors' influence on nontraditional students in the college environment.

Academic Variables

Academic variables focus on institutional as well as characteristic variables related to the academic experience. Bean and Metzner (1985) define these variables in the model as being related to study skills and habits, access and use of academic advising, absenteeism, certainty of major, and course availability. As Bean and Metzner's (1985) model is based on the traditional student model of Tinto (1975), they point that academic variables are "prominent in models of traditional student attrition as indicators of academic integration…" (p. 499). As such, extending the model to non-traditional students, Bean and Metzner's (1985) model predict that academic variables are "expected to have indirect effects on dropout through GPA, through the psychological outcome variables…and through intent to leave" (p. 499).

For more contemporary purposes, I propose an expansion of the definition of *academic* variables to include college policy as a factor affecting student success. Researchers for decades have noted that colleges have policies in place that may be barriers to student success. These can include, financial aid, admissions, and academic (such as class offerings, class times, or class modes). Applying current institutional context, placement policies that misplace students into remedial coursework can be seen as environmental factors affecting nontraditional students.

Background Variables

Background variables, as defined by Bean and Metzner (1985), are concepts such as age, high school performance, enrollment status, residence, educational goals, ethnicity, and gender. Age, per the theory, is expected to influence student attrition as it is "assumed that older students will have more family responsibilities, hours of employment, and higher levels of absenteeism

than younger students" (p. 494). High school academic performance is listed as an extremely important predictor of student persistence. Bean and Metzner (1985) noted that "In general, measures of high school academic performance currently seem to be among the strongest pre-enrollment predictors of persistence…" (p. 497). Bean and Metzner (1985) discussed that this is because HS GPA has been correlated with increased persistence in college and that, typically, non-traditional students have lower HS GPAs than traditional students. Enrollment status refers to the number of hours non-traditional students take during any given semester. It is expected that non-traditional students will have more family and work obligations than traditional students, thus negatively influencing the number of hours that are taken compared to traditional students. Residence describes whether a student is residing on or off-campus and may need to commute to college. Again, it was predicted per the theory that non-traditional students will primarily be off-campus commuter students; however, this was listed primarily as a defining feature of non-traditional students and not as a factor that directly affects attrition. Educational goals are defined as goals set by students at the beginning of their educational journey (Bean & Metzner, 1985). Educational goals set at the time of entering college assist in establishing "…importance ascribed to obtaining a college education, and the likelihood of completing and educational goal at the present institution (p. 495).

Psychological Variables

Bean and Metzner's (1985) framework defined psychological variables as utility, satisfaction, goal commitment, and stress. Satisfaction is considered to be "an indicator of the degree to which a student enjoys the role of being a student and reports lack of boredom with college courses" (Bean & Metzner, 1985, p. 523).

In defining goal commitment, Bean and Metzner (1985) wrote that "This variable refers to the amount of personal importance that a student ascribes to obtaining a college education…after the student has gained some experience in the college environment" (p. 524). While students may enter college with high goal commitment, when placement policies (environmental) act as barriers to college completion, other environmental factors for non-traditional students may lower that commitment. Since student misplacement into DE has been shown to lower students' likelihood of completing any credential due to frustration with the extended time needed to take various levels DE courses, boredom of content, or even financial issues related to the coursework (see Bailey, 2009), it is expected that factors related to institutional policy (*academic*) increase attrition. Per the theory, academic and environmental variables are expected to influence psychological variables the most and through indirect means, "acting through intentions that are designated in this model as *intent to leave*" (Bean & Metzner, 1985, p. 522).

Environmental Variables

In Bean and Metzner's (1985) study, environmental factors were defined as "factors over which the institution has little control but which might pull the student from the institution" (p. 502). These would be themes such as "perceived (or real) lack of finances, working for long hours, lacking encouragement, family responsibilities, and perceived opportunity to transfer" (Bean & Metzner, 1985, p. 502). Bean and Metzner (1985) pointed out how prior researchers have identified several ways of accounting for students' ability to finance including "parents' SES…students' or parents' income…and students' perceptions about their finances…(p. 502). For non-traditional students, finances are of particular importance, especially if the student has dependents they are supporting. For hours of employment, Bean and Metzner (1985) discussed

that hours of employment generally influenced persistence in college. In summarizing previous literature, they elaborated that:

> Astin (1975) reported that students who were employed fewer than 20 hours per week exhibited greater persistence in college than unemployed students. Most researchers agreed that employment in excess of 20-25 hours per week was negatively related to persistence. (p. 503)

Outside encouragement was measured as “the extent of encouragement to remain at college that a student receives from influential persons in the student’s life who are not employed by the college” (p. 504).

Applying the Theory

With respect to placement policies, it was expected that MMAs using *background* (namely, HS Performance) variables had equal or better placement results than test-only policies. As such, variables of interest related directly to these two categories. Indirectly, placement policies can also affect *psychological* variables (such as satisfaction and stress). As examined in Chapter 2, using test-only placement policies as a sole measure of college-readiness often lead to misplacement into incorrect math courses and can lead to students dropping out due to the feeling of mismatched skills, stress, and low satisfaction with placement results. It also affects retention from students simply not completing the lengthy sequences to which many are assigned. The proposed solution of the study was to examine the background variables of entering non-traditional students and using these factors in MMAs which have been shown to increase placement accuracy (usually increasing number of students placed into college-level math; see Scott-Clayton, 2012) thus increasing satisfaction and goal commitment (*psychological* outcomes) which the model predicts will increase student retention.

The theory describes specific situations and variables that Bean and Metzner (1985) expect to influence student attrition and success. For example, Bean and Metzner (1985)

suggested that high school percentile rank (usually as determined by HS GPA) would be an indicator of past academic achievement and "should influence decisions by affecting college GPA" (p. 492). In terms of operationalizing variables, college GPA and "pass/fail" (as defined by "C or better" and "lower than "C") are essentially equivalent. The theory also mentions the importance of non-traditional students' ability to take the courses they feel they need to take in a timely manner, the lack of which may lead to students choosing to leave the institution. Bean and Metzner (1985) stated that "Factors involved in course availability include whether the desired courses are (a) offered by the college, (b) scheduled at times when students are able to enroll, and (c) have sufficient capacity for student demand" (p. 502).

As students are misplaced into remedial courses they may not need to take, this leads to confusion about their academic abilities as well as frustration over not being able to take courses that might lead them to graduation or transfer faster. The result of which is that students may feel the remedial class is beneath their academic ability or that they are taking a class that is not needed which is delaying their academic plans.

Significance of the Study

As colleges struggle to enroll and subsequently retain students, greater emphasis on retention and completion, as well as policies that reflect, this will be essential for current future student success. Though many colleges tend to focus on enrollment, conversations at the state and federal level, along with policies surrounding college completion (such as performance funding), have brought about an examination of the unethical nature of enrolling large numbers of students only to have many of them not complete a credential. As college leaders will continue to be expected to take charge on this issue, this study sought to guide college

administration towards policy changes that can be implemented quickly and (hopefully) effectively to reduce attrition caused by remedial math misplacement to increase retention.

The most significant population influenced by the study was the students. Community colleges, being an entry-point for many non-traditional, low-SES and underrepresented minority students, often enroll a high number of students from these demographics. For many of these students, college is the primary means of upward social mobility in an attempt to reach the middle-class or otherwise find meaningful careers. Due to the high number of students from these demographics placed into remedial math courses each year, research indicating remedial placement reduces likelihood of completion, and other research indicating gross misplacement of students into remedial work, this study seeks to improve outcomes for students most likely to be placed into remediation and not complete.

The study also contributed to the overall body of research by examining the inclusion of *time since high school (age)* as a placement factor. The study also assisted in creating a ubiquitous algorithmic model which community colleges in the State of Arkansas can implement to increase placement, thus increasing college-level math completion. This could lead to greater numbers of student being retained and increase overall completion rates.

Summary

With the general shift in higher education away from access towards completion as a measure of success, it is as important as ever to ensure students are accessing and completing necessary gateway courses that will lead to the completion of college credentials. The low likelihood of completion for students in developmental education courses, coupled with the questionable predictive success of standardized placement tests, shows the need for a better model to assess success in entry-level college math courses. In line with this need, the study

sought to provide valuable information for Arkansas community college administrators in the use and implementation of multiple measures designs, presented a guiding framework and model, and provided the field with an important look into the value of using multiple measures assessments to replace test placement scores.

Chapter II - Review of the Literature

Introduction

As the landscape of research on placement policies, developmental education, and non-traditional students has evolved in recent years, information on best practices has evolved as well. Coupled with this are stakeholders who have increasingly focused on cost-saving measures, increased calls for completion of credentials over access to education, and how remedial education is delivered and who needs to take these courses. As a result, higher education has re-evaluated how its policies affect student outcomes and are weighing whether these policies are having the intended effect of improving student success. As non-traditional students enter community colleges, ensuring accurate placement into remedial and college-level courses will be crucial to increasing the number of students completing gateway courses and moving onto graduation and transfer.

This chapter provided a detailed overview of the literature related to non-traditional students, multiple measures assessments, remedial/developmental education, and remedial student characteristics. I focused on a review of the literature to establish historical, contextual, and theoretical foundations of the study. I also presented and defined each concept related to multiple measures placement, explored the relationships between those concepts, and summarized the chapter.

Scope of the Literature Review

To identify and explore sources and literature for this review, many databases and research collections were used. Google Scholar and Proquest were used first to get a general idea of the scope of the research available. Searches were limited to peer-reviewed articles and books related to *multiple measures assessments, non-traditional students, and community college*

developmental education. Upon examination of the results, future searches were narrowed by using targeted search terms. The University of Arkansas libraries database search engine was used to search the Proquest and Ebsco (ERIC) databases by searching for: *remedial education in community colleges, Arkansas developmental education, Arkansas multiple measures assessments, adult learners,* and *community college placement.* Outside organizations such as the Center for the Study of Community Colleges (CSCC), Community College Research Center (CCRC), *The Chronicle of Higher Education*, The Aspen Institute, and the Center for the Analysis of Postsecondary Readiness (CAOR) were also used to conduct searches for content.

The Community College

Community colleges are unique institutions that serve a wide demographic of students under a multitude of missions. At present (2020-2021), the number of community colleges serving students in the U.S. is 920 (National Center for Education Statistics, n.d.a). Community colleges are responsible for educating a large number and variety of students as well. In 2019, 2-year public institutions had an enrollment of 7,700,167 students constituting 29.5% of all students in the U.S (National Center for Education Statistics, n.d.c, Table 6). Many of these students come from diverse racial, ethnic, income, and age backgrounds (Bahr & Gross, 2016; Malcom-Piqueux, 2018). Bahr and Gross (2016) discussed that "community colleges have become a primary portal to higher education for first generation students, low-income students, underprepared students, underrepresented minority students, and students of nontraditional age and circumstances" (p. 463). However, this diversity was partly non-intentional on the part of community colleges. Malcom-Piqueux (2018) discussed how:

> Community colleges were intended to be the entry point into higher education for those students perceived to be unworthy of admission into flagship state university systems. This intention, combined with the systemic racial and socio-economic inequities in K-12 educational opportunity, rendered community colleges diverse by design. (p. 25)

In discussing socio-cultural research, Malcom-Piqueux (2018) further goes on to discuss how "…college 'choice' is a misnomer, as low-income students and students of color often make constrained choices at best, and are commonly left with no choice" (p. 26).

Despite universities enrolling more students overall, community colleges serve a higher percentage of underrepresented minority and non-traditional students (Cohen et al., 2013; National Center for Education Statistics, n.d.c, Table 6). During the 19-20 academic year, the percentage of underrepresented minority students (Asian; Black or African American; Hispanic or Latino; American Indian or Alaska Native; Native Hawaiian or Other Pacific Islander; and Two or more races) served by public 4-year universities was 43.1% while public 2-year colleges served 48.6% (National Center for Education Statistics, n.d.c., Table 6). Malcom-Piqueux (2018) also discussed that, "Nationally, racial groups that are historically underrepresented in higher education…enroll in community colleges at higher rates than White and Asian students" (p. 23). This stratification is the result of a myriad of complex realities that plague US higher education including (but certainly not limited to) differences in K-12 rigor by region, state and federal policies, and socioeconomic factors (Malcom-Piqueux, 2018). Community colleges also tend to serve a high percentage of low-SES students. In the 19-20 academic year, the percentage of undergraduates at 2-year institutions receiving Pell was 31.5% (National Center for Education Statistics, n.d.a). Due to the varied background that community colleges serve, colleges have adapted to serve a great variety of student needs, often aligning their institutional missions with that of community needs.

Originally, community colleges began as an extension of high school, offering students an alternative pathway for degree-seeking students (Cohen et al., 2013; Thelin, 2011). In addition to high school completion coursework, these colleges also offered "terminal occupation

coursework and…remedial education to better prepare students for the rigors of college-level coursework…" (Bahr & Gross, 2016, p. 465). As time went on, enrollments grew and students diversified, forcing community colleges to evolve to meet new needs. Eventually, these institutions grew to offer an alternative to the traditional university that would allow them to gain credits towards credentials that could lead to transfer to a four-year university. Today, community colleges serve four main functions for students: providing transfer opportunities to four-year universities, offering associate degrees intended for immediate workforce entry, providing community classes and events, and offering Adult Basic Education (ABE) services for those lacking a high school credential (Cohen et al., 2013; Schuh et al., 2011). To accomplish these functions and honor their missions, "…community colleges are knit together by five interrelated principles. These principles are open access, comprehensiveness, lifelong learning, community centeredness, and teaching focus" (Bahr & Gross, 2016, p. 471).

Community colleges, due to their open-access policies, can often serve as a starting point for students who are otherwise unable to access 4-year universities (Frey, 2007). Students often begin their college careers with the intent to transfer to a 4-year university and, as such, community colleges are designed to assist students transferring by offering general education courses along with subject specific coursework. Alternatively, community colleges also offer degrees intended specifically for immediate entry into the workforce. These degrees (often referred to as "applied science" degrees) offer students not intending to transfer an opportunity to gain quick, applicable skills in a specific area in order to expedite their entry into the workforce. As such, many common core courses such as history, social sciences, and fine arts are replaced with coursework related to the area of interest. For non-traditional students who may not be able to follow the more traditional route of transferring to a 4-year institution, applied science degrees

represent a pathway for them to attain employable credentials at their own pace. For non-traditional students who may just need to brush-up on certain skills or benefit from short-term training, community colleges have historically offered specific coursework or training programs intended to be shorter in length than traditional degree programs.

A major problem that arises due to the mission, demographics, and nature of the community college is that many of the students who enter do not actually complete any degree or credential. This has led to community colleges having very low retention and graduation rates compared to their four-year counterparts. According to the US Department of Education, the 150% graduation rate for the 2014 cohort of students in community college (first-time, full-time) was 33.9% (Ginder et al., 2018). For four-year universities, the 150% completion rate for the 2014 cohort was 60.1%, indicating a drastic difference between outcomes for two- and four-year universities (National Center for Education Statistics, n.d.d).

Many students that enter community colleges are non-traditional, from underrepresented minority groups, need remedial work, or some combination thereof; however, placement policies, institutional barriers, and outside barriers often further cause these students to struggle towards degree completion. This is particularly true for students placed into developmental math that must climb the remedial ladder to reach college-level math courses.

Math in the Community College

In higher education, math courses are by-far the biggest point of contention for many students attempting to complete their degree, especially at community colleges. Lattimore and Depenbrock (2017) discussed how “At American community colleges, 60 percent of those enrolled are required to take at least one math course. Most — nearly 80 percent — never complete that requirement” (par. 4). While there is little research or data on exact numbers of

students that pass (or more importantly don't pass) college-level math, it is generally recognized that passing college-level math courses are a significant barrier to student success and degree completion. Since students attending community colleges often enter with lower math skills than their university counterparts, leading to students placing into remedial work (59% versus 33%, respectively), an instant gatekeeper is created between students and their ability to complete a credential (Chen, 2016). Further complicating this, though, are variations in delivery methods, sequencing (co- versus pre-requisite), and difficulty of courses.

All states' core education requirements for associate and baccalaureate degrees requires the completion of a basic, college-appropriate math course. The most common math course used to satisfy college-level math requirements for degrees in the US is College Algebra (Ganga & Mazzarielo, 2018). However, in response to low success rates for math, colleges have more recently begun to allow for the use of other courses such as Quantitative Reasoning, statistics courses, or even intermediate-level algebra (Ganga & Mazzarielo, 2018; Rosin, 2012; Rutschow & Diamond, 2015). For example:

> A communications, history or Spanish major might satisfy his or her college math requirement with a quantitative reasoning course, while a political science, journalism or nursing student might take statistics…Some colleges offer math courses for specific majors, such as math for elementary education or math for business. (Ganga & Mazzarielo, 2018, p. 2)

Typically referred to as "mathematics pathways," these alternative math options attempt to match skills needed for a student's major to an appropriate introductory math course (Bickerstaff et al., 2018). Organizations, such as the Dana Center (DC) and Carnegie Math Pathways (CMP), have assisted with this push towards diversified math pathways by designing and implementing research projects aimed at further understanding the impact of alternative math pathways on

student outcomes (Bickerstaff et al., 2018; Ganga & Mazzarielo, 2018; Rutschow & Diamond, 2015).

In 2012, the Dana Center assisted in the implementation of the Dana Center Math Pathways (DCMP) at higher education institutions in Texas which looked to provide alternate pathways to math completion in hopes of increasing overall student completion (Bickerstaff et al., 2018; Ganga & Mazzarielo, 2018). In 2014, the Center for the Analysis of Postsecondary Readiness (CAPR), in conjunction with the Dana Center, implemented a randomized-controlled trial of the DCMP at four Texas community colleges (Rutschow, 2018). At the time of examination, it was found that “27 percent of program group students enrolled in college-level math and 18 percent passed the course, rates more than double those of students in the group taking traditional courses” (Rutschow, 2018, p. 4). This project sparked the Dana Center to launch the Mathematics Pathways to Completion (MCP) initiative which sought to implement the DCMP model in pilot states to begin “implementing and scaling multiple, transferable mathematics pathways that enable students to complete a college-level mathematics requirement aligned to their program of study within one year, regardless of their initial level of preparation” (Bickerstaff et al., 2018, p. 2). The results of these projects are still on-going.

As with many other classes offered by community colleges, the digital age has allowed for many math courses (both remedial and college-level) to be offered online as opposed to the traditional face-to-face format. This has created some concern from teachers and administrators as to the effectiveness of teaching math online.

Non-traditional Students

Non-traditional students have been a prominent population in higher education for many years, especially in community colleges (Jesnek, 2012). While there has been a general decrease

in the past few years in enrollment of non-traditional aged students (25+), it is projected that by 2025 enrollment of 25-34 and 35 and older students will increase 16% and 23% respectively (Hussar & Bailey, 2017). As opposed to traditional students who enter college directly out of high school, non-traditional students have many features that make them different, in both needs and demographics. They are often first-generation college students, academically underprepared, and may lack self-confidence about their ability to succeed in what they see as education designed for traditional students (Hardin, 2008; Horn & Carroll, 1996). Non-traditional students are also less likely to engage in social aspects of higher education and instead focus on the academic nature of the institution (Bean & Metzner, 1985). Researchers have also noted many personal characteristics that can define this population including being 24 or over, having dependents, attending school part-time, having a gap year between exiting high school and starting college, or having a GED or alternative high school credential (Bean & Metzner, 1985; Hardin, 2008; Horn & Carroll, 1996; Schuetze, 2014). Due to the nature of characteristics typically held by non-traditional students, many struggle to navigate the school/life balance. In discussing this balance, Markle (2015) specified:

> …four types of interrole conflict: family-school (family demands make it difficult to meet school demands), school-family (school demands make it difficult to meet family demands), work-school (work demands make it difficult to meet family demands), and school-work (school demands make it difficult to meet work demands. (p. 270)

Horn and Carroll (1996) defined non-traditional student characteristics as “risk-factors” in their own study of non-traditional students due to the negative impact the characteristics often have on non-traditional student retention (p. 1). While the list of characteristics presented is not exhaustive, it is enough to show the multitude of ways in which a student can be defined as “non-traditional.” An important note is that, while non-traditional students are distinctly different

than traditional students, “The term nontraditional can include traditional-aged students who share common characteristics with their adult counterparts” (Hardin, 2008, p. 50).

Because of community colleges low point-of-entry (open access) as well as their varied offerings, they “often provide the access, affordability and convenience adults require and serve as the point of entry to a college degree or certification” (Frey, 2007, p. 3). Non-traditional students often begin or return to college later in life for a myriad of reasons. For some non-traditional students, entry into a community college signals their first attempt at a degree or credential (Beer et al., 2021; Hardin, 2008; Schuetze, 2014). For others, they may already have a college degree and are looking to “change careers or strengthen their work skills” (Hardin, 2008, p. 49). Others may enter college seeking short-term coursework to update specific skills or to take courses for purely personal reasons (Hardin, 2008; Schuetze, 2014).

An issue, though, is that most colleges still use more traditional policies and approaches that create obstacles for non-traditional students (Hardin, 2008; Hittepole, 2019; Osam et al., 2017). Despite the attempts of institutions to offer alternatives to “traditional” educational choices, many colleges struggle to accommodate the needs of non-traditional students, often lumping their needs in with that of traditional students. Hittepole (2019) pointed out that “Despite their growing presence within higher education, colleges and universities are still catering to the needs of traditional students” (p. 2). As Chen (2017) discussed, while many changes to higher education have occurred in recent years, “Traditional-aged students have held and continue to hold a privileged position within postsecondary education as represented by these institution-side changes” (p. 3). Lack of accommodation for needs such as flexible course times, childcare, set pathways for part-time students to complete, and access to institutional resources (such as financial aid, advising, academic resources, and funding through scholarships)

create problems for non-traditional students attempting to navigate institutions' highly traditional bureaucracy (Chen, 2017, Hardin, 2008).

This flexibility and support will be particularly important as this population increases among community colleges as they are more at-risk of dropping-out than their traditional counterparts (Hardin, 2008; Horn & Carroll, 1996). Horn and Carroll (1996) found that "nontraditional students were more than twice as likely to leave school…" versus traditional students (p. ii). They also discussed how "…about one-third (31 percent) of nontraditional students had attained a degree within 5 years, compared with more than half (54%) of traditional students" (p. ii). To exacerbate this attrition issue, community colleges are mostly "open-door," meaning they require little-to-no entrance requirements to be admitted to the college. Community colleges, by nature of their missions and these open-door policies, serve a large number of non-traditional students compared to their university counterparts; however, open-door policies, coupled with the fact that many non-traditional students have not attended HS or GED coursework in years, leads to students who may not be academically prepared for college-level coursework. This in-turn leads to student being placed into remedial coursework which has been shown to have low completion rates, leading to students not completing credentials (Bailey, 2009; Bailey et al., 2015).

Because non-traditional students have higher attrition rates due to the nature of their circumstances (e.g. first-generation student, working, extended time since high school, high stress from family or financial obligations), the impact of various barriers on this population has heavy educational consequences. Hardin (2008) identified four main barriers non-traditional students face in their educational journey: institutional, situational, psychological, and educational barriers. Specifically, in discussing educational barriers of non-traditional students,

Hardin (2008) explained that "Some adult students experience academic difficulties because they have been away from an academic setting for an extended time" (p. 54). In terms of other barriers affecting this population, complicated financial aid policies, complexity of college bureaucracy, lack of access to student resources, inopportune class times and offerings, and placement policies also affect student success (Osam et al., 2017; Remenick, 2019). This is particularly true for non-traditional students who are often first-generation college students with no one to guide through this complexity. This can lead to students being directed towards remedial courses to cover the gap in knowledge between high school and college even when remediation may not be needed.

Developmental/Remedial Education

Developmental education (also referred to as remedial education) is defined as any coursework below college-level where the purpose of the curriculum is to prepare students for college-level coursework (Bailey & Cho, 2010; Bailey et al., 2015; Cohen et al., 2013). These courses are usually either non-credit courses or for-credit courses that cannot be applied towards the student's degree or graduation requirements. At the community college level, many students enter college needing to take at least one or more remedial classes (Bailey et al., 2010; Chen, 2016). In a recent study by Chen (2017), it was found that around 68% of students in community colleges took at least one developmental course and about 48% took two or more.

Even though many non-traditional students completed a high school or equivalent credential, well over half of community college students find themselves underprepared for college-level math and English courses (Bailey, 2009; Bailey et al., 2008). This is especially true for math as more students are often referred towards remedial math than they are English. Bailey et al. (2008) found that 59% of students examined were referred to remedial math over the 33%

of students referred to remedial English. Scott-Clayton et al. (2014) found that, among their sampled colleges, the overall remediation rate was around 75% with math remediation being the highest category (63% and 70%). This often means that these students are required to take potentially lengthy remedial coursework in order to gain skills needed to succeed in college-level math courses. In recent years, focus in higher education by researchers and policy makers has shifted away from access to education to completion of credentials (Bailey, 2016). With the push from the Obama administration to have more college graduates by 2020, coupled with many states' implementation of performance funding policies tying funding directly to completion metrics, policymakers and higher education administrators have driven the shift towards the goal of completion and away from access (Garcia, 2017). Towards that end, researchers and policy makers have devoted research and legislation to developmental education (DE) reform as well as access to, and completion of, basic college-level courses such as math and English (Bailey, 2009; Bailey et al., 2008; Bailey & Cho, 2010; Bahr, 2010; Bahr et al., 2019; Bailey et al., 2015; Rutschow et al., 2019; Scott-Clayton, 2012; Scott-Clayton et al., 2014). With costs associated with DE as well as the high number of students who do not complete the work and enter college-level courses, DE and placement policies have been keen areas of reform interest by colleges.

One main issue with these courses is that they can consist of multiple levels of remediation, thus lowering the chances of completing the sequence and delaying graduation. This is of particular note as scholars have found that the more time added to degree completion typically results in lower chances the student will actually graduate (Horn & Nevill, 2006). In examining data from the *Relative Impact of Interventions to Improve Achievement and Retention in Postsecondary Occupational Programs* study, Bremer et al. (2013) found that students taking either developmental English, reading, writing, or math courses "in the first term decreased a

student's likelihood of completion…" within the two years examined (p. 168). Research has shown that fewer than half, and as low as 33%, of students assigned to developmental coursework actually complete their sequence (Bailey et al., 2008; Bailey et al., 2015). Bailey et al. (2008) also pointed out that "between 60 and 70 percent of students who fail to complete the sequence to which they were referred do so even while having passed all of the developmental courses in which they were enrolled" (p. 2). Reasons for such low numbers of completers are often attributed to students either finding the extra work cumbersome, failing the remedial coursework, or from simply dropping out due to the extra coursework (Fong et al., 2015). Xu and Dadgar (2018) found that, for remedial math courses, students testing into the lowest-levels of the sequence gained few benefits from the course and possibly reduced students' chances of degree completion compared to higher sequence starters. Ngo and Kwon (2015) also discussed that "Although developmental courses can serve as necessary and helpful stepping-stones to college success, they can also delay access to critical gateway courses necessary for degree attainment or transfer to 4-year colleges" (p. 443). This critique is particularly poignant considering how many students actually make it through remedial math sequences. In examining Achieving the Dream colleges, Bailey et al. (2008) found that, of students who tested into three or more levels below college-level math, only 16% actually completed their sequence within three years (31% aggregate for all math levels). While policymakers believe that the classes are needed as support structures for students woefully underprepared for college-level courses, researchers argue that the overall low success rates off-set any benefits gained. In a summary of literature discussing effectiveness, Bailey (2009) mentioned that while "these analyses show that taking developmental education does not hurt students, they also suggest that these courses do not help them either" (p.15).

Due to the documented ineffectiveness of remedial sequences, developmental coursework can be troublesome for non-traditional students who already face other barriers (within and outside of the institution) to transfer and credential completion (Bailey, 2009; Bailey et al., 2015). With the large number of students that are identified as non-traditional in community colleges, coupled with the notion that most students that enter remedial sequences don't complete them, this creates a large student success issue in terms of credits attainment, retention, credential completion, and money spent. Bailey (2009), in examining a study using National Education Longitudinal Study data, discussed that for students referred to remediation, "less than one-quarter of community college students...complete a degree or certificate within eight years of enrollment in college" (p. 14). This is not even considering the high cost of offering remedial education (in both time and money) to students as well as the actual cost to the student (Bailey & Cho, 2010). Scott-Clayton et al. (2014) discussed how "Besides financial aid, remedial education is perhaps the most widespread and costly single intervention aimed at improved college completion rates" (p. 1). They also estimated that that the total annual cost of developmental education in the US is $6.7 billion (Scott-Clayton et al., 2014).

In an attempt to combat low success and completion rates in these courses and get students through gateway courses faster, many institutions across the country have explored different remedial modes as an alternative to pre-requisite remedial models (Childers et al., 2021; Rutschow et al., 2019). These alternative methods have been shown in many reduce time to college-level course completion, increasing success and lowering overall cost as a benefit. These model changes have often resulted from pressure by legislators for colleges to address low graduation rates and credential completion (Childers et al., 2021). Childers et al. (2021) discussed that, as a result of stakeholder pressure, "several remediation reform designs have

emerged in mathematics, which include modularization, mastery based, elimination, acceleration, and co-requisite" (p. 167). In recent years, this pressure has come in the form of performance funding which directly ties student success outcomes to college funding (Dougherty et al., 2014; Garcia, 2017).

Even with alternative remediation designs becoming popular, a majority of community colleges still use lengthy, multi-semester developmental models, particularly for math. Rutschow et al. (2019) found that 86% of all 2-year institutions still used multi-semester remedial sequences for math preparation. While the results of alternative developmental models have shown promise in assisting students in getting to college-level coursework faster, current college placement policies are still responsible for directing students to remediation who may not have needed it due to outdated placement measures.

Alternatively, there is some research that suggests there is no discernable difference between students who are placed into developmental courses versus those who place into college-level (Crisp & Delgado, 2014; Sanabria et al., 2020). Crisp and Delgado (2014) argued that many instances of research finding differences between the developmental and non-developmental students' success or matriculation was, in many cases, due to failure to control for selection bias. Using Propensity Score Matching (PSM) and logistic regression analyses, Crisp and Delgado (2014) found that "Enrollment in developmental coursework…was not found to be significantly related pre- or post-matching to students' decisions to persist to the second year of college" (p. 109). Using inverse probability weighting to examine graduation rates among students, Sanabria et al. (2020) found that "Students who took and passed their remedial coursework at both 2-year and 4-year colleges were more likely to graduate from college than similar students who did not take remediation" (p. 459). While this research does argue that

remediation is not the direct cause of low completion rates, it does not address the reasons that students may not be completing the sequences, nor does it address the student factors affecting students' success.

Remedial Student Characteristics

Students that are placed into developmental/remedial education are generally different from those who are placed directly into college-level courses. Crisp and Delgado (2014) discussed how "Although findings are somewhat mixed, overall research suggests that developmental students likely differ from non-developmental students in terms of gender, ethnicity, age, first-generation status, and academic preparation prior to college" (p. 102). Research has also indicated that women tend to be more likely than other genders to be placed into remedial coursework (Crisp & Delgado, 2014; Scott-Clayton et al., 2014). For both of the school systems examined, Scott-Clayton et al. (2014) found that female students were more highly represented in remedial education than male students; however, they did also discover that after placement was based on HS transcript information instead of only placement test scores, the number of female students referred to remedial courses dropped. Research has also found that underrepresented minority students from Latinx, Hispanic, and Black backgrounds are highly represented in remedial coursework (Bahr, 2010; Scott-Clayton et al., 2014). Not only are underrepresented racial minority students more prevalent in remedial coursework, they are also often less successful (Bahr, 2010). Using a logistic regression analysis to examine remedial success rates, Bahr (2010) found that "the odds of remediating for White students are 3.1 times the odds for Black students and 1.6 times that of Hispanic students" (p. 220). Fong et al. (2015) found that "African American students are less likely to progress through the sequence compared to White students. Compared to White students, Latino students have higher odds of attempting

each math level but lower odds of passing each level…" (p. 734). It is important to note, though, that race is not the cause of students' placement into, or subsequent success in, remedial education courses. Bahr (2010) poignantly pointed out that "…race itself is not a *cause* of the disparities; rather, it is the many correlated facets of inequality that lead to lower preparation and achievement among historically disadvantaged racial groups" (p. 212). As colleges continue to explore new remedial models and alternative policies (such as multiple measures assessments) to increase accuracy of placement into college-level courses, decreased amounts of remedial work may be needed by students typically identified as needing it, thus reducing time to graduation and increasing retention.

College Placement Policies

Standardized Tests

Standardized placement tests have been a very popular method of assessing student readiness for college-level coursework for many years. Many colleges (especially community colleges) in the United States rely on these tests to determine whether students will be successful in college-level courses (Fields & Parsad, 2012; Hodara et al., 2012). Fields and Parsad (2012) found that "Seventy-one percent of postsecondary education institutions reported using some mathematics test for determining the need of entry-level students for remedial courses in mathematics" (p. vi). More recently, Rutschow et al. (2019) found that as of 2016, around 99% of 2-year colleges used placement exams in determining student placement in math. They also found that over one-third of 2-and 4-year colleges "use only one measure to assess students' college readiness" and that "Among these colleges, 90 percent rely exclusively on standardized assessments" (Rutschow et al., 2019, p. 15). In the community college system, one of the most widely used placement tests is the Accuplacer®® (Mattern & Packman, 2009). As opposed to

the ACT or SAT, which CollegeBoard markets as admissions exams (though, they are often also used for placement), the Accuplacer®® is specifically designed for determining student placement in math and English (Mattern & Packman, 2009).

However, there are issues with test-only placement policies, especially for non-traditional or underrepresented students who may not have encountered any type of math coursework since high school or have had access to resources needed to be successful on such tests. Bailey et al. (2015) discussed three main issues with test-only policies:

> First, most incoming students are unaware of the purpose and consequences of the placement tests…Second, placement test content is often poorly aligned with academic standards and expectations of college-level coursework…Third, and perhaps most important, the skills that can be tested on a short multiple-choice test represent only a small subset of those needed to be successful in college. (p. 127)

An analysis by Fay et al. (2013) found four reasons why students do not prepare for math exams: "misperceptions about the stakes of the assessment and placement process;" "lack of knowledge about preparation materials;" "misunderstandings about why and how to prepare…;" and "a deep lack of math confidence" (p. 1). Hodara et al. (2012) discussed three specific limitations of standardized test scores: lack of understanding of the test and process; gaps between content on tests and college curriculum and standards; and "the use of a single measure for placement" (p. 2).

A major concern with these tests is that test scores have been shown to have low correlation to course and college success and provide little to no additional predictive value when high school information is available (Belfield & Crosta, 2012; Scott-Clayton et al., 2012; Scott-Clayton et al., 2014). Belfield and Crosta (2012) found that, while placements tests were weakly positively correlated with college GPA, this relationship disappears when controlling for high school GPA. This is important in that, currently, most students or their families pay out-of-

pocket to take placement tests, the cost of which can run between $10-$175 depending on the test. There is also a challenge for non-traditional students who work in having to take time off to take the exam. A situation like this often results in lost income for non-traditional students who are more-than-likely employed (as they will need time off) or, in some cases, lost income due to childcare needed to take the test.

Accuracy of Standardized Tests

The most pressing concern lies in questioning the validity and accuracy of standardized tests to measure students' ability to be successful in college math courses. Recent research has tested the idea of whether students can be accurately placed into college-level courses using placement tests alone (Scott-Clayton, 2012; Scott-Clayton et al., 2014). Calculating what they call "severe error rates," Scott-Clayton et al. (2014) found that up to one-fourth of community college students were misplaced (approximately 18% under-placed and 6% over-placed) in math courses when placement decisions were based only on test scores. Some researchers have noted that the reason for the inaccuracy and low validity of placement exams could be that the tests are not well aligned with "academic standards and expectations of college-level coursework" (Hodara et al., 2012, p. 2). Shelton and Brown (2010) found that alignment of various math standards was poor between California Community Colleges' and California high schools' curriculums, potentially resulting in increased remedial placement in college. Rutschow et al. (2019) discussed how "Many states and policymakers are concerned with alignment between the curriculum and content taught in K-12 schools and postsecondary education, arguing that fewer students would place into developmental education if these systems were well aligned" (p. 15).

Overall, this misplacement can lead to longer developmental sequences, decreasing students' chances of entering college-level coursework, which in-turn leads to higher levels of

attrition. Discussing the effect of misplacement on college completion, Bahr (2016) stated that "The result is an elevated risk of attrition from college, which undoubtedly is related to the unnecessary expenditure of time, money, and effort completing remedial courses to prepare for college-level courses work in which the students often would have succeeded without the developmental intervention" (p. 1). This is especially true for students who may be, in actuality, academically capable of completing college-level courses. Scott-Clayton et al. (2014) discussed how "Prepared students who are assigned to remediation may garner little or no educational benefit, but incur additional tuition and time costs and may be discouraged from or delayed in their degree plans" (p. 372). As such, increasing student access to college-level coursework has been shown to increase student retention and completion rates. Community colleges currently struggle in retaining students to graduation, with attrition from remedial sequences certainly being a contributing factor. Per an American Associate of Community Colleges review of National Student Clearinghouse data, "the overall 6-year completion rate for students who started in the fall of 2010 at public 2-year institutions and completed was 27%" (Juszkiewicz, 2017, p. 5). With research highlighting the issues with using placement-test-only policies, an alternative model in the way of multiple measures assessments has been explored as a possible replacement.

Multiple Measures Assessments

In recent years, more information has come to light about the usefulness of factors outside of test placement scores to predict student success and place students into entry-level college courses. As a result, multiple measures assessments (MMAs) are becoming an increasingly popular method used to determine student placement into college math and English courses (Rutschow et al., 2019). While MMAs vary in terms of what factors are looked at,

generally, they are the use of other measures, including or without standardized test scores, to determine student readiness for college-level coursework. There are three main types of MMA models typically used by community colleges: decision rule, decision band, and algorithm (Bickerstaff et al., 2021). Decision rule models place students "according to a series of 'if-then' statements…" where "if a student scores above a specified threshold on at least one measure, then they receive a college-level placement" (Bickerstaff et al., 2021, p. 2). Decision band placement is when students are placed "according to where they fall relative to a specified range of scores on a certain measure" (Bickerstaff et al., 2021, p. 2). This usually involves ranges for multiple criteria being examined and considered together. Lastly, algorithmic placement "uses historical data to determine how well different factors (placement test scores, high school GPAs, time since high school graduation etc.) predict student success in college-level courses" (Bickerstaff et al., 2021, p. 2). This type of model is very common as it allows a more robust picture of the student's ability to successfully complete college-level coursework.

Studies have found that, overall, MMAs tend to more accurately, or with equal accuracy, place students with regards to college-level coursework compared to test-only policies (Ngo & Kwon, 2015; Scott-Clayton, 2012; Woods et al., 2018). With the COVID-19 pandemic upending many testing sites and forcing institutions to re-examine how they determine placement, MMAs offer a research-based alternative to traditional testing policies. While there is no one way to design and implement an MMA placement policy, logistic regression models, decision tree analyses, and hierarchical placement have been found to be useful methods (Bahr et al., 2019; Barbitta & Munn, 2018; Ngo & Kwon, 2015). Identified in many of these models are factors found to be predictive of success in college-level courses. Specifically, research has shown that using HS GPA is at least equal to, and in many cases better at, predicting student success in

college-level math (Bahr, 2016; Bahr et al., 2019; Belfield & Crosta, 2012; Cullinan & Kopko, 2022; Scott-Clayton et al., 2012). Using a decision tree analysis model, Bahr et al. (2019) found that "…high school GPA is a key predictor of passing math and English courses at all levels of skill" (p. 196). When examining the correlations between test scores, HS GPA, and success in various levels of math, Belfield and Crosta (2012) found that "HS GPA is not only a better predictor but also more consistent than the placement tests" (p. 13). The results of their analysis revealed correlations of .03-.25 for placement tests, whereas HS GPA was found to be between .34-.36 (Belfield & Crosta, 2012). Outside of HS GPA, other high school information often considered includes cumulative HS GPA in the subject area, number of classes taken in the subject, grade of last course taken in subject, number of honors courses, and number of Advanced Placement (AP) courses (Bahr et al., 2019; Ngo & Kwon, 2014; Woods et al., 2018).

Due to these findings, concerns with student completion and success, and the validity concerns of standardized testing, many institutions are now assessing information outside of (but sometimes including) standardized testing to evaluate student readiness for entry-level math and English (Rutschow et al., 2019). There are even some states and systems that have updated policies to require or recommend colleges include these factors in placement decisions or allow students to opt out of developmental coursework (Bahr et al., 2019; Barbitta & Munn, 2018; Cullinan et al., 2018; Cullinan & Kopko, 2022; Ganga & Mazzariello, 2019; Woods et al., 2018). While many placement policy adjustments resulted as a response to the COVID-19 pandemic, others were already in the process of, or had already instituted, MMAs. In North Carolina, the North Carolina Community College (NCCC) system adopted a hierarchical MMA placement policy that examined (among other things) HS GPA and subject area standardized test scores to determine placement (Barbitta & Munn, 2018). In California, the state legislature "passed A.B.

705 in 2017" which "requires community colleges to maximize the probability that new students will complete transfer-level English and Math courses within one year…" (Ganga & Mazzariello, 2019, p. 5). To add to this, a ruling from a 1988 California court case "prohibited California's community colleges from relying solely on standardized exams for student assessment and placement. Instead, the colleges must consider additional information about student academic readiness…" (Bahr et al., 2019, p. 187). Recently, Virginia community colleges, as a response to the COVID-19 pandemic, updated their policies to allow students to assess their placement level using self-reported GPA; however, the most recent version of the policy requires HS GPA be assessed along with standardized test scores (Bickerstaff et al., 2021).

For non-traditional students who have obligations outside of academics, MMAs could offer alternatives to test-score-only placement policies that are more flexible and less costly than placement tests. With the increase in accuracy research has shown MMAs can provide, this also means that non-traditional students, who have been shown to be more at-risk of dropping out than traditional students, are more accurately placed into college-level courses, thus increase the chance they will continue their academics. In addition, with the high number of underrepresented students that are placed into remediation in community colleges, MMAs could assist in bridging the completion gap for a great number of these students by allowing them into college-level courses or reducing the number of remedial levels needed to get to college-level (Scott-Clayton et al., 2014). In a study examining MMA placement policies for colleges in New York, Minnesota, and Wisconsin, MMA placement was shown to increase "enrollment and completion of college-level courses by roughly 10 percentage points" in both math and English (Cullinan & Kopko, 2022, p. 3).

Summary

With standardized tests having been shown to be poorly related to student success in college-level math courses, a new method is called for. Multiple measures assessments have been shown to be more accurate in placing students, which can lead to higher levels of college math completion, which in-turn could lead to higher completion rates. Since nontraditional students differ from traditional students, taking factors such as HS GPA and time since HS completion into account can increase the accuracy of placement models. The misplacement of students into developmental coursework leads students to leave college early, which leads to students not achieving goals they set out to accomplish. Community colleges will need to improve their placement models to increase accuracy of placement and student success, leading to better student completion of credentials, which will lead to more highly skilled workers in the workforce.

Chapter III - Methodology

Introduction

This chapter provided a discussion of the methods used to conduct the research for this study. The chapter began with a review of the research questions and hypotheses and lead into the methods section. Here, I provided the setting of the study, participant demographics and information, define each variable and how it is being operationalized, how data were collected, and how data were analyzed to answer the research question and sub-questions. The chapter concluded with a discussion of validity issues and a final summary.

Methods

Study Design

The study used a cross-sectional logistic regression analysis utilizing secondary data sets. Logistic regression models were created using the variables *HS GPA, Classic Accuplacer®® math scores, age, last math course taken in HS,* and *grade in last HS math course*. Arkansas has two primary math pathways, College Algebra and Quantitative Reasoning; however, for the purpose of this study only College Algebra was examined. This is namely due to the fact that the data range that was requested (2016-2019) falls outside of the scope of the state's push and ubiquitous implementation of Quantitative Reasoning. This led to too small of a sample size to consider running an analysis for Quantitative Reasoning. A model was created to examine multiple measures assessment predictive success for College Algebra as well as what variables are significant in predicting student success.

Study Setting

Arkansas in Context

This study focused on the State of Arkansas to concentrate the analysis on a specific set of criteria to increase the accuracy and applicability of the findings. Since each state is responsible for setting the educational agenda for its colleges, coupled with the fact that the research being conducted is to have practical applications, a single-state study was deemed more viable than a multi-state study. While the hope was that this research could be used in contexts outside of Arkansas, the criteria for success as determined by the Arkansas Department of Higher Education (ADHE) is the primary variable of examination and thus limits the current context to a single state. This type of single-state study, while less popular, holds value in its ability to specifically examine state-level policy to determine the unique needs of the students of the State of Arkansas. This logic is defended by Nicholson-Crotty and Meier (2002) who wrote that:

> Single state studies are appropriate when the researcher wishes to generalize to a unit of analysis other than the states themselves, when conditions in a given state provide a unique opportunity for the most rigorous test of a hypothesis, and when the measurement advantages of a single-state study outweigh the costs of limited generalization. (p. 411)

The reasoning for choosing Arkansas as the state to examine has much to do with the fact that I worked for many years at an Arkansas community college and have a passion and want to better community colleges in the state to better assist students.

Arkansas has 22 community colleges responsible for educating approximately 3,025,891 citizens (Arkansas Community Colleges, 2020; United States Census Bureau, 2021). Enrollment in these institutions as of Fall 2020 was 30,515 students which was 11.5% lower than 2019 (Arkansas Community Colleges, 2020). Of those students, female enrollment was higher than male enrollment and White enrollment was higher than all other demographic groups (see Table

Table 1.
*Demographic Characteristics of Arkansas Community Colleges Students, 2020**

Demographic Characteristics	Number of Students
Race	
Black or African American	5,960
Asian	313
Hispanic or Latino	3,104
White (not Hispanic or Latino)	19,005
Gender (does not include non-binary)	
Male	10,503
Female	19,915
Age	
18-20	14,512
21-24	5,407
25-29	3,642
30+	6,399

**Data collected from Arkansas Community Colleges, 2020*

1). Demographically, Arkansas is primarily homogenous in terms of race and ethnicity (see Table 2) with White being the most represented (72%) (United States Census Bureau, 2021). In terms of educational attainment, as of 2020, Arkansas was ranked 48th in percentage of population over 25 years old (15.2%) who hold a bachelor's degree (author's calculations using data from the United States Census Bureau, 2020). The average for the same timeframe for all states (including D.C.) was 19.96% indicating that Arkansas is well below the national average (author's calculations using data from the United States Census Bureau, 2020). Exacerbating this issue is the percentage of adult and non-traditional students being placed into remedial coursework in Arkansas. The Arkansas Department of Higher Education (2015a) found that students aged 25-34, 35-44, 45-54, and older than 55 had math remediation rates of 71%, 77.4%, 74.3%, and 81.5%, respectively. Considering the remediation rate in Arkansas community colleges for those 18 and younger, 18-19, and 20-24 are 41.3%, 42.3%, and 63.6%, respectively,

Table 2.
Demographic make-up of Arkansas, July 2021

Demographic Characteristics	Percent of Population
Race	
Black or African American	15.7%
American Indian and Alaska Native	1.0
Asian	1.7
Hispanic or Latino	7.8
White (not Hispanic or Latino)	72.0
Gender (does not include non-binary)	
Male	49.1
Female	50.9
Age	
Under 5 years	6.2
Under 18 years	23.2
18-64 years	53.2
65+ years	17.4

**Data collected from United States Census Bureau, 2021*

it seems that many students who would be considered non-traditional by age alone have a much higher remediation rate than what current research has shown around the country (around 68%; see Chen, 2016) (Arkansas Department of Higher Education, 2015a). For Arkansas, the high rate of developmental placement for those 24 and older compared to those below 24 shows that the state has a long way to go to bridge the remediation gap.

Participants and Placement

Data included a sampling of non-traditional students from all community colleges in the State of Arkansas for the 2016-2020 academic years who took either College Algebra. The 2016-2020 academic years were chosen in an attempt to gather as much data as possible while avoiding data contamination due to the COVID-19 pandemic. Since the study did not focus specifically on the effects of COVID-19 on student success, it would not be appropriate to pollute the data analysis with academic years 2020-2022. Due to the myriad of attributes that can

define a student as non-traditional, selecting a criterion for sampling is very important. For the purpose of the study, non-traditional students were defined as any student with at least a one-year gap between completing high school and starting college (Radford et al., 2015).

The data set contained a total of 11,409 students; however, due to the inclusion of a number of students with test types outside of the Accuplacer® (such as ACT, SAT, and Compass tests) as well as missing data, final sample was greatly reduced to 278 students. This was done by filtering out all test scores that were not called "Accuplacer® Classic" and removing any lines where missing data were found. Finally, *Age* (time since HS) was calculated using the provided HS graduation year and college entry academic year. Demographic data were examined once data set was retrieved and analyzed. Per the power analysis using G*Power, the analyses will need at least 253 cases to conduct a robust logistic regression capable of detecting any significant findings (w = .3; α = .05; 1-β =.95; df = 8).

Materials

Materials used in the study included information as found on high school transcripts including GPA and course history. Since HS GPA has been shown to be a strong indicator of success in college, it was a useful measure to include in the analysis (Bahr et al., 2019; Belfield & Crosta, 2012; Cullinan & Kopko, 2022; Scott-Clayton et al., 2012). Last math course taken in high school as well as grade in last math class have also been found to be relevant predictors of success in college-level math.

Since test-placement policies were examined in the study, the impact of test scores on success in college-level math was important to consider. *Classic Accuplacer*® scores were used in the analysis as the standardized placement test. Specifically, "College Algebra" and "Accuplacer® Classic" scores from the *Classic Accuplacer*® were used in the analysis since that

is the main portion of the test that was used by community colleges to determine placement into College Algebra. Per communication with ADHE, since community colleges during the examined time period were not required to specify what level of scores were being reported until later, both “College Algebra” and “Accuplacer® Classic” scores represent the same college-level score that would place students into College Algebra. All materials used were collected from the Arkansas Department of Higher Education in conjunction with the Arkansas Department of Education.

Research Questions and Hypotheses

The research questions that guided the study are again as follows:

4. What was the demographic profile of the subjects included in the research sample?
5. Did multiple measure assessments equally or better predict non-traditional student success in College Algebra than *Classic Accuplacer math scores*?
    c) What factors predicted non-traditional students’ success in passing entry-level college math courses?
    d) Did *age* influence the relationship between HS GPA and success?
6. Did the final multiple measures model equally, or more accurately, assess underrepresented non-traditional minority placement into College Algebra?

Research question one was answered using demographic data collected for analysis.

To answer research question two, the following hypothesis was generated:

H1: *HS GPA*, *Classic Accuplacer® math scores*, *age*, *grade in last HS math class*, *last HS math course taken*, and *age*HS GPA* are better at predicting success in college-level math than Accuplacer® math scores alone.

- H0: $\chi^2 = 0$

- H1: $\chi^2 \neq 0$

To answer sub-question *a*, the following hypothesis was generated:

H2: *HS GPA, Age, grade in last HS math course, last HS math course taken* and *age*HS GPA* are significant predictors of success in college-level math. *Classic Accuplacer® math scores* were non-significant when including HS GPA and Age.

- H0: $B_1 = B_2 = B_3 = B_4 = B_5 = B_6 = 0$
- H1: $B_1 \neq B_3 \neq B_4 \neq B_5 \neq B_6 \neq 0$; $B_2 = 0$

To answer sub-question *b*, the following hypothesis was generated:

H3: *Age* (time since HS graduation) has an interaction effect with *HS GPA* and will be curvilinear nature.

- H0: $B_{\text{GPA*AGE}} \geq 0$

  $B_{\text{GPA*AGE}^2} \geq 0$

  $B_{\text{GPA*AGE}^3} \geq 0$

- H1: $B_{\text{GPA*AGE}} \leq 0$

  $B_{\text{GPA*AGE}^2} \leq 0$

  $B_{\text{GPA*AGE}^3} \leq 0$

H4: To answer research question three, Microsoft Excel was used to filter the data by gender and race to examine model improvement of prediction accuracy over original *Classic Accuplacer® math score* placement. It was hypothesized that the model would better predict passing and failing of underrepresented students better than test placement scores alone.

Measures

The goal of this research was to create a practical, algorithmic model to use as an MMA, only certain variables were chosen for use. Bean and Metzner's (1985) framework predicted that "Students with poor academic performance are expected to drop out at higher rates than students who perform well…" (Bean & Metzner, 1985, p. 490). In addressing *background* variables, while ethnicity and gender may be important theoretical variables to consider, for practical purposes only *age* (as measured by time since HS completion) and high school performance (GPA) were examined. As has been seen thus far, previous academic performance (e.g. HS GPA) is an important factor in determining student success in entry-level college math courses. The study did not measure or examine student satisfaction directly and, as mentioned previously, many students become discouraged and dissatisfied with their college experience when placed into developmental education. As such, it stands to reason that increasing student placement via MMAs would also result in the increase of student satisfaction with regards to aligning student perceived academic readiness with correct coursework; however, *environmental* and *psychological* variables as defined by Bean and Metzner (1985) were also not used to select variables of interest since they fall outside the scope of this particular study. Variables of interest that were examined can be seen in Table 3.

Elaborating further was the addition of *age* (time since high school) as a variable. Though age is a factor considered by Bean and Metzner's (1985) model, it is not specifically stated as a moderating variable to other *background* information; however, Bean and Metzner (1985) did leave open the possibility for interaction terms by having stated that background variables "may be mediated by other endogenous variables in the model" (p. 490). Expanding this to the study conducted, *age* (time since HS graduation) was used to moderate the influence of previous

Table 3**.**
Variables of Interest and the Theoretical Underpinnings

Variables	Measurement	Research Procedures
HS GPA	Continuous; 0.0-4.0	Bean and Metzner, 1985
Age	Continuous; 1-50	Bean and Metzner, 1985
Grade in Last HS Math	Categorical	Bahr et al., 2019
Last HS Math Course	Ordinal; 1-5	Ngo and Kwon, 2014
Classic Accuplacer® College Algebra Scores	Scale; 200-300	Scott-clayton, 2012; Woods et al., 2018

background information (e.g. HS GPA). This moderation variable was also supported by Bahrick and Hall (1991) who, in their study of retained knowledge of high school math, found that years since high school math and percentage correct on a math test had a negative, often curvilinear, relationship. Though the relationships examined by Bahrick and Hall (1991) were also measured as a function of highest math taken in high school, this research supports the inclusion of *age* as a moderator to math knowledge (as measured in this study as HS GPA).

The dependent variable in each regression model was successful student completion of college-level math ("0" for passing; "1" for not passing). This was defined as whether or not the student passed the examined math course with a grade of "C" or better. Anything below a grade of "C" (including "W" for withdrawals) was considered not passing and was coded as such. Independent variables that were examined include *HS GPA* (*GPA*), *age (age)*, last high school math course taken (*math*), grade in last math course taken (*grade*), *Classic Accuplacer*®® math scores, and the interaction of *HS GPA*age* including exploring curvilinearity of a*ge*. GPA was defined as the weighted value that represents success in coursework taken from grades 9-12 and

is measured on a 4.0 scale. This information was collected from what is reported on students' final HS transcripts (via ADHE). *Age*, for the purpose of the study, was considered the number of years between when a student graduates from high school and enters college as measured in years. This was calculated by looking at the difference between the high school graduation date and date of college entry. Because there was an interaction variable examined in the study that included *age* in the interaction, *age* was first examined with no transformations, then as a mean-centered variable to determine if a high correlation between the interaction and *age* could be resolved.

Last HS math course taken looked at the last (note, not the highest) math course taken by the student while in high school. Because the data for this variable were heavily skewed towards "geometry," the data were coded into two categories: "up to geometry" and "up to Calculus." This assisted in giving the regression model enough in single categories to be able to perform the analysis. *Grade in last HS math course* was considered the last math course taken in high school. Since the State of Arkansas does not require four years of math in high school, this could be any math course taken in the 11-12 grades of high school. This was measured as any grade A-F and coded as such.

For Accuplacer®® scores, the *Classic Accuplacer®®* was used due to the timeframe the data was requested from (AY 2016-2019). This was done to account for the effects of COVID-19 on success rates in college-level math courses. The *Classic Accuplacer®®* math section consists of three possible sub-sections all graded on a scaled score between 20-120: *Arithmetic*, *Elementary Algebra*, and *College-Level Math* (CollegeBoard, 2018). For the *Arithmetic* section, three content areas are measured with 17 questions presented: whole numbers and fractions, decimals and percentages, and applications (CollegeBoard, 2018). For the *Elementary Algebra*

section, three content areas are measured with 12 questions presented: integers and rational numbers, algebraic expressions, and equations, inequalities, and word problems (CollegeBoard, 2018). Finally, the third section, *College-Level Math*, consists of six content areas with 20 questions asked: algebraic operations, solutions of equations and inequalities, coordinate geometry, applications and other algebra topics, functions, and trigonometry (CollegeBoard, 2018). For the purposes of this study, *Classic Accuplacer® College-Level Math* scores (coded by ADHE at the time as either *College Algebra* or *Accuplacer® Classic*) will be used.

Since the timeframe that was examined, the *Next Generation Accuplacer®®* was launched to replace the *Classic Accuplacer®*. Though the tests were both created to assist colleges in college-level course placement, they do operate on different scales. The math portion of the *Next Generation Accuplacer®* test consists of three possible sections, *Arithmetic*, *Quantitative Reasoning, Algebra, and Statistics*, and *Advanced Algebra and Functions* (CollegeBoard, 2017). Each section ranged from 200-400 and within each section, CollegeBoard (2017) has split the possible range of scores into five parts: 236 and below, 237-249, 250-262, 263-275, and 276 and above. An examination of college placement policies revealed that most community colleges in Arkansas have different score cutoffs that determine college-level placement. A commonly occurring theme, though, is that it seems that the placement score for College Algebra and Quantitative Reasoning lies within the *Quantitative Reasoning, Algebra and Statistics* (QAS). As such, this specific level will be examined and treated as a continuous variable. The variable *Age* is also of interest as a moderating variable to *GPA*'s influence on success. Bahrick and Hall (1991) found that the amount of time since taking a math test had a curvilinear relationship with score on the math test, dependent upon the highest level of math taken. Extrapolating this to the current study, an interaction term, *age*HS GPA* was created to

explore the interaction. Curvilinearity for *age* was also examined to test the hypothesis of a curvilinear interaction term between *age* and *HS GPA*. It was assumed that if no curvilinear term existed for *age,* it would be unlikely a curvilinear interaction term would be possible, and thus, would not need to be examined. As such, a Box-Tidwell test was conducted as an initial check for curvilinearity with the variable *age*.

Data Collection

Data were collected through the Arkansas Department of Education's (ADHE) data system in conjunction with the Arkansas Department of Education (ADE). Pre-existing data were requested from ADHE with all needed information to run the analyses. This included students' HS GPA, grade in last math class, highest math class, HS graduation date, college entry date, and *Classic Accuplacer*®® scores. The sample was requested through the Arkansas Department of Higher Education (ADHE); any data not normally collected by them (such as high school information) was filled in by the Arkansas Department of Education (ADE; K-12) and sent back to ADHE to remove any identifiers. Data were requested in June 2022 and was delivered by September 2022. Data were summarized using demographic information and frequency analysis to indicate demographic breakdown, averages for all variables, range of data, standard deviations/standard errors, and to check for issues of normality.

Data Analysis

To answer the main research question and sub-questions, binary logistic regression analysis was used. Logistic regression is a statistical method that provides odds ratios and probability output to analyze binary dependent variable outcomes. Specifically, its regression coefficients provide odds ratios that examine the importance of specific variables in predicting the binary outcome (e.g. yes/no; pass/fail).

Logistic regression was a good fit for the research for two main reasons. First, the State of Arkansas specifically defines how students can be placed into college-level math and English courses. As previously mentioned, the state defines these placement criteria as “a greater than 75 percent likelihood of passing” (ADHE, 2016, p. 3.08.2). Since the final product of a logistic regression is a conditional probability based on specific variable information, it allowed the research to use “likelihood” values and to determine student readiness for college-level math (e.g. does a student have a “greater than 75 percent likelihood of passing”). Second, because I am examining whether or not students pass or fail a given course, the binary outcome makes it a good candidate for logistic regression analysis.

To assist in answering the research questions a variety of methods were used. First, the frequencies of the demographic information were examined to determine whether sample was reflective of the population. Next, hierarchical logistic regression modeling was used to examine variables related to predicting student success in College Algebra. Hierarchical modeling involves entering variables into the model in blocks to see how they affect the overall model significance and fit. The final product is a side-by-side comparison of all models to assess the change in model significance and variable importance. The hierarchical models being presented for this research are as follows:

Model 1: $\hat{y} = b_0 + b_1X_{GPA} + b_2X_{AGE} + b_3X_{MATH} + b_4X_{GRADE}$

Model 2: $\hat{y} = b_0 + b_1X_{GPA} + b_2X_{AGE} + b_3X_{MATH} + b_4X_{GRADE} + b_5X_{GPA}X_{AGE}$

Model 3: $\hat{y} = b_0 + b_1X_{GPA} + b_2X_{AGE} + b_3X_{MATH} + b_4X_{GRADE} + b_5X_{GPA}X_{AGE} + b_6X_{SCORE}$

This modeling format allowed me to answer research questions *2*, *2a*, and *2b*. The first model sets a baseline as to explore the eventual addition of the interaction term as well as test scores. This was done to allow for model comparison between the baseline model and future models to

examine the significance of the added variables as well as model fit improvement. The second model then added the interaction terms between *GPA* and *Age* to explore the significance of the interaction. The final model included *Classic Accuplacer*®® "College Algebra" and "Accuplacer® Classic" scores (same score, different names) to test for significance of adding placement scores to the model. As is common with regression, variables found non-significant will not be included in models 2 or 3 to create a more parsimonious final model.

Since *research question 2* focuses on whether multiple measures placement is more accurate in predicting success in college-level math than placement scores alone, this hierarchical modeling structure allowed me to examine if adding Accuplacer®® math scores in addition to high school information and time since high school graduation added any significant predictive power to the model. This was done by examining the significance of the Chi-squared change ($\Delta\chi^2$) between regression models 1 and 2, and models 2 and 3 (known as the -2loglikelihood) to determine model fit.

Sub-question "a" (model 2) looked to answer what variables are significant in predicting student success in college-level math. To answer sub-question "a," beta-values for final model were examined to determine statistical significance. It was predicted based on prior literature that *Classic Accuplacer*®® math scores would not be significant when controlling for other factors such as *HS* GPA (Scott-Clayton, 2012). Sub question *b* (model 3) examined the interaction effect between age and GPA while controlling for other factors. Since there was research that indicates a possible curvilinear relationship between *age* and *HS GPA,* the Box-Tidwell test was conducted to see whether *age* was curvilinear in nature. Once curvilinearity was determined via the Box-Tidwell test, the regression was conducted to find the significant terms that could be

used for the final model. Hierarchical modeling showed whether interaction effect was present and significant.

To answer *research question 3*, the final model created was entered into Microsoft Excel 365 to see the specific prediction accuracy breakdown by race. All students that identified as White were removed from the sample leaving only historically underrepresented racial minority students. The prediction rates of the model versus the actual pass/fail rates were compared to identify the rate of accuracy for this specific population.

Statistical assumptions for logistic regression differ slightly than normal OLS multiple linear regression. As discussed by Osborne (2015), the main assumptions of interest in logistic regression are:

- Independence of observations
- Linear relationship with the dependent variable ***on the logit***
- No influential outliers

Unlike ordinary least squares multiple linear regression, assumptions of variance do not apply and distributions do not have to be normally distributed. To examine whether variables are linear on the logit, a Box-Tidwell test was run by using both the continuous independent variables suspected of being curvilinear and the Box-Tidwell variable. The formula for the Box-Tidwell transformation is as follows:

$$V_i = X_i(\ln X_i)$$

where V equals the variable of interest (X) multiplied by its log transformation ($\ln X$) (Osborne, 2015). If the variable V is statistically significant in the regression equation when the original variable is present, curvilinearity should be assumed to be true. To incorporate this term, an

initial regression analysis was conducted with all relevant variables (including the variable suspected of curvilinearity), then a second analysis was run with the Box-Tidwell transformation included. I would like to be clear that the point of running the logistic regression with the Box-Tidwell variable *was not* to determine model fit or variable significance; it was merely to examine the significance of the Box-Tidwell transformation.

To check for potential influential outliers, Df Beta values were produced in the initial regression as part of the Box-Tidwell check for influential outliers. Per Osborne (2015), a method to eliminate influential outliers is to look for any extreme deviations from the 99th percentile and beyond and 1st percentile and below and to remove them to increase reliability of the model. Once DF Betas were calculated in SPSS, data was moved over to excel to utilize the percentile calculation formula as well as the "IF" function to easily identify outliers. The "IF" function was coded to produce a "yes"/"no" outcome to identify outliers. Outliers were then deleted per guidance from Osborne (2015). After examination of Df Betas for scores above the 99th percentile and below the 1st percentile, 14 total cases were excluded from the sample leaving 264 cases in the sample. Software used to run all analyses was SPSS 28 and Microsoft Excel was used to calculate percentiles.

Internal and External Validity

The two main threats to internal validity included confounding variables and alternative hypotheses (McDavid et al., 2012). Since analyses only examined five total variables (not including polynomial or interaction terms), any outside factors that may influence the outcome variables were not examined. Factors such as race, ethnicity, or socioeconomic status were not examined due to the desire for this research to be able to be applied in a practical manner. Since including such variables in a placement model and then using that model in practice would be

highly unethical, I made the decision to not examine those factors; however, future research should include such variables to examine if certain groups benefit more or less from the research conducted here and how those groups may be represented in the target population in this research.

Alternative hypotheses were also potentially present in this research. Since I am not conducting a random control trial (RCT) with random selection, I have no way to know for sure that the data collected represents an actual effect happening within the population as I am describing it. There may be other influences that occurred during the target years examined that affected the analyzed data. To attempt to account for this, since I will be using population data from a specific timeframe, random sampling will be used within the population data to collect enough data for the study per G*power analysis.

Threats to external validity included applying the regression outside of the context of the State of Arkansas and the population examined. Since the study focused specifically on one state with specific guidelines and unique population diversity, applying these analyses specifically to other groups outside of the state may not be appropriate. Any researcher looking to apply the research outside of this context will need to run the regression model using their specific data sample to ensure that variables identified as significant in this research still apply in a manner consistent with other research.

Summary

With high remediation rates for non-traditional students in Arkansas, finding a more accurate model that can be implemented is paramount. To assist with improving these rates, the study sought to provide an algorithmic placement model that can be quickly implemented by community colleges in Arkansas. This chapter explored the research questions and hypotheses

guiding this research study. Other discussion included the methodology, participant information, and statistical analyses examined and used to explore the relationship between HS GPA, Accuplacer®® test scores, age, grade in last high school math course, and the interaction of HS GPA and age. Logistic regression was used to determine whether null hypotheses can be rejected and data were examined to determine any issues with assumptions related to logistic regression. The chapter ended with a discussion detailing how data were cleaned was also discussed along with possible threats to internal and external validity.

Chapter 4 - Findings and Results

Introduction

As noted throughout the study, there is a need to more accurately predict the placement of community college students into math courses. Successfully doing so will benefit both the institution and the student. The chapter provides a summary of the overall study including the purpose, significance, design, and data collection regarding the study. The results of the logistic regression analysis are also discussed as well as answers to the questions and hypotheses. The chapter concludes with a summary of the findings.

Summary of the Study

Purpose of the Study

The purpose for conducting the study was to create a multiple measures placement model that could equally or more accurately place community college students into college-level math than test-only placement policies. The problem, specifically, is that many students are mis-placed by test-only policies (see Scott-Clayton, 2012), so finding more accurate alternative is essential in preventing students from unnecessarily taking remedial coursework. In addition to the extra time and money it takes to complete remedial coursework, it has been shown that students who are placed into remedial coursework are typically less likely to complete those sequences, leading to lower retention and completion rates.

Significance of the Study

The study is significant to a variety of higher education stakeholders. Professionals and administrators working in community colleges could greatly benefit from the results of the study. With the goal of any community college professional being student success, the results of the study could be directly applied at any community college to create new placement policies that

would hopefully increase retention and completion rates. For Arkansas, this also means increased funding as the State of Arkansas utilizes a performance funding model for its colleges that provides additional funds for completed credentials. For legislative stakeholders, reducing the number of students needing remedial coursework means the state has to provide less funding for remedial education, of which those funds could be routed to other important expenditures in higher education.

Design of the Study

To answer the research questions, a cross-section logistic regression was conducted. The result of the analysis was a model that represented variables relevant to student success in College Algebra. Variables of interest included *HS GPA*, *age* (time since high school), *last math course taken in HS*, *grade in last HS math course*, and *success in College Algebra*. *HS GPA* and *age* were both treated as continuous scale variables. *Last math course taken in HS* was collapsed into two sub-categories due to the heavy skew of students with Geometry as their last math in HS: “up to Geometry” and “above geometry.” This was treated as a categorical variable with “up to Geometry” being the reference group (coded as “0”). *Grade in last HS math course* was also treated as a ordinal variable (which in SPSS is treated as a scale variable). S*uccess in College Algebra* had six separate grades (“A,” “B,” “C,” “D,” “F,” and “W”) that were reduced down to two categories: “’C’ or better” and “below ‘C’.” Because logistic regression requires a binary outcome and the goal was to examine the independent variables’ ability to predict “success” in College Algebra, the grades were essentially grouped into “pass” and “fail” with “pass” containing grades of “C” or higher and “fail” containing grades of “D” or lower (including withdrawals).

Data Collection

Data were collected via a request to the Arkansas Department of Higher Education. Data were delivered via email September 29th, 2022. The dataset included all first-time Arkansas community college students who attended and tested into College Algebra during the 2017-2019 academic years. The dataset contained 11,409 total students. After cleaning the sample by checking for any data outside of the expected ranges (such as "ages" less than 1 year) removing any cases with missing data, and examining influential cases with DF Betas, 264 students remained to conduct the analysis. Categories in the data included college attended, academic year of entry, gender, test type, test scores, IPEDS race categories, grade in College Algebra, HS graduation year, final HS GPA, last math course taken in HS, and grade in last math course taken in HS. Age (time since HS graduation) was added to the dataset by calculating the difference between the given HS graduation date and the academic year of college entry.

Results

As shown below, although all variables were initially run in the regression to examine their significance in the model, some were removed due to collinearity issues and lack of significance. The final regression model included *HS GPA* and *age* as relevant predictors.

Demographics and Correlations

A frequency analysis of the information included in the dataset pertaining to gender and race was conducted to get an idea of the diversity of the sample. Results showed there were 161 females and 103 males included in the sample (see Table 4). This was not surprising as those identifying as female tend to outnumber those that identify as male in higher education. Comparing this the population of Arkansas, these numbers also make sense as those identifying as females are more represented in the state's population than are males. In terms of race, White

Table 4.
Demographic Breakdown of Sample by Race and Gender

Race	*n*	Percent
White	153	57.95%
Black	75	28.41
Hispanic	24	9.09
American Indian	2	.76
Native Hawaiian/Pacific Islander	1	.38
Two or more races	6	2.27
Unknown	3	1.14
Total	264	
Gender		
Male	103	39.02
Female	161	60.98
Total	264	

students (n = 153) were the overwhelming majority of students contained in the sample with Black students (n = 75) being the next highest group represented. Since the population for the State of Arkansas is predominately White, the sample seem to reflect the demographic trends of the state. Other groups represented were Hispanic (n = 24), Native Hawaiian (n = 1), American Indian (n = 2), two or more races (n = 6), and unknown (n = 3). The subgroup of Asian was contained in the original dataset, but no students who identified as Asian were in represented the final examined sample after eliminating all non-necessary elements from the dataset (for breakdown, see Table 4). Descriptive analysis revealed no particular issues with most of the variables. Analysis did show very high kurtosis and skewness for *age* and *age*GPA,* well above two standard deviations above the mean; however, because assumptions of normality do not apply to logistic regression the variables were still included in the analysis. Results of the Box-Tidwell analysis indicated that the Box-Tidwell transformation *was not* significant indicating it is not necessary to include curvilinear terms for *age* in the main analysis. Therefore, no curvilinear terms were used in the model. Before running the main analysis, results from the bivariate

correlation analysis were examined to determine preliminary correlations and examine whether there were any instances of multicollinearity (see Table 5 for correlation matrix). Results of the correlation analysis indicated overall low correlations between the dependent variable and the independent variables. Results also indicated a high correlation between *age* and the interaction variable *age*GPA* ($r = .96$). A second correlation analysis was conducted after mean-centering the *age* variable and recalculating the interaction term using that new variable. Results indicated that a high correlation still existed ($r = .98$). Though this likely indicates multicollinearity, the interaction term was included in the second model to check for possible significance and model improvement.

Correlation analysis revealed two variables with medium correlations to the dependent variable. Both *HS GPA* ($r = .24$) and *grade in last math course* ($r = .24$) were significantly correlated to *success in College Algebra*, $p < .001$. The interaction variable *age*HS GPA* also seemed somewhat correlated, though not as significantly as the aforementioned variables ($r = .15$, $p < .05$). *Age*, *last math* course, and *Accuplacer® test scores* were all not significantly correlated to the dependent variable. Also surprising was that *age* was positively correlated with the dependent variable. It was assumed that *age* would act as a counterbalance to *HS GPA* and lower the percentage probability of success, but that does not appear to be the case. This was also reflected in the results from the regression model.

Logistic Regression Model

After cleaning the data, removing cases based on DF Betas, examining the correlations and checking for curvilinearity via the Box-Tidwell variable, logistic regression tests were conducted that examined *HS GPA, age, grade in last math course, last math course taken in HS, HS GPA*age,* and *Classic Accuplacer® math scores.* Hierarchical modeling allowed for me to

Table 5.
Correlation Table of Examined Variables

Variables	1	2	3	4	5	6	7
Success in College Algebra (1)	-						
HS GPA (2)	.24**	-					
Age (MC) (3)	.12	-.35**	-				
Grade in Last HS Math (4)	.24**	.61**	-.15*	-			
Last Math Course Taken (5)	.16*	.12*	.10	.16*	-		
Accuplacer® Math Scores (6)	.06	.18**	-.09	.08	.10	-	
Interaction (age(MC)*HS GPA) (7)	.15*	-.20**	.97**	-.05	-.63	.11	-

*. $p < .05$; **$p < .01$

see if the addition of each variable was not only significant to the model (determined by checking the stepwise Chi-Squared significance and the -2 loglikelihood), but also significant as a co-variant (determined by looking at the significance of the regression coefficient). Because the models are nested analyses, direct comparisons of the resulting -2loglikelihood was possible to determine the regression with the best model fit. The first regression model was used to determine the baseline variables that should be considered to examine alongside the interaction variable as well as to check significance of adding Classic *Accuplacer® math scores.* Coefficient significance was determined based on the significance of the corresponding Wald's test significance.

An important note of interpretation of output for logistic regression is that the outcomes produced by logistic regression models are expressed in terms of log-odds (the logit form of odds-ratios). However, discussing outcomes in terms of log-odds is not only generally confusing to understand, but also an impractical means of interpretation of the model coefficients. As such,

the coefficient results are discussed below in terms of the odds ratios (exp(B)) also calculated by the analysis. For further clarity of interpretation, conditional probabilities were also calculated for certain examples as it more pertains to "likelihood" than odds ratios.

Regression Model 1

The first regression analysis included *HS GPA, age, grade in last math course,* and *last math course taken in HS.* Results showed that the overall model fit with the four variables compared to a model with no variables is χ^2 (4, 264) = 33.77, $p < .001$. The -2loglikelihood associated with the model change was found to be 321.10. With no other models to compare against, the -2loglikelihood was not worth considering at this time. Per the classification table provided from the analysis, the model had an overall prediction accuracy of 65.9, meaning it correctly predicted 65.9% of all cases in relation to the dependent variable (see Table 6 for all model results). Results from the coefficient analysis indicated that *HS GPA* and *age* were both significant predictors in the model (OR = 2.85, CI = [1.35, 5.99], $w = 7.58$, $p < .01$ and OR = 1.28, CI = [1.09, 1.51], $w = 8.74$, $p < .01$ for *HS GPA* and *age*, respectively) while *last math course taken in HS* and *grade in last HS math course* were both non-significant. As such, *last math course taken in HS* and *grade in last HS math course* were both removed from consideration in the second analysis.

Regression Model 2

The second regression analysis was run hierarchically with *HS GPA* and *age* (mean-centered) included in block 1 and the interaction of *HS GPA*age* included with the other variables in block 2. Results of the overall model that included the interaction variable showed an overall model fit of χ^2 (3, 264) = 28.60, $p < .001$ indicating a worse fit than the first regression model (χ^2 (4, 264) = 33.77, $p < .001$). This was also supported by the -2loglikelihood as block 1

Table 6.
Regression models with corresponding standardized betas, odds-ratios, and standard errors

	Model 1 *N* = 264		Model 2 *N* = 264		Model 3 *N* = 264	
	β (SE)	e^{β}	β (SE)	e^{β}	β (SE)	e^{β}
HS GPA	1.046* (.38)	2.85	1.60** (.43)	4.95	1.45** (.31)	4.21
Age	0.25* (.08)	1.28	0.51 (.47)	1.67	0.27** (.82)	1.12
Last HS Math Course	0.60 (.40)	1.81	-	-	-	-
Grade in Last Math Course	0.27 (.17)	1.30	-	-	-	-
Age*HS GPA		-	-.10 (.19)	0.91	-	-
Classic Accuplacer® Math Score		-	-	-	0.002 (.01)	1.00
Intercept	-3.66		-3.76		-3.90	

* = $p < .01$, ** = $p < .001$

was 326.53 whereas block 2 was 326.26 ($\Delta\chi^2 = .27$, $p = .60$) meaning there was no significant addition to model fit from adding the interaction variable to the model. The overall prediction rate was also lower than the previous model with this model showing a prediction rate of 62.9%. For predictors, not only was the interaction term found to be non-significant, it also sharply decreased the significance of *age* to the point of it becoming non-significant. Because of this, the interaction variable will not be included in future models.

Regression Model 3

The third regression analysis was also run hierarchically and contained *HS GPA and age* included in block 1 and *Classic Accuplacer® math scores* included with the remaining variables in block 2. Results of the analysis showed an overall model fit of χ^2 (3, 264) = 28.44, $p < .001$. Block 1 had a -2loglikelihood of 326.53, $\chi^2 = 28.44$. The addition of *Classic Accuplacer® math*

scores did not contribute significantly to the model when compared to block 1 (-2LL = 326.53, $\Delta\chi^2$ (1, 264) = .110, p = .74). This also meant that the coefficient for *Classic Accuplacer® math scores* was also non-significant (OR = 1.002, CI = [.99, 1.01], w = .110, p = .74). As such, it was not considered for inclusion in the final model.

The Final Multiple Measures Model

After all variables were examined for significant contributions to the model fit, the final model included only *HS GPA* and *age*. It was expressed below with the corresponding ***logged*** coefficients:

$$\hat{\mathbf{Y}}\mathbf{(ln(p/1\text{-}p)) = -4.32 + }\boldsymbol{b}\mathbf{(.31)X_{GPA} + }\boldsymbol{b}\mathbf{(.08)X_{AGE}}$$

It is worth noting, though, that while the overall accuracy from the classification table (see Table 7) was 62.9%, the accuracy for predicting success in college algebra was much higher, with a percentage of 80.5%. This meant that the model was predicting success at a far higher rate (over double) than it was predicting failure of College Algebra (failure rate prediction was 36.2%). *HS GPA* was found to have an odds-ratio of 4.27 (OR = 4.27, CI = [2.32, 7.85], w = 21.76, p < .001). As a continuous variable, this indicated that for every one-point increase in *HS GPA*, the odds of a student with similar other characteristics passing College Algebra were 4.27 times that of a student one point below that GPA. For example, if Student 1 had a HS GPA of 3.3 and was two years out of high school was compared to Student 2 who has a 2.3 HS GPA and was two years out of high school, the former student would be 4.27 times as likely to pass College Algebra than the latter student. Another interpretation is that Student 1 would have 327% higher odds of passing than Student 2. For further clarification, an example can be given using conditional probability. Using the same scenario, Student 1 would have a 73.2% chance of passing College Algebra of (i.e. a 73.2% likelihood) while Student 2 would have a 39.1%, a

Table 7.
Classification table for final model that included HS GPA and age

Observed		***Predicted***		***% Correct***
		Below "C"	"C" or better	
Success in College Algebra	Below "C"	38	67	36.2
	"C" or better	31	128	80.5
Overall Percentage				62.9

difference of 34.1%.

The variable *age* was also found to be significant for inclusion in the final model. *Age* was found to have an odds-ratio of 1.31 (OR = 1.31, CI = [1.12, 1.54], $w = 10.86$, $p < .001$). The analysis showed that for every one-year increase in *age* (time since high school), the odds of success in College Algebra were 1.31 times that of a student one year lower. Putting it another way, a student one-year higher in age taking College Algebra would have 31% higher odds of passing than a student one year below. That would mean that if Student 1's *age* was one year higher than of Student 2 who had similar other characteristics would have increased odds of passing of 1.2 times that of the other student. So, if Student 1 had a 3.3 HS GPA and was 5 years out of high school, their likelihood of passing would be 86%. If Student 2 has a HS GPA of 3.3 and is 4 years out of high school, their likelihood of passing would be 82.4%, a difference of 3.6%.

Model Accuracy with Underrepresented Students

To assess how well the model predicted success in College Algebra for racially underrepresented non-traditional students, the predicted pass rate based on my final model was calculated for all non-White students in the sample using *HS GPA* and *age*. It was found that the model predicted that only 15 of the 112 (13.4%) students would pass College Algebra. In actuality, 49 of 112 (43.8%) students actually passed college algebra, a difference of 30.4%

(error rate). When looking at percentage of students correctly placed (predicted pass/actual pass [15/49]) that number is 30.6%, meaning my model correctly predicted 30.6% of underrepresented students who actually passed College Algebra. Test scores alone were able to correctly predict passing grades for 51 of 112 students (45.5%).

For prediction of failure, my model predicted that 96 of 112 (85%) students would fail College Algebra despite *Classic Accuplacer®* test scores predicting all 112 should be able to pass. The actual number of students who failed was 61 of 112 (54.5%). Because the 112 students were all predicted to pass based on test scores, this means that over half of those predicted to pass based on test scores alone were misplaced. My model would have only misplaced 30.6% (predicted fail % - actual fail %) of students predicted to fail compared to the percentage of students who did end up failing based on math scores alone (54.5%).

Research Questions and Hypotheses

Results of the analysis were used to determine whether or not the research questions and hypotheses were answered or accepted. Each question and its corresponding hypothesis were discussed below.

1. *What was the demographic profile of the subjects included in the research sample?*

Research Question 1 was used to understand whether the demographic information of the collected sample was similar to that of the population of the State of Arkansas. An important aspect in quantitative research is seeing whether your research can be generalized to a population, in this case the State of Arkansas. The demographic information showed that the sample was very similar in composition to the population of Arkansas. Those that identified as female (n = 161) were the majority in the sample compared to those that identified as male (n = 103). The sample seemed to contain a higher percentage of those that identified as female

compared to the state as a whole. Females represented 60.9 % of the sample and males 39.9% compared to 49.1% for females and 50.9% for males for the population of the state. This is not entirely unusual though as previous research has shown that higher education as a whole tends to enroll a larger number of females than males. Racially, White students (58%) appeared to be the overwhelming majority in the sample, a similar phenomenon that occurs in the population of Arkansas (71%). The second highest demographic in the sample was Black (28%), again, following the overall trend in the Arkansas population (16%). In terms of R*esearch Question 1*, it was shown that the demographics of the sample align closely with the state of Arkansas.

2. *Did multiple measure assessments equally or better predict non-traditional student success in College Algebra than Classic Accuplacer® math scores?*
    a. *What factors predicted non-traditional students' success in passing entry-level college math courses?*
    b. *Did age influence the relationship between HS GPA and success?*

To answer Research Question 2, the following hypothesis was generated:

H1: *HS GPA*, *Classic Accuplacer® math scores*, *age*, *grade in last HS math class*, *last HS math course taken*, and *age***HS GPA* are equal to or better at predicting success in college-level math than *Classic Accuplacer® math scores* alone.

- H0: $\chi^2 = 0$
- H1: $\chi^2 \neq 0$

Hypothesis 1 related to Research Question 2 was fully supported by the study. The results of the analysis showed that *Classic Accuplacer® math scores* contributed no additional predictive significance to the overall model when other factors were examined, leading it to be removed from the final model.

To answer Research Question 2A, the following hypothesis was generated:

H2: *HS GPA*, *age*, *last HS math course taken*, *grade in last math course*, and *age*HS GPA* are significant predictors of success in college-level math. Accuplacer® math scores were non-significant when including HS GPA and Age.

- H0: $B_1 = B_2 = B_3 = B_4 = B_5 = B_6 = 0$
- H1: $B_1 \neq B_3 \neq B_4 \neq B_5 \neq B_6 \neq 0$; $B_2 = 0$

Research Question 2A was found to be partially supported from the study. Results indicated that both *HS GPA* and *age* had significant regression coefficients and also contributed to the significance of the overall model accounting for a 62.9% accuracy rate in predicting success in College Algebra. However, *last HS math course taken*, *grade in last HS math course, age*HS GPA*, and *Classic Accuplacer® math scores* were all found to be non-significant.

To answer *research question 2b*, the following hypothesis was generated:

H3: Age (time since HS graduation) has an interaction effect with GPA and will be curvilinear nature.

- H0: $B_{\text{GPA*AGE}} \geq 0$

  $B_{\text{GPA*AGE}^2} \geq 0$

  $B_{\text{GPA*AGE}^3} \geq 0$

- H1: $B_{\text{GPA*AGE}} \leq 0$

  $B_{\text{GPA*AGE}^2} \leq 0$

  $B_{\text{GPA*AGE}^3} \leq 0$

Hypothesis 3 relating to Research Question 2B was fully rejected based on the analysis. Though *age* was included as a significant variable in the final model, the interaction term used in

the initial was found to be non-significant. Curvilinearity was also rejected based on the results of the Box-Tidwell variable used to test for curvilinearity.

3. *Did the final multiple measures model equally, or more accurately, assess underrepresented non-traditional minority placement into College Algebra?*

H4: To answer Research Question 3, Microsoft Excel was used to examine the accuracy of prediction for all non-White students in the sample. This was accomplished by entering the final model into the program and using the students' information to calculate their likelihood of passing College Algebra. From there, a comparison between the predicted and actual pass fail was conducted to see the percentage of placement (or misplacement). It was hypothesized that the model would place underrepresented students more accurately than test placement scores alone. Overall, the MMA was found to be more accurate (or, less inaccurate) than *Classic Accuplacer® math* scores when predicting failure; however, *Classic Accuplacer® math scores* more correctly predicted success than the MMA. Though the inaccuracy rate for both the MMA and *Classic Accuplacer® math scores* were considerable, the placement scores had a lower rate of misplacement (predicted to pass but didn't) than the MMA (45.5% versus 30.6%). This was also true for students predicted to fail, but actually passed. As such, the results showed that MMAs better predicted success of failure, while *Classic Accuplacer® math scores* were better able to predict success for racially underrepresented non-traditional students. This led to a partial acceptance of H4.

Summary

The chapter was used to examine the results from the study. A summary of the overall study was provided including the purpose, significance, design, data collection, data analysis, and hypotheses. The demographic information in the sample was closely aligned to that of the

State of Arkansas' population, providing support for the ability of the study findings to be generalized across the case study state. When analyzing the variables in question via logistic regression modeling, it was found that *HS GPA* and *age* were both predictive of success in College Algebra. It was also found that *Classic Accuplacer® math scores* were non-significant when examining other factors such as HS GPA and years since high school. A further examination of the interaction term's significance and exploration of curvilinearity with *age* found no evidence of either. Finally, the chapter looked at the model's impact on underrepresented racial minority non-traditional students. It was identified that although the model has a better prediction rate than placement test scores when predicting underrepresented non-traditional students' failure in College Algebra, it performs slightly worse than placement test scores when predicting success. This led to a partial rejection of H4, partially answering Research Question 3. This section concluded with a summary of the findings.

Chapter 5 - Conclusions and Recommendations

Introduction

This section provides a summary of the study as well as a discussion of the findings and recommendations for practice. The chapter concludes with recommendations for future research, a conclusion of thoughts, and a final summary of the chapter.

Summary of the Study

Purpose of the Study

The purpose for conducting the study was to create a multiple measures placement model that could equally or more accurately place students into college-level math than test-only placement policies. It was also to determine whether standardized placement tests are still worth considering in placement when the presence of other student information is examined. This is important as previous research has shown that MMAs ability to predict success in college-level courses is equal to, and often greater than, placement test scores (Bahr, 2018; Scott-Clayton, 2012; Scott-Clayton et al., 2014; Woods et al., 2018). Because many students are mis-placed by test-only policies (see Scott-Clayton, 2012), finding an alternative, accurate alternative is essential in preventing students from unnecessarily taking remedial coursework. In addition to the extra time and money it takes to complete remedial coursework, it has been shown that students placed into remedial coursework are typically less likely to complete those sequences, leading to lower retention and completion rates.

Significance of the Study

The study was significant to a variety of higher education stakeholders. To begin, professionals and administrators at community colleges would greatly benefit from the results of the study. With the goal of any community college professional being student success, the results

of the study could be directly applied at any community college to create new placement policies that would hopefully increase retention and completion rates. For Arkansas, this also means increased funding as the State of Arkansas utilizes a performance funding model for its colleges that provides additional rewards for completed credentials. For state legislative stakeholders, reducing the number of students needing remedial coursework means fewer resources have to be invested towards remedial education.

Design of the Study

Cross-sectional logistic regression analyses were conducted to assist in answering the research questions. Demographic information was also examined to determine whether the demographic make-up of the sample was similar to that of the State of Arkansas. Error rates were also calculated based on a combination of the logistic regression and demographic data to examine the model's predictive ability with underrepresented, racial minority non-traditional students. Independent variables examined were *HS GPA*, *age*, *last math course taken in HS*, *grade in last HS math course*, and *HS GPA*age*. The dependent variable was *success in College Algebra*. *HS GPA* and *age* were both treated as continuous variables. *Last HS math course taken* was collapsed into two sub-categories: "up to Geometry" and "above geometry." This was treated as a categorical variable with "up to Geometry" being the reference group (coded as "0"). *Grade in last HS math course* was treated as an ordinal variable ("A" = 5, "B" = 4, "C" = 3, "D" = 2, and "F" = 1). S*uccess in College Algebra* was comprised of six separate grades ("A," "B," "C," "D," "F," and "W") that were reduced to two categories: "'C' or better" and "below 'C'."

Data Collection

The data were collected from the Arkansas Department of Higher Education and the resulting dataset included first-time Arkansas community college students that attended and

tested into College Algebra during the 2017-2019 academic years. The initial dataset contained 11,409 total students, but after cleaning the dataset of errors and unusable data, 264 students remained to be included in the data analysis. Categories in the data included college attended, academic year of entry, gender, test type, test scores, IPEDS race categories, grade in College Algebra, HS graduation year, final HS GPA, last math course taken in HS, and grade in last math course taken in HS. Age (time since HS graduation) was added to the dataset by calculating the difference between the given HS graduation date and the academic year of college entry.

Data Analysis

Research Questions and Hypotheses

Below are the research questions used to guide the study along with whether or not the data supported the hypotheses:

1. *What was the demographic profile of the subjects included in the research sample?*

An examination of the demographic breakdown of the data revealed that the sample contained a very similar composition to that of the State of Arkansas. In terms of gender, students who identified as female represented a higher portion of the sample than those who identified as male (161 and 103, respectively). For race, White students represented the large majority of sample at n = 153 (57.95%) followed next by Black students (n = 75, 24.41%). Other races included in the sample were Hispanic (n = 24, 9.09%), Native Hawaiian (n = 1, .38%), American Indian (n = 2, .76%), two or more races (n = 6, 2.27%), and unknown (n = 3, 1.14%).

2. *Did multiple measure assessments equally or better predict non-traditional student success in College Algebra than Classic Accuplacer® math scores?*
   a) *What factors predicted non-traditional students' success in passing College Algebra?*
   b) *Did age influence the relationship between HS GPA and success?*

H1: *HS GPA*, *Classic Accuplacer® math scores*, *age*, *grade in last HS math class*, *last HS math course taken*, and *age*HS GPA* are equal to or better at predicting success in college-level math than *Classic Accuplacer® math scores* alone.

H1 was used to examine whether an MMA using factors outside of test scores would benefit from their addition to the model. This was done to see whether the predictive power of MMAs was improved with the addition of *Classic Accuplacer® math scores* or whether information from high school could just as accurately predict success in College Algebra. Results showed that the inclusion of *Classic Accuplacer® math scores* did not improve the predictive accuracy of the model, leading to a rejection of the null hypothesis and an acceptance of H1.

H2: *HS GPA*, *age*, *last HS math course taken*, *grade in last math course*, and *age*HS GPA* are significant predictors of success in college-level math. Accuplacer® math scores were non-significant when including *HS GPA* and *age*.

H2 was used to examine what specific factors, if any, contributed to the predicted accuracy of an MMA. It was predicted that *HS GPA*, *age*, *last HS math course taken*, *grade in last math course*, and the interaction of *HS GPA*age* would be significant in the model. It was also predicted that *Classic Accuplacer® math scores* would not be a significant variable when other factors were examined. Analysis showed that only *HS GPA* and *age* were significant in the model as determined by the Wald's statistics associated with the analysis. As predicted, *Classic Accuplacer® math scores* were not significant in the model when *HS GPA* and *age* were included. This led to a partial acceptance of H2.

H3: *Age* (time since HS graduation) has an interaction effect with *HS GPA* and will be curvilinear nature.

H3 was used to examine whether an interaction term may exist between *HS GPA* and *age*. It was also used to test whether there may be higher order terms (curvilinearity) for *age* and, if so, whether those higher order terms extended to the interaction. After examining the Box-Tidwell results it was determined that no curvilinearity existed in the *age* variable, and, as such, higher order terms were not included in any of the tested models. To examine the significance of an interaction, the interaction term was included in model 2. Results showed that *HS GPA*age* was not significant in the model and was subsequently removed from inclusion in future models. Results from the analysis led to a full rejection of H3 and acceptance of the null hypothesis.

3. *Did the final multiple measures model equally, or more accurately, assess underrepresented non-traditional minority placement into college-level math?*

H4: To answer research question three, Microsoft Excel was used to filter the data by gender and race to examine model improvement of prediction accuracy over original *Classic Accuplacer®* *math score* placement. It was hypothesized that the model would better predict passing and failing of underrepresented students better than test placement scores alone.

Results

Results of the study showed that the sample used was relatively in-line with the overall population of the State of Arkansas. Demographic analysis showed that the sample contained 161 students who identified as female and 103 who identified as male. When examining race, the analysis revealed that White students were the majority identified in the sample ($n = 153$) followed by Black ($n = 75$), Hispanic ($n = 24$), two or more races ($n = 6$), unknown ($n = 3$), American Indian ($n = 2$), and Native Hawaiian ($n = 1$).

Results of the logistic regression analyses revealed that *HS GPA* and *age* were the only significant variables related to *success in College Algebra*. Three models were used to determine

variables of significance, culminating in a final regression model containing *HS GPA* and *age*. The final model created from the examination was:

$$\hat{\mathbf{Y}}\mathbf{(ln(p/1\text{-}p)) = -4.32 + \mathit{b}(.31)X_{GPA} + \mathit{b}(.08)X_{AGE}}$$

HS GPA was found to have an odds-ratio of 4.27 (OR = 4.27, CI = [2.32, 7.85], $w = 21.76$, $p < .001$) indicating that for every one-point increase in GPA, the odds of successfully completing College Algebra were 4.27 times that of a student one-point below. It was also found that *age* had an odds-ratio of 1.31 (OR = 1.31, CI = [1.12, 1.54], $w = 10.86$, $p < .001$) meaning that for every one-year increase in *age*, the odds of successfully completing College Algebra are 1.31 times that of a student one year below. When examining the final model's ability to better predict placement of underrepresented, racial minority non-traditional students, it was found that the model was better at predicting failure of College Algebra, while *Classic Accuplacer® math scores* were slightly better at predicting success.

Conclusions

The results from the analysis of the data were examined and used to draw four main conclusions based on the original hypotheses. Those conclusions are:

1. Overall, pre-existing student high school information were more accurate in determining student placement into College Algebra than test scores alone. Because hierarchical regression techniques were used, I was able to see if adding *Classic Accuplacer® math scores* increased the model's accuracy and significance beyond what was already accounted for by the other high school related variables. The answer was, no, adding placement test scores did not add any predictive power to the model, neither in terms of overall model significance nor model accuracy. This would indicate that *Classic Accuplacer® math scores*

are not useful predictors of potential success in College Algebra for students at Arkansas community colleges.

2. Hypothesis 2 stemmed from the need to understand what, if any, of the research-based variables selected for consideration would contribute meaningfully to the final model. As such, it was important to examine the variables in such a way that would allow me to create the most parsimonious model to be used as the final model. The analysis revealed that *HS GPA* and *age* were the only significant factors. *HS GPA* had the strongest correlation with the outcome variable, confirming previous research that found HS GPA to be the most significant factor when predicting success in college-level math. Though *age's* correlation and subsequent coefficients were relatively low, it was still found to make a significant contribution to prediction.
3. *Age* as an interaction term with *HS GPA* does not seem to influence a student's ability to successfully complete College Algebra. It was originally hypothesized that not only would *age* and *HS GPA* have an interaction, but also that the interaction would contain some type of curvilinear term. Neither of these original presumptions were supported by the data. This could indicate that no negative effect exists for non-traditional community college students who are further out of high school than more traditional students. As such, it may not be prudent to consider such terms when creating an MMA placement policy.
4. *Classic Accuplacer® math scores* were better in predicting underrepresented, racial minority non-traditional students' ability to pass than the model. The placement test scores predicted that all 112 students identified as underrepresented students would pass (otherwise, they would not have been placed into College Algebra to begin with). Well over half of the students predicted to pass based on *Classic Accuplacer® math scores* did not pass College

Algebra (54.5%; meaning an accuracy rate of 45.5%). When compared to the prediction of MMAs, the model predicted that only 15 students would pass; however, 49 students actually passed the course, accuracy rate of 30.6%. When predicting failure, MMAs only had an error rate of 30.4% (97/112 predicted to fail minus 61/112 who actually failed). Overall, MMAs were better at predicting failure whereas *Classic Accuplacer® math scores* were better at predicting success.

Discussion

The logistic regression analyses revealed some interesting information. The study's unique contribution to the literature was to examine *age* (time since HS) as a unique variable that could be used in an MMA; however, there were many interesting findings in relation to the variable. First, curvilinearity was suspected to be present with the variable *age*. Some previous research that indicated age could have a curvilinear relationship with information loss (measured in that research as scores on a math test; see Bahrick & Hall, 1991) as a function of highest level of math taken in HS. Despite this, the Box-Tidwell test determined that no curvilinearity was present in the sample.

In addition, not only was *age* not found to be curvilinear in the sample, there was also no interaction between *age* and *HS GPA*. This showed that age may not mitigate the influence of HS GPA on the ability for students to successfully pass College Algebra. As a reminder, *Research Question 2B* hypothesized that *age* would not only have influence the relationship between *HS GPA* and *success in College Algebra*, but that the relationship would likely be negative. In theory this is sound as previous research has shown that the longer students don't apply information they have learned, the less they will be able to recall as time passes (Bahrick & Hall, 1991). This is a particularly emphasized point in relation to how we understand HS GPA as measurement.

High schools have certain learning requirements that must be met throughout a student's education. We typically think of HS GPA as the measure of the knowledge gained throughout one's HS career; however, the lack of significance of the interaction term would indicate that knowledge loss may not be as relevant of a factor as we believe as related to *HS GPA*. It may be possible that the lack of significant findings of the interaction term indicates that *HS GPA* as a measure is encompassing of other non-cognitive factors such as GRIT, motivation, study habits, and/or access to resources. This could explain the lack of a negative influence from *age* despite previous research indicating knowledge loss over time.

The analysis also revealed that not only was there no interaction, but that *age* had a positive correlation with *success in College Algebra.* Bean and Metzner (1985) discussed how age plays a significant factor in student persistence in higher education. Though, they suggested that older students have more responsibilities (families, jobs, social, etc…) which would interfere with a student's ability to succeed (Bean & Metzner, 1985). The findings of this study ran counter to this as *age* was shown to *increase* the odds of success for non-traditional students. One reason for this could be that as non-traditional students become older, their motivations for succeeding may increase. This would mean that despite the fact they may not recall much of the math they learned in high school, they possess a higher propensity to succeed in college and therefore apply more effort to their class. Another surprising find was that *age* was not significantly correlated when all variables were present; however, the addition of *age* to the model was found to be significant in the regression for both the model overall and as a co-variable. I believe this could be due to some of the other non-significantly correlated variables were acting as suppressor variables, thus hiding *age*'s potential as a significant variable.

Second, though previous research has provided some guidance on what high school information may be worth examining in MMAs, *last math course taken in HS* and *grade in last HS math* were both found to be non-significant. Though the significance of the variables was not high enough to include them in the final model, previous research has shown that in some instances they can provide additional predictive information in addition to other included variables and therefore may warrant further study. Unsurprisingly, *HS GPA* was found to be highly significant in all three models as supported by previous research (Bahr, 2016; Scott-Clayton, 2012; Scott-Clayton et al., 2014; Woods et al., 2018). Bean and Metzner (1985) suggested that HS GPA could be a predictor of attrition in non-traditional students. They discussed that this could be due to either an inability to do well in college-level coursework or possibly a motivational issue for students (Bean & Metzner, 1985). Applying that to the study, it was predicted that *HS GPA* would a significant variable for consideration.

With COVID-19 having exposed many of the flaws in the higher education system, one great change was the implementation and use of new policies, procedures, and technologies. As the literature review explored, up until COVID-19 many colleges (especially community colleges) were heavily relying on placement tests as a major factor in determining student readiness for college-level courses (Rutschow et al., 2019). This was questionable since some researchers have explored the extreme unreliability of those tests (Belfield & Crosta, 2012; Scott-Clayton, 2012; Scott-Clayton et al., 2014). As a result of these policies, many students who potentially could have passed college-level courses were placed into remedial courses, delaying their graduation or causing them to leave higher education. This is especially true for college-level math (College Algebra) with it being a noted gatekeeper course among community college students. During COVID, when colleges were unable to rely on test-only measures due to lack of

sites available to offer the exams, community colleges were forced to find alternative, equally accurate assessments to place students. The results in many cases were the implementation of multiple measures assessments (MMAs) which could use other information outside of standardized test scores to determine student readiness for college-level courses. However, due to their lack of ubiquity, MMAs often vary from college-to-college in not only their effectiveness, but also what is being examined.

The study looked to assist community colleges in the State of Arkansas by examining important variables related to student success in College Algebra in hopes of providing an alternative placement model with research examined variables. Specifically, *age* was included to examine whether non-traditional students are negatively affected by the lapse in time since high school. To assist in determining important factors related to success, *HS GPA, age, last math taken in HS, grade in last math course, HS GPA*age,* and *Classic Accuplacer® math scores* were examined. The result of the study indicated that *HS GPA* and *age* (time since HS) are viable variables that could be used in an algorithmic MMA to examine student potential for success in College Algebra. Results also indicated that *Classic Accuplacer® math scores* did not add any additional predictive power to the model when other factors were examined. Per the crosstabulation chart, the model was found to have a 62.9% prediction rate, putting it at least as equally predictive of success as what research has determined standardized tests, such as the *Classic Accuplacer®*, can provide. Hopefully, Arkansas community colleges can make use of the information in the study to better understand methods of creating an MMA and what factors to consider.

Recommendations

Recommendations for Practice

As colleges are finding new ways to determine whether students are ready for college-level coursework, guidance is needed to assist them in understanding what options and methods are available and reliable. For Arkansas, though the Arkansas Department of Education has very good information on the usefulness of MMAs, they fall short of giving proper guidance to colleges in how to set up such models. Though they do provide a list of measures that could be included in an MMA, no weight is given to any of the measures to assist colleges in determine the best choice of variables to examine. The results of this study assisted with this lack of guidance in helping to establish a method of measurement and research-based variables that could be used to create a more holistic model of student success. As previous research suggests, MMAs have been shown to be very effective in properly placing students into coursework, especially compared to placement tests. I recommend that colleges in the State of Arkansas use their existing historical student data and apply the variables examined in the study to create their own algorithmic MMA. Once a baseline is set using this data, colleges could simply update the data every few years to adjust for any changes in the student population.

The main advantage to implementing this type of assessment is two-fold. First, it eliminates a concern among non-traditional students related to test-taking. Many non-traditional college students tend to do poorly on placement exams because they don't understand the point of the test or are not given proper time to prepare. Since MMAs have been shown to have accuracy rates equal to, or better than, standardized tests, allowing students to be placed without the need for a stressful exam would greatly benefit students. Second, because algorithmic MMAs create models where the result is a single output, it is easily interpretable based on whatever

threshold the state or college has decided on. Since the output would be based on an algorithm, any change in variables would be automatically accounted for, again giving a simple, easily interpreted output. This is important since Arkansas requires a “greater than 75% likelihood of passing” as the criteria for placement into coursework (Arkansas Department of Higher Education, 2016). Even more important is the fact that the output of logistic regression is a conditional probability of likelihood, making it perfect for colleges in Arkansas to use to establish placement policies.

I also recommend colleges stop using placement test data altogether for assessment purposes. This study reaffirmed what previous research had suggested which is that placement test scores, when examined with other reliable variables, do not add any predictive power in determining student readiness for college-level math (in this case, College Algebra). With their low correlation to student success and low predictive capabilities (especially when HS information is available), placement tests are becoming more obsolete as time passes. This is especially pertinent given that many community college students, particularly non-traditional students are more likely to be first-time students, often do not understand the importance of placement exams and thus are often not prepared to take such a test (Bailey et al., 2015). To add to this, many students that enter community colleges are from low-SES backgrounds and may have trouble paying the examination fee for the test.

Recommendations for Future Research

Future research on this topic should include the application of these models in conjunction with one or more Arkansas community colleges. Though the models show important factors and provide useful information (such as coefficients), because the model relies on state-wide data it cannot be directly applied at a single institution. Research should examine these

models with unique institution data to determine thresholds for individual colleges, then those models should be cross-checked by running them against a sample of students placed into remedial courses. From there, calculating the "severe-error rate" as defined by Scott-Clayton (2012) should take place to see the severity of misplacement as well as to ensure the model is actually improving placement based on the set criteria.

Another area of future examination should be to see what the impact of such models are based on gender. Though the study provided some insights into how the variables used in the final MMA affected underrepresented racial minority students, affects on gender were not examined. This is a particularly important lens as well since previous research has indicated that students who identify as female are placed into remedial courses as a higher rate than students who identify as male. One of the goals of research related to MMAs and their success is to provide more accurate college-level placement for students. A necessary step towards this goal is to ensure that the models created are not perpetuating or increasing gender or racial bias that may be inherent in higher education placement policies, leading to further discrimination of already vulnerable populations. Therefore, future research should examine and consider variables' impact on students of different genders.

Since GED students were not examined in the study, future research related to this should also focus on identifying thresholds for that population. Since many non-traditional students did not complete high school and instead obtain a GED, ensuring that there is a model to account for GED students will be important to improve placement for all students. Beyond this, future work should also examine placement into co-requisite college-level work as opposed to pre-requisite-based courses. With co-requisite models having become popular in the last few years, and with

research to show that not only are they faster but have better outcomes, examining the MMAs accuracy in co-requisite courses will be important.

Though the study did examine data related to math courses taken during high school, a large (and unforeseen) issue related to this was that much of the sample used was heavily skewed towards "geometry" as the last math course taken in high school. Because of that, the variable was collapsed into two categories of math: "up to geometry" and "above geometry." Though the variable was found to be non-significant in the model, future research should explore a more robust sampling of high school math courses. Specifically, instead of "last math course taken in high school," future research may want to instead include "highest math course taken" as it seems a multitude of students in Arkansas take Geometry as their final math course. Examining the highest math course taken may provide some variability in the sample and help with placement.

Although the findings from this study did not uncover aspects of curvilinear or interaction terms, I believe these variables to be worth examining in future research. As of now, the inclusion of such variables is still understudied in relation to MMAs. Though the analysis used was sufficiently powered given the number of variables in the initial model, a more robust sample may uncover details related to *age* that were missed in this study.

As previously mentioned, the *Next Generation Accuplacer*® was introduced as the replacement to the *Classic Accuplacer*® in 2019 (CollegeBoard, 2018). As such, it would be prudent for future research to examine the significance of the *Next Generation Accuplacer*® in the context of the non-test variables mentioned in the study. It is important that research try to keep up with new forms of measurement as related to their effect on students. Although the results of the study showed that the *Classic Accuplacer*® math scores provide no additional

predictive importance beyond the other factors considered, the *Next Generation Accuplacer®* should also be tested to see if that result still holds true. It could be that the newest iteration of the test has significant improvements to its ability to predict student success in college-level coursework and thus *should* be included in a multiple measures assessment. Also related to this is fact that the range for *age* was quite small (10 years).

Another area related to this conversation is also *age's* effect on placement test scores. If community colleges in Arkansas plan on continuing to use placement exams as a factor in determining college-readiness, an examination of whether *age* has the potential to negatively affect test scores would be an important idea to consider. It is well established that a large percent of community college students are considered non-traditional by age alone. Applying Bahrick and Hall's (1991) findings in this context, it would be expected that students further out of high school would likely do worse on such placement tests, thus leading to older students being placed into remedial courses more often than more traditional students. Also applying Bean and Metzner's (1985) theory in this context, it would be expected that not only could previous HS performance play a role in students' performance on placement tests, but also that outside obligations (such as family, social responsibilities, work, etc...) may also influence their scores on placement exams. This information is important to understand because it would allow colleges insight into whether more support for these students is needed during the intake process to better prepare them to take such an examination. Also, colleges would want to provide better information in regards to the purpose of the test so that students understand the possible outcomes of their performance on a placement test. Since the sample that was examined contained first-time students who *directly placed* into College Algebra, it may be worth having future research look into whether or not students further out of high school have lower outcomes

on placement tests. This could provide further insight into whether or not placement tests (such as the Accuplacer®) are acting as gatekeepers to college-level courses for older non-traditional students, thus increasing their chances of attrition. If my model were to be applied to students that *did not* test directly into College Algebra whose *age* exceeds that of the sample, it could be found that many of the students who were denied entry into College Algebra could have passed based on other factors.

Summary

This chapter provided summary of the study and as well as the conclusions that emerged from the study. A discussion of the conclusions that were drawn and recommendations for practice and future research were also discussed. The chapter concluded with a final summary of the chapter.

References

Arkansas Community Colleges. (2020). *Arkansas community college fall 2020 enrollment summary*. Arkansas Community Colleges. Retrieved from https://static1.squarespace.com/static/5718f21001dbae63bf3315d0/t/6009a009fae2197b0c4de67e/1611243529938/ACC+Fall+2020+Enrollment.pdf

Arkansas Department of Higher Education. (2016). *Student placement into general education core courses*. Agenda item no. 9. State of Arkansas. https://static.ark.org/eeuploads/adhe/08_-_Student_Placement_into_General_Education_Core_Courses.pdf

Arkansas Department of Higher Education. (2015a). A*nnual report on student retention and graduation.* Agenda item no. 2. State of Arkansas. https://static.ark.org/eeuploads/adhe/publications/Retention_Graduation_Rate_2015.pdf

Arkansas Department of Higher Education. (2015b). *Annual report on first-year student remedation.* Agenda item no. 7. State of Arkansas. https://static.ark.org/eeuploads/adhe/publications/Remediation_Report_2014_Fall.pdf

Bahr, P. R. (2010). Preparing the underprepared: An analysis of racial disparities in postsecondary mathematics remediation. *The Journal of Higher Education,* 81(2), 209-237. https://doi.org/10.1080/00221546.2010.11779049

Bahr, P. R. (2016). *Replacing placement tests in Michigan's community colleges*. Ann Arbor, Michigan: Center for the Study of Higher and Postsecondary Education, University of Michigan.

Bahr, P. R., Fagioli, L. P., Hetts, J., Hayward, C., Willett, T., Lamoree, D., & Baker, R. B. (2019). Improving placement accuracy in California's community colleges using multiple measures of high school achievement. *Community College Review*, *47*(2), 178-211.

Bahr, P. R., & Gross, J. L. (2016). Community colleges. In Bastedo, M. N., Altbach, P. G., & Gumport, P. J. (Eds.), *American higher education in the twenty-first century: Social, political, and economic challenges* (pp. 462-502). JHU Press.

Bahrick, H. P., & Hall, L. K. (1991). Lifetime maintenance of high school mathematics content. *Journal of experimental psychology: General*, *120*(1), 20-33. https://doi.org/10.1037/0096-3445.120.1.20

Bailey, T. (2009). Challenge and opportunity: Rethinking the role and function of developmental education in community college. In J. Jez and A. Venezia (Eds.), *Special Issue: Policies and Practices to Improve Student Preparation and Success, New directions for community colleges*, *No. 199* (pp. 11-30). Jossey-Bass. https://doi: 10.1002/cc.352

Bailey, T. (2016). From access to completion: The need for comprehensive reform. In N. L.

Maxwell and A. E. Person (Eds.), *Comprehensive Reform for Student Success*, *New Directions for Community Colleges*, No. 176, (pp. 11-21). Jossey-Bass. https://doi.org/10.1002/cc.20218

Bailey, T., & Cho, S. W. (2010). Issue brief: Developmental education in community colleges. *Community College Research Center, Columbia University*.

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

Bailey, T., Jeong, D. W., & Cho, S. W. (2008). Referral, enrollment, and completion in developmental education sequences in community colleges. CCRC Working Paper No. 15. *Community College Research Center, Columbia University*.

Barbitta, S., & Munn, W. (2018). Multiple measures placement in North Carolina. *New Directions for Community Colleges*, *182*, 59-73. https://doi.org/10.1002/cc.20302

Barnett, E. A., Bergman, P., Kopko, E., Reddy, V., Belfield, C., & Roy, S. (2018). Multiple measures placement using data analytics: An implementation and early impacts report. Center for the Analysis of Postsecondary Readiness.

Bean, J. P., & Metzner, B. S. (1985). A conceptual model of nontraditional undergraduate student attrition. *Review of Educational Research*, *55*(4), 485-540. https://doi.org/10.2307/1170245

Beer, A., Brown, K., & Juszkiewicz, J. (2021). Value of community college short-term credentials. Washington, D.C. Association of Community College Trustees. Retrieved from https://files.eric.ed.gov/fulltext/ED616929.pdf

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

Bickerstaff, S. E., Chavarín, O., & Raufman, J. (2018). Mathematics pathways to completion: Setting the conditions for statewide reform in higher education. *Community College Research Center, Columbia University*. https://doi.org/10.7916/d8-qqt8-3p61

Bickerstaff, S., Kopko, E., Lewy, E. B., Raufman, J., & Rutschow, E. Z. (2021). Implementing and scaling multiple measures assessment in the context of COVID-19. Research Brief. *Center for the Analysis of Postsecondary Readiness*.

Bremer, C. D., Center, B. A., Opsal, C. L., Medhanie, A., Yoo, J. J., & Geise, A. C. (2013). Outcome trajectories of developmental students in community colleges. *Community College Review, 41*(2), 154-175. http://dx.doi.org/10.1177/0091552113484963

Chen, J. C. (2016). Remedial coursetaking at U.S. public 2- and 4-year institutions: Scope, experiences, and outcomes *(INCES 2016-405). U.S. Department of Education*. National Center for Education Statistics. https://nces.edu.gov/pubsearch

Chen, J. C. (2017). Nontraditional Adult Learners: The neglected diversity in postsecondary education. SAGE Open. https://doi.org/10.1177/2158244017697161

Childers, A. B., Lu, L., Hairston, J., & Squires, T. (2021). Impact and effects of co-requisite mathematics remediation. *PRIMUS: Problems, Resources, and Issues in Mathematics Undergraduate Studies*, 31(2), 167-183. https://doi.org/10.1080/10511970.2019.1639865

Chronicle of Higher Education. (2021). *Age distribution of college students by sector, fall 2019*. Chronicle of Higher Education. https://www.chronicle.com/article/age-distribution-of-college-students-by-sector-fall-2019

Cohen, A. M., Brawer, F. B., & Kisker, C. B. (2013). *The American community college* (6th edition). Jossey-Bass. Retrieved from http://ebookcentral.proquest.com

CollegeBoard (2017). *Skills Insight*. Retrieved from https://Accuplacer®.collegeboard.org/Accuplacer®/pdf/consolidated-skills-insight-statements.pdf

CollegeBoard (2018). *Accuplacer® program manual*. Retrieved from https://Accuplacer®.collegeboard.org/Accuplacer®/pdf/Accuplacer®-program-manual.pdf

Crisp, G., & Delgado, C. (2014). The impact of developmental education on community college persistence and vertical transfer. *Community College Review, 42*(2), 99-117. Retrieved from https://www.proquest.com/scholarly-journals/impact-developmental-education-on-community/docview/1518507453/se-2?accountid=8361

Cullinan, D., & Kopko, E. M. (2022). *Lessons from two experimental studies of multiple measures assessment*. Center for the Analysis of Postsecondary Readiness. *Community College Research Center, Columbia University*. Retrieved from https://ccrc.tc.columbia.edu/media/k2/attachments/multiple-measures-assessment-reflections.pdf

Cullinan, D., Barnett, E. A., Ratledge, A., Welbeck, R., Belfield, C., & Lopez-Salazar, A. (2018). Toward better college course placement: A guide to launching a multiple measures assessment system. *Community College Research Center. Columbia University*. https://doi.org/10.7916/D8892PK8

Dougherty, K. J., Jones, S. M., Lahr, H., Natow, R. S., Pheatt, L., & Reddy, V. (2014). Performance funding for higher education: Forms, origins, impacts, and futures. *The ANNALS of the American Academy of Political and Social Science*, 655(1), 163–184. https://doi.org/10.1177/0002716214541042

Fay, M. P., Bickerstaff, S., & Hodara, M. (2013). Why students do not prepare for math placement exams: Student perspectives. CCRC Research Brief. Number 57. *Community College Research Center, Columbia University*.

Fields, R., & Parsad, B. (2012). *Tests and cut scores used for student placement in postsecondary education: Fall 2011*. ERIC Clearinghouse. Retrieved from https://files.eric.ed.gov/fulltext/ED509935.pdf

Fong, K. E., Melguizo, T., & Prather, G. (2015). Increasing success rates in developmental math: The complementary role of individual and institutional characteristics. Research in Higher Education, 56(7), 719-749. https://doi.org/10.1007/s11162-015-9368-9

Frey, R. (2007). Helping Adults Learners Succeed: Tools for Two-Year Colleges. *Council for Adult and Experiential Learning (NJ1)*.

Ganga, E., & Mazzariello, A. (2018). Math pathways: Expanding options for success in college math. *Education Commission of the States*. Retrieved from https://files.eric.ed.gov/fulltext/ED590584.pdf

Ganga, E., & Mazzariello, A. (2019). Modernizing college course placement by using multiple measures. *Education Commission of the States*. https://doi.org/10.7916/d8-fa8c-py77

Garcia, L. L. (2017). Introduction: Generation x presidents and new challenges. In M. M. Ellis and L. L. Garcia (Eds.), *Generation x presidents leading community colleges: New challenges, new leaders* (pp. xv-xxiv). Rowman and Littlefield.

Ginder, S. A., Kelly-Reid, J. E., & Mann, F. B. (2018). Graduation rates for selected cohorts, 2009-14; Outcome measures for cohort year 2009-10; Student financial aid, academic year 2016-17; and admissions in postsecondary institutions, fall 2017. First look (Provisional Data). NCES 2018-151. *National Center for Education Statistics*.

Hardin, C. J. (2008). Adult students in higher education: A portrait of transitions. *New directions for higher education*, *2008*(144), 49-57.

Hittepole, C. (2019). Nontraditional students: Supporting changing student populations. *University of Denver*. Retrieved from https://www.naspa.org/images/uploads/main/Hittepole_NASPA_Memo.pdf

Hodara, M., Jaggars, S., & Karp, M. J. M. (2012). Improving developmental education assessment and placement: Lessons from community colleges across the country. *Community College Research Center, Columbia University*. https://doi.org/10.7916/D8SB4F49

Horn, L. J., & Carroll, C. D. (1996). *Nontraditional undergraduates: Trends in enrollment from 1986 to 1992 and persistence and attainment among 1989-90 beginning postsecondary students. Postsecondary education descriptive analysis reports. Statistical analysis report*. US Government Printing Office.

Horn, L., Nevill, S., & Griffith, J. (2006). Profile of undergraduates in US postsecondary education institutions, 2003-04: With a special analysis of community college students. Statistical Analysis Report. NCES 2006-184. *National Center for Education Statistics*.

Hughes, K. L., & Scott-Clayton, J. (2011). Assessing developmental assessment in community colleges. *Community College Review, 39*(4), 327-351. Retrieved from https://www.proquest.com/scholarly-journals/assessing-developmental-assessment-community/docview/910699520/se-2?accountid=8361

Hussar, W. J., & Bailey, T. M. (2017). Projections of Education Statistics to 2025. NCES 2017-019. *National Center for Education Statistics*. Retrieved from https://files.eric.ed.gov/fulltext/ED576296.pdf

Jesnek, L. M. (2012). Empowering the non-traditional college student and bridging the digital divide. *Contemporary Issues in Education Research*, 5(1), 1-8. https://doi.org/10.19030/cier.v5i1.6780

Juszkiewicz, J. (2017, November). *Trends in community college enrollment and completion data, 2017*. American Association of Community Colleges. Academic Press. Retrieved from https://vtechworks.lib.vt.edu/bitstream/handle/10919/86967/CollegeEnrollment2017.pdf?sequence=1&isAllowed=y

Lattimore, K., & Depenbrock, J. (2017, July 19). *Say goodbye to x+y: Should community colleges abolish algebra?*. NPR. https://www.npr.org/2017/07/19/538092649/say-goodbye-to-x-y-should-community-colleges-abolish-algebra

Malcom-Piqueux, L.E. (2018). Student diversity in community colleges: Examining trends and understanding the equity challenge. In Levin, J. S. & Kater, S. T (Eds.), *Understanding community colleges.* Routledge.

Markle, G. (2015). Factors influencing persistence among nontraditional university students. *Adult Education Quarterly*, 65(3), 267-285. https://doi.org/10.1177/0741713615583085

Mattern, K. D., & Packman, S. (2009). Predictive validity of ACCUPLACER®® scores for course placement: A meta-analysis. Research Report No. 2009-2. *College Board*. Retrieved from https://files.eric.ed.gov/fulltext/ED561046.pdf

McDavid, J. C., Huse, I., & Hawthorn, L. R. (2012). *Program evaluation and performance measurement: An introduction to practice* (2nd edition). Sage Publications.

National Center for Education Statistics. (n.d.a). Number of Title IV institutions, number changing Title IV status, number of changing level or control of institutions, and percentage change, by sector of institution: United States and other U.S. jurisdictions, academic years 2019-20 and 2020-21. *IPEDS data explorer*. Retrieved from https://nces.ed.gov/ipeds/Search?query=number%20of%20institutions&query2=number

%20of%20institutions&resultType=table&page=1&sortBy=relevance&collectionYears=2020-21&collectionYears=2019-20&collectionYears=2018-19&overlayTableId=28458

National Center for Education Statistics. (n.d.b). Number of students, by age category, enrolled in postsecondary institutions in the fall (limited by sector of institution). *Trend Generator*. Retrieved from https://nces.ed.gov/ipeds/TrendGenerator/app/answer/2/8?f=1%3D4&rid=5&cid=89&cidv=8%7C9%7C10%7C11%7C12%7C13

National Center for Education Statistics (n.d.c). Table 6. Unduplicated headcount enrollment and percentage distribution at Title IV institutions, by control of institution, student level, level of institution, gender, and race/ethnicity: United States, 2019–20. *IPEDS Data Explorer*. Retrieved from https://nces.ed.gov/ipeds/Search?query=&query2=&resultType=all&page=1&sortBy=date_desc&overlayTableId=28462

National Center for Education Statistics. (n.d.d). Graduations rates (150% of normal time) and transfer-out rates: Aug 31, 2020. *Summary Tables*. Retreived from https://nces.ed.gov/ipeds/SummaryTables/report/801?templateId=8010&year=2020&expand_by=0&tt=aggregate&instType=1

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

Nicholson-Crotty, S., & Meier, K. J. (2002). Size doesn't matter: In defense of single-state studies. *State Politics & Policy Quarterly*, *2*(4), 411-422.

Osam, E. K., Bergman, M., & Cumberland, D. M. (2017). An integrative literature review on the barriers impacting adult learners' return to college. *Adult Learning*, *28*(2), 54-60.

Osborne, J. W. (2015). *Best practices in logistic regression*. Sage Publications.

Radford, A. W., Cominole, M., & Skomsvold, P. (2015). Demographic and enrollment characteristics of nontraditional undergraduates: 2011-12. Web tables. NCES 2015-025. *National Center for Education Statistics*. Retrieved from https://files.eric.ed.gov/fulltext/ED581707.pdf

Remenick, L. (2019). Services and support for nontraditional students in higher education: A historical literature review. *Journal of Adult and Continuing Education*, *25*(1), 113-130.

Rosin, M. (2012). Passing when it counts: Math courses present barriers to student success in California community colleges. Issue Brief. *EdSource*. Retrieved from https://files.eric.ed.gov/fulltext/ED606403.pdf

Rutschow, Z. E. (2018). Making it through: Interim findings on developmental students' progress to college math with the Dana Center mathematics pathways. Research brief. *Center for the Analysis of Postsecondary Readiness*. Retrieved from https://files.eric.ed.gov/fulltext/ED586095.pdf

Rutschow, E. Z., & Diamond, J. (2015). Laying the Foundations: Early Findings from the New Mathways Project. *MDRC*. Retrieved from https://files.eric.ed.gov/fulltext/ED558504.pdf

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

Sanabria, T., Penner, A., & Thurston, D. (2020). Failing at remediation? college remedial coursetaking, failure and long-term student outcomes. *Research in Higher Education, 61*(4), 459-484. http://dx.doi.org/10.1007/s11162-020-09590-z

Schuetze, H. G. (2014). From adults to non-traditional students to lifelong learners in higher education: Changing contexts and perspectives. *Journal of Adult and Continuing Education*, *20*(2), 37-55.

Schuh, J. H., Jones, S. R., & Harper, S. R. (2011). *Student services: A handbook for the profession* (Fifth ed.). John Wiley & Sons.

Shelton, A. R., & Brown, R. S. (2010). Measuring the alignment of high school and community college math assessments. *Journal of Applied Research in the Community College*, *18*(1), 1-10.

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

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

Thelin, J. R. (2011). *A history of American higher education*. JHU Press.

Tinto, V. (1975). Droput from higher education: A theoretical synthesis of recent research. *Review of Educational Research, 45*. 89-125

United States Census Bureau. (2020). *American community survey: Educational attainment (S1501)* [Data set]. US Census Bureau. https://data.census.gov/cedsci/table?q=educational%20attainment&t=Populations%20and%20People&g=0100000US%2404000%24001,%240400000

United States Census Bureau. (2021). *Quickfacts: Arkansas.* US Census Bureau. https://www.census.gov/quickfacts/fact/dashboard/AR/PST045221

Woods, C. S., Park, T., Shouping, H., & Betrand, J. T. (2018). How high school coursework predicts introductory college-level course success. *Community College Review, 46*(2), 176-196. http://dx.doi.org/10.1177/0091552118759419

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

Appendix A – IRB Approval

UNIVERSITY OF ARKANSAS

To:	Johnathon Paape
From:	Chair, Douglas J Adams IRB Expedited Review
Date:	06/08/2022
Action:	**Review Not Required**
Action Date:	06/08/2022
Protocol #:	2206404573
Study Title:	Improving Math Placement of Non-Traditional Students in Arkansas Community Colleges Using Multiple Measures Assessments

Please keep this form for your records. Investigators are required to notify the IRB if any changes are made to the referenced study that may change the status of this determination. Please contact your IRB Administrator if you have any questions regarding this determination or future changes to this determination.

cc: Michael T Miller, Key Personnel

Page 1 of 1