RELATIONSHIPS BETWEEN PLACEMENT CRITERIA AND STUDENTS' ONLINE DEVELOPMENTAL MATH FINAL GRADES

by

Michael Gibson

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ABSTRACT

Students placed into developmental math courses experience significantly increased costs for obtaining a college degree. They are also considerably more likely to drop out of college without obtaining a degree. However, many students need developmental math if they are going to succeed in their college level math courses. As a result, it is vitally important to both students and educators concerned with student success that students are placed into the correct courses. Little, if any, work has done been in this area for online math courses despite the explosive growth of online college level education in the last two decades. The present study measures the accuracy with which a multiple measures placement process using ACT/SAT mathematics score, a local algebra skills assessment, and unweighted high school GPA predicts final course grades for students in an online developmental math course. A quantitative correlation design was used for the study. The research used archival data from a private university located in the eastern United States with a very large online student population. Data for all three predictive variables as well as course grades for a developmental math course was retrieved from the university record system for 3843 students enrolled between Fall 2016 and Spring 2019. Multiple linear regression analysis showed no significant predictive relationship with respect to the criterion variable. Additional analysis revealed significant correlations between the online developmental math final grades and both high school GPA and the local algebra skills test. The study concludes with recommendations for further research including studying differences by age of student and using data from other universities.

Keywords: developmental math, online, on ground, face-to-face, math placement, multiple measures math placement, SAT, ACT

Dedication

I dedicate this dissertation to my wife and children, who have lived with and supported a husband and father who was much more absent that he would have been had it not been for this PhD and the dissertation that went with it. Cheryl, Michael, Susan and Daniel have all been consistently full of love and support for me through this process.

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List of Abbreviations

ACT (produced by and formerly called American College Testing, the ACT is now just ACT)

Algebra Skills (Math) Assessment (ASMA)

Face to Face (F2F)

Grade Point Average (GPA)

Scholastic Assessment Test (SAT)

CHAPTER ONE: INTRODUCTION

Overview .

The purpose of this study was to explore the accuracy with which a multiple measures placement process using ACT/SAT mathematics score, a local algebra skills assessment, and unweighted high school GPA could predict final course grades for students in an online developmental math course. Chapter one discusses the background related to the study, the problem statement, and the purpose and significance of this study. Finally, the research questions will be presented, and key definitions related to this study.

Background

Students placed into developmental math courses face a range of increased costs for obtaining a college education. They are significantly less likely to earn the degree that they are seeking and more likely to owe substantial sums without the benefit of a college degree to help them earn money (Valentine, Konstantopoulos, & Goldrick-Rab, 2017). Therefore, placement into a developmental mathematics course is a serious issue worthy of careful consideration.

In addition to being important to both students and institutions, accurate placement is quite difficult. A range of academic and demographic factors have some relevance to effective placement. Where they are placed in a remedial course sequence affects students differently depending on their levels of academic preparedness. Studies have shown that students who were close to testing directly into college level, non-developmental courses were subject to an overall negative effect from being placed into a developmental course. However, students who were further away from testing into college level classes have been shown to be harmed by being placed directly into college level courses (Boatman & Long, 2018). Mathematics placement is a sensitive process as being placed in the wrong course can cause problems for students.

Higher education math placement processes used (and often still use) single measures such as a nationally standardized test or an algebra skills test to determine entry level math placement (Xu & Dadgar, 2018; Ngo & Kwon, 2015). However, no single test, measure, or factor has yet been found which predicts student success well enough to effectively determine appropriate placement in entry level and/or developmental level college math courses. The best single predictor appears to the latest version of the SAT math score which accounts for slightly less than 25% of the variation in student success in their first college level course (Shaw et al., 2016). As a result, many researchers and practitioners are turning to what is called multiple measures placement processes that combine the results of measurements of multiple factors to determine course placement and to increase the accuracy of placement decisions (Barbitta & Munn, 2018; Barnett & Ready, 2017).

Developmental mathematics education and thus mathematics placement has been a key topic in college level education for several decades (Stahl, Theriault, & Armstrong, 2016). However, the history of developmental education for math, as well as other subjects, is much longer than just the last few decades. Developmental coursework has been an issue in college education in the US since the first colleges and universities were founded in the 1600's (Arendale, 2011). The most recent phase in this lengthy history has been characterized by enormous growth in the percentage of US citizens pursuing college degrees which has led to even greater growth in the number of developmental students (Bailey, 2009). Today approximately half of US college students enroll in a developmental course, with math being by far the most common type (NCES, 2016). This growth has greatly increased the number of entering students who might need developmental education and thus increased the need for accurate placement for these students.

The rise of online education has added another dimension to questions about accurate math placement. In the fall semester of 2016 approximately one third of college and university students in the US were taking at least some online courses and that percentage had grown every year for the past 14 years. The absolute number of students taking online classes has increased each of these years (Johnson, 2015). Furthermore, online education involves known and sometimes obvious differences from more traditional face-to-face (F2F) education in pedagogy, delivery format, and student characteristics (Wollf, Wood-Kustanowitz, & Ashkenazi, 2014; Johnson, 2015). Online students have been shown to be generally older, have lower expectations of success for their college coursework, and use technology less frequently than residential students (Johnson, 2015). All of these differences could potentially lead to differences in ideal placement practices for online versus residential students.

This study examined the effectiveness of a multiple measures math placement process at placing entering students into online developmental mathematics courses. The concept behind multiple measures is to use instruments measuring meaningfully distinct factors affecting student academic success in a particular discipline and combine the results of these instruments to determine student placement in courses in that academic discipline. The measures used in the placement process being studied are ACT/SAT math scores, a local algebra skills test, and unweighted high school GPA.

Problem Statement

Many students enter college lacking the necessary mathematical skills to succeed to in their college level math courses. However, placement into a developmental math course is associated with substantial costs in terms of financial cost, time to degree completion, and probability of success (Valentine, Konstantopoulos, & Goldrick-Rab, 2017). Therefore, the goal of any higher education math placement program is to place students at the highest possible level of math course that is both in keeping with their degree plans and provides a high likelihood of success in the course.

Institutions of higher education relied mostly on the use of single measures for math placement for many years and many still use just one measure in their placement process (Xu & Dadgar, 2018; Ngo & Kwon, 2015). The lack of any single measure that captures most of the variation in student results makes this problematic. Probably the best single predictor of entry level college math success is the most recently updated SAT math test which accounts for less than 25% of the variation in student success in entry level college math courses (Shaw et al., 2016). Recent research indicates that the use of multiple measures is likely to produce better results (Ngo & Kwon, 2015; Barbitta & Munn, 2018). However, there is no consensus on which measures are best. Nor is there any consensus on how to use the selected measures. The College Board recommends the use of a weighted average of the SAT math score and high school GPA (Shaw et al, 2016). North Carolina public institutions enforce a hierarchical placement policy that uses six different measures including ACT/SAT math scores, high school GPA, and a local algebra skills test. However, the various scores are not weighted and the measures are used in a hierarchical fashion. Students are sorted into groups by their scores for one factor. Then the next factor is applied to some or all of the groups determined by the previous factor. For example, any student with a high school GPA in excess of 2.6 who has completed an appropriate high school math course may enroll in any entry level college math course, thus avoiding all of the developmental courses (Barbitta & Munn, 2018). After students are sorted in groups of those needing developmental math and those not needing it, another factor is applied to each group with the rules being different between the groups. Public colleges and universities in California are mandated by the state to use a multiple measures placement system, but are not required to use similar systems. California institutions vary significantly in the way that they apply this mandate for multiple measures. They also are often fundamentally different from both the College Board recommendations and what is used in North Carolina (Ngo & Kwon, 2015). These differences are representative of the literature which simultaneously indicates continued use of single measures, recommends use of multiple measure, and reaches no consensus about how to implement multiple measures.

There exists a range of multiple measures placement systems in use at both the state and institution level. Yet none of these systems or the published research about them distinguishes online placement from on ground physical campus placement. The problem is there is little to no mention of placement processes specific to online degree programs despite significant known differences between on ground and online student populations (Johnson, 2015).

Purpose Statement

The purpose of this study was to measure the accuracy with which a multiple measures placement process using ACT/SAT mathematics score, a local algebra skills assessment, and unweighted high school GPA could predict final course grades for students in two online developmental math courses. This quantitative predictive correlational study used a multiple linear regression to measure the correlation between the predictor variables (ACT/SAT mathematics score, a local algebra skills assessment, and unweighted high school GPA) and the criterion variable (final course grade). Furthermore, the study used archival data for online undergraduate students attempting the lowest level developmental math course at a large private university in the Eastern US.

Significance of the Study

According to the National Center for Educational Statistics, approximately one-third of college students in the US take developmental mathematics courses in college (NCES, 2016). One study which analyzed a large sample of college transcripts found that actual developmental enrollments are probably greater than what is reported in NCES data (Radford & Horn, 2012). In addition, placement into developmental education increases financial costs, time costs, and opportunity costs for obtaining a degree. It also reduces the likelihood of obtaining a college degree (Valentine, Konstantopoulos, & Goldrick-Rab, 2017). Students who place into developmental math courses are 74% more likely to drop out of college (Barry & Dannenberg, 2016) and thus not obtain the economic and personal benefits of a college degree. Students who drop out of college are four times as likely to default on their student loans as those who earn their college degree. A painfully high percentage of entering college students are placed into developmental math and many if not most of these students will face significantly higher chances of failure and increased costs. It is therefore vitally important to make the best possible decisions with regards to placing students into developmental math courses.

During the 2015-2016 academic year, online college and university enrollments in the US grew for the 14th year in a row, and residential enrollments decreased for the fourth year in a row. College students taking at least one online course made up 32% of all college students and those taking online only courses make up 15% of all college students. Over 6 million students were taking at least one online college course by fall 2016 (Seaman, Allen, & Seaman, 2018). If current trends continue, the day is fast approaching when online college enrollments exceed on ground college enrollments in the US. In addition, online and residential student bodies show some significant differences that might affect student success—and thus ideal placement—into math courses. Online students are generally older and thus more likely to have been out of school for several years, to be raising children, and to have full-time employment. Due to these factors, these students are more likely to have lower expectations of success in college and less familiarity with technology (Johnson, 2015). The known differences between online and residential students combined with the enormous number of online students and the continued growth of the online sector combine to create a great need for research in the area of online mathematics placement.

Furthermore, very little if any work has been done in the area of placement for online math courses. The present study was designed to work as a companion study to a study performed by Sherman (2019). Both studies tested the predictive value of the same set of three predictor variables for student success in the same course at the same university. Sherman's (2019) study examined the accuracy of the placement process for the residential versions of these classes while this study examined the accuracy of the placement process for the online versions. This study expanded the current base of research literature in two ways. First, it focused on initial placement into an entry level online college math course, which is an area of research that appears to missing from the current literature. Second, it provided a solid starting point for comparison between online and residential developmental math placement by using the variables at the same institution as Sherman's 2019 study on residential entry level math placement. Moreover, this appears to be the first pair of published companion studies designed to provide an effective comparison of online versus residential math placement.

Research Question

RQ: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local algebra skills assessment predict the Math

100, Fundamentals of Mathematics final grade for online students who completed the course at a private university during the 2016-2019 academic years?

Definitions

1. *Developmental math course* – Math Courses offered by higher education institutions that are designed to help students who are determined to be lacking in essential academic skills to gain those skills (Park et al., 2016).
2. *Face-to-face course* – traditional on campus courses where students meet with the teacher of the course and see each face to face (F2F) (Acosta, North, & Avella, 2016).
3. *Online* – Refers to courses or programs taught entirely in an online format over the internet with no face to face interaction between faculty and students except that which might be mediated by video conferencing software (Bettinger, Fox, Loeb, & Taylor 2017).
4. *On ground* – Refers to courses or programs taught entirely or primarily in a physical classroom (James, Swan, & Daston, 2016).
5. *Multiple measures math placement* – a math placement process that uses measures for multiple factors in the placement process (Barnett & Ready, 2017)
6. *Remedial courses* – an older term for developmental courses (Davidson, 2016).

CHAPTER TWO: LITERATURE REVIEW

Overview

College and university mathematics faculty and researchers seeking better student success rates for the sake of happier students, better retention, and more effective operation are beginning to turn to multiple methods math placement processes (Barbitta & Munn, 2018; Barnett & Ready, 2017). This literature review examines the scholarly literature related to the accurate placement of students into online developmental math courses using the multiple measures of ACT/SAT mathematics scores, high school GPA, and a local algebra skills test. The review is organized in three major sections. The first section describes the theoretical framework of this study. The second section synthesizes the results of research into developmental math, online mathematics education, math placement methods, and the three placement measures of ACT/SAT math scores, high school GPA, and a local algebra skills placement test. The last section summarizes the literature review and describes a gap in the literature that this research seeks to fill.

Theoretical Framework

Historically the study of human intellectual development can be divided into the three overarching categories of empirical, rational, and historico-cultural (Case, 1987). Much of the theoretical foundation for the present research comes from the rationalist tradition through Kant and Piaget and the ideas of cognitive constructivism that developed from their work. Further contributions to the theory underlying this study of multiple measures math placement come from Bandura's social learning theory (Bandura, 1977) and Bandura's development of the concept of self-efficacy and its effects on cognitive development and functioning (Bandura, 1993). The first two predictive criterion in the present study–SAT/ACT math scores and a local algebra skills placement test–are supported by the concepts related to cognitive schema common to various cognitive constructivist theories. The third predictive criterion, high school GPA, is supported by both Bandura's social learning theory and his work on self-efficacy.

Kant, Piaget, and Cognitive Constructivism

Kant theorized that people acquired knowledge by imposing their own logical ordering on information provided to them by their senses, instead of receiving the ordering when they perceived the information (Case, 1987). This idea was later further developed by Dewey and Piaget who refined this concept to say that people construct their own knowledge and understanding. Dewey's development of this concept applied to teaching. He theorized that in order to be effective, teaching must provide experiences that are linked closely enough to a student's previous experiences to facilitate their self-directed building of understanding and knowledge from current classroom experiences (Ultanir, 2012). Piaget's contribution was a little more abstract in that he focused more on the process of constructing knowledge. Piaget described Kant's ordering of sensory information as the creation of cognitive structures which he called schema (Ultanir, 2012). Piaget, in his work on learning, created a framework for how we learn and build problem solving skills that is still in use today with modifications. Later researchers refined Piaget's work to focus on schema related to particular environments and situations which they called domain specific schema (Knight & Sutton, 2004). Cognitive schema theory derived from Piaget and neo-Piagetian researchers involves general assumptions about human thought and learning that receives nearly universal acceptance from modern cognitive researchers. There currently exists a wide array of theories and positions about various details of cognitive schema that share the core concepts of Piaget's cognitive schema theory. Piaget's ideas (with some changes) form the foundation of current day cognitive constructivism

(Derry, 1996). Thus, modern cognitive constructivist viewpoints trace their roots to Kant, Dewey, and Piaget (Ultanir, 2012).

According to Piaget, (1970) essential functions of the mind are shaped by building a foundational structure consisting of knowledge and understanding and then applying innovation to construct new realities. Knowledge must be actively built in a step by step process (Glasserfield, 1995). These ideas can be expanded somewhat by understanding that the individual must transform information into their own structure in order really know it and that people actively construct their own knowledge (Thorne, 2013). According to Boghossian (2006) one of the core concepts of constructivist understanding is that we construct our own knowledge. All of these descriptions of cognitive learning theory share the common concept that people build knowledge from prior knowledge and previously acquired mental structures (schema) combined with current observational input through our senses.

Bandura's Social Learning and Social Cognitive Theory

Bandura's (1977) social learning theory model includes situation specific skills, incentives, self-efficacy expectations, and outcome expectations. As relates to mathematical performance, the specific skills would be relevant mathematical skills as reflected by previous math course grades. Siegel, Galassi, & Ware (1985) conducted a study of mathematical performance in a first year college math class. They found that Bandura's social learning theory variables accounted for significantly more of the variation in final course scores than did SAT math scores even when the SAT Math scores were combined with math anxiety measures (Siegel, Galassi, & Ware, 1985).

Probably the best known element of Bandura's theory is the concept of self-efficacy. Self-efficacy–which is defined as a person's belief in their ability to successfully perform a particular task–is one of the central components of his social cognitive theory (Butz & Usher, 2015). Bandura describes self-efficacy as a central concept in understanding human behavior. “Given appropriate skills and adequate incentives, however, efficacy expectations (and by inference, outcome expectations) are a major determinant of people's choice of activities, how much effort they will expend, and of how long they will sustain effort in dealing with stressful situations” (Bandura, 1977, p. 194). In summary, our belief in our own ability to make changes in our lives greatly affects the amount of control that we exercise over our lives (Bandura, 1977). With respect to education, self-efficacy has been shown to be a significant predictor of student academic achievement, motivation, and engagement (Bandura, 1997; Klassen & Usher, 2010; Pajares & Kranzler, 1995; Pajares & Urdan, 2006). How the individual feels when thinking or performing the given activity also affects self-efficacy (Bandura, 1977). An individual’s beliefs about their own academic capabilities are built on their past experiences and modified over time as the individual encounters further related experiences, receives messages from others, and sees others perform similar activities.

Application to This Research

The present study examines the effectiveness of a multiple measures math placement process at placing students into online developmental mathematics courses. The first two measures (ACT/SAT and a local algebra skills test) are both supported by cognitive schema theory in that their method is to measure student ability to answer selected mathematical questions in a single sitting. In order for students to answer these questions in this kind of setting, they must have the appropriate cognitive structures already in place in their minds. Those who lack the appropriate schema are not given the opportunity to build much in the way of new schema, as they must answer their current test questions in a single session.

In contrast with the tests that make up the first two measures, the third measure, high school GPA, is the cumulative result of years of a student's work in a secondary educational institution. Existing research shows that high school GPA is influenced mostly by factors whose effects can be seen over time, as well as having some social element in their make-up. High school GPA has been linked to social networks (Gašević, Zouaq, & Janzen, 2013), emotional dysregulation (Hartman, Wasieleski, & Whatley, 2017), emotional intelligence, self-efficacy (Hen & Goroshit, 2014), parental relationships, ethnic membership (Scherer, Talley, & Fife, 2017), and socio-economic status (Zwick & Himelfarb, 2011). It also represents academic data collected over a four year time period. It is one of the factors in Bandura's social learning theory that he identifies as affected by self-efficacy and other social factors (Bandura, 1977; Siegel, Galassi, & Ware, 1985). The placement measure of high school GPA is therefore supported by Bandura's social learning theory.

Related Literature

This section seeks to expand on the understanding of the nature of using ACT/SAT scores, a local algebra skills assessment, and high school GPA to predict success in online developmental math classes. Comprehension of this topic requires knowledge about developmental mathematics, the online college educational setting, multiple methods placement, the ACT and SAT tests, algebra skills testing, and the use of high school GPA in collegiate mathematics placement. This section of the present review of literature addresses these issues by synthesizing the academic research literature on these topics.

Developmental (Remedial) Mathematics

"It can be asserted accurately that bridging the academic preparation gap has been a constant in the history of American higher education and that the controversy surrounding it is an

American educational tradition" (Brier, 1984, p. 2). The need for remedial education at the college level has been a major issue in the American educational landscape since the beginning of the higher education system in America. Arendale (2011) identified six different phases of remedial college education in the United States arranged chronologically from the 1600s to the present. The latest phase, beginning in the 1990's, was described by Arendale (2011) as a time of expansion of developmental education driven by a major expansion of the American higher education system. There were dramatic increases in the number of adults seeking college degrees. Since this time, millions of new students matriculate every year without the academic skills they need to succeed in their college courses. This has led higher education institutions of all kinds to attempt to meet this need with extensive developmental programs designed to teach students the skills required for success in their college level courses (Chen, 2016). Developmental education programs–including developmental mathematics programs–have played a major role in higher education in the US for centuries and that role has increased significantly in recent decades.

Both two and four year colleges and universities have offered remedial courses since before detailed data sets were available. Developmental mathematics courses have consistently had the highest enrollments of all remedial courses (NCES, 2018). Less than two decades ago, about one in five college students in America joined developmental programs (NCES, 2013). Today, roughly half of US college students take developmental courses of some kind. Math is by far the most commonly remediated subject. Approximately two-thirds of developmental coursework is in math. This means that a third or more of entering US college freshmen are enrolled in developmental math classes (NCES, 2016). Analysis of college transcripts indicates that actual developmental enrollments probably exceed those reported in NCES data (Radford &

Horn, 2012).

Remedial mathematics education has been a major topic of conversation in college level developmental education for many years. The first issue of a journal devoted entirely to this topic (the *Journal for Developmental and Remedial Education*) was published in 1978 by the Center for Developmental Education at Appalachian State University. In addition to be being common topics of conversation, developmental mathematics education and improving developmental math education have been common focuses of educational research for more than four decades and are still a major research issues today (Stahl, Theriault, & Armstrong, 2016).

Effectiveness of developmental mathematics education.

Determining all the causes of the high number of students needing developmental courses is profoundly difficult. One problem is that the decision making processes used by post-secondary institutions to determine which students should be placed into developmental classes vary. These processes are sometimes set at the state level, sometimes set at the system level, and sometime set at the institutional level. There are many potential causes of this lack of college readiness, including academic opportunities, student preparation, student motivation, and poor teaching. A lack of uniformity in placement methods further complicates the issue of assessing the effectiveness of developmental placement (Boatman & Long, 2018). Furthermore, separating out the causes of why developmental students are so much less likely to succeed is a difficult task in and of itself. It is not clear how much of the effects of being placed into developmental courses are due to weakness in the academic preparation and skills of the students and how much might be due poor placement or poor design of the developmental courses (Valentine, Konstantopoulos, & Goldrick-Rab, 2017; Goldrick-Rab, 2010). The wide range of potentially contributing factors to both developmental enrollments and developmental course success makes determining the causes of the various problems extremely difficult.

The results of one meta-analysis of research studies, which used regression discontinuity analysis to explore the effects of being enrolled in development college courses, suggested that placement into developmental course work is connected in a strong, negative, and statistically significant manner with three different negative outcomes. These outcomes were first, a lower probability of completing the needed college course or courses supported by the developmental course work; second, a strong likelihood that fewer college credits would be earned; third, a significantly lower chance of graduating from college (Valentine, Konstantopoulos, & Goldrick-Rab, 2017). According to Boatman and Long (2018), a majority of the current research about developmental courses hindering students applies primarily to students who scored close to the cutoff for requiring remediation and often compares these students to those who scored only a few points above the cutoff. There is limited research on those who need more than one developmental math course (Boatman & Long, 2018). Even though developmental courses are in the best interests of many students, it is clear that being enrolled in a developmental math course is as powerful predictor of multiple undesirable outcomes.

Boatman and Long's (2018) study used longitudinal data from the Tennessee Board of Regents and the Tennessee Higher Education Commission which included data from six different four year universities and 13 two year colleges. Effects of enrollment into remedial courses were isolated from the data using a regression discontinuity design. Remedial course placement affected students differently depending on their levels of academic preparedness. Students who were close to testing out of the highest level of developmental mathematics were subject to an overall negative effect from being placed into a developmental course. Students who placed two courses below college level were more likely to obtain a degree than similar students who were placed directly into college level math courses.

Costs of developmental mathematics education.

Despite the pervasive presence of developmental courses in US colleges and universities dating back for centuries, the efficacy of these programs is a matter of debate. Large numbers of students appear to obtain unsatisfactory outcomes from their developmental courses (NCES, 2016). According to Coleman, Skidmore, and Martirosyan (2017) developmental students are experiencing substantially less success than their college peers who are not placed into developmental courses. Placement into developmental education increases financial costs, time costs, and opportunity costs for obtaining a degree and reduces the likelihood of obtaining a degree that would provide the student a much stronger probability of recouping these losses in an expeditious manner (Valentine, Konstantopoulos, & Goldrick-Rab, 2017).

Strictly analyzing the direct financial costs (without making any effort to calculate the opportunity costs) each developmental course costs students an average of $3,000 and adds an average of $1,000 in student loan debt. In addition, states are generally growing more concerned about paying again for courses taken in high school (Barry & Dannenberg, 2016). One of the things many states have done to reduce this cost is to severely limit the number of developmental classes taught at their public four year institutions. This policy has forced many students who wanted to pursue a college education to start their post-secondary education at a community college where costs are significantly lower for the state (Goldrick-Rab, 2016).

The hidden cost of developmental math is staggering. Many students who are placed into developmental math courses will take this as a sign that they are unlikely to succeed in college and as a result choose not to attend college (Valentine, Konstantopoulos, & Goldrick-Rab, 2017; Bailey, Jeong, & Cho, 2010; Scott-Clayton & Rodriguez, 2015). In 2013 the state of Florida took the far-reaching step making placement tests optional at all state institutions of higher education. Park, Woods, Richard, Tandberg, Hu, and Jones (2016) conducted a study at two Florida universities to examine the choices that students would make once they had the opportunity to avoid developmental math. The study involved students whose were recommended to take at least one developmental mathematics course. Of these students, 41.9% enrolled in a developmental course, 22.5% enrolled in a college-level course instead, and 35.7% took no mathematics course at all. Note that over a third of students who were not required to act on their math placement score effectively discontinued their college educations by choosing to never take a college math course. In an archival study using Virginia Community College data for 24,140 freshmen entering college for the fall semester of 2004, the pass rate for those who enrolled in developmental math courses was 28%. Four years later, only 25% of students who enrolled in a developmental mathematics course successfully completed a single college level course. This low pass rate was largely because most never attempted a college level course (Roska, Jenkins, Jaggers, Zeidenberg, & Cho, 2009). A major hidden cost of placing students into developmental mathematics courses is that many students placed into these courses never enroll in a math course and thus have no chance to earn a college degree.

Using data from the Complete College America database for more than 30 colleges in the Appalachian region, Armstrong and Zaback (2014) performed a study of college completion rates. This data indicated that only 12.9% of remedial math students obtain an Associate’s degree and only 33.8% obtain a bachelor’s degree. These numbers for all developmental students were 17.7% and 38.5% respectively. In addition, only 40% of students enrolled in remedial courses ever completed them. No data was provided about how many of those placed into developmental classes never enrolled in any course (Armstrong & Zaback, 2014).

Graduation rates for students placed into developmental math courses are alarmingly low.

According to Davidson (2016), most students who are enrolled in a developmental math course never pass a college level math course. The purpose of this study was to assess student persistence through the remedial math sequence and through passing a college-level credit-bearing math course using binary, cumulative, and continuation ratio logistic regression at two and four year public institutions. The author only used data for students who started with the course (Pre-Algebra) at the lowest level of the developmental math sequence. His primary interest was seeing to what degree a student's grade in Pre-algebra was a predictor of completing a college level math course. There were 2,014 participants in the study. Overall only 11.3% of students who placed into Pre-algebra completed a single college level math course. 34.0% of the students received an A or B in Pre-algebra and of these students 33.2% eventually successfully completed a college level mathematics course. Essentially none of the students receiving a W, F, D, or C in their Pre-algebra course ever passed a college level math course (Davidson, 2016). There are indications that students who earn less than a B in a developmental math course are extremely unlikely to graduate from college.

The enormous growth in the number of students attending college over the last century has greatly increased the percentage of US adults who are involved in higher education at some time in their lives. Unfortunately, many of these students are from populations that formerly did not pursue a college education and thus are more likely to be first generation college students. This means that they are often not academically ready for college at the time of their enrollment and consequently have found little to no success in college (Bailey, 2009). Using a meta-analysis of research studies on developmental math, Bailey (2009) found that only 16% of students who were placed into the lowest level of a developmental math sequence ever completed the sequence. Bailey (2009) also found that students in this group who received grades of C or lower in their first developmental class rarely passed any further developmental math classes. Similarly, Roska et al. (2009) found that only 19% of students assigned to the lowest level of a remedial math sequence ever enrolled in a college level math course. Being placed into the lowest levels of a developmental math program is highly predictive of never graduating from college.

Developmental mathematics education does work for many students

The story of developmental math is by no means all bleak. Using archival data from a cohort of nearly 45,000 college freshmen, Roska et al. (2009) found that 75% of community college students who started at the lowest level of developmental math made it to their first college level course and successfully completed it. Boatman and Long (2018) found that developmental math students who placed more than one course below college level were more likely to obtain a degree than similar students who were placed directly into college level math courses.

Melguizo, Bos, Ngo, Mills, and Prather (2016) found that the initial time penalty for being placed into the highest developmental math course disappeared over a year at two of four California colleges studied. This result indicates that there are likely colleges where developmental success rates are substantially higher than the average. Moreover, analysis of data from five California colleges revealed that students who started in developmental math and ultimately enrolled in a college level math course were slightly more likely to succeed in that course than students who were placed directly into the course. They were also equally as likely to graduate from college as those who placed directly into an entry level college mathematics course (Fong, Melguizo, & Prather, 2015). Numerous alternative methods for delivering developmental mathematics to community college and university students have been attempted by a wide range of institutions (Kosiewicz, Ngo, & Fong, 2016). While many of these innovations have fallen short, some have proven effective or show some promise (Chingos, Griffiths, & Mulhern, 2017). Despite all the negative connotations of developmental math courses, many students who are placed into developmental math courses do succeed.

Recent promising ideas in developmental math education

One method of addressing these issues of low pass rates is to provide extra instruction in an accelerated format. In 2008, several community colleges in New York implemented a program where select students were invited to enroll in a single five credit one semester course that replaced two 3 credit semester long courses. This course met 5 days a week for 5 hours a day. Results were dramatic with a nearly three-fold increase in the number of students completing the developmental math sequence as compared to the traditional model. However, a five-credit course that meets 25 hours a week is not attractive to many colleges and students (Cafarella, 2016). In order to have wide scale effect, a program needs to both prepare students to succeed and be able to attract substantial numbers of students.

The co-requisite model is another method for providing extra instruction that has shown to be effective, at least for students who are not too far below the cutoff score for testing into the next level. A co-requisite model generally assigns students to a class that is one level above that indicated by their placement results and requires them to simultaneously take a companion course designed to provide assistance in developing the skills necessary for the main course (Campbell & Cintron, 2018). Co-requisite courses have been successful in many situations.

In Florida, students are given placement options and can choose not to take the remedial math courses into which they are placed. About a third of students who receive recommendations to start with a course in Florida's three course developmental system choose to take Intermediate Algebra, which is the highest level of development math. Many of these students placed into lower courses. Among those students who placed lower but decided to take the upper level course, those who took an optional support course (often called a co-requisite course) did significantly better on average than those students who did not take the support course (Park, Woods, Richard, Tandberg, Hu, & Jones, 2016). The evidence seems to clearly support the idea that co-requisite course models are effective for many students.

A pilot study of a co-requisite course involving 335 developmental math students was run in 2012 at two and four year colleges across the state of Louisiana. This co-requisite pilot placed students within 5% of testing out of developmental math into a college level math course and simultaneously into a co-requisite support course. Pass rates for students who enrolled in the co-requisite courses and those who took only a developmental math course were not significantly different. Since those who successfully completed the co-requisite courses had completed a college level math course while those who passed only a developmental math course had not even enrolled in a college level math course, this was considered a major success (Campbell & Cintron, 2018). The co-requisite model seems to be especially effective for students who are close to placing out of developmental math.

Online Education

Lecture as a method of teaching dates back for several centuries and seems to be widely considered by members of the academic world to be the preeminent form of content delivery. However, recent research has demonstrated that active learning methods are usually more effective than the more passive (for students) lecture method (DeRogatis, Honerkamp, McDaniel, Medine, Nyitray, & Pearson, 2014). Despite its popularity and history as the primary educational delivery method, traditional lecture as the principal teaching technique has been connected with a variety of unattractive outcomes. It is by no means the ultimate method of instruction (Lochner, Wieser, Waldboth, & Mischo-Kelling, 2016). Numerous research studies have explored the use of a wide range of active learning techniques in college courses. The results suggest that active learning methods generally increase student engagement, learning, and retention as compared to traditional lecture as a primary delivery method (Dyer & Elsenpeter, 2018). The relative effectiveness of active learning methods suggests that the mode of delivery–online versus face-to-face (F2F)–is less vital to student success than the degree to which the teaching method actively involves the students.

Online content delivery can and often does utilize many of these active learning techniques as well as video delivery of lecture based content. However, as the following synthesis of peer reviewed academic literature will demonstrate, the effectiveness of online education with its lack of face to face contact between students and teachers remains a topic of some debate in the academic literature. Recent research includes a range of seemingly contradictory comparisons between the effectiveness of traditional F2F methods of content delivery and online educational approaches.

Research Studies in Online Education

Acosta, North, & Avella (2016) conducted a study using four years of historical data for 290 randomly selected community college students. The study used logistic regression analysis to determine which of the studied factors had a significant correlation with success in a college level math course after taking a developmental math course. Success was defined as earning a C or better in the course. Delivery mode (online vs F2F) was found not to be a significant factor in predicting successful completion of a college level math course. The primary limitations in this study were that only students who took both courses in the developmental math sequence were included in the study and that all students were from the same college.

Another large study, using an instrumental variables design with archival data for more than 230,000 students in more than 750 classes taken over four years, was conducted at a very large for profit four-year university. Two-thirds of the students in the study took a majority of their classes online. Online and in person sections of the courses were identical in most ways because the university made a conscious effort to make its online and F2F courses as identical as possible. Analysis was performed by comparison of mean grade in the online course to mean grade in the F2F course. Student GPA in the semesters both before and after the analyzed courses were compared using an instrumental variables approach. The study found that taking online courses lowered the expected GPA both for the current semester and for the succeeding semester. Furthermore, the study found that the lower the student GPA, the greater the impact taking a course online had on the student's GPA (Bettinger, Fox, Loeb, & Taylor, 2017). In summary, this study found that students performed better in residential than online versions of a course and that the effect was magnified for weaker students. Moreover, this effect lasted into the next semester.

Joyce, Jaeger, Crockett, Altindag, & O'Connell (2015) conducted a study whose purpose was to investigate the effect of removing a significant portion of classroom time and replacing it with online content on student success. The study used an experimental design where 725 students were randomly placed into either a traditional twice a week classroom setting or into the experimental sections of the course where students met with the professor once a week versus twice a week in the traditional. All necessary course material (textbook, PowerPoints, and videos) was provided to both types of classes through online materials. The setting was a freshman level microeconomics class at a large urban public university on the east coast of the United States consisting of 725 out of 776 students spread over four sections of the class. The differences in the final exam score and overall score for the class were not statistically significant. However, when students were segregated into lower, middle, and upper thirds based on prior GPA, students in the middle third did significantly perform slightly worse in the partially online.

A different study, conducted with 56 online and 49 F2F community college students enrolled in an environmental biology course, investigated 11 predictors of student performance in both online and F2F classes. Online students were found to be less successful at the .05 level of significance. However, the student population for the online classes was both significantly older and significantly more likely to be working more than 12 hours per week than the student population in the F2F classes. In addition, the online students were more likely to have dependent children in their homes. Future research was indicated for the effects of both age and amount of time spent working per week as well as for having dependent children in the home. Research into the predictive ability of different placement testing programs was also indicated (Wollf, Wood-Kustanowitz, & Ashkenazi, 2014). The fact that the online students were significantly more likely to be working more hours and to have dependent children at home raises questions about what caused the lower grades for the online students.

Student success in online mathematics courses has been shown to be affected by a range of factors. Lack of social interaction with peers and teachers as well as delayed or missing feedback from instructors have been identified as possible factors (Kim, Park, & Cozart, 2014). Cho & Heron (2015) investigated the effects of self-regulated learning in online developmental mathematics students using a survey of 229 students. They found that certain student emotions–

anger, anxiety, boredom, enjoyment, hopelessness, pride, and shame–are correlated with student success.

James, Swan, & Daston (2016) conducted an extensive study designed to explore the effectiveness of online education. The study used archival data from five predominantly on ground (non-online) community colleges, five predominantly on ground four year universities, and four predominantly online universities. Well over half-a-million student records were included in the study. One year retention rates were compared for students who were fully on ground (no online classes), students taking both online and on ground classes, and students taking only online classes. Students at the on-ground community colleges who took only online classes did have slightly lower retention rates than students who were on ground only or online only. However, these differences were the result of extraneous factors; they disappeared once the researchers controlled for them. No meaningful differences were found in retention rates between mixed, on ground only, and online only students at four year predominantly on ground colleges. At the predominantly online four year institutions, students who took a mix of online and on ground courses had slightly higher retention rates than students in the other two groups, while the other groups had no significant differences in retention rates. Gender made no difference in retention rates in any of the groups of students or colleges. Age had an interesting effect. At predominantly online four year institutions and predominantly on ground community colleges, older students (defined as students 26+ years of age) taking exclusively online courses had higher retention rates than younger students. Overall, taking online courses did not appear to be a significant factor in determining student success.

In summary, there is contradictory information about whether or not delivery format effects student success and/or retention. Some studies show that differences between online and

F2F performance might vary by level of student performance, but disagree about how the level of student performance interacts with delivery method (Acosta, North & Avella, 2016; Bettinger, Fox, Loeb, & Taylor, 2017; Joyce, Jaeger, Crockett, Altindag, & O'Connell, 2015). Some studies show a difference but identify extraneous factors as the likely cause. There is even disagreement about the relevant extraneous factors. (Wollf, Wood-Kustanowitz, & Ashkenazi, 2014; James, Swan & Daston, 2016; Wladis, Conway & Hachey, 2016). Furthermore, self-efficacy has been shown to positively correlate with the performance of online math students (Kim, Park, & Cozart, 2014). In addition to self-efficacy, the strength of certain emotions and some measureable motivation factors correlate significantly with online student performance (Cho & Heron, 2015). Therefore, any study that does not control for these factors can potentially be compromised by them, because the effects of delivery mode on student performance is a complex topic.

Characteristics of online students

Students with lifestyle factors that make traditional residential courses more difficult appear to be more likely to enroll in online college courses. Factors associated with increased likelihood of taking online courses such as working full-time, raising children and being married are also more commonly found with older students. In addition, socio-economic status seems to have an effect. Economically disadvantaged students are less likely to enroll in online courses (Ortagus, 2017).

James, Swan, & Daston (2016) found that students age 26 and older were much both much more likely to take online courses and much more likely to enroll at predominantly online institutions. Both the on ground and online courses at predominantly online institutions had more than twice as many older students as the institutions in the study that were predominantly on ground. A study conduct by Wladis, Conway, & Hachey (2016) at the City University of New York (CUNY) found similar results. This study examined archival data for all students attending a CUNY institution during the fall semester of the 2014-2015 academic year. Online students were more likely to be employed full time and worked an average of more than 50% more hours per week. They were also almost twice as likely to be raising at least one child. Raising one or more children was negatively correlated with student success. No significant differences were found in ethnicity between online and on ground students. Online programs do appear to increase access to higher education for non-traditional student populations, including older students (Goodman, Melkers, & Pallais, 2019).

Multiple Measures Mathematics Placement

The term multiple-measures denotes a placement process that determines student placement into college courses using more than one measurement and/or instrument to measure students' mathematical readiness. Multiple measures often include, but are not limited to, more than one test score, high school GPA, high school grades in specific classes, number of high school math classes passed, and life experiences as well as input and referrals from academic advisors (Qin, 2017). The logic behind using multiple measures is fairly simple. Including more than one measure increases the amount of information being used in the placement process. The idea is that more is better. Additionally, proper use of multiple regression techniques ensures that the worst case for adding more measures is no change in the predictive power (Ngo & Kwon, 2015). Recent research verifies this idea by showing that multiple measures placement processes are likely to result in more accurate placement decisions than placement processes using single measures. (Ngo & Kwon, 2015; Barbitta & Munn, 2018). However, while single measure processes generally use placement tests as their single measure, the multiple measures processes currently in place utilize a range of measures. Moreover, there is no agreement on how to use the selected measures.

There is a growing body of literature supporting the idea that single measures place many students too low (Bahr et al., 2019). Low placement is especially pernicious because it is not apparent to faculty the way high placement is. A student that is placed too low has the prerequisite skills for the course into which they are placed. The problems with low placement are that it is demotivating, it adds unnecessary time and financial costs to the student, and it may increase the likelihood that the student will drop out of the program (Valentine, Konstantopoulos, & Goldrick-Rab, 2017, Quin, 2017). These issues are usually difficult to detect by the teacher of the course. Students who are placed too high are much more obvious to teachers because they tend to lack the prerequisite skills needed for success in the course. Students that are placed too low have no similarly obvious indicators (Qin, 2017). These consequences of low placement combined with the expected increased accuracy of multiple measures placement have led several states to require math placement decisions to use some form of multiple measures (Ngo & Kwon, 2015). Overall, the use of multiple measures placement shows some promise for improving the college math educational process for development students.

The amount of improvement that is reasonable to expect when switching from a single measure to multiple measures is not clear. The California Community College System switched to multiple measures placement for math due to a state law mandating the change. The law did not make any requirements about how multiple measures should be applied. As a result, California Community Colleges chose a range of methods. Several of the colleges chose to use a system which continued to use a placement test for the initial assessment and then increased the placement score for students with higher high school GPAs and the successful completion of more advanced high school math classes. This increase was called a boost (Ngo & Kwon, 2015).

Ngo & Kwon (2015) studied students whose boost ultimately led to them being placed into a higher level class than their initial placement score would have indicated. Only 4.2% of students who were initially placed into developmental math classes were boosted into a higher class. Students who moved up a class level due to receiving the boost passed the next course at the same rate they would have been expected to pass their original course. However, those boosted students who passed the course they were placed into were 8% less like to pass that course than students placed into the course without a boost. This is still a marked increase in overall pass rate because an 8% decrease resulted in a much higher pass rate than the combined pass rate for students who needed to pass both classes. Note that the average pass rate includes data for students whose initial test scores were as much as 30 points higher than those of the boosted students. In practice, only students who placed into the top edge of a class prior to boost were able to be boosted up to the next class. Some of the 4.2% of students who were boosted into the next class were still in developmental classes. The study examined the several different ways that the various community colleges incorporated information about high school performance and concluded that other than high school GPA, there was no clear indicator that any of the several other measures were more or less effective at predicting college success. These findings suggest that while the effect is likely to be limited, community colleges can improve placement accuracy in developmental math and increase access to higher-level courses by considering multiple measures of student preparedness in their placement rules.

Another large community college system in changed their math placement system to use a computer adaptive test as their primary measure. While this seems likely to have been a positive change in many cases, in this particular case the computer adaptive system proved to be less accurate than the system that it replaced (Ngo & Melguizo, 2016). This provided a unique opportunity to test the effect of the accuracy of the math placement system on student success in developmental and entry level math courses. Unsurprisingly, analysis of student success rates showed that average success rates decreased and both the failure rate and time spent in developmental courses increased. The study did not attempt to measure changes in the number of students who never enrolled in their assigned math course. Decreased placement accuracy reduced student success (Ngo & Melguizo, 2016). This suggests that more accurate placement would improve student results.

Individual Placement Measures

Institutions of higher education relied mostly on the use of single measures for math placement for many years, and many still use just one measure in their placement process (Xu & Dadgar, 2018; Ngo & Kwon, 2015). Community Colleges have generally used Compass, Accuplacer, or a locally developed test while four year colleges more frequently use SAT and ACT math scores (Xu & Dadgar, 2018; Ngo & Kwon, 2015; Bahr et al., 2019). Probably the best single predictor of entry level college math success is the most recently updated SAT math test which has an r value of 0.49, indicating that this test accounts for slightly less than 25% of the variance in student success in students' first college level math classes (Shaw et al., 2016). In addition, few states require that institutions perform any kind of validity or accuracy check of their selected math placement instruments (Fulton, 2012). These weaknesses in even the best single measures contribute to the search for a better means of math placement.

Recent research indicates that the use of multiple measures is likely to produce better results (Ngo & Kwon, 2015; Barbitta & Munn, 2018). However, little research has been conducted on which individual measures are best or how they might work together. Much research has been done on the correlation between college mathematics outcomes and a range of measures such as ACT math scores, SAT math scores, high school GPA, and math efficacy scores. A variety of non-cognitive measures have also been shown to have significant positive correlation with college success and persistence (Porchea, Allen, Robbins, & Phelps, 2010; Kim, Park & Cozart, 2014; Cho & Heron, 2015). Legislation has even been passed in some states which specifically allows the use of non-cognitive measures for math placement when used in conjunction with cognitive methods (Burdman 2012; Texas Higher Education Coordinating Board (THECB), 2012). Nonetheless, little work has been done showing how effective many of these measures are at actual entry level college math placement (Ngo & Kwon, 2015). ACT math scores, SAT math scores, high school GPA, and some other measures of high school math achievement have been shown to have statistically significant positive correlations with success in entry level college mathematics courses (Ngo & Kwon, 2015; Bahr et al., 2019; Barbitta & Munn, 2018; Donovan & Wheland, 2008).

Nationally standardized tests versus locally developed assessments

The SAT and ACT are the two primary nationally standardized tests used for placement in college math placement programs (Bracco et al., 2014). There are good reasons for this. Both tests have been widely shown to be among the better single predictors of entry level college success. These tests are very well known and thus safe choices for administrators in a politically charged climate. Standardized tests provide the best basis for comparison across national student populations. Moreover, these tests have been designed by testing experts with access to large amounts of student testing data.

However, there are some reasons to prefer locally developed tests (Smith, Clements, &

Olson, 2010). Locally developed tests are more likely to closely reflect any unique features of the local curriculum and more exactly match up class content. Also, local tests can be much more easily modified to reflect changes in the curriculum and can be designed to test for factors of particular local interest. Percentile rankings in nationally normed tests are very sensitive to small changes in the actual number of correct answers (Banta & Polumba, 2015). In one instance, scores for a particular month in 2003 on Educational Testing Service Major Field Achievement Test in Business caused a 19 percentile point swing for scores in a certain range (Bycio & Allen, 2007). It should be noted that while the scoring methodologies are the same, no known similar event has happened with the much more widely used ACT and SAT tests. Both local and national tests have advantages with the two dominant national tests being more widely used.

Time and financial costs vary widely between local and national tests. Development of local tests requires significant investment of both time and money on the part of the local educational institution. In some cases, these costs can be offset by obtaining government grants. All development costs for national tests have been absorbed by the testing companies. Costs to students vary as well. Local tests can be administered free of charge or at nominal cost to students while the administration costs as well as profits for the national testing companies are paid for by students (Banta & Polumba, 2015).

ACT

The ACT test is administered by the ACT organization (formerly American College Testing). Its stated purpose is to measure what students have learned in high school in order to determine their level of academic readiness for college (ACT, 2019a). This is a broader purpose than just correct college placement with respect to developmental math. This broader purpose can be seen in the design of the math section of the ACT.

The ACT Math section is a 60 question test for which students are given 60 minutes. Some of the topics are directly related to the algebra taught in most developmental math classes. The SAT labels these topics as “number and quantity,” algebra, and functions. There are also two overarching themes of “Integrating Essential Skills” and modeling running through these topics. Questions are administered following both of these themes in increasing level of complexity and difficulty. The higher end questions of these themes appear to be outside the scope of developmental classes. In addition, topics of geometry, statistics, and probability are covered (ACT, 2019b). These last few topics are not covered in the developmental classes taught at the institution featured in this study.

SAT

The purpose of the SAT is to measure the degree to which students are ready for college level academics and to predict student success in entry level higher educational course work (College Board, 2015). The purpose of the math section of the SAT is to test the following claim:

> In keeping with the evidence about essential requirements for college and career readiness described in Section II, the redesigned SAT requires a stronger command of fewer, more important topics. To succeed on the redesigned SAT, students will need to exhibit mathematical practices, such as problem solving and using appropriate tools strategically. The SAT also provides opportunities for richer applied problems (College Board, 2015, p. 132).

As with the ACT, this is a much broader purpose than just determining correct placement with respect to college developmental math courses and the questions in this instrument are in keeping with its broader purpose. The SAT Math section consists of 58 questions and students are given 80 minutes to complete the math portion of the test. The questions are grouped into content areas called “Heart of Algebra,” “Problem Solving and Data Analysis,” “Passport to Advanced Math,” and “Advanced Topics in Math” (College Board, 2015). Many of these questions range far beyond the developmental math level and include a substantial number of questions in geometry and statistics (College Board, 2015). T.

Local assessment test

The local developed assessment test used in this study is an algebra skills test designed to be a survey of the topics found in the two developmental math classes taught at the institution. The test consists of two parts. The first part consists of some questions commonly considered to be Pre-Algebra with the bulk of the questions covering topics commonly found in Algebra I courses. All of the topics covered can be found in the course description section of the Fundamentals of Math syllabus in Appendix A. The second section of the test consists of an additional 20 and only opens for students who answer at least 23 of the 30 questions in the first section correctly. This section of the test is a survey of the topics found in the Intermediate Algebra class and exclusively covers topics found in the syllabus for this class, which is in Appendix B. The primary added value of this local test is that it is focused specifically on the algebra skills covered in the developmental math classes taught at the local university.

GPA

High school GPA is both widely used in higher education mathematics placement at many institutions and recommended by many researchers as an excellent predictor of college performance (Bahr et al., 2019; Ngo & Kwon, 2015; Higdem et al., 2016; Maruyama, 2012). High school GPA is also frequently used by practitioners and researchers as a factor for use along with mathematics placement tests such as the ACT and SAT math tests (Shaw et al., 2016; Bahr et al., 2016; Maruyama, 2012). Generally speaking, high school GPA is reported in both weighted and unweighted formats. Unweighted high school GPA is computed as class letter grades converted to a 4.0 scale and then averaged using no weighting other than credit hours. Weighted high school GPAs vary, but usually involved a mixture of grades on a 4.0 and 5.0 scale where more challenging courses such as AP or honors courses are given an additional point to provide extra credit students for taking more difficult courses (Suldo, Thalji-Raitano, Kiefer, & Ferron, 2016; Warne et al., 2014). Both the weighted and unweighted systems of reporting GPAs appear to be widely used by US high schools.

In a study using 710 medical school applicants to medical schools across Texas, researchers found that unweighted high school GPA was a better predictor of college GPA (Warne et al., 2014). In addition, a using data from 10,492 first year college calculus students found that the most common methods of weighting high school GPAs provided approximately double the extra point value of the optimum weighting. The optimum weighting in this is a weighting that maximizes the predictive value of high school GPA for first year college GPA. This extreme overweighting combined with the wide variance in the details of how extra weights are assigned led the researchers to recommend using unweighted high school GPA (Hansen, Sadler & Sonnert, 2018).

Equity Considerations in Placement Testing

In the present societal and political context that places a high emphasis on race blindness, the use of the current nationally standardized tests may become problematic. Use of these tests tends to place minority students too high which could ultimately result in lower success rates for minority students (Mattern et al., 2008). In addition, higher educational institutions that either have a significant international student population or wish to increase the size of their international student population may need to exercise caution when using the tests written in English and standardized across a population of US students. These tests tend to under place students whose first language is not English (Shewach, Shen, Sackett & Kuncel, 2017).

A study conducted by Black, Cortes, & Lincove (2016) using data from the Texas higher education system found that SAT/ACT scores are good predictors of early college success. They also found that using SAT and/or ACT scores as part of a college placement program causes significant reduction in the numbers of minority and low income students who enroll in the higher educational system. The Texas Public University System has a unique feature that gives guaranteed admission to students who graduate in the top 10% of a Texas high school class. Other factors are used as well for admissions to the more selective Texas universities. This unique feature of the Texas system allowed the researchers to use data from several higher education institutions and control for effects for factors such as SAT/ACT scores, high school exit exams, and advanced high school coursework.

The researchers found that adding SAT/ACT score cutoffs as an additional admissions factor would likely increase the average freshman GPA in the system by 0.19 points (about 6%) over the current average freshman GPA. Furthermore, this admissions policy would increase 4-year retention rates from approximately 50% to approximately 56%. This tighter admissions policy would also reduce the number of Hispanic students eligible for automatic admissions by 69%; the number of African American students eligible for automatic admissions by 73%; and the number of eligible students from lower socio-economic status (SES) families by 62%. Despite the overlap in minority and SES status, no effort was made to control for one of these factors when measuring the others. (Black, Cortes, & Lincove, 2016).

The College Board collected high school GPA, SES, and freshman year of college GPA for 415,599 students at 148 colleges and universities. The institutions were chosen so as to create a sample that was diverse across school size, public versus private, and degree of selectivity of the institution. SES status, sex, race and ethnicity were self-reported by a survey taken at the time of taking the SAT. Initial average SAT scores were lower some racial and ethnic groups as well as for lower SES students. However, after controlling for effects of racial and ethnic group memberships, SES had minimal effect on SAT scores and freshman year of college GPA (Higdem et al., 2016). The differences in average scores by racial and ethnic group creates an element of controversy around the use of the SAT and ACT as placement instruments. However, correlation is not causation. The source of most of the disparity seems to be not in the tests, but in societal factors that ultimately lead to lower test scores (Letukas, 2016). Also, because the SAT has been shown to over-predict freshman year college performance for minorities who obtain lower scores on average, the use of the SAT (and likely the ACT given its similar general results) does not harm members of these minorities with respect to college admissions. Neither their chances for admission to college nor their initial class placements are lowered by the use of these tests in the admissions and placement process (Mattern et al., 2008; Shewach, Shen, Sackett, & Kuncel, 2017).

Summary

Placement into developmental math courses is a high cost proposition for students. Students placed into developmental math take longer to graduate, experience higher financial costs, and are significantly more likely to drop out of college than students who are not placed into developmental math. (Valentine, Konstantopoulos, & Goldrick-Rab, 2017). However, large numbers of students enter college with a mathematical skill set that is well short of what is needed to succeed in even basic college level math courses. As a result, many entering freshmen will need to be placed into developmental mathematics and it is important that their colleges and universities make the best possible decisions with regards to their initial math placements (Boatman & Long, 2018).

Math placement processes using multiple measures are widely recommended in the literature (Shaw et al., 2016; Ngo & Kwon, 2015; Qin, 2017; Barbitta & Munn, 2018; Bahr et al., 2019). Though much variety exists in the details of implementation, multiple measures methods are used in several statewide college and university systems as well as in a range of individual higher education institutions (Ngo & Kwon, 2015; Qin, 2017; Barbitta & Munn, 2018; Bahr et al., 2019). The present study uses a multiple linear regression to examine the efficacy of multiple measures math placement into online developmental math courses using ACT/SAT math scores, a local math assessment, and high school GPA as predictor variables.

The first two predictive criterion in the present study–SAT/ACT math scores and a local algebra skills placement test–are supported by the concepts related to cognitive schema common to various cognitive constructivist theories. The third predictive criterion, high school GPA, is supported by both Bandura's social learning theory and his work on self-efficacy. Cognitive schema theory says that people gain new knowledge and understanding by building new logical structures in their minds that are based on current knowledge. This concept supports the use of both the national and local placement tests because these tests seek to measure students' current mathematical knowledge and understanding. Bandura's social learning theories support the use of high school GPA because it is built over time, is connected to the quality of students' support networks, and has been shown to be related to self-efficacy (Siegel, Galassi, & Ware, 1985; Bandura, 1997).

Online student populations have been shown to have some significant differences from traditional on ground student populations and are generally older, more likely to be raising children, work significantly more hours per week, and more likely to be married (James, Swan & Daston, 2016; Ortagus, 2017; Goodman, Melkers & Pallais, 2019). No work appears to have been done about how these differences in the online student population might affect developmental math placement for these students. The present study seeks to contribute to filling this gap.

CHAPTER THREE: METHODS

Overview

This chapter identifies and explains the methods and procedures that were used in this study. The primary purpose of the study was to determine how well a particular multiple measures math placement system predicts student success in an online developmental mathematics course. This chapter explains the design of the research and then examines the hypotheses, participants, setting, procedures, and data analysis methods for the study.

Design

This research was performed using a quantitative correlational design to investigate the nature of the relationships between the success of online students in a developmental math course and selected archival student data. All of the data for all variables in the study was quantitative and archival. Archival data is widely available from a range of post-secondary sources and both academic researchers and university leaders commonly use this data to inform their comprehension of higher education (Freitas et al., 2015). The stated purpose of examining the predictive relationship between a set of predictor variables and a criterion variable is one of the primary purposes of quantitative correlational design (Gall, Gall & Borg, 2007). The quantitative correlational approach was also a good choice because it allows a solitary study to be used for the analysis of relationships among multiple variables (Gall, Gall & Borg, 2007). Furthermore, this design was appropriate because this research sought to determine the factors influencing or predicting an outcome (Creswell, 2014). Correlational designs also allow for the exploration of the degree of relationship between the variables (Gall, Gall, & Borg, 2007).

The predictor variables employed were ACT/SAT math scores, high school GPA, and scores on a locally designed algebra skills assessment. The ACT and SAT are the two most widely recognized nationally standardized tests employed for college admissions and placement (Bracco et al., 2014). High school GPA is both widely utilized in higher education mathematics placement at many institutions and recommended by many researchers as an excellent predictor of college performance (Bahr et al., 2019; Ngo & Kwon, 2015; Higdem et al., 2016; Maruyama, 2012). Locally developed tests have some advantages over nationally normed exams including the fact that the locally developed tests match more exactly with the local class content (Smith, Clements, & Olson, 2010).

Research Question

RQ: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local algebra skills assessment predict the Math 100, Fundamentals of Mathematics final grade for online students who completed the course at a private university during the 2016-2019 academic years?

Hypothesis

H_0: There is no statistically significant predictive relationship between the criterion variable (final grade for Math 100) and the linear combination of predictor variables (ACT/SAT math score, unweighted high school GPA, and score on a local algebra skills assessment) for online students who completed the course at a private university during the 2016-2019 academic years.

Participants and Setting

This subsection of the paper describes the population, setting, and samples used in this study. Care is taken to describe each element in enough detail to assess their probable effects on the study for the sake of informing any attempts to replicate this study (Gall, Gall, and Borg, 2015). The participants in this study were students attending a large, private, regionally accredited university in the southeastern United States which had an online enrollment of approximately 90,000 students at the time of the study. Participants were randomly selected undergraduate online students placed by the university math placement system into Math 100 which is the first of the university's two developmental mathematics courses.

Samples

Random samples of student grade and demographic data were selected from the population of students assigned to Math 100 from fall 2016 through spring 2019. See Appendix A for a current Math 100, Fundamentals of Mathematics syllabus. Data records for students who withdrew from or otherwise did not complete the course were removed from the sample, as were records from students for whom any of the data being collected was missing. The sample began with 4,388 individual records, from which one record was removed because it was a duplicate record. The final sample included 1495 male students and 2335 female students and 13 students who did not report a gender, with 1753 students who identified as White or Caucasian, 594 as African-American or black, 159 as Hispanic or Latino, 20 as American Indian or Alaskan Native, 6 as native Hawaiian or Pacific Islander, 14 as Asian, 84 as two or more races, 4 as nonresident alien, and 1239 who did not report. Student ages ranged from 13 to 77 with a median age of 35 and an average age of 36.3. The sample included 256 freshmen, 501 sophomores, 727 juniors and 2359 seniors. The sample size is that of all of the records used in this study. The multiple regression using all three factors described in this study only had 69 records. The sample size of 69 students met the minimum sample size requirement of $N = 66$ for a multiple linear regression with three predictor variables (Gall, Gall. & Borg, 2007). The other regressions that were run as part of the data analysis for this study all had record counts ranging from 860 to 2,529.

Instrumentation

The variables measured in this study were SAT and ACT math scores, local algebra skills assessment scores, unweighted high school GPA, and final course grades in Math 100.

ACT/SAT Math Scores

Many colleges and universities have historically used scores from the SAT and ACT as either their main measure (Melguizo, Kosiewicz, Prather, & Bos, 2014; Xu & Dadgar, 2018) or one of multiple measures for mathematics placement. All public post-secondary state institutions in Colorado, North Carolina, Indiana, Kentucky, and Louisiana use both the SAT and ACT as part of a multiple measures placement system for placing entering college and university students (Bracco et al., 2014).

American College Testing administers their ACT test, which they describe as measuring high school learning and college readiness. Moreover, the ACT is accepted by every four-year university in the US ("ACT Test," n.d.). The ACT math section is composed of 60 questions with Cronbach's alpha on individual questions ranging from 0.90 to 0.92 and an overall alpha of 0.91. The standard deviation is 5.36 on a scale from 1 to 36 (American College Testing, 2018).

The ACT includes four separate subject tests of English, Mathematics, Reading, and Science. Each of these subjects has a score range from 1 to 36. This study only uses the Mathematics score. The Mathematics section includes 60 questions with a score of 1 indicating that the test taker answered all or almost all of the questions incorrectly and a score of 36 indicating that the test taker answered all or almost all of the questions correctly. The exact number of questions answered correctly per point of score varies as the point distribution is smoothed to even out the distribution. All of the questions are multiple choice questions with five answer options for each of the mathematics section questions (American College Testing, 1988).

The overall ACT test is administered in the order of English (45 minutes), Math (60 minutes), a 10 minute break, Reading (35 minutes), and Science (35 minutes). All work on each section must be completed during the time window for that section. Other than the 10 minute break between Math and Reading, the only gap between each test is the couple of minutes required for one of the test administrators to read the directions for the next section. The total testing time is 2 hours and 55 minutes not including the break or the time the test administrator takes to read the instructions (American College Testing, 2018).

The Scholastic Aptitude Test (SAT) is administered by the College Board, which is made up of over 6,000 educational institutions, for the purpose of promoting college success for students by accurately measuring college readiness (College Board, 2019). In addition, a validity study based on pilot results of the latest version of the SAT published by the College Board found the SAT to be valid and reliable as a predictor of success in first year college mathematics (Shaw et al., 2016). The SAT math section is composed of 54 questions with Cronbach's alpha on individual questions ranging from 0.92 to 0.94 and an overall alpha of 0.93. The standard error of the mean is 29 on a scale from 200 to 800 (College Board, 2015).

The SAT includes the two separate subject tests of Mathematics and Evidence Based Reading and Writing (EBRW). Both tests have a minimum score of 200 and a maximum score of 800. The mathematics test consists of a 25-minute section no calculator section with 20 questions and a 55-minute calculator section with 38 questions. The EBRW test has a 65-minute reading section with 52 questions and 35-minute writing and language section with 44 questions. The exact matching of score to number of questions answered correctly varies slightly with the actual score distribution for different versions of the test. For mathematics, a score of 200 means that the test taker answered 0 or 1 of the 58 questions correctly and a score of 800 means that they answered 57 or 58 of the questions correctly. The maximum and minimum scores for the EBRW test have the same meaning as those for the Math test.

The SAT is administered in three sections in a single sitting. The Reading section is administered first followed by a 10-minute break. The next section is the no calculator Math section followed by a 5-minute break and the last section is the calculator Math section. The SAT takes 3 hours and 15 minutes including breaks and not including time for the test administrator to read the instructions for each section. All work on each section must be completed during the time window for that section.

Unweighted High School GPA

Many institutions, including the university that was the setting for this study, use high school GPA as part of their math placement decision making process (Atuahene & Russell, 2016; Bracco et al., 2014; Hiss & Franks, 2014; Jackson & Kurlaender, 2014). In addition, The College Board recommends the use of high school GPA as the best supplemental measure to the SAT mathematics score for college math placement (Shaw et al., 2016). The university determines applicants' unweighted high school GPAs from official transcripts received through the admissions process. Unweighted means that all grades are computed on the traditional four-point scale. Many high schools add a point to grades in classes that they consider to be advanced such as Advance Placement and honors classes. For example, an A in one of these classes is worth 5 points and a B is worth 4 points etc. The university removes all of these extra points and then computes the unweighted GPA as the average after all of these extra points are removed. This unweighted GPA is then manually entered into the university's student information system. This definition of unweighted GPA is consistent with definitions in peer-reviewed academic literature (Suldo, Thalji-Raitano, Kiefer, & Ferron, 2016).

Local Algebra Skills Assessment

Locally designed algebra skills assessments have some advantages with respect to national standardized assessments such as the ACT and SAT (Banta & Palomba, 2015). Some of the mathematics faculty at the university in this study desired to include a more direct test of pre-algebra and algebra skills than that which is provided by the ACT and/or SAT math tests. As a result, they designed the university's math assessment test (called the ASMA) which is a fifty-question test designed to assess a range of essential algebra skills. The researcher in the present study has been involved in several discussions about the validity and purpose of this test with some of the faculty who designed the test (including the leader of the design group). Also, a comparison of the questions on the test and the syllabi for developmental math courses show that all the questions are taken from the course content for these two courses as described in their syllabi. See Appendix A for sample course syllabi.

The Algebra Skills Assessment has two sections. The first section is made up of 30 pre-Algebra and Algebra I questions. The second section is made up of 20 Algebra I and Algebra II questions. All questions are multiple choice with four answer options. Scores simply count the number of questions answered correctly with a score range on the first section of zero to 30 and a score range on the second section from zero to 20. Students are only shown the second section of the test if they receive a score of 23 or higher on the first section.

The test is administered online without proctoring. Each of the two sections is administered in a single session with no breaks. Students taking the second section may either take it immediately on completion of the first section or come back and take the second section at another time. Test takers are given 120 minutes to complete the first section and an additional

90 minutes for the second section if applicable. Students whose scores place them into Math 100 generally do not score high enough on the first section to take the second section of the test.

Fundamentals of Mathematics (Math 100) Final Grades

The criterion variable was final grades in the lowest level developmental math course taught at the university. The course title and number are Fundamentals of Mathematics – Math 100. The course is taught online using a combination of Blackboard and WebAssign software. All assignments are completed online. These assignments include weekly sets of math problems as homework as well as quizzes, tests, a final exam, and two discussion board assignments. Blackboard is used for communication between teacher and students and houses the discussion board assignments. All other types of assignments are in WebAssign. The measure used for final grades in the course was each student's final grade reported as a percentage out of 100. This data was obtained from Banner which is the university record system.

Procedures

The researcher received permission to conduct this study from the university's Institutional Review Board and from the Dean of the College of Arts and Sciences and the Mathematics Department Chair. See Appendix C for the written statements granting permission. All data for all variables involved in the multiple regression was obtained from the university's student information system (Banner) and was both retrieved and anonymized by the university's Analytics and Decision Support department before being delivered to the researcher. Only data for first attempts at Math 100 for students who were placed directly into each course was used. Also, data for students who did not complete their course was removed before the any statistical analysis was performed.

Basic demographic information including gender, birth year, and ethnicity was collected for all the participants whose data will be used in the study. Student anonymity was maintained by the use of randomized student ID numbers which were inserted into the data before it was delivered to the researcher. These randomly selected ID numbers were then used to match the demographic information to the other data. All data was delivered to the researcher via email after being anonymized. The data was entered into SPSS and analyzed.

Data Analysis

Linear regression provides appropriate data analysis for research aimed at determining relationships between predictor and criterion variables (Gall, Gall & Borg, 2007). This study investigated the relationship between multiple predictor variables (ACT/SAT math scores, high school GPAs, and algebra skills assessment scores) and the criterion variable (Final Exam grades in Math 100). Therefore, a multiple linear regression was more appropriate than a simple regression (Gall et al.; Hanley, 2016).

According to Warner (2013), there are two general requirements about the type of data and three further prerequisite assumptions that need to be verified as part of the data screening process for multiple linear regression calculations. The general assumptions about the type of data are that it is at the interval or ratio level of measurement and that the observations are independent. All data used in the regression was quantitative data at the ratio level of measurement. Moreover, each data value was associated with a unique student and any repeat values were removed before any analysis was conducted. As a result, the observations were independent.

The first assumption was of bivariate outliers. This assumption was verified through visual examination of scatter plots of all pairs of predictor variables (x, x) and all pairs of predictor and criterion variables (x, y). If any outliers were found, they were checked for accuracy and corrected if any errors were present. If no errors are found, they were included in the data unless otherwise specifically noted. The second assumption was that the data was distributed according to a multivariate normal distribution. This assumption was verified through visual examination of scatter plots for each pair of predictor variables (x, x) and each pair of criterion variables (x, y). This assumption was verified by checking for a classic "cigar shape" to the data in each scatter plot. If there was any evidence of a violation of this assumption, the data was carefully examined for data entry errors and any such errors were corrected before continuing to the next step. The third assumption was the assumption of non-multicollinearity among predictor variables. This assumption was verified by calculating the tolerance and variance inflation factor (VIF). If any of the tolerance values approached zero and the VIF value approached 10, one of the multicollinearity variables was removed (Warner, 2013).

All hypotheses were tested at a 95% confidence interval which corresponded to an alpha of .05 (Warner, 2013). Significance was tested using an *F*-stat, and effect size will be measured via Pearson's r^2. In keeping with Warner (2013), for correlational studies like the present study, the effect size was reported by r^2. An r^2 of 0.01 or less is considered a small effect size, while an r^2 of .09 is considered medium, and an r^2 greater than 0.25 is considered a large effect size (Cohen, 1988). All these selections were in keeping with Gall, Gall, and Borg (2007) and Warner (2013).

CHAPTER FOUR: FINDINGS

Overview

The purpose of this chapter was to present the results of this research into how well students' SAT/ACT math scores, high school GPA, and scores on a local algebra skills test could predict their final grades in an online developmental math course (Math 100). The chapter begins by presenting the research question and its related null hypothesis. The subsequent pages describe data screening, descriptive statistics, assumption testing, and the results of the multiple regression analysis. This chapter describes the results of additional data analysis that was performed.

Research Question

RQ: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local algebra skills assessment predict the Math 100, Fundamentals of Mathematics final grade for online students who completed the course at a private university during the 2016-2019 academic years?

Null Hypothesis

H_0: There is no statistically significant predictive relationship between the criterion variable (final grade for Math 100) and the linear combination of predictor variables (ACT/SAT math score, unweighted high school GPA, and score on a local algebra skills assessment) for online students who completed the course at a private university during the 2016-2019 academic years.

Data Screening

There were 3843 records in the original data file that contained data for at least one of the predictor variables for students enrolled in online Math 100 who completed the course and for whom it was their first attempt. The researcher sorted the data and scanned for inconsistencies on each variable. One duplicate record was found and removed. No other errors were found. Participant data for all three of the predictor variables used in the study were only found on 69 of the records.

Descriptive Statistics

Descriptive statistics were obtained on each of the variables. The sample consisted of records for 69 participants. Scores on all 3 predictor variables were converted to percentages of the maximum score for each variable so that they would be on matching scales. SAT math scores range from 200 to 800. The potential range of scores is therefore 25.00 to 100.00. ACT math scores range from 1 to 36. The potential range of ACT math scores is therefore 2.78 to 100.00. In cases where both SAT and ACT scores were present, an average of the two percentage scores was used. A high score on either test indicates a strong math aptitude compared to the general population of college students in the US. A low score on either test indicates a weak aptitude for math. A high GPA score indicates a strong combination of academic aptitude and skills at the time of graduation from high school. A low GPA score indicates weak combination of academic aptitude and skills at high school graduation. Algebra skills test scores potentially range from 0 to 30 and were converted to percentages of the maximum score. The potential range of scores is therefore 0.00 to 100.00. Higher scores represent stronger algebra skills while lower scores indicate weaker algebra skills. The criterion variable, overall numerical scores in Math 100, potentially ranges from 0 to 1000 and were not converted to a percentage basis. Descriptive statistics can be found in Table 1.

Table 1

Descriptive Statistics

	N	Min.	Max.	Mean	Std. Dev.
SAT/ACT	69	13.33	71.00	41.41	10.94
HSGPA	69	44.00	100.00	74.98	14.40
Algebra Skill	69	16.67	100.00	58.70	19.11
M100	69	112.35	983.29	822.58	151.07
Valid N	69				

Assumption Testing

Assumptions of Linearity, Bivariate Outliers, and Bivariate Normal Distribution

The multiple regression requires that an assumption of linearity be met. Linearity was examined using a matrix scatter plot. The assumption of linearity was met. A matrix scatter plot was used to detect bivariate outliers between each of the predictor variables and between the predictor variables and the criterion variable. The multiple regression also requires that the assumption of a bivariate normal distribution be met. The assumption of bivariate normal distribution was examined using a scatter plot. Generally cigar shaped patterns can be seen in the higher density areas of each plot. The scatter plots showed some deviation from the ideal bivariate normal pattern, however, the research continued with the analysis. In addition, the scatter plot was examined for extreme bivariate outliers. No extreme bivariate outliers were found. See Figure 1 for the matrix scatter plot.

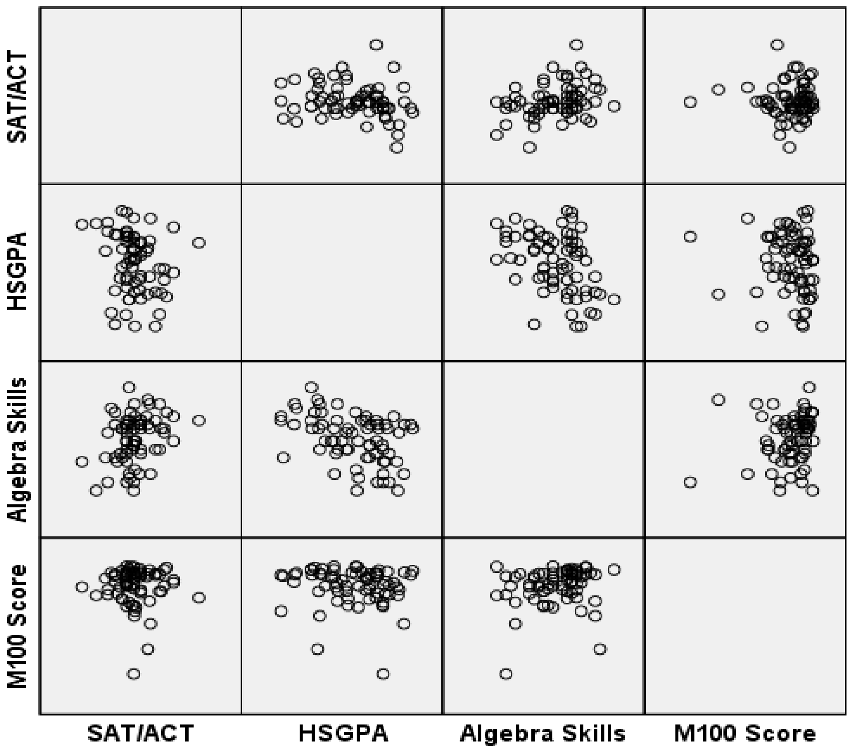

Figure 1. Matrix scatter plot.

Assumption of Multi-collinearity

A Variance Inflation Factor (VIF) test was conducted to assure the absence of multi-collinearity. This test was run because if a predictor variable (x) is highly correlated with another predictor variable (x), they essentially provide the same information about the criterion variable. If the Variance Inflation Factor (VIF) is too high (greater than 10), then multicollinearity is present. Acceptable values are between one and five. All three VIFs were between one and two. The assumption of multicollinearity was met between the variables in this study. See Table 2 for the collinearity statistics.

Table 2

Collinearity Statistics

Model		Collinearity Statistics	
		Tolerance	VIF
1	SAT/ACT	.886	1.129
	HSGPA	.827	1.209
	Algebra Skills	.773	1.294

a. Dependent Variable: M100 Grade

Results

A multiple regression was conducted to see if there was a predictive relationship between the criterion variable (Math 100 final grades) and the linear combination of predictor variables (SAT/ACT, local algebra skills test scores, and high school GPA) for online college students. The researcher failed to reject the null hypothesis at the 95% confidence level where $F(3, 65) = 0.982$, and $p = .407$. No statistically significant predictive linear relationship was found between the predictor variables and the criterion variable. See Table 3 for regression model results and Table 4 for regression coefficients.

Table 3

Regression Model Results

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	67,300.36	3	22,433.45	0.982	.407[b]
Residual	1,484,693.05	65	22,841.43		
Total	1,551,993.41	68			

a. Dependent Variable: M100

b. Predictors: (Constant), Algebra Skill, SAT/ACT, HSGPA

Table 4

Coefficients

	Unstandardized		Standardized		
Model	B	Std. Error	Beta	t	Sig.
(Constant)	819.82	145.25		5.64	0.000
SAT/ACT	-1.17	1.76	-0.09	-0.66	0.509
HSGPA	-0.44	1.44	-0.04	-0.31	0.761
Algebra Skill	1.44	1.09	0.18	1.31	0.194

a Dependent Variable: M100

ADDITIONAL ANALYSIS

The number of data records for the multiple regression barely met the minimum standard and the effect sizes were in the small to medium range (Warner, 2013). Many more records were available for each of the individual predictor variables than were available for all three predictors together. Moreover, the records with all three predictor variables and those with SAT/ACT had substantially lower average ages than the other records. See Table 5 for details. Therefore, the researcher decided to perform further correlational analysis to determine if the higher record counts for the individual variables would lead to significant individual linear correlations. In addition, because the scatter plots showed noticeable deviation from the ideal bivariate normal pattern, the researcher chose to perform this further analysis using Kendall-tau non-parametric test for linear correlation.

Table 5

Average Age and Record Count by Predictor Variable(s)

Description	**Avg Age**	**Record Count**	**Percent of Records**
All 3 predictors	22.1	69	2%
SAT/ACT	24.2	231	6%
Algebra Skills	36.3	2,152	56%
GPA	36.4	2,529	66%
Any of the 3 predictors	36.3	3,843	100%

Further testing using the larger data sets and Kendall's tau yielded two significant correlations. Significant linear correlations were found at the 95% level between High School GPA and Math 100 grades ($r_\tau = .054, p = .000$) and between Algebra Skill scores and Math 100 grades ($r_\tau = .176, p = .000$). Assuming similar effects for Kendall's tau and Pearson's r, these effect sizes are small and medium respectively. No significant linear correlation was found between SAT/ACT scores and Math 100 grades ($r_\tau = .020, p = .325$).

CHAPTER FIVE: CONCLUSION

Overview

If current growth trends in online college education continue, the day is fast approaching when online college enrollment will exceed on ground college enrollment (Seaman, Allen, & Seaman, 2018). Deeper understanding of all aspects of online college education continues to grow in both value and importance. This chapter concludes this exploration of the predictive accuracy of a multiple measures placement scheme for final course grades for students in an online developmental math course. The chapter will discuss the study findings with respect to the research question as well as with respect to the further explorations indicated by the data. Implications and limitations of the study in addition to recommendations for further research will also be examined.

Discussion

The purpose of this study was to explore the accuracy with which a multiple measures placement process using ACT/SAT mathematics score, an algebra skills assessment, and unweighted high school GPA could predict final course grades for students in an online developmental math course. This section will begin with an examination of the findings with respect to the hypothesis at the center of the study. Then it will move to explore the results from the further analysis performed by the researcher.

Null Hypothesis and Three Factor Multiple Regression

The researcher failed to reject the null hypothesis of no significant linear relationship at the 95% confidence level between a linear combination of the predictors ACT/SAT math score, the local algebra skills assessment test, and unweighted high school GPA and the criterion overall course grades in an online developmental math course (Math 100). The applicability of the results of this multiple regression to the larger dataset was called into question by the fact that less than 2% of the student records used in the study had data for all three predictor variables. This was largely driven by the lack of records with SAT and/or ACT mathematics scores. Approximately 6% of the records contained a value for either test. This low percentage of records containing all three predictors means that the results for this particular regression can't be considered representative of the overall dataset. Further evidence that these subsets are likely not representative of the larger data set can be seen in the variance between the mean age of the students in these subsets and the mean age of the students in the overall dataset. See Table 5 in Chapter four for average age and record count data.

The literature for both SAT and ACT scores describe both as being good predictors of success in entry level college math classes (ACT, 2019a; Shaw et al., 2016; Xu & Dadgar, 2018; Ngo & Kwon, 2015; Bahr et al., 2019). However, the literature about the value of SAT and ACT as predictors is for success across all levels of first year college math courses (ACT, 2019a; Shaw et al., 2016; Xu & Dadgar, 2018; Ngo & Kwon, 2015; Bahr et al., 2019) instead of just the lowest level of developmental math that is in this study. Perhaps these test scores are less significant at this level of course. Furthermore, studies showing significant correlations used primarily with residential students whose younger age are much closer in time on average to their high school educations (Ortagus, 2017; James, Swan & Datsun, 2016; Wladis, Conway & Hachey, 2016). It seems reasonable to expect that tests like the SAT and ACT would lose accuracy in their predictive ability as time passed.

Sherman's (2019) study testing these same three predictor variables for the residential version of this same Math 100 course supports the expectation of weaker correlations for just this lowest level of developmental courses to some degree. Sherman's (2019) study used data from academic years 2015, 2016, and 2017. The semi-partial r^2 correlations were 0.030, 0.014, and 0.033. These values indicate that differences in SAT/ACT score was responsible for less than three percent of the variation in Math 100 final grades. By comparison, the r^2 of .25 for SAT scores across all levels of entry level college math is an order of magnitude higher. However, Sherman (2019) did find that SAT/ACT scores were significantly correlated with Math 100 overall grades for all 3 academic years. It should be noted that the participants in Sherman's study were on residential students in a type of student population that typically has an average age of approximately 21 years old while the participants in the present study were online students with an average age of 36 years.

Additional Statistical Tests

Three single factor linear correlation tests were run using Kendall's tau test. The first test was between High School GPA and Math 100 grades; the second was between Algebra math scores and Math 100 grades; and the third was between SAT/ACT math scores and Math 100 grades. This was done because the substantial variation in the number of records containing each of the predictor variables combined with the small to medium effect sizes made it clear that the larger data sets with records for individual predictors might show significant linear correlations. The non-parametric Kendall's tau test was selected because of the deviations observed from the ideal bivariate normal distributions observed in the scatterplots.

The test for a linear relationship between SAT/ACT math scores and Math 100 grades showed no significant relationship at the 95% level. This was not surprising because it matches the results for the three factor analysis whose records made up a large portion of the records in this analysis. Also, this was by far the smallest of the three data sets used for individual correlational analysis. Factors correlated with age such as increased likelihood of having dependent children in the home and likelihood of full-time employment (Wollf, Wood-Kustanowitz, & Ashkenazi, 2014; Ortagus, 2017; James, Swan, & Daston, 2016; Wladis, Conway, & Hachey, 2016) might also be having an effect. Other yet to be determined factors related to differences in delivery mode (online vs face to face) might also have affected the results of this study.

Significant linear correlations were found at the 95% level between High School GPA and Math 100 grades ($r_\tau = .054, p = .000$) and between Algebra Skill scores and Math 100 grades ($r_\tau = .176, p = .000$). In the original multiple linear regression as well as these Kendall's tau tests, the effect sizes for these two sets of relationships were larger than that for SAT/ACT and Math 100 grades. The data obtained for this study also had approximately 10 times as many records for these two sets of relationships.

Standardized tests like the ACT and SAT tests are measurements taken at a single point in time. High school GPA is measured over a student's entire time in high school and is reflective of broader characteristics such as self-efficacy (Butz & Usher, 2015). For these reasons it may be that the relationships between SAT/ACT scores and college math grades is more effected by the greater gap in time between measurement and the enrollment in the college class being studied. Differential results by age of student in entry level college math courses are supported by Mayo (2012). The algebra skills test was administered by the local university at or after the time of enrollment in the university. There was no increased time gap affecting this relationship with college math grades.

Implications

The primary implications of this study relate to the distance in time between high school and current college enrollment that is commonly measured in decades for online students. Math placement processes for online students may need to place a greater emphasis on data that originates close to the time of enrollment. Standardized placement tests like the ACT and SAT in particular might be a much less valuable indicator of college readiness for students who have been out of high school for a decade or more. Locally developed tests like the algebra skills test are easily administered to students at the time of application for admission. Perhaps more resources should be devoted to the development of similar tests.

The secondary implications relate to the sparseness of the data records containing the predictive factors used in this study. The relative lack of data in this area magnifies the need for more research in this area of online placement. If a lack of this kind of data is a pervasive condition in the online college education industry, then research in this area will be challenging. However, the need is great and challenging in no way means impossible.

Limitations

Several limitations exist that should be considered. The sample size for the three factor multiple regression only had 69 records which barely met the minimum standard for this analysis (Warner, 2013). The sample sizes for the three factor analysis and for the SAT/ACT single regression were very small percentages of the overall dataset. They might not be representative of the dataset. However, to compensate for the lack of sample size, the researcher performed further analysis using Kendall-tau non-parametric test between each of the predictor variables and the criterion variable. Finally, all of the data used in this study came from students attending the same university. As a result, the applicability of this study to other colleges and universities is severely limited. The likely limited applicability of this study to other online programs is another limitation. Additional unknown factors may be affecting the results.

Recommendations for Further Research

The research and results in this study highlight several opportunities for further research. Some of these recommendations are due to weaknesses of the present study highlighted in the Limitations section above and others are due to apparent gaps in the literature in the areas of multiple measures math placement in general and initial math placement for online college students in particular.

1. Similar research should be conducted at other universities.
2. Research conducted both at online universities and at primarily on ground universities that offer some online degree programs would also be valuable.
3. Research into the predictive effectiveness of the SAT, ACT and other national tests for students who graduated from high school 10 or more years ago might be useful.
4. More research on the effects of age on college student success and on the accuracy of various predictors of student success is needed.
5. Studies exploring the predictive effectiveness the SAT, ACT and other national tests for online students.
6. Research about the predictive effectiveness of high school GPA for college and university students who graduated from college 10/20/30+ years before their current college enrollment would add value to the current body of literature.
7. A general study exploring predictive factors of success for adult learners enrolled in college could be useful to many.
8. Research into optimum factors for multiple measures math placement and ways to determine optimum methods to use those factors would fill obvious gaps in the current literature.

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APPENDIX A: Math 100 Syllabus

[redacted]
UNIVERSITY
Online · College of Arts & Sciences · General Math & Sciences

MATH100_[redacted]_MASTER_202030A

MATH-100

Summer B 2020 Section TEM 07/01/2018 to 12/31/2199 Modified 02/21/2020

Contact Information

See detailed faculty information in Blackboard.

Course Description

A review of basic arithmetic and elementary algebra. A grade of C or better is required in order to go on to a higher-numbered mathematics course. This course may not be used in meeting General Education requirements in mathematics. (Developmental Math is a component of the Bruckner Learning Center.)

Requisites

Prerequisites

PLMA of 40-69 OR successful completion of CLST 103 (Part 1 assessment score <23)

Rationale

MATH 100 is designed as a review of beginning algebra in order to prepare the non-mathematics major who does not have a strong background in Algebra I or has never taken an algebra course. The concepts covered will provide knowledge needed to meet the prerequisites for MATH 110.

Measurable Learning Outcomes

Upon successful completion of this course, the student will be able to:

A. State and apply definitions, postulates, and theorems related to number systems, solving equations and inequalities, exponents, polynomials, factoring, applications, rational expressions, graphing linear equations, and solving word problems.
B. Apply the appropriate mathematical skills for the concepts listed above.
C. Use mathematics to solve problems in the sciences, business, and various other fields of study.

Course Resources

Required Resource

The resource(s) below is(are) provided in the course at no cost to the student. However, if the student prefers a physical copy of the resource(s), he or she may purchase it(them) through the [Liberty University Online bookstore (http://bookstore.mbsdirect.net/liberty.htm)](http://bookstore.mbsdirect.net/liberty.htm), MBS Direct. The purchase of physical copies is optional.

Tussy, A. S., & Gustafson, R. D. (2013). *Elementay algebra* (5th ed.). Belmont, CA: Cengage publishing.

Disclaimer: The above resource provides information consistent with the latest research regarding the subject area. Liberty University does not necessarily endorse specific personal, religious, philosophical, or political positions found in this resource.

Additional Materials for Learning

A. Computer with basic audio/video output equipment
B. Internet access (broadband recommended)
C. Blackboard recommended browsers (https://liberty.service-now.com/kb_view.do?sys_kb_id=38a8e4bd75c210c0b9a9ec15cb9606a2)
D. Microsoft Office
E. Camera or Scanner

Course Assignments

Textbook readings and lecture presentations

Course Requirements Checklist

After reading the Course Syllabus and Student Expectations, the student will complete the related checklist found in Module/Week 1.

Study Skills Assignment

After reading the lecture note, the student will complete 5 short answer questions in Blackboard.

Exercises (48)

After reading the sections in the textbook, the student will complete exercises using the WebAssign software. The student must earn a score of 70% on these exercises before taking any quizzes that may be present in the same module.

Module Quizzes (10)

Quizzes will be administered through the WebAssign software. Each quiz has 10 questions and will be based on the reading and homework of the assigned module. There is no time limit for completion.

Test Review Assignments (8)

Before each Test and the Final Exam are two review assignments, a Test Review assignment and a Testing Policies assignment. Each Test Review assignment allows the student to review the topics from the prior modules before taking the test on those modules. Each Testing Policies assignment requires the student to review and agree to the testing policies before completing the test. The student must earn 70% on each Test Review assignment and 100% on the Testing Policies assignment in order to take the test.

Tests (3)

Using the WebAssign software, the student will take 3 tests throughout the course. Tests are based on the reading and Exercises. The test will remain inaccessible until the minimum score is reached on the test review assignments and the instructor will provide a password to access the test at the appropriate time. All tests will have a time limit. The use of a basic calculator is allowed. The student must submit all written work for the test questions. Tests submitted without the accompanying work will not be accepted.

Final Exam

The student will complete a comprehensive Final Exam in WebAssign. A comprehensive Final Exam Review is provided to help prepare the student for the actual exam. The test will remain inaccessible until the minimum score is reached on the test review assignments and the instructor will provide a password to access the test at the appropriate time. The Final Exam will have a time limit. The use of a basic calculator is allowed. The student must submit all written work for the final exam questions. Any Final Exam submitted without the accompanying work will not be accepted.

Course Grading

Course Requirements Checklist	10

Study Skills Assignment	15
Exercises (48 at 4 pts ea)	192
Module Quizzes (10 at 15 pts ea)	150
Test Review Assignments (4 at 4 pts ea)	16
Testing Policies Assignments (4 at 1 pt ea)	4
Tests (3 at 140 pts ea)	420
Final Exam	203
Total	1010

Course Policies

Policies

Mathematical Late Assignment Policy

Mathematical assignments that are submitted after the due date without prior approval from the instructor will receive the following deductions

1. Late *mathematical* assignments submitted within one week after the due date will receive a 10% deduction.
2. *Mathematical* assignments submitted more than one week late or after the final date of the course will not be accepted.
3. Discussion board assignments submitted within one week after the due date will receive a 10% deduction.
4. Discussion board submitted more than one week and less than 2 weeks late will receive a 20% deduction.
5. Discussion board submitted more than 2 weeks late will not be accepted.
6. Group projects, including group discussion board threads and/or replies, and assignments will not be accepted after the due date.

Special circumstances (e.g. death in the family, personal health issues) will be reviewed by the instructor on a case-by-case basis.

For other assignments, please refer to the standard Late Assignment Policy, below.

Late Assignment Policy

Course Assignments, including discussion boards, exams, and other graded assignments, should be submitted on time.

If the student is unable to complete an assignment on time, then he or she must contact the instructor immediately by email.

Assignments that are submitted after the due date without prior approval from the instructor will receive the following deductions:

1. Late assignments submitted within one week after the due date will receive up to a 10% deduction.
2. Assignments submitted more than one week and less than 2 weeks late will receive up to a 20% deduction.
3. Assignments submitted two weeks late or after the final date of the course will not be accepted outside of special circumstances (e.g. death in the family, significant personal health issues), which will be reviewed on a case-by-case basis by the instructor.
4. Group projects, including group discussion board threads and/or replies, and assignments will not be accepted after the due date outside of special circumstances (e.g. death in the family, significant personal health issues), which will be reviewed on

a case-by-case basis by the instructor.

Disability Assistance

Students with a disability and those with medical conditions associated with pregnancy may contact Liberty University's Online Office of Disability Accommodation Support (ODAS) at LUOODAS@liberty.edu for accommodations. Such accommodations require appropriate documentation of your condition. For more information about ODAS and the accommodations process, including how to request an accommodation, please visit https://www.liberty.edu/online/online-disability-accommodation-support/ (https://www.liberty.edu/online/online-disability-accommodation-support/). Requests for accommodations not related to disabilities or pregnancy must be directed to the Registrar's Office, which generally handles medical needs support.

If you have a complaint related to disability discrimination or an accommodation that was not provided, you may contact ODAS or the Office of Equity and Compliance by phone at (434) 592-4999 or by email at equityandcompliance@liberty.edu. Click to see a full copy of Liberty's Discrimination, Harassment, and Sexual Misconduct Policy (https://www.liberty.edu/media/1226/Liberty_University_Discrimination_Harassment_and_Sexual_Misconduct_Policy.pdf) or the Student Disability Grievance Policy and Procedures (http://www.liberty.edu/media/8021/Disability_Grievance_Procedures.pdf).

Course Attendance

In an effort to comply with U.S. Department of Education policies, attendance is measured by physical class attendance or any submission of a required assignment within the enrollment dates of the course (such as examinations, written papers or projects, any discussion board posts, etc.) or initiating any communication with one's professor regarding an academic subject. More information regarding the attendance policy can be found in the Academic Course Catalogs (https://www.liberty.edu/index.cfm?PID=791). Regular attendance in online courses is expected throughout the length of the term. Students who do not attend within the first week of a sub-term by submitting a required academic assignment (such as the Course Requirements Checklist, an examination, written paper or project, discussion board post, or other academic activity) will be dropped from the course. Students who wish to re-engage in the course are encouraged to contact Academic Advising to discuss their enrollment options. Students who begin an online course, but at some point in the semester cease attending, and do not provide official notification to withdraw, will be assigned a grade of "FN" (Failure for Non-Attendance (https://wiki.os.liberty.edu/display/IE/Online+Attendance+and+Non-Attendance)). Students wishing to withdraw from courses after the official start date should familiarize themselves with the withdrawal policy.

Grading Scale

A	B	C	D	F
900-1010	800-899	700-799	600-699	0-599

For courses with a Pass/NP final grade, please refer to the Course Grading section of this syllabus for the assignment requirements and/or point value required to earn a Passing final grade.

Add/Drop Policy

The full policy statement and procedures are published in the Policy Directory (https://wiki.os.liberty.edu/display/IE/Dropping+and+Adding+Online+Classes).

Honor Code

Liberty University comprises a network of students, Alumni, faculty, staff and supporters that together form a Christian community based upon the truth of the Bible. This truth defines our foundational principles, from our Doctrinal Statement to the Code of Honor. These principles irrevocably align Liberty University's operational procedures with the long tradition of university culture, which remains distinctively Christian, designed to preserve and advance truth. Our desire is to create a safe, comfortable environment within our community of learning, and we extend our academic and spiritual resources to all of our students with the goal of fostering academic maturity, spiritual growth and character development.

Communities are predicated on shared values and goals. The Code of Honor, an expression of the values from which our Doctrinal Statement was born, defines the fundamental principles by which our community exists. At the core of this code lie two essential concepts: a belief in the significance of all individuals, and a reliance on the existence of objective truth.

While we acknowledge that some may disagree with various elements of the Code of Honor, we maintain the expectation that our students will commit to respect and uphold the Code while enrolled at Liberty University.

Adherence to the principles and concepts established within facilitates the success of our students and strengthens the Liberty community.

The Code of Honor can be viewed in its entirety at http://www.liberty.edu/index.cfm?PID=19155 (http://www.liberty.edu/index.cfm?PID=19155).

Schedule

MATH 100

Textbook: Tussy & Gustafson, *Elementay Algebra* (2013).

Module/Week	Reading & Study	Assignments	Points
1	Tussy & Gustafson: chs. 1.1 – 1.3	Course Requirements Checklist DB - Introduction Module 1 Exercises Module 1 Quiz	10 0 24 15
2	Tussy & Gustafson: chs. 1.4 – 1.8 1 lecture note	Study Skills Assignment Module 2 Exercises Module 2 Quiz	15 20 15
3	Tussy & Gustafson: chs. 1.8 – 2.2	Module 3 Exercises Module 3 Quiz	20 15
4	Tussy & Gustafson: chs. 2.2 – 2.4	Module 4 Exercises Module 4 Quiz	16 15
5	Tussy & Gustafson: Review chs. 1.1 – 2.4 1 presentation	Test Review 1 Testing Policies Test 1	4 1 140
6	Tussy & Gustafson: chs. 2.5, 2.7, 3.1 1 lecture note	Module 6 Exercises Module 6 Quiz	16 15
7	Tussy & Gustafson: chs. 3.2 – 3.5	Module 7 Exercises Module 7 Quiz	16 15

8	Tussy & Gustafson: chs. 3.6, 5.1 – 5.2	Module 8 Exercises Module 8 Quiz	20 15
9	Tussy & Gustafson: Review chs 2.4 – 3.6, 5.1 – 5.2 1 presentation	Test Review 2 Testing Policies Test 2	4 1 140
10	Tussy & Gustafson: chs. 5.4 – 5.8 1 lecture note	Module 10 Exercises Module 10 Quiz	20 15
11	Tussy & Gustafson: chs. 6.1 – 6.4, 6.6 1 lecture note	Module 11 Exercises Module 11 Quiz	20 15
12	Tussy & Gustafson: chs. 6.7 – 7.3	Module 12 Exercises Module 12 Quiz	20 15
13	Tussy & Gustafson: Review chs. 5.4 – 7.3 1 presentation	Test Review 3 Testing Policies Test 3	4 1 140
14	Tussy & Gustafson: Review all chapters 1 presentation	Final Exam Review Testing Policies Final Exam	4 1 203
Total			1010

DB = Discussion Board

NOTE: Each course module/week (except Modules/Weeks 1 and 14) begins on Tuesday morning at 12:00 a.m. (ET) and ends on Monday night at 11:59 p.m. (ET). Module/Week 14 ends on Friday night at 11:59 p.m. (ET).

APPENDIX B: Math 110 Syllabus

[redacted]
UNIVERSITY
Online · College of Arts & Sciences · General Math & Sciences

Intermediate Algebra

MATH-110

Spring B 2020 Section B04 01/13/2020 to 03/06/2020 Modified 01/08/2020

Contact Information

See detailed faculty information in Blackboard.

Course Description

Review of exponents, polynomials, factoring, roots and radicals, graphing, rational expressions, equations and inequalities, systems of linear equations and problem solving. This course may not be used to meet the General Education requirement.

Requisites

Prerequisites

MATH 100, PLMA of 70, or (CLST 103 and ASMA of 23)

Rationale

Intermediate Algebra is designed for students who have a weak background in Algebra II or for those who have completed Math 100 (Fundamentals of Mathematics) and need the intermediate level of algebra to prepare them to take higher level mathematics courses. A grade of A, B, or C is required to enroll in the next higher level math course.

Measurable Learning Outcomes

Upon successful completion of this course, the student will be able to:

A. State and apply definitions, postulates, and theorems related to various concepts listed in the course description.
B. Apply the appropriate mathematical skills to problems and problem solving for the concepts listed in the course description.
C. Use mathematics to solve problems in the sciences, business, and other fields of study.

Course Resources

The resource below is provided in the course at no cost to the student. However, if the student prefers a physical copy of the resource, he or she may purchase it through the Liberty University Online bookstore (http://bookstore.mbsdirect.net/liberty.htm), MBS Direct. The purchase of physical copies is optional.

Aufmann, R. M., & Lockwood, F. M (2016). *Mathematics: Journey from basic mathematics*

through intermediate algebra (1st Edition). Boston, MA Publisher: Cengage.

Disclaimer: The above resource provides information consistent with the latest research regarding the subject area. Liberty University does not necessarily endorse specific personal, religious, philosophical, or political positions found in this resource.

A. Computer with basic audio/video output equipment

B. Internet access (broadband recommended)
C. Blackboard recommended browsers (https://nam04.safelinks.protection.outlook.com/?url=https%3A%2F%2Fhelp.blackboard.com%2FLearn%2FStudent%2FGetting_Started%2FBrowser_Support&data=02%7C01%7Ceameadors%40liberty.edu%7C3410ce7314254e5f0c5b08d7474fec95%7Cbaf8218eb3024465a9934a39c97251b2%7C0%7C0%7C637056280898735990&sdata=ZSR9n%2FBox3P%2F0cd2EJZwpq2cFo%2FbjFCc5nAKwlifq4Y%3D&reserved=0)
D. Microsoft Office
E. A scientific calculator is allowed, but not required.
F. This course requires a scanner and/or camera. The student may use a smartphone if he/she downloads CamScanner to take pictures and upload his/her work

Course Assignments

Textbook readings, video lessons, and lecture presentations

Course Requirements Checklist

After reading the Course Syllabus and Student Expectations, the student will complete the related checklist found in Module/Week 1.

Discussion Board Forum (1)

Discussion boards are a collaborative learning experiences. Therefore, the student will participate in a Discussion Board Forum at the beginning of the course. The student will write a 100-word thread in response to the instructor's prompt. In addition to the thread, the student will also write a 50-word reply to at least 1 other classmate's thread.

Orientation Assignment: (1)

The Orienation Assignment is located within WebAssign to allow student to learn how the program works and how to read and enter answers. It also reviews some of the policies for this class but is of no real math content and thus only work 1 point.

Module Exercises (27)

The student will complete Module Exercises using the WebAssign software. The student must earn a score of 70% on these exercises before taking any quizzes that may be present in the same module/week.

Module Quizzes (5)

Module Quizzes will be administered through the WebAssign software. Each quiz has questions that will be based on the reading and exercises of the assigned module/week. There is no time limit for completion. The Module Exercises in each module/week must be completed first in order to unlock the quiz.

Test Reviews (3)

There is a test review assignment before each test. The test review will only count as 1 point toward your final grade. Please note, the test will remain locked until at least 70% has been earned on that assignment.

Complete Test Review for the first, second, and third test by 11:59 p.m. (ET) on Sunday of the assigned modules/weeks.
Complete Test Review for the Final Exam by 11:59 p.m. (ET) on Thursday of Module/Week 16

Tests (3)

Using WebAssign, the student will take 3 Tests throughout the course. Tests are based on the readings and Module Exercises. For each Test, the student must first take a Test Review and earn a score of at least 70%. The test will remain inaccessible until this minimum score is reached. All tests are cumulative. Test 2 will include some questions from Test 1 material, and Test 3 will include some questions from Test 1 and Test 2 material. All tests will have a time limit.

***You must submit all written work for the test questions. Tests submitted without the accompanying work will not be accepted. (each test work submission is worth 1 pt each)

Course Grading

Course Requirements Checklist		10
Orientation Assignment Discussion Board Forum		1 15
Module Exercises	(27 at 5 pts ea)	135
Module Quizzes	(5 at 43 pts ea)	215
Test Reviews Test 1	(3 at 1 pt each)	3 190
Test 2		205
Test 3		236
Total		1010

Course Policies

Policies

Late Assignment Policy

Course Assignments, including discussion boards, exams, and other graded assignments, should be submitted on time.

If the student is unable to complete an assignment on time, then he or she must contact the instructor immediately by email.

Assignments that are submitted after the due date without prior approval from the instructor will receive the following deductions:

1. Late assignments submitted within one week after the due date will receive a 10% deduction.
2. Assignments submitted more than one week and less than 2 weeks late will receive a 20% deduction.
3. Assignments submitted two weeks late or after the final date of the course will not be accepted.
4. Group projects, including group discussion board threads and/or replies, and assignments will not be accepted after the due date.

Special circumstances (e.g. death in the family, personal health issues) will be reviewed by the instructor on a case-by-case basis.

Instructor Feedback and Response Time

Responses to student emails will be provided within 36 hours and assignment feedback will be given within 5 days from the assignment due date.

Disability Assistance

Students with a disability and those with medical conditions associated with pregnancy may contact Liberty University's Online Office of Disability Accommodation Support (ODAS) at LUOODAS@liberty.edu for accommodations. Such accommodations require appropriate documentation of your condition. For more information about ODAS and the accommodations process, including how to request an accommodation, please visit www.liberty.edu/disabilitysupport. Requests for accommodations not related to disabilities or pregnancy must be directed to the Registrar's Office, which generally handles medical needs support.

If you have a complaint related to disability discrimination or an accommodation that was not provided, you may contact ODAS or the Office of Equity and Compliance by phone at (434) 592-4999 or by email at equityandcompliance@liberty.edu. Click to see a full copy of Liberty's Discrimination, Harassment, and Sexual Misconduct Policy or the Student Disability Grievance Policy and Procedures.

Course Attendance

In an effort to comply with U.S. Department of Education policies, attendance is measured by physical class attendance or any submission of a required assignment within the enrollment dates of the course (such as examinations, written papers or projects, any discussion board posts, etc.) or initiating any communication with one's professor regarding an academic subject. More information regarding the attendance policy can be found in the Academic Course Catalogs. Regular attendance in online courses is expected throughout the length of the term. Students who do not attend within the first week of a sub-term by submitting a required academic assignment (such as the Course Requirements Checklist, an examination, written paper or project, discussion board post, or other academic activity) will be dropped from the course. Students who wish to re-engage in the course are encouraged to contact Academic Advising to discuss their enrollment options. Students who begin an online course, but at some point in the semester cease attending, and do not provide official notification to withdraw, will be assigned a grade of "FN" (Failure for Non-Attendance). Students wishing to withdraw from courses after the official start date should familiarize themselves with the withdrawal policy.

Grading Scale

A	B	C	D	F
900-1000	800-899	700-799	600-699	0-599

For courses with a Pass/NP final grade, please refer to the Course Grading section of this syllabus for the assignment requirements and/or point value required to earn a Passing final grade.

Add/Drop Policy

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Honor Code

Liberty University comprises a network of students, Alumni, faculty, staff and supporters that together form a Christian community based upon the truth of the Bible. This truth defines our foundational principles, from our Doctrinal Statement to the Code of Honor. These principles irrevocably align Liberty University's operational procedures with the long tradition of university culture, which remains distinctively Christian, designed to preserve and advance truth. Our desire is to create a safe, comfortable environment within our community of learning, and we extend our academic and spiritual resources to all of our students with the goal of fostering academic maturity, spiritual growth and character development.

Communities are predicated on shared values and goals. The Code of Honor, an expression of the values from which our Doctrinal Statement was born, defines the fundamental principles by which our community exists. At the core of this code lie two essential concepts: a belief in the significance of all individuals, and a reliance on the existence of objective truth.

While we acknowledge that some may disagree with various elements of the Code of Honor, we maintain the expectation that our students will commit to respect and uphold the Code while enrolled at Liberty University.

Adherence to the principles and concepts established within facilitates the success of our students and strengthens the Liberty community.

The Code of Honor can be viewed in its entirety at http://www.liberty.edu/index.cfm?PID=19155.

Schedule

MATH 110

Module	Reading & Study	Assignments	Points
1	Aufmann & Lockwood: chs. 7.1, 7.4-7.5, 8,1, 8.3-8.5 1 lecture note	Course Requirements Checklist DB Forum 1 Math 110 Orientation Module 1 Exercises Module 1 Quiz	10 15 1 30 43
2	Aufmann & Lockwood: chs. 9.1-9.2, 9.4, 10.1, 10.3-10.5, 11.1-11.4	Module 2 Exercises Module 2 Quiz	30 43
3	Aufmann & Lockwood: chs. 14.1 Review Aufmann/Lockwood 1 presentation	Module 3 Exercise Test Review 1 Test 1 Test 1 Work Submission	5 1 190 0
4	Aufmann & Lockwood: chs. 12.1-12.4	Module 4 Exercises Module 4 Quiz	20 43
5	Aufmann & Lockwood: chs. 13.1-13.5, and 14.5	Module 5 Exercises Module 5 Quiz	25 43
6	Aufmann & Lockwood: chs. 14.1-14.3 and more 14.5 Review Aufmann/Lockwood	Module 6 Exercises Test Review 2 Test 2 Test 2 Work Submission	5 1 205 0
7	Aufmann & Lockwood: chs. 15.1 and 8.2	Module 7 Exercises Module 7 Quiz	20 43
8	Review Aufmann/Lockwood	Test Review 3 Test 3 Test 3 Work Submission	1 236 0

Total	1010

WA = Web Assign

DB = Discussion Board

NOTE: Each course module/week (except Module/Week 1) begins on Tuesday morning at 12:00 a.m. (ET) and ends on Monday night at 11:59 p.m. (ET). The final module/week ends at 11:59 p.m. (ET) on Friday.

APPENDIX C: Permissions

LIBERTY UNIVERSITY
INSTITUTIONAL REVIEW BOARD

November 7, 2019

Michael Gibson
IRB Application 4058: Relationships between Placement Criteria and Students' Online Developmental Math Final Grades

Dear Michael Gibson,

The Liberty University Institutional Review Board has reviewed your application in accordance with the Office for Human Research Protections (OHRP) and Food and Drug Administration (FDA) regulations and finds your study does not classify as human subjects research. This means you may begin your research with the data safeguarding methods mentioned in your IRB application.

Your study does not classify as human subjects research because it will not involve the collection of identifiable, private information.

Please note that this decision only applies to your current research application, and any changes to your protocol must be reported to the Liberty IRB for verification of continued non-human subjects research status. You may report these changes by submitting a new application to the IRB and referencing the above IRB Application number.

If you have any questions about this determination or need assistance in identifying whether possible changes to your protocol would change your application's status, please email us at irb@liberty.edu.

Sincerely,

[redacted]

G. Michele Baker, MA, CIP
Administrative Chair of Institutional Research
Research Ethics Office

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From: Perry, Cynthia Goodlet (General Math and Science) [redacted]
Sent: Tuesday, October 8, 2019 7:48 PM
To: Gibson, Michael (General Math and Science) [redacted]
Subject: RE: Doctoral Research Data Request

Mike,
Yes, I approve this research and am looking forward to seeing the results. Thank you!

Cindi Perry
Department Chair
General Math and Science

(434) 592-6150

[redacted]

From: Gibson, Michael (General Math and Science) [redacted]
Sent: Tuesday, October 8, 2019 3:57 PM
To: Perry, Cynthia Goodlet (General Math and Science) [redacted].edu>
Subject: Doctoral Research Data Request

Hi Cindi.

I'm completing IRB forms for my dissertation and must provide evidence that you—as the chair of the Online General Education Math and Science (GEMS) Department—approve my intended research. I will be assessing the accuracy of ACT/SAT scores, local math placement test scores, and high school GPAs as predictors of MATH 100 final grades for online Liberty University students assigned to Math 100 over the last three completed academic years. I will request that all data be anonymized before it is sent to me. I need your approval to access the data necessary for this research.

Thank you,
Mike

Michael Gibson
Assistant Professor
General Math and Science

(434) 592-7347

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