RELATIONSHIPS BETWEEN PLACEMENT CRITERIA AND STUDENTS' EMPORIUM-BASED DEVELOPMENTAL MATH FINAL GRADES

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ABSTRACT

With computer-based math emporiums serving many post-secondary students who are assigned developmental coursework, the need to evaluate the predictive value of math placement criteria for math emporium courses presented an opportunity for research. This quantitative, predictive, correlational study explored how accurately the predictor variables of students' ACT/SAT math component scores, local math assessment results, and unweighted high school GPAs foretold the criterion variable of students' final math grades in MATH 100, an entry-level, residential, developmental math course taught through a private university's math emporium. The research relied on archival data pulled from the university's system of records, and the samples included 565 students for the 2017-2018 academic year, 1,168 students for the 2016-2017 year, and 1,500 students for the 2015-2016 year who for the first time attempted residential MATH 100 and earned a grade without withdrawing. Multiple linear regression results with a 95% confidence interval for 2017-2018, 2016-2017; and for 2015-2016 all yielded significant values. High school GPA was the most accurate of the three predictors while ACT/SAT math component and local assessment scores took turns as the second most accurate. This study portrays developmental math placement as operating in a dynamic and somewhat unpredictable environment, and it aligns with other studies suggesting multiple method placement practices are better than single method practices as it suggests little difference exists between placement effectiveness for math emporiums versus other venues. The manuscript closes with recommendations for further research.

Keywords: developmental math, math placement, math emporium, ACT, SAT, local assessment, GPA

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

Assessment Math (ASMA)

Grade Point Average (GPA)

Scholastic Assessment Test (SAT)

CHAPTER ONE: INTRODUCTION

Overview

This chapter summarizes the most pertinent literature to provide historical, societal, and theoretical contexts for a research project about post-secondary placement tools' accuracies in predicting students' final grades in an emporium-based developmental mathematics course. The chapter opens by summarizing the background of the issue, including its evolution, associated theory, and key constructs. It then presents the problem statement and purpose statement, discusses the study's significance, introduces three research questions, and describes the variables. The chapter closes by defining relevant terms.

Background

The Mathematical Association of America (Adams, n.d.) presented the story of a student whose excitement at beginning college turned to frustration after a placement exam led to an unplanned course. The course felt like high school content, cost like college, failed to count toward a degree, and delayed graduation. Now, with decreased motivation, the student may quit.

Graduating from college brings benefits to individuals and to society (Selingo, 2013; Toutkoushian & Paulsen, 2016), but an average year of higher education costs $22,432 (NCES, 2018), and costs are increasing ("Rising," 2014). Graduating late raises expenses while delaying and decreasing rewards. Institutions assign developmental courses for students whose knowledge and skills they judge as insufficient for college-level classes (Boatman & Long, 2018; Park et al., 2016), and developmental students often graduate a year late (Melguizo, Bos, Ngo, Mills, & Prather, 2016)—or do not graduate at all (Fong, Melguizo, & Prather, 2015). The National Student Clearinghouse Research Center reported 56.9% of the Fall 2011 college cohort graduated within six years (Shapiro et al., 2017), but fewer than 30% of students assigned developmental coursework met the six-year graduation standard (Armstrong & Zaback, 2014). Roughly one-third of post-secondary students claimed participation in developmental courses (U.S. Department of Education, 2017; NCES, 2016), and transcript reviews suggested actual developmental enrollment probably exceeded that percentage (Radford & Horn, 2012).

With few exceptions, developmental students did not decide to take developmental courses. Rather, based on placement decisions that determined they were academically unprepared for college-level work, higher educators assigned the students to the courses to raise their knowledge and skills to required levels (Boatman & Long, 2018). While mathematics skills matter academically (Kyoung Ro, Lattuca, & Alcott, 2017; Quarles & Davis, 2017; Wang, Degol, & Ye, 2015), they also help in the jobs marketplace (Koedel & Tyhurst, 2012) and can improve one’s quality of life (Undurraga et al., 2013). Still, math presents as the most remediated subject (NCES, 2016); it serves about 80% of developmental students (Radford & Horn, 2012). Given the high stakes associated with math skills, new knowledge about math placement and its relation to students’ developmental math success can help individual students and society.

Historical Overview

This subsection of the paper summarizes the evolution of developmental math placement, and it does so in the context of developmental math overall. The subsection opens by describing the history of developmental math, moves into the modern era of computer technology and the advent of the math emporium, then addresses developmental math placement practices.

Developmental math. Students often arrive at college unprepared for college-level work (Boatman & Long, 2018), and Arendale (2011) noted that since America’s earliest years higher education professionals have relied on developmental education to help students gain the academic skills required for post-secondary admission. Developmental programs changed over time, and until a period of transition that began in the 1940s and ended in the 1970s, the efforts centered on precollege academies and tutoring primarily for wealthy white male students. With the 1970s began a new era of remediation that opened doors to a more diverse array of students through classroom instruction. Innovation meant encouraging faculty members to continually communicate with students (Koch, 1992), but that evolved during subsequent decades as traditional classes gave way to newer approaches intended to address the needs of practically any learner (Arendale, 2011). The number of students participating in developmental courses also changed. Less than two decades ago, about one in five college students in America joined developmental programs (NCES, 2013). Analysis of more recent data suggests the ratio now sits at approximately one in three (NCES, 2016).

The innovative era of developmental education extends to the present day (Arendale, 2011), and institutional leaders introduce new ideas—including peer and summer bridge programs, learning communities, instructional specialists, and more—to address the challenges of developmental math success (Kosiewicz, Ngo, & Fong, 2016; NCES, 2016; Ulmer, Means, Cawthon, & Kristensen, 2016). Many innovations seem to fall short (Chingos, Griffiths, & Mulhern, 2017; Ngo & Kosiewicz, 2017), but computer-enhanced learning shows some promise (Foshee, Elliott, & Atkinson, 2016).

Technology and the math emporium. Much of the scholarly literature about computer technology as a tool to help developmental math students indicates it works (Childers & Lu, 2017; Foshee, Elliott, & Atkinson, 2016). This is perhaps because computer algorithms can affordably personalize lessons for each students' unique needs (Christensen, Horn, & Johnson, 2011). Student-level customization sits in contrast to traditional, one-size-serves-all lectures that treat students as if they collectively share the same interests, abilities, motivations, and learning styles (Twigg, 2009). Further, lectures fail to deliver the supportiveness Wambach, Brothen, and Dikel's (2000) developmental theory demands for developmental students, and lectures tend to neither afford opportunities for collaborative learning nor encourage active participation (Twigg, 2009), all of which improve learning (Goacher, Kline, Targus, & Vermette, 2017; Kinney, 2001; McCarthy, 2015; Sun, Liu, Luo, Wu, & Shit, 2017; Vogel, et al., 2016).

In 1999, with the support of an $8.8 million Pew Charitable Trusts grant, the National Center for Academic Transformation (Twigg, 2015) at Rensselaer Polytechnic Institute founded the Program in Course Redesign (Twigg, 2009) to overhaul high-enrollment courses so the courses could—through computer technology—positively impact high numbers of students while saving money. Institutions competed for shares of the redesign funding (Twigg, 2015). From this effort, in 1999 at the Virginia Polytechnic Institution and State University (Virginia Tech), sprang the first math emporium (Kasten, 2000). Though not all scholars agreed that technology was key to developmental math (Childers & Lu, 2017), other schools opened math emporiums (Fuller, Deshler, Kuhn, & Squire, 2014; Hodges & Murphy, 2009; Twigg, 2011) and one scholar—consistent with Christensen, Horn, and Johnson's views (2011)—noted the model holds the power to transform education "from a passive learning environment to an active one in which the student controls and individualizes the learning" (Twigg, 2009, p.151).

Developmental math placement. Placement into a developmental mathematics course costs both time (Melguizo, Bos, Ngo, Mills, & Prather, 2016) and money (Selingo, 2013; Toutkoushian & Paulsen, 2016), and it may discourage a student from continuing at all (Fong, Melguizo, & Prather, 2015). Given the challenges developmental math students face, one may not be surprised that placement practices garner attention not only from students and educators, but from scholars and lawmakers as well. Bracco et al. (2014) wrote that placement historically relied on standardized exams, but that higher educators now increasingly turn toward multiple measures for placement decisions. Other scholars also studied multiple methods (Ariovich & Walker, 2014). Ngo and Melguizo (2016) found multiple methods in widespread use as they explored alternative remediation placement policies through a quasi-experimental research design that relied upon California Community College systems data. The California system included 112 schools that served over two million diverse students each year, and this wide array of schools educating a diverse student population operated with several different developmental placement systems. Ngo and Kwon (2015) also reported about the use of placement measures beyond standardized tests—measures that included high school GPA and other factors. Still, developmental math challenges seem to overwhelm higher educators' abilities to cope. The National Center for Education Statistics (2016) reported that several states implemented "drastic measures" (p. 3) to deal with developmental students' issues, and according to Cox (2018), the state of Georgia broadly denies admission to prospective post-secondary students who fail to score sufficiently on the ACT or SAT exam. Florida legislators decided on a different direction and offered some students the ability to opt out of developmental courses (Park et al., 2016). In summary, little agreement exists regarding developmental math placement practices.

Constructs and Theory

The concept of computer-based math emporiums and the three math placement constructs of ACT/SAT math component scores, high school GPAs, and local math assessment results may be closely related to Sweller's (1988) cognitive load theory—with support from the principle of computer self-efficacy (Gist, Schwoerer, & Rosen, 1989). ACT and SAT scores historically served as higher educators' primary developmental mathematics placement tool (Bracco et al., 2014), and many institutions rely on them today (Bai, Chi, & Qian, 2016; Barbitta & Munn, 2018). Other institutions consider high school GPA in their placements (Bracco et al.; Hiss & Franks, 2014), and research suggests both that doing so benefits students (Jackson & Kurlaender, 2014) and that the benefits are only marginal (Atuahene & Russell, 2016). While standardized tests offer strengths, local assessments provide the advantages of greater faculty buy-in and content customization (Banta & Palomba, 2015), and some institutions use them for developmental placement. This may present an entry point for Sweller's cognitive load theory.

Sweller (1988) wrote that individuals develop schemas allowing them to categorize a problem as similar to challenges they encountered before and to therefore see a solution path. Drawing upon Fisk and Schneider's (1984) dual task paradigm that recognized dividing attention between tasks degrades one's abilities on at least one of the tasks (proportionate to the cognitive effort required by the other tasks), Sweller determined schema employment requires substantial cognitive effort and that schema acquisition in dual task scenarios is difficult. Separately, Gist, Schwoerer, and Rosen (1989) suggested computer self-efficacy leads some individuals to feel stress with technology and to perform relatively poorly on computer-related tasks.

When combining Sweller's (1988) cognitive load theory with Gist, Schwoerer, and Rosen's (1989) ideas regarding varied computer confidence and skills, one expects students who perform well on computer-based tests to also perform better in computer-based math emporiums than should students who perform poorly on the tests. Some recent education-related studies relied on Gist, Schwoerer, and Rosen's (1989) ideas regarding computers (Celik & Yesilyurt, 2013) and on how the ideas relate to computer-based testing (Balogun & Olanrewaju, 2016; Nwagwu & Adebayo, 2016). Research also explored cognitive load theory (Sweller) and split attention (Fish & Schneider) as they apply to computer-based testing (Jarodzka, Janssen, Kirschner, & Erkens, 2015).

In summary, the developmental math landscape includes challenges, innovations, and uncertainty. Developmental students face disadvantages ranging from greater costs than their peers (Selingo, 2013; Toutkoushian & Paulsen, 2016) to lower graduation rates (Fong, Melguizo, & Prather, 2015). The math emporium serves as one example of a higher education innovation that may help these students succeed. At the same time, placement practices that once relied primarily upon standardized testing now often also consider multiple methods such as high school GPA and local assessment results (Ariovich & Walker, 2014; Bracco et al., 2014; Ngo & Melguizo, 2016). Sweller's (1988) cognitive load theory, with support from Gist, Schwoerer, and Rosen's (1989) ideas regarding computer skills, may relate to placement tools' accuracies in predicting developmental students' math emporium final grades.

Problem Statement

Utilitarian principles suggest education should serve students' and society's needs (Bentham & Lafleur, 1948; Gutek, 2013; Mill, n.d.), and maximizing financial gains offers a way to measure service in utilitarian terms (Samuelson, 1974). Research indicates appropriate student placement may contribute to both a timely (Ngo & Kosiewicz, 2017) and a financially efficient (Toutkoushian & Paulsen, 2016) education system. Academicians must determine how to place students into appropriate learning environments—developmental or college-level—to maximize utility. Higher educators long relied on standardized tests alone for this (Bracco et al., 2014), and many schools still rely solely on such tests (Crynes, 2013; Melguizo, Kosiewicz, Prather, & Bos, 2014; Xu & Dadgar, 2018), though several scholars now suggest use of multiple methods—perhaps including high school GPAs, local test scores, or other components—delivers superior results (Barbitta & Munn, 2018; Jackson & Kurlaender, 2014). A specific problem, then, is that educators must know what mix and balance of available placement tools best supports appropriate decisions. Math emporiums present a relatively new teaching innovation (Kasten, 2000) that differs from traditional classroom instruction and serves students in individualized ways (Twigg, 2009). Little research has been done on math emporiums (Wilder & Berry, 2016; Twigg, 2011), and the literature seems silent regarding the relationship between three constructs' (ACT/SAT math component scores, high school GPAs, and local assessment results) relation to math emporiums. The problem is that, based on the literature, higher education decision makers lack information regarding placement components that best predict students' performance in math emporium-based developmental courses.

Purpose Statement

The purpose of this quantitative predictive correlational study was to determine whether ACT/SAT math component scores, unweighted high school GPAs, and results on a local math skills assessment could predict final math emporium developmental math course grades for residential, undergraduate students at a private university. The researcher, consistent with Gall, Gall, and Borg (2007), employed a multiple linear regression aimed at determining the relationship between the three predictor variables and the criterion variable. This research depended upon archival data related to residential, undergraduate students who for the students' first time attempted and completed the first of two developmental mathematics courses through a private university's math emporium during the 2017-2018, 2016-2017, or 2015-2016 academic years.

Significance of the Study

Graduation delays and college drop-outs lessen the benefits of higher education without erasing the expenses (Selingo, 2013; Toutakoushian & Paulsen, 2016), so much depends on developmental math student placement--including whether a student graduates on time (Melguizo, Bos, Ngo, Mills, & Prather, 2016) or even graduates at all (Fong, Melguizo, & Prather, 2015). Literature indicates several possible input components for developmental math placement decisions. The historically-preferred method of relying on standardized test results—ACT, SAT, and others such as COMPASS (Bracco et al., 2014)—serves many schools today as a sole placement measurement tool (Crynes, 2013; Melguizo, Kosiewicz, Prather, & Bos, 2014; Xu & Dadgar, 2018). Evidence suggests consideration of high school GPA may also provide useful information about students' math competencies (Atatuhene, 2016; Hartman, 2017). At the same time, though scant scholarly literature considers local instruments for math placement, local instruments can provide advantages over standardized instruments through high levels of customization and greater faculty engagement (Banta & Palomba, 2015).

Into the inconclusive collection of outcomes regarding developmental math placement, one must interject the idea that at some institutions (Fuller, Deshler, Kuhn, & Squire, 2014) math emporiums present a new instructional approach (Twigg, 2015) with greater learner customization and stronger elements of demandingness and supportiveness than found in traditional instructional settings (Kinney, 2001; Wambach, Brothen, & Dikel, 2000). This proposed study of ACT/SAT scores', high school GPAs', and local assessment results' accuracies in predicting developmental math students' success in math emporium courses contributes to the body of knowledge because it helps higher educators who use or are considering using the math emporium model determine what factors best predict developmental students' success in an emporium. In addition to supporting decisions related to placement tool components, findings may also inform higher educators' expectations of developmentally-placed students' general strengths and weaknesses and may lead to future research concerning placements and course content.

Research Questions

RQ1: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment predict the MATH 100, Fundamentals of Mathematics final grade for students who completed the course through a math emporium at a private university during the 2017-2018 academic year?

RQ2: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment predict the MATH 100, Fundamentals of Mathematics final grade for students who completed the course through a math emporium at a private university during the 2016-2017 academic year?

RQ3: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment predict the MATH 100, Fundamentals of Mathematics final grade for students who completed the course through a math emporium at a private university during the 2015-2016 academic year?

Definitions

1. *Developmental courses* – Developmental courses are higher education courses—usually assigned by an institution based on skills determinations (Park et al., 2016)—aimed at helping undergraduate students develop academic skills necessary for regular, college-level coursework (Boatman & Long, 2018). Developmental courses are also called remedial courses.

2. *Math emporium* – A math emporium is a relatively recent innovation—about 20 years old—through which students at some institutions undergo customized mathematics instruction through computer technology while instructors or tutors stand ready to assist (Kasten, 2000).
3. *Remedial courses* – higher education courses—usually assigned by an institution based on test results (Park et al., 2016)—aimed at helping undergraduate students develop academic skills necessary for regular, college-level coursework (Boatman & Long, 2018). Remedial courses are also called developmental courses.

CHAPTER TWO: LITERATURE REVIEW

This literature review synthesizes scholarly, empirical research related to the accuracy of ACT/SAT math scores, local math assessment performance, and high school grade point averages (GPAs) as predictors of students' final grades in developmental math courses delivered through a math emporium. Three major sections synthesize the literature. The first introduces theory and major constructs. The second develops the issue through research into developmental math, the math emporium model, math placement practices, and the major constructs of ACT/SAT scores, local assessments, and high school GPA. A final section summarizes main points and draws clear attention to the apparent gap in literature related to developmental math placement and students' performance in math emporiums.

Theoretical Framework

A combination of cognitive load theory (Sweller, 1988), the computer self-efficacy model, and developmental math placement constructs relate to developmental math placement. This section of the literature review describes the theory and model and explains how research may assess the theory and inform actions related to theory application. The section leaves treatment of the three constructs (ACT/SAT scores, local assessment scores, and unweighted high school GPA) for later in the chapter.

Cognitive Load Theory

Sweller's (1988) cognitive load theory served as the primary of two underpinnings that, with the three constructs described later, provided the framework for this literature review. Understanding cognitive theory requires knowledge of schemas and of the dual task paradigm.

Dual task paradigm. Fisk and Schneider (1984) found when an individual is tasked to perform two simultaneous activities, the individual's ability to perform either or both tasks may suffer for the other task or tasks. Further, the level of impact on accomplishment of one task depends in part on the difficulty of (and focus required for) the other task or tasks. Sweller (1988) suggested the dual-task paradigm could help determine whether schema acquisition and employment require significant or little cognitive processing.

Schemas. Sweller (1988) defined schemas as domain-specific knowledge that distinguishes experts from novices. This knowledge—or schema—facilitates the expert's ability to recognize that a problem belongs in a certain category of problems for which the expert knows steps toward finding a solution. In other words, through schemas an expert sees through a problem to a solution based upon the expert's recall of experiences addressing similar problems.

Cognitive load theory conclusions. Sweller (1988) drew five conclusions regarding cognitive load theory. They were that problem solving imposes a heavy cognitive load, that problem solving and schema development seem distinct, that problem solving may therefore not facilitate schema development, that extensive problem-solving emphasis in education may retard development from novice to expert, and that the teaching and learning theories and practices of the time may have been due for adjustment. The first of Sweller's conclusions, that problem solving—specifically math assessment problems—imposes a heavy cognitive load on the problem solver seems particularly related to math emporium development placement. Sweller's third through fifth conclusions regarding the challenge of developing schemas when one's cognitive capacity faces strains that in addition to those directly resulting from schema acquisition also seems related to placement. Computer self-efficacy may relate to placement as well, but in a secondary fashion.

Computer Self-efficacy Model

Computer self-efficacy has its roots in Bandura's (1986) theory of self efficacy and supposes one's beliefs about one's abilities impact one's actions and performance. Subsequent to Bandura's publishing, Gist, Schwoerer, and Rosen (1989) conducted an experiment involving 108 university administrators and computer software, and results indicated those who felt confident in their abilities performed better with computers than those who lacked confidence in their computer skills. These ideas together formed the concept of computer self-efficacy, suggesting individuals who consider themselves good with computers will tend to perform better with computer-related tasks than those who do not consider themselves proficient with the technology. A key component of the principle as regards the topic of developmental math placement into math emporiums is that computer skills tend to apply consistently to computer-related activities, such that if one is good at one computer-related task, one tends to be good at others, and vice-versa.

Combining Cognitive Load Theory and Computer Self-efficacy

Accuracy of ACT/SAT math component scores, unweighted high school GPAs, and local assessment results as predictors of math emporium developmental math final grades may connect to Sweller's (1988) first cognitive theory conclusion that schema employment engages a large percentage of an individual's cognitive abilities. It may also rely upon Bandura's self-efficacy as Gist, Schwoerer, and Rosen (1989) applied it to computer tasks in that one who feels confident with computers will tend to perform well with all computer-related tasks.

Application to this Research

Sweller's (1988) idea that schema employment engages a high percentage of one's cognitive load suggests that if individuals face a high-priority task—such as answering questions on a high-stakes, computer-based assessment (local math assessments present a pertinent example)—one who is skilled with computers will have cognitive capacity to employ learned schemas and to solve the assessment problems while one with low computer self-efficacy will find one's attention split between the two challenging tasks (computer use and assessment problems) such that schema employment will prove challenging (Gist, Schwoerer, & Rosen, 1989). Further, context makes a difference in learning when information is involved (Johnson, 2003), and a computer-based testing or learning environment provides a different context than a classroom. Considering these ideas, it may be reasonable to suspect computer self-efficacy and computer skills relate to scores on computer-based assessments.

In addition to computer self-efficacy impacting one's ability to employ schemas as problem-solving tools, computer self-efficacy as demonstrated by Gist, Schwoerer, and Rosen (1989) suggests placement in a computer-based math emporium may affect one's cognitive load and schema acquisition. Drawing from Sweller's (1988) conclusions regarding the limitations of schema acquisition abilities in two-task situations (Fish & Schneider, 1984), one expects students with low computer self-efficacy or skills to perform poorly in computer-based math emporiums relative to students with high computer self-efficacy or skills. Consistent with these expectations, Huang and Mayer (2016) found adding anxiety-reducing components to computer-based training improved students' learning.

Determining whether students' scores on computer-based, local math assessments are better or worse predictors of developmental students' computer-based math emporium course final grades evaluates the validity of Sweller's (1988) cognitive load theory. If computer-based local math assessment scores prove a better predictor of students' final grades in developmental math courses taught through a computer-based emporium than do than high school GPAs and paper-based ACT/SAT math component scores, Sweller's theory gains strength. If otherwise, the research will fail to validate Sweller's theory, at least in this context.

Recent research relied on portions of the ideas this review drew from theory. Education-related studies relied on Bandura's (1986) theory (Kelly, 2017; Bierer, Prayson, & Dannefer, 2015), on computer self-efficacy (Celik & Yesilyurt, 2013), and on computer self-efficacy as it relates to computer-based testing (Balogun & Olanrewaju, 2016; Nwagwu & Adebayo, 2016). Recent education research also explored cognitive load theory (Sweller) and split attention (Fish & Schneider) as they apply to computer-based testing (Jarodzka, Janssen, Kirschner, & Erkens, 2015).

Related Literature

Understanding predictors of developmental math students' final grades in developmental math courses taught through a math emporium requires knowledge of developmental math, developmental math challenges, and the math emporium model. It also requires understanding the major constructs examined as possible predictors of developmental math final grades: ACT/SAT math scores, local math assessment scores, and high school GPAs. This section of the review addresses these concerns, but it first indicates why the matter of mathematics delivers importance to educators.

Importance of Math Skills

Utilitarian principles (Bentham & Lefleur, 1948; Gutek, 2013) suggest post-secondary professionals should provide to students an education that helps the students maximize their usefulness to themselves and society. Research indicates mathematics skills facilitate students' academic achievements and also support higher quality of life outside formal schooling. These contributions make mathematics important to educators.

Math skills relate to academic success. Math skills relate to academic success, both by playing a role in students' decisions to enter academic programs and by helping students succeed in the programs they enter. Kyoung Ro, Lattuca, and Alcott (2017) quantitatively examined a sample of 1,119 engineers to investigate influences that impacted the individuals' decisions to begin graduate school. Findings at $p < .05$ included that students' math proficiency levels significantly predicted engineering graduate program entrance as well as attendance in non-engineering graduate programs. The researchers concluded math proficiency is key to students' advancement from undergraduate to graduate levels. Quarles and Davis (2017) also investigated math skill levels and academic promise. Their sample, pulled from a large Washington State community college, considered math scores and subsequent college enrollments, grades, and completions for 426 intermediate algebra students. Though findings cast doubt on the value of procedural math development instruction, they indicate conceptual math skills support later academic success. Similarly, Wang, Degol, and Ye (2015) conducted a qualitative study at a large, urban, Midwestern community college. Relying on interviews and surveys involving both faculty members and students, the trio of researchers noted math was a critical cornerstone for subsequent learning and academic success. Good math skills seem correlated not only with higher graduate enrollment rates (Kyoung Ro, Luttuca, & Alcott, 2017), but also with undergraduate academic success (Quarles & Davis, 2017; Wang, Degol, & Ye, 2015). The literature suggests advantages of possessing high math skills extend beyond one's academic pursuits, too.

Math skills contribute to well-being outside academics. Several scholarly studies suggest math skills contribute to one's well-being outside the academic environment. McDonough and Tra (2017), for example, relied upon the importance of math skills as their foundation when they built research into computer-based tutorials and economic benefits. Undurraga, et al., (2013) noted research in industrial nations pointed to math skills as positively correlated with both non-market and market outcomes, but then looked outside these developed-nation settings to a sample of 1,121 farmers and foragers from 40 native Amazonian villages. The researchers compared measured math skills for their sample villagers with assets owned, body mass index, perceived stress, child morbidity, and other supposed life success metrics. Results from multivariate regressions determined higher math skills translated to higher lifestyles in a continuous way, and individuals who successfully accomplished four math-related tasks on an assessment averaged $96.98 more periodic income than those who accomplished none of the assessment tasks. Further, the successful group owned a corresponding $144.26 additional capital wealth with $p < .01$.

Koedel and Tyhurst (2012), presented a perhaps clearer and more locally applicable picture of the market value of math skills through their quantitative experiment that sought to answer the question of what impact math skills—indicated on applicants' resumes—exerted on employers' responses to job seekers. The pair of researchers relied on 3,236 resumes sent in groups of four to employers who had posted 809 clerical, sales, and customer service job openings on one or both of two specific online job boards. Each group of four resumes included two pairs the researchers had matched as similar in qualifications for the positions, but the researchers after matching had added indications of strong math skills to one resume from each pair. Halfway through their experiment the researchers reversed the math skills assignments such that each resume that had lacked additional math skills then, for the second half of the data collection period, indicated strong skills, and vice-versa. The researchers subsequently collected, cataloged, and coded employer responses. Their findings indicated stronger math skills reflected in resumes held a large impact over employer response rates and content for sales positions, a modest impact over response rates and content for clerical positions, and no impact for customer service vacancies. In no case were higher indicated math skills negatively correlated with employers' responses.

Research suggests math skills help individuals academically (Kyoung Ro, Lattuca, & Alcott, 2017; Quarles & Davis, 2017; Wang, Degol, & Ye, 2015) and improve one's employment prospects (Koedel & Tyhurst, 2012), income level, and general quality of life (Undurraga et al., 2013). Math skills even connect with national optimism (Bishop, 2015). In short, the literature makes clear that math skills matter to students and to society, so they matter to educators. The developmental math landscape, though, presents challenges.

Developmental Math

Developmental courses—also known as remedial courses—are programs post-secondary institutional leaders use to help under-prepared undergraduate students gain the academic skills required for regular, college-level coursework (Boatman & Long, 2018). Though remediation commonly occurs in subjects such as English and reading (NCES, 2018), math presents as the most-remediated subject (NCES, 2016) and has garnered significant attention over the years. Stahl, Theriault, and Armstrong's (2016) analysis of four decades of *Journal of Developmental Education* interviews included the summary comment that mathematics has for decades provided a critical conversation topic in developmental education. Unfortunately, the developmental math landscape presents a picture of many students who, usually assigned to classes they do not wish to take (Park et al., 2016), face long odds. The portrait also exhibits post-secondary educators who innovate—often with poor results—in their attempts to help these challenged students. Though many attempts to help the students seem to fall short, the literature indicates some innovations show promise. This section of the literature review opens with a brief history of developmental math and describes where developmental math sits today, including the advent of the math emporium.

History of developmental math. According to Arendale (2011), higher education leaders have long relied on developmental programs to help academically under-skilled students reach the skill levels required for admission into college-level courses. Students, with few exceptions, entered (and still enter) developmental math programs because their institutions required them to do so based on results of a mathematics knowledge assessment rather than through the students' own desire to enter developmental studies (Park, et al., 2016). These developmental courses, wrote Arendale (2011), evolved over time. A change took place between the 1940s and 1970s that saw an era of precollege academies and tutoring that served primarily wealthy, white students give way to a more modern time of remedial classes that aimed at meeting the needs of a considerably more diverse array of students through traditional classroom instruction rather than through tutoring and special academies. Innovation during this time, wrote Koch (1992), meant encouraging faculty members to communicate constantly with their students. Over the following decades, according to Arendale (2011), traditional classroom remediation gradually gave way to more modern approaches intended to address the remedial needs of almost any student who wished to pursue higher education. While the delivery methods changed, so did students' participation rates. Less than twenty years ago approximately one out of every five college students entered developmental programs (NCES, 2013), but more recent data indicates the ratio of developmental students to non-developmental students sits at about one in three (NCES, 2016)—or perhaps even worse (Radford & Horn, 2012). The innovative era of developmental education, according to Arendale (2011), continues to the present day. One may see evidence of this through the variety of new activities educational leaders undertake to address developmental math students' challenges (Kosiewicz, Ngo, & Fong, 2016; NCES, 2016).

High developmental math participation levels. The National Center for Education Statistics in 2016 had much to say about the state of developmental math. For example, during the last decade about one-third of all college students reported having taken developmental coursework, and math was the most commonly engaged developmental subject; and while two-year state institutions saw about 40% of their students enter developmental courses, even four-year institutions served 29% of their students with developmental programs. Other government sources validated these figures ("*Developmental*," 2017). Valentine, Konstantopoulos, and Goldrick-Rab (2017) wrote in their report on their meta-analysis of 11 regression discontinuity studies that institutions place almost two out of every five beginning college students into developmental education, and the researchers further noted developmental math remediation is more than twice as common as is participation in English, reading, or writing remediation. The high developmental math placement rate indicates developmental math placement decisions present as a topic worthy of scholarly attention, and perhaps quite so because empirical evidence also indicates students placed into developmental math courses tend to fare poorly.

Developmental math students face long odds. Developmental mathematics students face very limited prospects for academic success (Coleman, Skidmore, & Martirosyan, 2017), and placement into developmental math programs costs time (Melguizo, Bos, Ngo, Mills, & Prather, 2016) and money (Adams, n.d.; Selingo, 2013; Toutkoushian & Paulsen, 2016) and negatively correlates with student graduation rates. The National Center for Education Statistics (2016) noted that in spite of the almost ubiquitous nature of remedial programs in our nation's colleges, the programs' efficacy remains uncertain and many students achieve unfavorable results from their remedial coursework. Valentine, Konstantopoulos, and Goldrick-Rab (2017), through a regression discontinuity meta-analysis, aimed to determine developmental placement's impact on remedial students. They looked at the probability of the students passing an assigned developmental course, at college credits gained, and also at degree completion rates. Using both fixed and random effect models, the researchers found negative, statistically significant, and large outcomes for each of the three studied, dependent variables with mean credits earned -1.86 using fixed effects at $p < .001$ and with -3.00 for random effects with $p = .002$. Probability of these students ever passing a college-level course in the remediated subject area decreased by 7.9% for developmental students with $p < .001$ under both random and fixed effects. The researchers reported degree attainment under both models dropped by 1.5% for these students with $p =.03$. Other research suggests these figures may understate the challenges.

Armstrong and Zaback (2014) quantitatively explored data from seven states and 216 institutions and found fewer than 30% of developmentally-assigned students graduated within six years. Similarly, Clotfelter, Ladd, Muschkin, and Vigdor (2015) sought to address the question of average effects of assignment to a developmental course within a state community college system. They employed a sample of 17,167 students who enrolled first in a North Carolina community college after having completed—and based on the results of—required state testing. Their findings included that a developmental math assignee experiences -.022, -.057, and -.073 successful outcome estimates using fixed effects with $p < .05$, $p < .01$, and $p < .01$ respectively. Clotfelter, et al. (2015) interpreted these results to mean assignment to pre-algebra resulted in a 17.9% decrease in student success. Further, the assigned students suffered a 22.2% reduction in the probability of ever passing a college-level math course and faced only a 32% probability of eventual success in any college-level mathematics course. The findings seem both validated and exacerbated by Clotfelter, Ladd, Muschkin, and Vigdor's (2015) literature review through which exploration of the variety of challenges developmental students face led to the researchers' conclusion that many students fail in the developmental courses, and if they succeed in the developmental courses they then often fail in subsequent college-level coursework.

Cox's (2015) research adds to the body of literature decrying the poor prospects of developmental students. Based on a study of developmental math teaching practices at two large, urban community colleges in the Northeastern United States, Cox sought to explore what the literature identified as a given: low developmental math pass rates. Davidson (2016) separately employed quantitative methods and relied on continuation ratio logistic regression to explore developmental math students' progressions through several levels of developmental courses and on to passing a first college-level math course with a grade of "D" or better. Davidson's sample included all of the state of Kentucky's Fall 2005 first time, undecided, associate and bachelor's degree seeking students enrolled in pre-algebra at both two-year and four-year institutions with $n = 2{,}170$. While Davidson found each students' success in their most recent developmental math courses predicted with some accuracy the students' likelihood of passing the first college math course, Davidson also reported that only 11.3% of the sampled students reached and passed that first college-level math course, and this with a reported $p < .0001$. In Davidson's words, "The majority of remedial math students never pass a college-level credit-bearing math class" (p. 138). A further focus on graduation rate differences seems warranted.

Graduation rates differ between the general student body and developmental students. Graduation rates differ between students assigned to developmental courses and the general student population, and the difference seems stark. Shapiro, et al. (2017) analyzed Fall

2011 college cohort data drawn from the National Student Clearinghouse Research Center, an organization that tracked 97% of all enrollments at all U.S. post-secondary institutions, including two-year, four-year, public, private, for-profit, and non-profit schools. This majority sample, *n* = 2,270,070, represented unduplicated headcounts because the data rely upon student-level data. Findings included that 56.9% of the studied cohort graduated from some institution—whether the institution at which the student began or some other school—within six years (Shapiro, et al., 2017). This six-year graduation rate differs significantly from the graduation rate for students assigned to developmental courses. Armstrong and Zaback (2014) reviewed partial or full state-reported data from seven states within or near the Appalachian region along with institution-reported data from schools within five of the same seven states to quantitatively explore graduation rates as of 2012, with *n* = 1,865,899. Though noting that results may not transfer to populations outside the studied institutions, Armstrong and Zaback's findings included that fewer than 30% of students assigned remedial coursework graduated within six years. Given the apparent difference in six-year graduation rates—56.9% of the overall student body and less than 30% of the developmentally-assigned student body—it makes sense to explore what happens within developmental math and developmental math placement.

Students who succeed in developmental math tend to succeed in later math. With findings in apparent contrast to Clotfelter, Ladd, Muschkin, and Vigdor's (2015) results regarding developmental-assigned students' lessened probably of ever passing a subsequent, college-level course; and in accord with Davidson's (2016) findings that students' grades in pre-algebra predict their pass rates in a first college-level math courses; Fong, Melguizo, and Prather (2015) sought to determine the percentage of students progressing through various stages of the developmental math sequence. Their sample included 62,082 California community college students from eight separate schools who, over a three-year period, tested for developmental math and subsequently enrolled in any course at the college through which the students had tested. Results indicated the students' likelihood of attempting a more advanced, developmental class increased as one progressed from the lower to the higher developmental levels, with 39% failing to attempt the lowest level, 32% stepping then out before the second level, 30% avoiding the third, and only 27% self-eliminating from the fourth and highest developmental math level—based on stepwise logistic regression with a reported $p < .01$. Ulmer, Means, Cawthon, and Kristensen (2016) took their research beyond the developmental sequence—similar to Davidson's (2016) work—and asked questions related to the relationship between remedial course performance and introductory college-level course performance for both math and English. Results from the 1,091 students of the 2007 math cohort and 1,098 from the 2008 math cohort Ulmer, et al. (2016) studied indicated a positive and significant association between developmental students' remedial math course performance and initial college-level math course performance. This body of research taken together suggests developmental math programs that help students do well in the developmental courses may also support students' college-level math course successes—if the developmentally-assigned students will persist. Overall, the literature indicates institutions assign many students to developmental math programs, and students so assigned generally face poor odds of getting through school. Higher education leaders have not been sitting idle, but have innovated to address the challenges.

Institutional leaders innovate. The National Center for Education Statistics (2016) reported that several states implemented "drastic measures" (p. 3) to deal with the crisis of high developmental enrollment and poor developmental student outcomes. States' actions, according to Cox (2018), include admissions denials for prospective Georgia post-secondary students who fail to score sufficiently on the ACT or SAT exam and revoking remedial education funding for Ohio's public institutions. Institutions make programming decisions based on funding (Kelchen & Stedrak, 2016; Thornton & Friedel, 2015)—and perhaps especially based on government funding (Pedraja-Rejas, Rodriguez-Ponce, & Araneda-Guirriman, 2016)—so a state's movement toward eliminating funding for developmental courses makes the courses less viable. Higher educators have tried other, perhaps less drastic measures as well.

Lengthening sequence seems unhelpful. Lengthening the developmental sequence appears to show little promise. Ngo and Kosiewicz (2017) looked at whether lengthening students' time in algebra by one semester helped the students succeed in both developmental math and in college overall. Quantitatively examining archival data from 12,805 California developmental math students who attended four large community colleges, including 6.228 assigned to extended-time developmental sequences, the researchers found 89% of the students with a standard developmental sequence began their regimens while only 71% of extended-sequence students attempted theirs. In some contrast to that finding, Ngo and Kosiewicz reported that students who began the extended sequence experienced 19% attrition compared to the traditional sequence students who faced 27% attrition—once they began their sequences. The researchers concluded that longer sequences delayed students from beginning necessary courses and therefore led to fewer college-level credits achieved over a set period of time than through the traditional model, so consistent with Kosiewicz, Ngo, and Fong's 2016 pronouncement, Ngo and Kosiewicz's (2017) research indicated the extended time in developmental courses seems not useful.

Providing optional, online supplemental training seems unhelpful. Chingos, Griffiths, and Mulhern (2017) researched whether offering an optional, low-cost, online summer math preparation program could improve students' math skills before the students entered their freshmen college years and whether such a program could support the students' performance throughout the first year of college. Their sample included 697 university students within the state of Maryland, 352 of whom the researchers had randomly selected to receive the offer of the optional, online treatment with treatment costs covered by outside sources (so the treatment was free-of-charge to the students). Though the students assigned to the treatment group performed slightly better in their developmental courses than did the students in the control group, findings otherwise dovetailed with the Ngo and Kosiewicz (2017) results in that the treatment group students ended their academic year with no gain in credits over the control group students. It seems possible, though, that the treatment group students may have performed better in the long term.

Faculty believe accelerating and compressing developmental math courses shows promise. Lengthening developmental sequences seems unhelpful for students (Ngo and Kosiewicz, 2017), but educators also tried shortening sequences (Ulmer, Means, Cawthon, & Kristensen, 2016). Cafarella (2016) noted that traditional developmental math delivery served as an obstacle for many students and turned to answer the question, "Based on faculty experience, what is the best fit for the practices of acceleration and compression in developmental mathematics" (p. 12)? Cafarella's research relied on qualitative methods and drew upon interviews with six developmental math instructors, two each from three community colleges. Findings included that faculty members believed developmental math students represented a very diverse subset of the full student body, and that though acceleration and compression do not work for all students, certain students may do better with the techniques than without.

Embedding developmental math content into non-math courses shows promise for some students. Parker, Traver, & Cornick (2018), in accord with research that indicated math skills matter in both academic (Kyoung Ro, Lattuca, & Alcott, 2017; Quarles & Davis, 2017; Wang, Degol, & Ye, 2015) and nonacademic (Koedel & Tyhurst, 2012; Undurraga et al., 2013) settings, wrote that mathematical literacy is critical both individually for financial and consumer activities and socially as one evaluates policy decision outcomes and considers possible veracity of various claims. Based on that foundation, Parker, et al., (2018) created an experiment that indicated embedding basic algebra content into sociology courses helped some students build their developmental math skills. The researchers called upon a sample of 17,033 ethnically and racially diverse students enrolled in degree and non-degree programs at two of seven City of New York community colleges during the fall of 2015. Students assigned to the treatment group participated in an Introduction to Sociology course that educators had embedded with three modules intended to deliver algebra in practical, sociology-connected scenarios. These students were also enrolled in an Elementary Algebra course. Control group students were in the Elementary Algebra course, but did not participate in the special sections of algebra-embedded sociology. All sampled students took one pre-test and two post-tests. Results indicated the treatment group students' average post-test scores increased over their pre-test scores while the control group students' scores decreased. The treatment group's average score increase was not statistically significant, so the researchers reported only limited success. Developmental math research involving technology also evidences reason for some optimism.

Technology and Math. Christensen, Horn and Johnson (2011) touted computer-assisted instruction as a revolutionary innovation able to affordably provide valuable, student-level instructional customization, and research indicates technology truly can assist. According to 20 faculty members who participated in a qualitative study of developmental math best practices, customizing instruction to each individual learners' specific needs seems particularly helpful for developmental math students (Cafarella, 2014). Relevant research into technology as a tool for helping math looked at both K-12 and post-secondary environments.

Computers supplementing instruction show some promise in the K-12 environment. Several studies indicate technology seems useful in the K-12 mathematics environment. McDonough and Tra (2017), for example, investigated results within the Clark County School District where computer-aided math tutorials assisted students prior to administration of the High School Proficiency Exam. The researchers' results provided "evidence of increased proficiency in mathematics related to tutorial participation" (p. 1041), and gains were especially notable for minority students. Zheng, Warschauer, Lin, and Chang (2016) conducted a meta-analysis that explored 65 journals and 31 doctoral dissertations from 2001 to 2015 to determine the significance and impact of one-to-one laptop technology programs on K-12 school students. Student gains in mathematics subjects led the way according to study results, with an effect size estimate of 82.15% based on seven studies. Crawford, Higgins, Huscroft-D'Angelo, and Hall (2016) also studied the effects of technology-related support tools using a convenience sample of 73 students in grades four to six. They reported with $p < .001$ that the use of the tools "positively predicted gains from the program" (p. 1163). These articles suggest technology can help in the K-12 environment, and findings at the post-secondary level seem also promising.

Computer-assisted developmental math instruction shows promise for college students. Childers and Lu (2017) wrote "failures of developmental math are no secret" (p. 2), noted the myriad of developmental math redesign efforts, and reported on one program that involved mastery learning in computer-based developmental math classrooms. The researchers quantitatively investigated completion rates, time in program, success in college-level math subsequent to computer-based developmental math participation, and factors contributing to success. They found that students in the treatment group performed better than those in the control group, but also that the control group students tended to catch up after program participation ended. Foshee, Elliott, and Atkinson (2016) explored the similar question of whether technology-enhanced learning techniques can boost developmental math completion rates. Creating a quantitative pre- and post-test longitudinal study of 2,880 students comprising a college's remedial mathematics cadre, the researchers provided a technology-based system that led students through practices, gave feedback that was both thorough and specific as well as consistent with Wambach, Brothen, and Dikel's (2000) developmental theory as demonstrated by Kinney (2001), and assessed student progress. In contrast with the Childers and Lu (2017) finding, Foshee, et al.'s results determined the remediation was successful, with 75% of participants eligible for college-level math after a single semester and 18% on track for college-level math after an additional semester. It seems noteworthy that the researchers did not employ a control group because they considered it unethical to withhold the treatment from any students.

Elaborative feedback stands out as a computer-assisted teaching component that seems particularly useful for developmental math instruction. Van der Kleij, Feskens, and Eggen (2015) conducted a meta-analysis of 40 studies that each concerned feedback regarding student outcomes within computer-aided learning environments. Findings included that the effect size of elaborative or explanatory feedback related to math was larger than for other subjects, suggesting computer-assisted instruction may adequately address developmental theory's (Wambach, Brothen, & Dikel, 2000) call for supportive feedback. One may wonder why educators do not try technology-based programs more often, and research may hold at least part of the answer to that question.

Many developmental math faculty members not comfortable with technology. One possible explanation for why traditional instruction seems still prevalent in a world where computer technology seems instructionally helpful is that some developmental educators are not comfortable with new instructional technologies. Zientek, Skidmore, Saxon, and Edmonson (2015) set out to determine what technology developmental math faculty members preferred, so they executed a quantitative study that analyzed survey results from 379 faculty members who represented 55 institutions. The researchers' findings included that more than one-third of the respondents failed to rate themselves as familiar with instructional technology. Separate research considered factors impacting students' perceptions of technology in math instruction.

Students' views regarding technology vary. While Zientek, Skidmore, Saxon, and Edmonson (2015) considered faculty views, Zogheib, Rabaa'i, Zogheib, & Elsaheli (2015) asked questions about students' attitudes. Their research relied upon quantitative methods, structural equation modeling, and a sample of 228 university students at a private American college in the Middle East, 85.5% of whom were aged 18-25 years and 72.8% of whom were females, enrolled in remedial and college algebra during the spring of 2015. All students used MyMathLab, a system of online courses available for Pearson textbooks that provided students with study plans and instructors with tools aimed at minimizing cheating. Findings from the students who responded to all questions on the researchers' survey (228 of 240) included that perceived usefulness of the technology delivered great impact on student attitude (B = 0.526, p < ,001) and user satisfaction connected strongly with perceived ease of use (B = 0.308, p < ,001). Bayrak and Akcam (2017), in a separate study, found that gender made no statistically significant difference in students’ perceptions of learning environments that incorporated or did not incorporate computer technologies.

The math emporium model. Much of the research into computer technology as a tool to help developmental math students indicates the tool seems helpful. One reason for his may be that computers allow instructional customizations for each individual students’ needs (Christensen, Horn, & Johnson, 2011). This personalization sits in contrast to traditional one-size-serves-all lectures that, according to Twigg (2009), treat students as if they collectively share the same interests, abilities, motivations, and learning styles. Because each student is individually unique (Christensen, et al., 2011), the lecture format fails to deliver the supportiveness demanded by Wambach, Brothen, and Dikel’s (2000) developmental theory. Further, Twigg noted lectures tend to neither afford opportunities for collaborative learning nor to encourage active participation—both of which can improve college students’ learning (Goacher, Kline, Targus, & Vermette, 2017; McCarthy, 2015; Sun, Liu, Luo, Wu, & Shit, 2017; Vogel, et al., 2016).

In 1999, with the support of an $8.8 million Pew Charitable Trusts grant, the National Center for Academic Transformation (NCAT) (Twigg, 2015) at Rensselaer Polytechnic Institute created the Program in Course Redesign (Twigg, 2009). With the idea that before that time students under most technology-based learning programs gained only about as much as through traditional means, the Program in Course Development set out to redesign high-enrollment courses in ways that could—through computer technology—positively impact high numbers of students while at the same time saving money over traditional methods. Hundreds of institutions from across the United States competed to become one of 30 selected to receive a share of the funding that aimed to redesign one high-enrollment introductory course at each selected institution (Twigg, 2015). With nearly 200 redesign projects initiated as of 2015, NCAT and its partnering colleges and universities had by then completed 156 projects, 72% of which improved student outcomes and 153 of which reduced costs by—on average—28% over traditional learning formats. These projects had by 2015 resulted in 253 redesigned courses enrolling approximately 250,000 students each year. Course completion rates, student attitudes toward subject matter, and student and faculty satisfaction all improved. From this foundation sprang the math emporium.

In 1999, with support of the Pew Charitable Trusts funding through NCAT as described above, the Virginia Polytechnic Institution and State University (Virginia Tech) replaced their traditional lecture-centered math classroom with a math emporium where students gained individualized instruction through computer technology (Kasten, 2000). Virginia Tech touted on their website ("Math emporium," n.d.) that the effort earned the 1999 XCaliber Award, short for exceptional, high-caliber contributions to technology-enriched learning activities ("*XCaliber Award*", n.d.). Some other institutions followed by creating math emporiums (Fuller, Deshler, Kuhn, & Squire, 2014; Hodges & Murphy, 2009; Twigg, 2011), but though recent research identifies technology integration as a cost-reducing tool (Goldwasser, Martin, & Harris, 2017), the math emporium model, a relatively recent innovation that transformed education from passive to active in which learners control the environment (Twigg, 2009, p.151), exists at only a limited number of institutions (Fuller, Deshler, Kuhn, & Squire, 2014).

Emporium experiment. Wilder and Berry (2016) performed one of the few—and perhaps the only—recent math emporium experiment available through scholarly journals. Though they explored the secondary rather than the post-secondary environment, their work delivers value to this literature review and to this research project because the emporium they examined was built upon the Virginia Tech emporium that originally launched the math emporium model (Twigg, 2009), because it identified a possible weakness and a strength from the emporium approach, and because the researchers looked at students who had scored relatively poorly on a pre-course test and therefore perhaps shared some similarities with post-secondary developmental students. Wilder and Berry (2016) noted the emporium they studied resulted from recent Common Core State Standards that called for inquiry-based K-12 instructional approaches and that the emporium addressed that need. The researchers asked two questions: (a) “Do students taught using emporium model perform higher on Algebra I achievement test than their counterparts who are taught using traditional methods” (pp. 59-60)?, and (b) “Do students taught using the emporium model have higher knowledge retention levels of the material than their counterparts who are taught using traditional methods” (p. 60)? They selected for their study a new science, technology, engineering, and math-focused high school—it had been open three years—that served other schools in the surrounding region, and their sample included 62 of the school’s freshmen who had scored below 70% on an achievement test and were therefore assigned to Algebra I. With n = 62, school officials randomly placed 30 into the treatment group that would experience the math emporium and 32 into the control group. One teacher served both groups. Because the school had existed for only three years, only freshmen through juniors presented within the sample. With that, the researchers noted a large range of students’ mathematical abilities and prior mathematics knowledge.

Wilder and Berry (2016) measured the sample students’ mathematics knowledge through an achievement test administered pre-treatment, after treatment at the end of the term, and again after treatment at the beginning of the next term. Treatment included math emporium participation consisting of online software aimed at helping the students learn the content through adaptive questioning and associated adaptive instruction based on each students' individually-determined knowledge level. The treatment group students were free to work in groups. The instructor's role was to individually answer questions the students asked and to assist those who were struggling, but nothing more. The control group experienced traditional lecture instruction—though at this school even the control group learned through guided questioning, inquiry-based lessons, and project-based learning activities as frequent lecture supplements.

The students assigned to the emporium scored slightly higher on the pre-test, but at a statistically insignificant rate with a very small effect size of $r = .01$. In the first post-test, the average achievement scores were again not significantly different between the treatment and control groups, with $p > .05$. Difference between average learning based on comparing the pre- and post-test results was also insignificant. However, scores in the second post-treatment achievement test, administered at the beginning of the term following treatment, indicated the control section students had lost considerably more knowledge (M = - 7.5, SE = 1.17) than had the treatment group students (M = - .87, SE = 1.49), $t(48) = 3.463$, p < ,01, with a medium-sized effect of $r = .45$. Wilder and Berry's (2016) results indicate the emporium approach can improve math content retention after an extended time.

Developmental Math Placement

As noted earlier in this paper, students typically do not choose to enter developmental math programs, but rather institutions assign them to the courses (Park et al., 2016s) to bring their mathematics knowledge and skills to levels required for college-level work (Arendale, 2011). Placement decision methods vary (Ngo & Kwon, 2015; Ngo & Melguizo, 2016), as do placement decision criteria (Bracco et al., 2014). This review focuses on two major categories of criteria as research constructs: examinations and high school GPA.

Examinations. This subsection of the literature review explores tests that various institutions—and the setting institution for this particular study—use within the math placement decision process. These include standardized (or national) tests—specifically the ACT and the SAT—and local assessments. American College Testing provides the ACT test and claims their exam, as the leading college admissions test, measures high school learning and college readiness ("*ACT Test*," n.d.). The College Board, with over 6,000 member organizations, provides the popular and similarly-purposed Scholastic Aptitude Test (SAT) to serve prospective college students and institutions during the acceptance and placement processes ("*About the College Board*," n.d.). Institutions have historically relied upon scores from these two assessments as their primary developmental math placement tools (Bracco et al., 2014), and many schools still rely solely upon them for developmental placement decisions (Crynes, 2013; Melguizo, Kosiewicz, Prather, & Bos, 2014; Xu & Dadgar, 2018). At the same time, some schools rely on local assessments, perhaps because locally-developed products carry advantages regarding institutional customization and greater levels of faculty engagement (Banta & Palomba, 2015).

Standardized (national) tests. Scholars note the value of standardized tests such as the ACT and SAT as math placement devices (Barbitta & Munn, 2018; Henry, Heiny, & Raymond, 2017), and some suggest their importance is growing (Letukas, 2016), but racial and socioeconomic variations present one challenge of relying on standardized testing for admissions and placement decisions (Black, Cortes, & Lincove, 2016; Nu, 2015; Park & Becks, 2015;

Shewach, Shen, Sackett, & Kuncel, 2017). At the same time, though, Higdem et al. (2016) argue socioeconomic factors make little difference, so disagreement exists.

Black, Cortes, and Lincove's (2016) exploration of multiple measures college readiness assessment found that including ACT/SAT scores among other rank-based admissions criteria resulted in significant minority enrollment decreases. Park and Becks (2015) looked at SAT preparation courses and determined financially advantaged students tended to engage in preparation courses and that the courses supported score gains of approximately 11 points on average, and they also found students who completed Advanced Placement (AP) courses in high school tended to perform better on SAT exams than their peers who had not taken the courses regardless of financial situation and without regard to whether a student had completed a test preparation course. Further, Park and Beck found Asian-American students averaged more than 20 points higher on the SAT than did their Caucasian peers. Shewach, Shen, Sackett, and Kuncel (2017) reported standardized tests tend to over-predict performance for English-speaking students and to under-predict for students of other races—such as Hispanic—which seems not in accord with Park and Beck's (2015) finding. In contrast to the majority of the literature that suggests the ACT and SAT may favor students of some races and social-economic status over others, Higdem et al. (2016) found socio-economic status served as only a minor predictor of academic performance and as a weaker prediction tool than both standardized test scores and high school GPA taken separately.

Local assessments. While standardized (or national) test scores present as popular math placement tools (Crynes, 2013; Melguizo, Kosiewicz, Prather, & Bos, 2014; Xu & Dadgar, 2018), local assessments offer alternatives or complements that bring advantages through customization and through higher levels of faculty engagement (Banta & Palomba, 2015). Only a very limited amount of scholarly literature investigates local assessment tools and placement. Barbitta and Munn (2018) seem to refer to local assessments as valuable tools in their study, but little else in the literature seems to touch the topic. A great deal of literature, though, explores national and local assessment tools more broadly.

While national assessments—such as the ACT and SAT—can support improvement (Maltese & Hochbein, 2012) and accreditation (Kirchner & Norman, 2014), so, too, can local devices (Barlow, Liparulo, & Reynolds, 2007; Bastian, Henry, Pan, & Lys, 2016). The two are not identical in nature or purpose, though (Kane, et al., 2017). While either device can take either direct or indirect forms, national assessment devices deliver a level of standardization that often permits comparisons across institutions (Yin & Volkwein, 2010) and may thereby allow higher educators to gauge their placement practices with other schools' practices. Local tools fail to support cross-institutional comparisons because they stay within a home institution, but they permit tailored approaches that can be valuable (Borrelli, Johnson, & Cummings, 2009). Local assessment devices also tend to invite greater faculty engagement, and that can be an important advantage over the generic approach of standardized assessments (Banta & Palomba, 2015; Phelps & Spangler, 2013).

While both national and local assessment tools offer value, the two types of tools stand in separate categories with somewhat different natures and purposes. One reason national and local assessments vary in their natures is that they draw from different populations. Price (n.d.) noted that the reason national assessments support comparisons between institutions is because they report results derived from samples drawn from many schools. He also pointed out that one can sometimes drill down to the point of comparison between specific institutions or groups of institutions that fit one's specific assessment comparison needs. Local assessments, according to

Price, contrast from national assessments because they rely on samples from only a specific, individual school.

Administration varies greatly between national and local assessment devices. Smith, Clements, and Olson (2010), addressing strengths and weaknesses of local and national exams in their article on assessments, noted locally-developed tools may require considerably more effort than national tools and that creating local devices “is a lot of bother” (p. 249). The authors tempered their observation as they echoed the point made earlier in this literature review that local assessment tools bring higher faculty engagement levels and improved teamwork to an institution. National assessment devices, in contrast to locally-developed tools, tend to be easy to manage (Thompson & Braude, 2016, p. 483), and they often offer self-scoring options that can save administrative time and effort.

Understanding what tools are available can help with many post-secondary education decisions (Gauthier, et al., 2015; McIntosh, Seaton, & Jeffrey, 2007), but assessment activities must also address data analysis. Analysis decisions depend upon the type of data collected and questions addressed (Gall, Gall, and Borg, 2007), and one university’s PowerPoint presentation had much to say on the topic. Liberty University (n.d.) noted that qualitative analysis involves five steps. The first is a search for patterns or themes, and the second looks for deviations from normal. The third step identifies engaging stories from the data, and a fourth step considers whether recognized themes suggest a need for additional data. The final of the five qualitative analysis steps is to look at whether identified patterns seem consistent with data available from other sources. This seems to connect with the multiple methods approach to placement.

A Liberty University (n.d.) presentation noted quantitative analysis looks for patterns and relationships, but that it usually involves statistical procedures and confidence calculations. The presentation suggested cautions for quantitative data, including that educators must be able to understand the data and that tests provide only a snapshot. Like the final step in qualitative data analysis, education professionals must consider quantitative results in context with findings from other sources, such as schools do when they practice multiple methods math placement that may include high school GPA (Barbitta & Munn, 2018; Black, Cortes, & Lincove, 2016).

High School GPA. Many schools consider GPA in math placement decisions **(**Atuahene & Russell, 2016; Bracco et al., 2014; Hartman, 2017; Hiss & Franks, 2014; Jackson & Kurlaender, 2014). Understanding high school GPA, then, is essential to understanding its possible value as a predictor of college performance and, as a subset of college performance, of understanding developmental students' math performance. Research into high school GPA falls into several categories. Two categories that are pertinent to this paper include GPA calculation practices and the meanings or components that go into determining or contributing to students' GPA, the latter including students' relationships and personalities.

GPA calculation practices. Warne, Nagaishi, Slade, Hermesmeyer, and Peck (2014) noted high schools employ a variety of different methods to calculate high school GPA, and unweighted and weighted GPAs describe two broad categories of these methods. Unweighted GPA, as defined in scholarly sources (Suldo, Thalji-Raitano, Kiefer, & Ferron, 2016; Warne et al.), assigns grades to a 4.0 scale regardless of the level or type of classes the students completed. Weighted GPA, according to these same sources, aims to provide greater consideration for particularly challenging courses—such as courses categorized as advanced placement—and recognizes higher and lower challenges by allowing grades in the more difficult courses to exceed the 4.0 maximum used in unweighted calculations.

Warne, Nagaishi, Slade, Hermesmeyer, and Peck (2014) wrote that GPA calculation differences make GPA comparisons across schools at least difficult, and perhaps impossible. The team coded data for 710 undergraduate students to determine predictive value of various GPA measurement techniques as regards college grade point average, likelihood a student would attempt the Medical College Admissions Test (MCAT), MCAT scores, and the likelihood of a student later graduating from medical school. Their results indicated unweighted high school GPA delivered a more accurate prediction of success in all areas than did weighted high school GPA. In apparent accord with this, Koretz and Langi (2018) found variation between schools tended to render freshman GPA predictions difficult based on GPA alone, but that such predictions were practical within schools. Vulperhorst, Lutz, de Kleijn, and van Tartwijk (2018) identified similar results that they attributed to course content differences. Deaton's (2014) research may have identified a reason for these findings. Exploring course relationships between students at several Appalachia post-secondary institutions, Deaton found college performance seemed not at all correlated with levels of courses taken in high school. Hansen, Sadler, and Sonnert (2018) conducted research that seemed to find a middle ground between the ideas that unweighted GPA is superior to weighted GPA and the idea that having completed advanced courses in high school makes no difference in college performance; they found GPA weighting tended to roughly double the advantage that should actually be provided for the more challenging courses.

Components and meaning of high school GPA. Students' parents, peers, friends, personality traits, and habits each seem to impact high school students' GPAs. Darensbourg and Blake (2014) quantitatively researched 181 sixth, seventh, and eighth grade students' situations and academic performance and reported two findings. First, both family and friends significantly impacted the students' individual values regarding academic performance. Second, the students' values, in turn, made a difference in academic performance as indicated by GPA. Lebedina-Manzoni and Ricijas (2013) similarly noted in their study of 938 school youth from seventh grade to junior year of high school that parents—and especially mothers—impacted students' academic performance. Gormley et al.'s (2018) research seconded those findings. Lebedina-Manzoni and Ricijas followed, though, that peer influence held the most impact as it accounted for 40% of the GPA variation between students, and the influence seemed particularly strong when related to sexual pressures. It seems, too, that beginning in middle school, the more diverse one's body of friends, the greater one's academic gains (Lewis et al., 2018).

While friends and peers impact one's academic performance, friends' friends appear also to hold sway over one's GPA (Carbonaro & Workman (2016). This only seems reasonable given that the first order relationship between oneself and one's friends depends upon a friend whose reacts to the influences of the friends' friends. Research indicates choice of friends makes a difference in GPA (Gašević, Zouaq, & Janzen, 2013). It seems also that positive views of one's school may help one overcome even negative attitudes of one's peers (Butler-Barnes, Estrada-Martinez, Colin, & Jones, 2015).

Friendships and peer influence present as even more complex, though. Cook, Deng, & Morgano's (2007) quantitative look at 901 middle-school students found that friendships seem domain-specific. That is, social friends impacted social behavior, and academic friends impacted academic performance. Consistent with other studies, the researchers found GPA strongly associated with one's friends. Here, though, it makes sense to recognize that one usually is not assigned one's friends, but rather one chooses with whom one will be friends. Barnes, Beaver, Yount, and TenEyek (2014) found youth tend to associate with peers whose grades are similar to their own. In other words, the students self-select their group of friends, and the question of whether friends influence students' grades or grades groupings lead students to select their friends seems unclear.

If relationships between high school students' GPAs and their friendships seem unclear, personality traits and habits add a different perspective. Personality impacts academic performance (Scherer, Talley, & Fife, 2017) and falls into many categories (Ferrow, 2018; Loeblin, 2018; Hen & Goroshit, 2014; Loehlin, & Martin, 2018; Vitulić & Zupančič, 2013). It may be that each individual actually comprises several personality types that vie for dominance at various times (Yolles & Di Fatta, 2018). When considering learning and academic performance, though some findings contradict the majority opinion (Brown, Peterson, & Yao, 2016), much research indicates the personality trait or practice of self-regulation correlates with GPA (Hartman, Wasieleski, & Whatley, 2017; List & Nadasen, 2017; Thibodeaux, Deutsch, Kitsantas, & Winsler, 2017). Self-regulation relates to motivation (List & Nadasen), and scholars recognize motivation also correlates with academic performance and GPA (Dykas, 2016; Neigel, Behairy, & Szalma, 2017; Wouters et al., 2017). This seems the case both in high school (Froiland & Worrell, 2016) and in college (Thibodeaux, Deutsch, Kitsantas, & Winsler, 2017). At the same time, the source of students' motivations may hold a key. A study by Chan and Want (2016) found positive correlation between motivation and GPA for students who reported motivation to learn or to broaden, but negative correlation for students who reported curricular motivation. Self-efficacy also seems to play a role (Tepper & Yourstone, 2018). These personality traits connect to habits and study skills and habits, and research indicates the skills and habits have much to do with academic performance.

Conscientious effort illustrates one study skill or habit that correlates with students' GPAs (Vitulić, & Zupančič, 2013), but others also impact academic performance. Addressing one's tasks early, for example, associates with better academic performance than does procrastinating (Hen & Goroshit, 2014). Cooper and Garung (2018) found self-testing to be a powerful tool supporting academic success. Attendance also impacts performance (Steward, Devine Steward, Blair, Jo, & Hill, 2008; Uretsky & Stone, 2016). In total, GPAs represent a diverse array of decisions, personality traits, motivations, and habits that scholars say indicate long-term performance (Acosta, North, & Avela, 2016; Thiele, Sauer, & Kauffeld, 2018) rather than simply snapshots.

Summary

The body of literature describes developmental math, indicates institutions assign many students to developmental math, and demonstrates that students assigned to developmental math face substantial challenges. It introduces innovations that show promise and others that perhaps do not, and it suggests the math emporium sits among the former. The literature (Gist, Schwoerer, & Rosen, 1989) describes computer self-efficacy—drawn from Bandera's ideas (1986)—as a principle supposing one who is confident in one's computer abilities will tend to do better with all computer-related tasks than will one who lacks confidence. Literature separately describes Sweller's (1988) cognitive load theory as suggesting that when one splits attention between high-cognitive load activities rather than focusing on only a single activity at a time, performance and ability to learn tend to decline. Together these ideas suppose students who score relatively well on computer-based tests (such as local math assessments) may also tend to receive relatively good grades in developmental math courses held in a computer-based math emporium, and that the inverse should also hold true; students who score relatively poorly on computer-based testing should perform relatively poorly in a computer-based math emporium.

While the literature discusses many concepts and practices related to developmental math, it seems to not address placement into math emporiums. More specifically, the literature seems silent regarding ACT/SAT math component scores, local math assessments, and high school GPAs as predictors of students' success in math emporium-based developmental courses. This apparent gap in the literature invites new research.

CHAPTER THREE: METHODS

Overview

This chapter introduces and describes research methods this study employed to explore post-secondary education placement tools' accuracies in predicting students' final grades in a math emporium-based developmental mathematics course. The chapter opens by identifying and justifying the selection of a quantitative predictive correlational research design, then presents three research questions and associated hypotheses. It next describes the research participants and setting, instrumentation, and procedures before closing with the data analysis plan the researcher followed.

Design

This research employed a quantitative correlational predictive design using archival data related to students' developmental math placement component scores and students' subsequent performance in a developmental math course through a university's math emporium. Creswell (2014) described four factors influencing general research method selection: the research problem, researcher's experiences, researcher's worldview, and anticipated audience. The problem lended itself to a quantitative approach because it aimed to identify factors influencing or predicting an outcome (Creswell, 2014), specifically placement criteria's accuracy in predicting college students' developmental math emporium performance. Further, a quantitative approach fit the intended audience because this research aimed to serve university administrators who may benefit from quantitative studies (Alao, Rollins, Brown, & Wright, 2017; Hora, Bouwma-Gearhart, & Park, 2017). The predictive correlational design was appropriate due to the search for a predictive relationship and the lack of variable manipulation (Gall et al., 2007). In addition, Miller and Salkind (2002) identified prediction studies as appropriate to estimate in advance individual performance, Gall, Gall, and Borg (2015) wrote that prediction studies can identify characteristics of students who will do well in subsequent academic programs, and Warner (2013) specifically mentioned standardized test results examples of predictor variables. Finally, other research used quantitative predictive correlational designs to address similar higher education research problems (Atuahene & Russell, 2016; Bai, Chi, & Qian, 2014; Jackson & Kurlaender, 2014; Melguizo, Bos, Ngo, Mills, & Prather, 2016; Ngo & Kwon, 2015).

Variables

ACT/SAT math component scores, unweighted high school GPAs, and results on a university's local math skills assessment (Assessment Math, or ASMA) served as the three predictor variables. Students' final grades on a 4.0 scale in MATH 100 served as the criterion variable.

Predictor variables. ACT/SAT math component scores served as the first predictor variable. American College Testing provides the ACT test and claims their exam, as the leading college admissions test, measures high school learning and college readiness ("*ACT Test*," n.d.). The College Board, with over 6,000 member organizations, provides the popular and similarly-purposed Scholastic Assessment Test (SAT) to serve higher education acceptance and placement processes ("*About the College Board*," n.d.). The researcher normalized the scores from the two exams by ensuring they were converted to raw percentages. Unweighted high school GPA served as the second predictor variable. Unweighted GPA assigns grades to a 4.0 scale regardless of level or type of class (Suldo, Thalji-Raitano, Kiefer, & Ferron, 2016; Warne, Nagaishi, Slade, Hermesmeyer, & Peck, 2014). For the math placement decision, the university converted GPAs to percentages relative to 4.0 such that a 3.0 GPA equaled 75% while a 3.5 GPA equaled 87.5%. Therefore, the researcher used raw percentages for the 4.0 grades such that

100% represented 4.0, 75% represented 3.0, and so forth. Scores on a local math assessment served as the final predictor variable. Local assessments exist as customizable alternatives or complements to standardized tests such as the ACT and SAT (Banta & Palomba, 2015). The studied local assessment, offered online only, involved two components, one that was mandatory for students and another that was optional. The first assessment component contained 30 multiple choice mathematics questions gauging basic mathematics and algebra skills, and the second component contained 20 multiple choice questions aimed at more advanced mathematics students—such as those studying engineering. Most students completed only the first section, and some elected to also complete the second. The researcher converted the local assessment scores to a single, raw percentage based on number correct out of either 30 or 50 total questions (30 for students who completed only the first assessment, and 50 for students who completed both assessments). These practices were consistent with the setting institution's placement decision practices at the time the data was recorded.

Criterion variable. Final grades in MATH 100, assigned by faculty members at or after the conclusion of each term, semester, or course, served as the criterion variable. The course, Fundamentals of Mathematics, was a three credit hour course delivered to residential students only through the private university's math emporium. The course was the first of two developmental math courses the university offered, and it reviewed basic arithmetic and elementary algebra. Because it was a developmental course it did not meet any of the university's degree requirements, but aimed to prepare students for classes that did meet requirements. See Appendix A for a MATH 100, Fundamentals of Mathematics syllabus, and see Appendix B for a recent MATH 110, Intermediate Algebra syllabus.

Research Questions

RQ1: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment predict the MATH 100, Fundamentals of Mathematics final grade for students who completed the course through a math emporium at a private university during the 2017-2018 academic year?

RQ2: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment predict the MATH 100, Fundamentals of Mathematics final grade for students who completed the course through a math emporium at a private university during the 2016-2017 academic year?

RQ3: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment predict the MATH 100, Fundamentals of Mathematics final grade for students who completed the course through a math emporium at a private university during the 2015-2016 academic year?

Hypotheses

$H_0$1: 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 math skills assessment) for students who completed the course through a math emporium at a private university during the 2017-2018 academic year academic year.

$H_0$2: 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 score, unweighted high school GPA, and score on a local math skills assessment) for students who completed the course through a math emporium at a private university during the 2016-2017 academic year.

$H_0$3: 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 score, unweighted high school GPA, and score on a local math skills assessment) for students who completed the course through a math emporium at a private university during the 2015-2016 academic year.

Participants and Setting

Gall, Gall, and Borg (2007; 2015) wrote that research reports should provide enough detail about the setting and other study components to allow replication. This subsection of the paper, consistent with Gall at al.'s (2007) guidance, describes each of the components in the context of this research project.

Population and Setting

Residential, undergraduate students who attended a private university during the 2017-2018, 2016-2017, or 2015-2016 academic years and were assigned by the university to the first of the institutions' two developmental math courses served as the population for this study. The institution was a large, private, regionally-accredited, nonprofit university located in a small- to medium-sized city that was surrounded by a rural area that, all inclusive, hosted a population of about 240,000 people ("Demographics," n.d.).

The institution's only two developmental math courses were MATH 100, Fundamentals of Mathematics and MATH 110, Intermediate Algebra. Consistent with the definition of developmental coursework (Adams, n.d.; Boatman & Long, 2018), neither MATH 100 nor MATH 110 directly supported any degree, but both aimed to prepare students for more advanced courses that directly supported degrees. MATH 100, the lower of the two developmental math courses, was a three credit-hour course that provided to students a basic review of mathematics and elementary algebra. A student must have received a grade of “C” or better in MATH 100 to progress to MATH 110. See Appendix A for the course syllabus. In the spring of 2012 the school opened its math emporium and established the requirement that each residential student must complete assigned developmental math courses through the math emporium. School administrators placed virtual blocks onto residential students’ registration paths to help ensure students took their developmental math courses through the math emporium rather than through an online format.

Math emporiums offer students customized mathematics instruction through computer technology while instructors or tutors stand ready to assist when needed (Kasten, 2000). The math emporium associated with this study required that developmental students attended class for one hour each week and that they spent at least three weekly hours in the math emporium where they could work individually and where they had tutors and faculty members available to assist in a one-on-one-manner when requested or when faculty members noted poor student performance. The director who founded the institution’s math emporium (Spradlin, personal communication, July 19, 2018) reported that the school’s emporium built upon developmental theory (Wambach, Brothen, & Dikel, 2000), and it therefore demanded high standards as it offered substantial supportiveness. According to the director, administrators set course standards high (typically 80%) to address developmental theory’s (Wambach et al.) demandingness aspect. Further, the team selected MyLabsPlus software for the emporium because it automatically provided remediation to students who missed points. Automatic remediation, combined with the availability of one-on-one personal assistance, addressed developmental theory’s (Wambach et al.) supportiveness demand. See Appendix A for a MATH 100, Fundamentals of Mathematics syllabus, and see Appendix B for a recent MATH 110, Intermediate Algebra syllabus.

Samples

This study relied upon archival data for residential, undergraduate students and drew from the population of students who attended a private university during the 2017-2018, 2016-2017, or 2015-2016 school years, who were assigned by the university to EDUC 100, the first of the institutions' two developmental math courses, and who earned a grade of "A," "B," "C," "D," "F," or "WF" ("WF" represented students who failed and stopped attending) in the course. Students who withdrew from or failed to complete EDUC 100 (except those assigned "WF") were excluded from the study. Warner (2013) stated minimum linear regression sample sizes must meet or exceed 10 times the number of predictor variables. This study, with three predictor variables (ACT/SAT math scores, unweighted high school GPAs, and local math assessment scores), easily exceeded the 30 cases, or $N = 30$, required to satisfy Warner's linear regression sample size standard.

2017-2018 EDUC 100, Fundamentals of Mathematics sample. The researcher began with 885 cases, then removed 320 cases from the study to meet population requirements—typically due to missing data or to a student having withdrawn from or earned an incomplete in MATH 100. The 2017-2018 EDUC 100, Fundamentals of Mathematics sample finally consisted of data from 565 students meeting the sample criteria. Criteria included university assignment to EDUC 100, the first of the institutions' two developmental math courses, and assignment of a grade of "A," "B," "C," "D," "F," or "WF" in the course ("WF" indicates failed and stopped attending). Students who withdrew from or failed to complete EDUC 100 were excluded from the study. Two-hundred ninety-nine male students and 266 female students comprised the group, with 284 who identified as White or Caucasian, 69 as African-American or black, 56 as Hispanic or Latino, 9 as American Indian or Alaskan Native, 7 as Asian, 28 as two or more races, 7 as nonresident alien, and 104 who did not report. Birth years ranged from 1988 to 2001 with a modal birth year of 1999. The 565 students who comprised the sample exceeded the minimum sample size of $N = 30$ appropriate for multiple linear regression with three predictor variables (Warner, 2013).

2016-2017 EDUC 100, Fundamentals of Mathematics sample. The researcher began with 1.155 cases, then removed 387 cases from the study to meet population requirements—typically due to missing data or to a student having withdrawn from or earned an incomplete in MATH 100. The 2016-2017 EDUC 100, Fundamentals of Mathematics sample finally consisted of data from 1,168 students who met the sample criteria. Criteria included university assignment to EDUC 100, the first of the institutions' two developmental math courses, and assignment of a grade of "A," "B," "C," "D," "F," or "WF" in the course ("WF" indicates failed and stopped attending). Students who withdrew from or failed to complete EDUC 100 were excluded from the study. Five-hundred sixty-five male students and 603 female students comprised the group, with 660 who identified as White or Caucasian, 120 as African-American or black, 98 as Hispanic or Latino, 15 as American Indian or Alaskan Native, 15 as Asian, 25 as two or more races, 10 as nonresident alien, and 225 who did not report. Birth years ranged from 1991 to 2000 with a modal birth year of 1998. The 1,168 students who comprised the sample exceeded the minimum sample size of $N = 30$ appropriate for multiple linear regression with three predictor variables (Warner, 2013).

2015-2016 EDUC 100, Fundamentals of Mathematics sample. The researcher began with 2,080 cases, then removed 580 cases from the study to meet population requirements—

typically due to missing data or to a student having withdrawn from or earned an incomplete in MATH 100. The 2015-2016 EDUC 100, Fundamentals of Mathematics sample finally consisted of data from 1,500 students who met the sample criteria. Criteria included university assignment to EDUC 100, the first of the institutions' two developmental math courses, and assignment of a grade of "A," "B," "C," "D," "F," or "WF" in the course ("WF" indicates failed and stopped attending). Students who withdrew from or failed to complete EDUC 100 were excluded from the study. Seven-hundred twenty-one male students and 779 female students comprised the group, with 768 who identified as White or Caucasian, 188 as African-American or black, 128 as Hispanic or Latino, 3 as American Indian or Alaskan Native, 32 as Asian, 32 as two or more races, 8 as nonresident alien, 3 as Native Hawaiian Pacific Islander, and 338 who did not report. Birth years ranged from 1986 to 1998 with a modal birth year of 1997. The 1,500 students who comprised the sample exceeded the minimum sample size of $N = 30$ appropriate for multiple linear regression with three predictor variables (Warner, 2013).

Instrumentation

Freitas et al. (2015) noted that a plethora of archival data now exists from a variety of post-secondary sources and that university leaders use the data to better understand higher education. This study relied upon such archival data—drawn from Banner, the institutions' system of records—to provide the variable values needed to assess the relationship between the three predictor variables and the criterion variable for each of the three academic years studied. Several scholars used archival data in analogous ways to address research questions resembling the questions addressed in this study (Bishop, 2016; Geven, Skopek, & Triventi, 2017; Knight, Wessel, & Markle, 2018; Turiano, 2014).

Predictor Variables

ACT/SAT math scores, unweighted high school GPAs, and local math assessment (Assessment Math, or ASMA) scores served as the three predictor variables for this study. The school gathered data for the variables during the institution's regular admissions and registration processes. Automated systems transferred the data into Banner, the school's system of records, or employees keyed the data into Banner. Employees, consistent with standard institution practices, converted all scores to raw percentages for developmental placement purposes. Administrators over recent years varied the relative weight of the three components in mathematics placement decisions.

ACT/SAT scores. American College Testing provides the ACT test and claims their exam, as the leading college admissions test, measures high school learning and college readiness ("*ACT Test*," n.d.). The College Board, with over 6,000 member organizations, provides the popular and similarly-purposed Scholastic Assessment Test (SAT) to serve higher education institutions' acceptance and placement processes ("*About the College Board*," n.d.). Scores from these assessments have historically served as post-secondary institutions' primary developmental math placement tool (Bracco et al., 2014), and many schools still rely solely upon the scores for placement decisions (Crynes, 2013; Melguizo, Kosiewicz, Prather, & Bos, 2014; Xu & Dadgar, 2018). The institution from which the sample was drawn demanded prospective residential students provide ACT or SAT scores as part of the admissions process, and administrators considered mathematics component scores among the criteria for developmental mathematics placement decisions. School employees received the official ACT/SAT scores from either American College Testing (for ACT) or the College Board (for SAT) and ensured the results were entered into Banner. For math placement purposes, school employees converted

ACT/SAT math component scores into raw percentages such that if a student scored 600 on an SAT math assessment that offered a maximum score of 800, the university employee keyed in 75% as the students' ACT/SAT math placement score. If a student scored 18 on an ACT math assessment with a maximum possible score of 36, the employee entered 50% as the score. The school allowed students to take the ACT/SAT examinations as many times as they wished, and the university considered only the highest of each students' math component scores in math placement decisions.

Unweighted high school GPA. Many institutions consider high school GPA in math placement decisions (Atuahene & Russell, 2016; Bracco et al., 2014; Hiss & Franks, 2014; Jackson & Kurlaender, 2014), and the setting institution was among them. The university collected each students' high school GPA from official transcripts received through the admissions process, and school employees keyed the GPA data into Banner. The school considered each students' overall, unweighted high school GPA where, consistent with scholarly definitions (Suldo, Thalji-Raitano, Kiefer, & Ferron, 2016; Warne, Nagaishi, Slade, Hermesmeyer, & Peck, 2014), unweighted meant scores appeared on a 4.0 scale where 4.0 was the maximum and equated to an “A” while a 3.0 equated to a “B,” a 2.0 equaled a “C,” a 1.0 equaled a “D,” and 0.0 equaled an “F” regardless of the level or type of course. For the math placement decision, university employees converted GPAs to percentages relative to 4.0 such that a 3.0 GPA equaled 75% while a 3.5 GPA equaled 87.5%.

Local assessment. Local assessments carry some advantages over national assessments such as the ACT and SAT (Banta & Palomba, 2015), and the school required a score from its local math assessment as a component of the developmental math placement decision. The institutions' local assessment—called Assessment Math and abbreviated ASMA—consisted of two parts, both delivered online through Blackboard, the institution's primary learning management system. The first component involved 30 multiple choice questions and addressed lower-level math, and the second had 20 multiple choice questions and addressed more advanced math that served students interested in entering higher-level math courses that served engineering, aeronautics, and similarly mathematics-focused degrees. The school required students complete the first part of the assessment after acceptance and before first registration, and the school did not require that students take the second portion of the assessment. Employees scored the local assessments in raw percentages such that if a student correctly answered 15 out of 30 on the first part and did not attempt the second, employees entered a score of 50%. If the same student then completed the second portion and correctly answered 5 of 20 questions on that second portion, the student's overall score for placement was 20 out of 50, and the employee recorded 40% as the component score. Relatively few students attempted the second portion of the local assessment.

Criterion Variable

MATH 100, Fundamentals of Mathematics final course grades served as the criterion variable for this study. Faculty members assigned final course grades at the end of each sub-term, and school employees ensured the final grades recorded in Banner. The institution offered the course each fall and spring semester. University policy stated residential students were required to complete the course through the math emporium. Coursework included a mandatory, weekly, 50-minute scheduled class with a participation grade assigned for attendance and a mandatory three hours in the math emporium each week with additional time available for students who wished to study within the emporium further. Students could attend for their three required hours and for additional time whenever the emporium was open, and it was typically open more than 70 daytime, evening, and weekend hours each week. Students were responsible for homework to be completed in MyLabsPlus, and they could attempt the homework any number of times to attain at least 80% before a weekly due date and time. They were also responsible for weekly MyLabsPlus quizzes with three attempts permitted for each quiz. The emporium computers automatically provided review notes and additional practice problems to students who failed to score at least 80% on a quiz attempt. Students faced the additional requirement of scoring at least 100% on practice questions before a quiz reattempt. Students were also required to pass time-limited MyLabsPlus tests available only to those who scored at least 70% on a practice test. Through MyLabsPlus software instruction and employee support, the emporium delivered individually-tailored math instruction with tutors and faculty members available to quickly address students' challenges on a one-to-one basis. Students who scored 900-1000 total from the assignments earned an "A," students scoring 800-899 earned a "B," students scoring 700-799 earn a "C," students scoring 600-699 earn a "D," students scoring below 600 earned the grade "F," and students who earned an "F" and stopped attending were assigned the grade "WF." The researcher dummy-coded the grades from 4 to 0 ("A" = 4, "B" = 3, "C" = 2, "D" = 1, and both "F" and "WF" = 0). See Appendix A for a MATH 100, Fundamentals of Mathematics syllabus.

Procedures

The Dean and Chair who supervised the math emporium provided to the researcher email permission to execute this study. The researcher also applied for and received an exemption ruling from the Institutional Review Board (IRB) before accessing data. See Appendix C for the emails granting permission and for the IRB exemption letter. Data for all variables resided in Banner, the institution's system of records, and the school's Analytics and Decision Support

(ADS) Department personnel could access the data. After the IRB granted approval, the researcher requested all required data from ADS through the university's standard, online Information Technology service request procedures. The request included predictor variable data: sampled students' highest ACT/SAT math scores, unweighted high school GPAs, and local assessment results, all as raw percentages, for the 2017-2018, 2016-2017, and 2015-2016 academic years. It also included criterion variable data: the sampled students' final MATH 100, Fundamentals of Mathematics grades for the 2017-2018, 2016-2017, and 2015-2016 academic years on a 4.0 scale. Banner stored the grades only as discrete letters ("A," "B," "C," and so forth). The researcher asked that if any student had attempted the course twice, the delivered data would include only the first attempt and would leave out any subsequent attempts. In addition, the researcher's data request called for sampled students' basic demographic information including gender, birth year, and ethnicity and for all data to be delivered in an Excel spreadsheet. The researcher emphasized in the data request that ADS was to remove all unique identifying information and was to randomly assign case numbers to provide manageable data while protecting individual students' identities. ADS personnel, consistent with standard university procedure, delivered results of the data request to the requestor through email.

The researcher, once having received the data, removed cases involving students who had withdrawn from or otherwise failed to complete MATH 100, except those students who had earned an "F" and stopped attending as indicated by the grade "WF." Once the researcher judged the data accurate and complete, the researcher loaded the data into IBM's Statistical Package for Social Sciences (SPSS), version 24, and began data screening and analysis using both Excel and SPSS.

Data Analysis

Gall, Gall, and Borg (2007) indicate regression provides appropriate data analysis for research aimed at determining relationships between predictor and criterion variables. Because this study investigates the relationship between more than two predictor variables (ACT/SAT math scores, high school GPAs, and local math assessment scores) and one criterion variable (final grades in MATH 100, Fundamentals of Mathematics), a multiple linear regression is more appropriate than a simple regression (Gall et al.; Hanley, 2016).

Multiple linear regression calculations should satisfy three basic assumptions that one may confirm through data screening (Warner, 2013). First was the assumption of bivariate outliers. The researcher planned to verify assumption satisfaction through visual scatter plot examination of all pairs of predictor variables (x, x) and all pairs of predictor and criterion variables (x, y). If outliers presented, the researcher intended to verify data accuracy, correct any identified data entry errors, and continue with remaining outliers present. Second was the assumption of multivariate normal distribution, upon which power of the analysis depended. The researcher aimed to verify assumption satisfaction through visual examination of scatter plots for each pair of predictor variables (x, x) and each pair of criterion variables (x, y). The classic "cigar shape" presents when this assumption is satisfied. If assumption violations presented, the researcher intended to seek to identify and eliminate any data entry errors before continuing. Third was the assumption of non-multicollinearity among predictor variables. The researcher planned to assess assumption satisfaction through tolerance and variance inflation factor examination (VIF). If the tolerance value approached 0 rather than 1 (and VIF value similarly approached 10 rather than 1), the researcher aimed to judge strong multicollinearity existed and the would exclude one of the offending variables (Warner, 2013).

The researcher planned to execute all data analysis with a 95% confidence interval, report significance through an F-stat, and interpret effect size through Pearson's R and R^2. Individual predictor variables' influences on the criterion variable were examined using Squared Semi-partial Correlations (sr^2). These practices are consistent with Gall, Gall, and Borg (2007) and Warner (2013).

CHAPTER FOUR: FINDINGS

Overview

This chapter presents findings regarding post-secondary education placement tools' accuracies in predicting students' final grades in a math emporium-based developmental mathematics course. The chapter opens by presenting the three research questions this study addressed (one question for each of three academic years) and their associated hypotheses. The chapter next provides descriptive statistics for the three samples that associated with the three research questions, then closes with data screening, assumptions testing, and analysis results for each of the three questions.

Research Questions

RQ1: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment predict the MATH 100, Fundamentals of Mathematics final grade for students who completed the course through a math emporium at a private university during the 2017-2018 academic year?

RQ2: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment predict the MATH 100, Fundamentals of Mathematics final grade for students who completed the course through a math emporium at a private university during the 2016-2017 academic year?

RQ3: How accurately can assessment components consisting of ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment predict the MATH 100, Fundamentals of Mathematics final grade for students who completed the course through a math emporium at a private university during the 2015-2016 academic year?

Hypotheses

H_01: 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 math skills assessment) for students who completed the course through a math emporium at a private university during the 2017-2018 academic year.

H_02: 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 math skills assessment) for students who completed the course through a math emporium at a private university during the 2016-2017 academic year.

H_03: 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 math skills assessment) for students who completed the course through a math emporium at a private university during the 2015-2016 academic year.

Descriptive Statistics

This study relied on archival data retrieved from a large, private university's system of records by personnel within the university's Analytics and Decision Support (ADS) Department. Data was drawn from Banner, the school's system of records, for three separate school years. Descriptive statistics for each of the three academic years sampled are presented below.

Descriptive Statistics (2017-2018 Sample)

The 2017-2018 sample consisted of 565 students who made their first attempt at and did not withdraw from MATH 100, Fundamentals of Mathematics. The predictor variables were ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment (ASMA). Each was reported as a raw percentage of the maximum possible. The criterion variable was students' final grades in MATH 100. The school recorded the grades as "A," "B," "C," "D," "F," or "WF" ("WF" represented students who earned a grade of "F" and who also stopped attending), and the researcher dummy-coded the grades from 4 to 0 ("A" = 4, "B" = 3, "C" = 2, "D" = 1, and both "F" and "WF" = 0). Table 1 displays descriptive statistics for the academic year 2017-2018 sample including the sample size, mean, and standard deviation for each of the three predictor variables and for the outcome variable.

Table 1

Descriptive Statistics, 2017-2018 Sample

	N	*M*	*SD*
ACT/SAT Math Component	565	55.21%	9.31%
High School GPA	565	72.65%	11.08%
ASMA	565	55.78%	15.67%
MATH 100	565	1.53	1.33

Descriptive Statistics (2016-2017 Sample)

The 2016-2017 sample consisted of 1,168 students who made their first attempt at and did not withdraw from MATH 100, Fundamentals of Mathematics. The predictor variables were ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment (ASMA). Each was reported as a raw percentage of the maximum possible. The criterion variable was students' final grades in MATH 100. The school recorded the grades as "A," "B," "C," "D," "F," or "WF" ("WF" represented students who earned a grade of "F" and who also stopped attending), and the researcher dummy-coded the grades from 4 to 0 ("A" = 4, "B" = 3, "C" = 2, "D" = 1, and both "F" and "WF" = 0). Table 2 displays descriptive statistics for the academic year 2016-2017 sample including the sample size, mean, and standard deviation for each of the three predictor variables and for the outcome variable.

Table 2

Descriptive Statistics, 2016-2017 Sample

	N	*M*	*SD*
ACT/SAT Math Component	1,168	54.43%	7.19%
High School GPA	1,168	74.74%	9.31%
ASMA	1,168	56.05%	13.81%
MATH 100	1,168	1.95	1.33

Descriptive Statistics (2015-2016 Sample)

The 2015-2016 sample consisted of 1,500 students who made their first attempt at and did not withdraw from MATH 100, Fundamentals of Mathematics. The predictor variables were ACT/SAT math scores, unweighted high school GPAs, and scores on a local math skills assessment (ASMA). Each was reported as a raw percentage of the maximum possible. The criterion variable was students' final grades in MATH 100. The school recorded the grades as "A," "B," "C," "D," "F," or "WF" ("WF" represented students who earned a grade of "F" and who also stopped attending), and the researcher dummy-coded the grades from 4 to 0 ("A" = 4, "B" = 3, "C" = 2, "D" = 1, and both "F" and "WF" = 0). Table 3 displays descriptive statistics for the academic year 2015-2016 sample including the sample size, mean, and standard deviation for each of the three predictor variables and for the outcome variable.

Table 3

Descriptive Statistics, 2015-2016 Sample

	N	*M*	*SD*
ACT/SAT Math Component	1,500	51.54%	7.37%
High School GPA	1,500	74.10%	9.96%
ASMA	1,500	55.62%	14.31%
MATH 100	1,500	1.53	1.33

Results

Hypothesis One (2017-2018 Academic Year)

This section of the chapter describes data screening, assumption testing and data analysis results for the first hypothesis. The researcher performed a multiple linear regression to test the data. The null hypothesis was presented as follows:

$H_0$1: 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 math skills assessment) for students who completed the course through a math emporium at a private university during the 2017-2018 academic year academic year.

Hypothesis One Data Screening and Assumption Testing

The researcher performed data screening before analyzing the data. The researcher began by examining frequencies of variable values in SPSS to ensure all data values were within possible ranges, and they were. The researcher next sorted the data by variable and removed all cases displaying missing values. This resulted in the dismissal of 320 cases from the 2017-2018 data (885 cases decreased to 565, a 35% reduction). The researcher then used scatterplots to assess satisfaction of the assumptions of bivariate outliers and multivariate normal distributions for the predictor variables (ACT/SAT math scores, unweighted high school GPAs, and scores on the local math skills assessment) and the criterion variable (Math 100 final grade). No extreme outliers were found and assumption of multivariate normal distribution across all variables was met. See Figure 1 for the scatterplots indicating satisfaction of both the bivariate outlier and the multivariate normal distribution assumptions for the 2017-2018 sample.

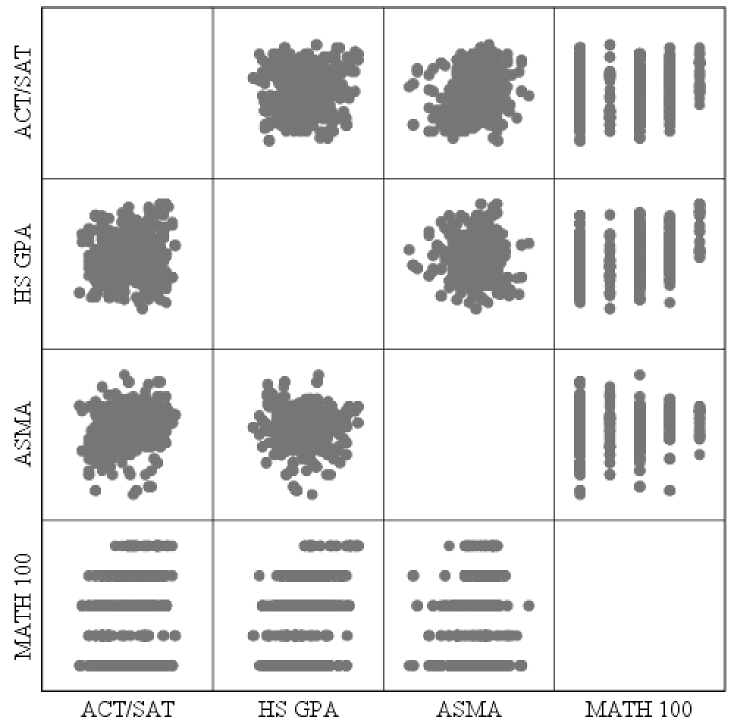

Figure 1. Matrix Scatterplot of Criterion and Predictor Variables, 2017-2018 Sample.

The researcher checked for the assumption of the absence of multicollinearity by calculating tolerances and variance inflation factors (VIF) for the predictor variables and seeking tolerance values near one and reciprocal VIF values between one and nine (Warner, 2013). The absence of multicollinearity assumption was met. See Table 4 for multicollinearity test results by predictor variable.

Table 4

Multicollinearity Test Results Indicating Assumption Satisfaction, 2017-2018 Sample

Variable	Tolerance	VIF
ACT/SAT Math Component	0.919	1.088
High School GPA	0.995	1.005
Local Math Assessment (ASMA)	0.923	1.083

Hypothesis One Results

The researcher used a multiple linear regression at the 95% confidence level to test the null hypothesis. Results for the combination of the predictor variables (ACT/SAT math component scores, high school GPA, and local math assessment results) in relationship to the criterion variable (MATH 100 grades) showed statistical significance where $F(3, 561) = 89.969$, $p < 0.001$, $R = 0.522$, $R^2 = 0.272$, adjusted $R^2 = 0.269$. The null hypothesis was rejected, and this indicated the combination of the three predictor variables together explained approximately 27% of the variation in students' final MATH 100 grades with a very large effect size (Warner, 2013). Individual coefficients for each of the three predictor variables were statistically significant where $p < 0.001$. The researcher followed Warner's (2013) recommendation and manually squared predictor variables' part correlations to arrive at the squared semi-partial correlations (sr^2), providing a method for determining the proportion of variance in the criterion variable explained by each the predictor variables. See Table 5 for squared semi-partial correlation results by predictor variable.

Table 5

SPSS Coefficient Beta and Semi-partial Correlations, 2017-2018 Sample

Variable	Std. Coeff. Beta	Sig.	sr^2*	*Effect Size*
ACT/SAT Math Component	0.190	0.000	0.033	Medium
High School GPA	0.431	0.000	0.185	Very Large
Local Math Assessment	0.158	0.000	0.023	Medium

* Correlation parts were manually squared to determine sr^2 (Warner, 2013)

Hypothesis Two (2016-2017 Academic Year)

This section of the chapter describes data screening, assumption testing and data analysis results for the second hypothesis. The researcher performed a multiple linear regression to test the data. The null hypothesis was presented as follows:

$H_0$2: 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 math skills assessment) for students who completed the course through a math emporium at a private university during the 2016-2017 academic year academic year.

Hypothesis Two Data Screening and Assumption Testing

The researcher performed data screening before analyzing the data. The researcher began by examining frequencies of variable values in SPSS to ensure all data values were within possible ranges, and they were. The researcher next sorted the data by variable and removed all cases displaying missing values. This resulted in the dismissal of 387 cases from the 2016-2017 data (1,555 to 1,168, a 25% reduction). The researcher then used scatterplots to assess satisfaction of the assumptions of bivariate outliers and multivariate normal distributions for the predictor variables (ACT/SAT math scores, unweighted high school GPAs, and scores on the local math skills assessment) and the criterion variable (Math 100 final grade). No extreme outliers were found and assumption of multivariate normal distribution across all variables was met. See Figure 2 for the scatterplots indicating satisfaction of both the bivariate outlier and the multivariate normal distribution assumptions for the 2016-2017 sample.

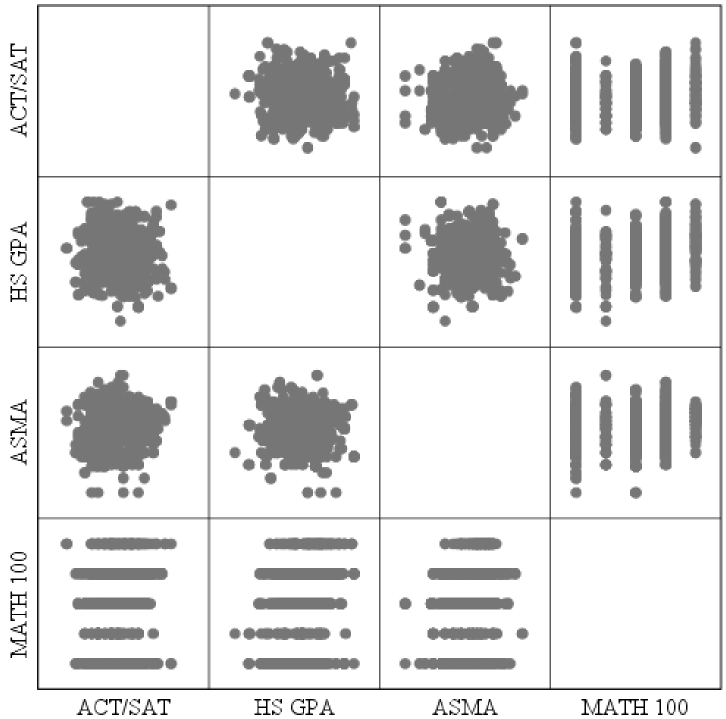

Figure 2. Matrix Scatterplot of Criterion and Predictor Variables, 2016-2017 Sample.

The researcher checked for the assumption of the absence of multicollinearity by calculating tolerances and variance inflation factors (VIF) for the predictor variables and seeking tolerance values near one and reciprocal VIF values between one and nine (Warner, 2013). The absence of multicollinearity assumption was met. See Table 6 for multicollinearity test results by predictor variable.

Table 6

Multicollinearity Test Results Indicating Assumption Satisfaction, 2016-2017 Sample

Variable	Tolerance	VIF
ACT/SAT Math Component	0.954	1.049
High School GPA	0.981	1.019
Local Math Assessment (ASMA)	0.971	1.030

Hypothesis Two Results

The researcher used a multiple linear regression at the 95% confidence level to test the null hypothesis. Results for the combination of the predictor variables (ACT/SAT math component scores, high school GPA, and local math assessment results) in relationship to the criterion variable (MATH 100 grades) showed statistical significance where $F(3, 1164) = 50.730$, $p < 0.001$, $R = 0.340$, $R^2 = 0.116$, adjusted $R^2 = 0.113$. The null hypothesis was rejected, and this indicated the combination of the three predictor variables together explained approximately 11% of the variation in students' final MATH 100 grades with a large effect size (Warner, 2013). Individual coefficients for each of the three predictor variables were statistically significant where $p < 0.001$. The researcher followed Warner's (2013) recommendation and manually squared predictor variables' part correlations to arrive at the squared semi-partial correlations (sr^2), providing a method for determining the proportion of variance in the criterion variable explained by each the predictor variables. See Table 7 for squared semi-partial correlation results by predictor variable.

Table 7

SPSS Coefficient Beta and Semi-partial Correlations, 2016-2017 Sample

Variable	Std. Coeff. Beta	Sig.	sr^2*	*Effect Size*
ACT/SAT Math Component	0.124	0.000	0.014	Small
High School GPA	0.286	0.000	0.081	Large
Local Math Assessment	0.154	0.000	0.023	Medium

* Correlation parts were manually squared to determine sr^2 (Warner, 2013)

Hypothesis Three (2015-2016 Academic Year)

This section of the chapter describes data screening, assumption testing and data analysis results for the third hypothesis. The researcher performed a multiple linear regression to test the data. The null hypothesis was presented as follows:

$H_0$3: 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 math skills assessment) for students who completed the course through a math emporium at a private university during the 2015-2016 academic year academic year.

Hypothesis Three Data Screening and Assumption Testing

The researcher performed data screening before analyzing the data. The researcher began by examining frequencies of variable values in SPSS to ensure all data values were within possible ranges, and they were. The researcher next sorted the data by variable and removed all cases displaying missing values. This resulted in the dismissal of 580 cases from the 2015-2016 data (2,080 to 1,500, a 28% reduction). The researcher then used scatterplots to assess satisfaction of the assumptions of bivariate outliers and multivariate normal distributions for the predictor variables (ACT/SAT math scores, unweighted high school GPAs, and scores on the local math skills assessment) and the criterion variable (Math 100 final grade). No extreme outliers were found and assumption of multivariate normal distribution across all variables was met. See Figure 3 for the scatterplots indicating satisfaction of both the bivariate outlier and the multivariate normal distribution assumptions for the 2015-2016 sample.

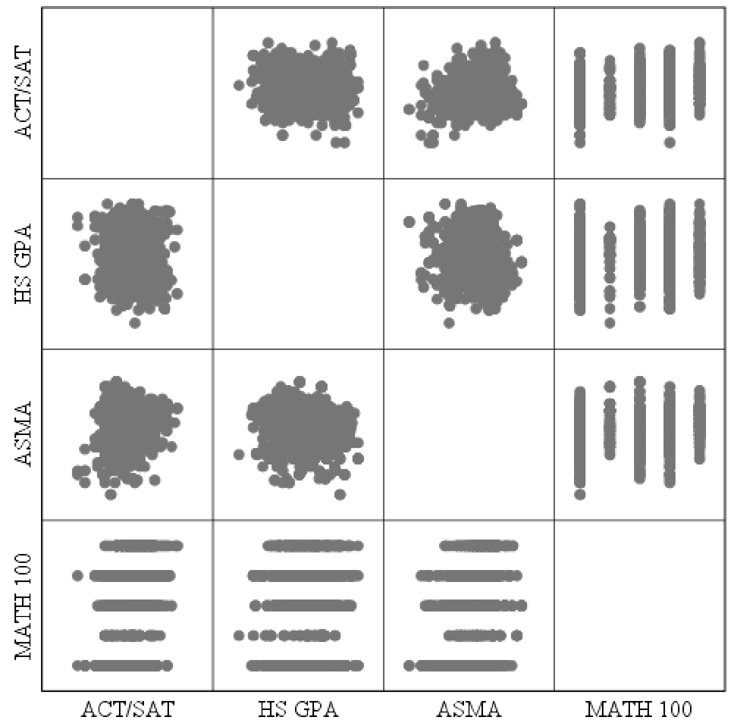

Figure 3. Matrix Scatterplot of Criterion and Predictor Variables, 2015-2016 Sample.

The researcher checked for the assumption of the absence of multicollinearity by calculating tolerances and variance inflation factors (VIF) for the predictor variables and seeking tolerance values near one and reciprocal VIF values between one and nine (Warner, 2013). The absence of multicollinearity assumption was met. See Table 8 for multicollinearity test results by predictor variable.

Table 8

Multicollinearity Test Results Indicating Assumption Satisfaction, 2015-2016 Sample

Variable	Tolerance	VIF
ACT/SAT Math Component	0.894	1.118
High School GPA	0.970	1.031
Local Math Assessment (ASMA)	0.910	1.099

Hypothesis Three Results

The researcher used a multiple linear regression at the 95% confidence level to test the null hypothesis. Results for the combination of the predictor variables (ACT/SAT math component scores, high school GPA, and local math assessment results) in relationship to the criterion variable (MATH 100 grades) showed statistical significance where $F(3, 1496) = 83.258$, $p < 0.001$, $R = 0.378$, $R^2 = 0.143$, adjusted $R^2 = 0.141$. The null hypothesis was rejected, and this indicated the combination of the three predictor variables together explained approximately 14% of the variation in students' final MATH 100 grades with a large effect size (Warner, 2013). Individual coefficients for each of the three predictor variables were statistically significant where $p < 0.001$. The researcher followed Warner's (2013) recommendation and manually squared predictor variables' part correlations to arrive at the squared semi-partial correlations (sr^2), providing a method for determining the proportion of variance in the criterion variable explained by each the predictor variables. See Table 9 for squared semi-partial correlation results by predictor variable.

Table 9

SPSS Coefficient Beta and Semi-partial Correlations, 2015-2016 Sample

Variable	Std. Coeff. Beta	Sig.	sr^2*	*Effect Size*
ACT/SAT Math Component	0.182	0.000	0.030	Medium
High School GPA	0.239	0.000	0.055	Medium
Local Math Assessment	0.231	0.000	0.049	Medium

* Correlation parts were manually squared to determine sr^2 (Warner, 2013)

CHAPTER FIVE: CONCLUSION

Overview

This chapter concludes this research into post-secondary education placement tools' accuracies—specifically the accuracies of ACT/SAT math component scores, unweighted high school GPAs, and scores on a local math assessment—in predicting students' final grades in a residential, math emporium-based MATH 100 developmental mathematics course. The chapter opens by discussing the study's three research questions in light of the literature, of other research, and of theory. It next considers likely implications of this study before presenting limitations of this research project, including an internal and an external threat to validity. The chapter closes with four recommendations for future research.

Discussion

The purpose of this quantitative predictive correlational study was to determine whether ACT/SAT scores, unweighted high school GPAs, and results on a local math skills assessment could predict final MATH 100 developmental course grades for residential, undergraduate students at a private university. Semi-partial correlation effect sizes by predictor variable and sampled year provide an overall view of the relative results. See Table 10 for this overall view.

Table 10

Semi-partial Correlation Effect Sizes by Predictor Variable and Sample*

	2017-2018	2016-2017	2015-2016
ACT/SAT Math Component	Medium	Small	Medium
High School GPA	Very Large	Large	Medium
Local Math Assessment	Medium	Medium	Medium

* Semi-partial correlations values were converted to effect sizes per Warner (2013)

The effect sizes for the predictor variables' squared semi-partial correlations indicated all three predictor variables contributed to the value of the criterion variable for each sample. ACT/SAT math component scores and local assessment scores were similar to each other in predictive accuracy. Further, these two predictive variables took turns as second and third most accurate of the three predictors between the samples. This suggests ACT/SAT math component scores and local assessment scores may have measured the same underlying construct, but multicollinearity testing indicated such was not the case. The variables do share some traits in common, though, as both variables depended upon multiple choice questions (100% of ACT math and local assessment questions and 75% of SAT math questions) and represented snapshot measurements (less than four hours for the standardized tests). Perhaps more notably among the findings was that high school GPA consistently delivered the most accurate of the three predictor variables' contributions to the MATH 100 grades, and quite strongly so with an overall proportional contribution that was about equal to the combined contributions of the other two predictor variables. This finding did not seem to suggest a connection between Sweller's (1988) cognitive load theory and math placement, but it invited consideration of why a particularly strong high school GPA/MATH 100 grade relationship existed in this study. See Table 11 for sr^2 by predictor variable for each sample.

Table 11

Semi-partial Correlations (sr^2) by Predictor Variable and Sample*

	2017-2018	2016-2017	2015-2016
ACT/SAT Math Component	0.033	0.014	0.030
High School GPA	0.185	0.081	0.055
Local Math Assessment	0.023	0.023	0.049

* Correlation parts were manually squared to determine sr^2 (Warner, 2013)

It may be that high school GPA was the most accurate of the predictor variables because it measured long-term effort rather than performance at only a moment in time, and that in that way it resembled MATH 100 final grades because the final grades represented a semester of effort rather than only a snapshot or a moment. Acosta, North, and Avela (2016) similarly speculated that GPA delivers relatively high predictive performance because it measures factors connected to long-term success, and they referenced students' inclinations to access helpful resources as an example (Acosta et al., 2016) of a habit contributing to long-term success. Their analysis sits in accord with research suggesting students who decide to get help perform better than students who do not (Colver & Fry, 2016).

Another higher education professional suggested GPA represents students' abilities to adapt or learn the rules of the game (Gentala, personal communication, February 8, 2019), and that that the math emporium is a place where students must learn and adapt to rules, both over time. MATH 100 is a course that requires students to work for a full semester, about 16 weeks, and undergo many assessments over time. Testing, on the other hand—including the ACT/SAT and local math assessment—provides only a performance snapshot (Liberty University, n.d.; Rychlý, Matisová-Rychlá, & Csomorová, 2014). Additionally, GPA reflects personality traits connected to long-term performance (Thiele, Sauer, & Kauffeld, 2018), characteristics such as motivation and competition with outside commitments (Zeidenberg, Jenkins, & Scott, 2012) that would reflect in a longer-term effort such as MATH 100 final grade and that may not be indicated by snapshot measurements. Stated simply, high school GPA and math emporium final grades both reflected long-term efforts compared to the ACT/SAT math component and local math assessment scores that each reflected short-term performance as snapshots.

Implications

This study carries at least three implications. The first and most obvious is that because high school GPA was the most accurate predictor across all years with about twice the average contribution of each of the other predictor variables, the many school leaders who consider GPA in placement decisions (Atuahene & Russell, 2016; Bracco et al., 2014; Hartman, 2017; Hiss & Franks, 2014; Jackson & Kurlaender, 2014) seem to be tapping a powerful predictive tool. Leaders at institutions using multiple methods for placement may do well to apply higher relative weight to GPA than to other factors. The second implication springs from the finding that the local assessment was a close second in the 2015-2016 sample and that the same assessment was a weak third in the 2017-2018 sample. From this, one may see that placement tools' accuracies may vary between times or groups, so the decision to place students into developmental math emporium classes seems best based on multiple methods rather than on any one prediction or placement tool. This is consistent with the body of existing literature regarding placement decisions unrelated to math emporiums (Barbitta & Munn, 2018; Black, Cortes, & Lincove, 2016). Finally, and drawn from the previous two implications, this study's results suggest there may be little difference in placement criteria accuracies between assigning developmental math students to math emporium courses and assigning developmental math students to math courses that are not taught through the emporium model.

Limitations

Gall, Gall, and Borg (2015) suggested all research suffers limitations, and this study is no exception. First among this study's limitations is the external threat to validity present because the researcher relied on samples drawn from only one institution. The researcher described both the institution and the samples to somewhat mitigate the challenges associated with the limitation, but readers must nevertheless use caution if wishing to generalize the study's results to goups outside the sampled institution or apart from the sampled years.

A second limitation presents an internal threat to validity. For this study, MATH 100 final grades were available only with ordinal ("A," "B," "C," and so forth) values rather than on a continuous point scale. While scholarly research indicates linear regression is a preferred method for analyzing data in such situations (Norris et al., 2006), the greater granularity provided by a continuous outcome variable may have presented greater insight into the models, the relative accuracies of the three predictor variables studied, and the general challenges of math emporium developmental math placement than this study was able to provide.

Recommendations for Future Research

Based on this study of ACT/SAT math component scores', unweighted high school GPAs', and local math assessment results' accuracies in predicting students' final grades in a developmental MATH 100 course taught exclusively through a computer-based math emporium, the researcher identified five possible avenues for future research. The first two seek to address the study limitations described above, and the remaining three spring from literature gaps that seemed apparent to the researcher.

1. Researchers may create value by conducting similar studies at other institutions.
2. Researchers may add to the body of knowledge by conducing similar studies with a continuous outcome variable (using points rather than letter grades to represent final developmental math course grades).
3. Opportunities present to explore predictive accuracies of various placement tools for developmental math course venues other than math emporiums, such as for online developmental math courses.
4. Because this researcher failed to identify scholarly articles assessing the impact of math emporiums on developmental students' success (perhaps measured by GPAs or by graduation rates), opportunities for important research in that direction seem open to investigation.
5. The literature seemed silent regarding optimum weighting between assessment tools when multiple methods are used for placement decisions. This presents an opportunity for research.

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APPENDIX A: MATH 100, Fundamentals of Mathematics Syllabus

Math 100 – Fundamentals of Mathematics

(3 credit hours)

Fall Semester 2018

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.

Rationale

Math 100 is designed as a review of beginning algebra in order to prepare the non-mathematics major who has a weak background in Algebra I or has never taken an algebra course. The concepts covered will provide knowledge needed to meet the pre-requisites for Math 110.

Prerequisite Statement

Basic arithmetic skills.

It is the student's responsibility to make up any prerequisite deficiencies, as stated in the University Catalog, which would prevent the successful completion of this course.

Materials List

Purchase A or B, not both.

Developmental Mathematics Notebook + Access Code by Squires & Wyrick, Second Edition (yellow cover), (ISBN 9781323118900). (Recommended)

Access to MyLabsPlus at [removed] ISBN 9780558927189) (Required)

A notebook to keep course documents and homework.(Highly Recommended)

Headphones or earbuds, pencils, paper, and thin dry-erase markers to use in class and in the Math Emporium. (Highly Recommended)

Learning Outcomes

The student will be able to…

A. Course Learning Outcomes

1. 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.
2. Apply the appropriate mathematical skills for the concepts listed above.
3. Use mathematics to solve problems in the sciences, business, and various other fields of study.

B. Math Core Competency Learning Outcomes

1. Solve problems (including word problems) utilizing arithmetic concepts and algebraic equations.
2. Interpret information presented in various graphs and diagrams.
3. Solve problems using insight or logical reasoning.

Assignments/Requirements

Cognitive Growth

1. Demonstrate ability to apply the knowledge acquired through problem solving and/or graphing.
2. Demonstrate mathematical proficiency by simplifying expressions or solving equations that require applying the concepts listed in the course description.

Product

Class Meetings:

Class meets once a week for 50 minutes at the scheduled time. The student's week starts on the day his class meets and ends on the day before the class meets the next time. Some exceptions apply to accommodate holidays. See the Course Chart for specific details.

Attendance is required. Students will receive a participation grade for each class meeting. Students must attend for 50 minutes, take notes, pay attention, stay awake, and follow the rules to earn the grade.

Class attendance counts toward the required 3 hours in the Math Emporium.

Any student who misses the first day of class may be dropped from the course. To re-enroll, go to the Math Emporium to appeal and watch a presentation.

All electronic devices must be turned off during class.

Homework:

All homework assignments are in MyLabsPlus. Each assignment may be attempted an unlimited number of times before it is due, which is 11:59 PM periodically throughout the week. See the Course Chart for exact due dates. Late assignments will receive a 10% per day penalty. The Help Me Solve This button is available on most of the exercises. Faculty and tutors are available in the Math Emporium to answer questions. A minimum grade of 80% is required on each assignment before the next one will open. Homework assignments will no longer be available on or after Reading Day.

Unit Assessments:

There is an optional assessment prior to each assignment for Units C through H. Homework assignments are personalized to the results. The topics answered correctly on the Assessment will automatically be graded as correct in the homework, allowing the student to skip over the topics he has already mastered. If a student is behind schedule, the Assessments will not be available. Assessments must be taken in the Testing Area of the Math Emporium. If a student chooses not to take an assessment, he must contact an instructor in the Math Emporium to continue on to homework assignments.

Quizzes:

There is one quiz each week due at 11:59 PM the night before the next class meeting. All quizzes are in MyLabsPlus. There are three attempts available for each quiz. Late quizzes will receive a 10% per day penalty. Quizzes will not have help buttons. Faculty and tutors will not answer questions on quizzes. After the first attempt a Post-Quiz Review will open, giving additional practice on the concepts missed. Once a 100% has been earned on the Post-Quiz Review, the second attempt will be available. Students who have not reached 80% on the quiz following three attempts will be required to complete a Quiz Review Worksheet, which is available in the Math Emporium. Once the Quiz Review Worksheet is completed you will be required to review this with someone on duty in the Math Emporium. Afterwards another attempt on the quiz will be made available. The best score of the quiz attempts will be recorded. Quizzes will no longer be available on or after Reading Day.

Tests:

There will be three tests in MyLabsPlus. Tests have a time limit. A password is required. Tests must be taken in the Math Emporium Testing Area. A prerequisite of 70% on the Practice Test is required before taking the test. There are two attempts on tests.

After the first attempt a Post-Test Review will open, giving additional practice on the questions missed. Once a 100% has been earned on both the Post-Test Review and also 80% on the Test Review, the second attempt will be available.

Students who have not reached 70% on the test following two attempts will be required to schedule a meeting with their Developmental Math instructor to devise a plan to earn an additional attempt. The best score of the test attempts will be recorded. See additional information under Testing Policies.

Students who are on track with the Course Chart and earn an A on the first attempt of Test 1 will be excused from Math Emporium hours (this does not include the weekly class meeting) through the scheduled time of Test 2. Students with an A on the first attempt of Test 2 and are on track with the Course

Chart will be excused from Math Emporium hours (this does not include the weekly class meeting) through the scheduled time of Test 3.

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.

If a student does not take Test 1 or Test 2 by the due date, a penalty of 10% will be applied.

If a student does not complete Unit K Quiz by 11:59 PM the day before Reading Day, he cannot take Test 3.

If a student does not take Test 3 by Reading Day, he will need an exam reservation to take it during Final Exam Week.

Process

Student attends class once a week.

Student works at least 3 hours in the Math Emporium attending class, viewing videos, working on homework and quizzes, and receiving assistance from faculty and tutors.

Student works in Math Emporium at scheduled times.

Student completes his required 3 hours per week by working additional times of his choice.

Student works as many additional hours as necessary to complete the assignments due each week.

Student meets with instructor when necessary.

Grading Policies

Course grade will be determined by the following point system:

Participation	81
Class Meetings	
Emporium Hours	
Homework (52 x 3 points each)	156

Quizzes (11 x 7 points each)	77
Test 1	180
Test 2	202
Test 3	304
Total	1000

Letter grades will be assigned according to the following scale. A minimum of 700 points is required to pass Math 100.

A	900 – 1000 points
B	800 – 899 points
C	700 – 799 points
D	600 – 699 points
F	Below 600 points

C. Failing to Complete the Course

A student will not pass the course if he does not successfully complete all assignments through Unit K before Reading Day. The student will need to re-enroll the following semester in order to maintain progress in the course through the last test. If a student does not enroll in the course the following semester, the student must start at the beginning of the course.

Any student who has grades from the previous semester due to not completing a course must email the new instructor no later than the end of the day of the first class meeting to request the grades through the last test he passed be transferred to the new course. Grades may only be transferred one time. If a student starts a course in the spring, he must complete it in the following summer or fall semester. If he starts in the fall, he must complete it in the spring. If the course is not passed in the second semester, the student must start the course at the beginning the next time he enrolls. Grades will only be transferred for students with participation grades of 90% or higher in the previous semester.

Starting the Next Course Early

If a student completes Math 100 early, he may enroll in Early Math 110 by the deadline stated in the Calendar for the Semester. This policy only applies to fall and spring semesters; students may not start a course early during summer session. If the student starts but does not finish the second course, he may enroll in the course the following semester and continue working in the unit following the last test he passed. The instructor will copy grades from MyLabsPlus to the new section. If a student starts a course in the spring, he must complete it in the following summer or fall semester. If he starts in the fall, he must complete it in the spring. If he skips a semester, he must start at the beginning of the course.

Completing Both Courses

If the student completes two courses in the same semester he will need to communicate with his professor and go to [removed] to request a prerequisite override to his next math course.

Attendance Policies

For the good of the University student body, a consistent attendance policy is needed so that all students in all majors will understand the expectations of faculty in all their courses. In general, regular and punctual attendance in all classes is expected of all students. Though at times, students will miss classes.

Absences for 100-200 level courses fall into two categories:

University Approved Absences

University Approved Absences include University sponsored events, athletic competition, and other Provost-approved absences.

The student must provide written documentation in advance for University Approved Absences.

Work missed for University-approved absences may be made up.

Student Elective Absences

Student Elective Absences include, but are not limited to, illness and bereavement.

Work missed for Student Elective Absences may be made up at the discretion of the faculty member. Questions regarding missed work for Student Elective Absences must be addressed by the student with the professor within one week of returning to class. In cases where this is not possible, the student must notify the Professor in writing of the circumstances impacting his or her absence. The student may appeal the Professor's decision in writing to the respective Chair within one week. Final appeals may be made to the Dean in writing within one week of the Chair's decision and the Dean's decision is final.

When circumstances result in excessive absences (e.g., serious medical illness, family crisis), upon return to campus, the student shall communicate in writing with the Registrar's Office (Registrar@[removed].edu) and provide an explanation of his or her situation with appropriate documentation. The Registrar will consult with the faculty member before making the final decision and will notify, in writing, the student and the faculty member.

Students who are more than 10 minutes late for class are considered absent.

Students who are late for class 10 minutes or less are considered tardy but present for the class. If a student misses in-class work due to tardiness, the faculty member may choose not to allow the student to make up this work. Three class tardies will be counted as one absence.

Number of Student Elective Absences Permitted:

For classes that meet three times per week, the student will be permitted four elective absences per semester.

For classes that meet twice per week, the student will be permitted three elective absences per semester.

For classes that meet once per week, the student will be permitted one elective absence per semester.

Penalties for each absence over the permitted number of elective absences per semester will be as follows:

50 points for classes that meet 3 times per week

75 points for classes that meet 2 times per week

100 points for classes that meet once per week

Other Policies

Dress Code

Students are expected to come to class dressed in a manner consistent with [policy].

Honor Code

We, the students, faculty, and staff of University, have a responsibility to uphold the moral and ethical standards of this institution and personally confront those who do not.

Limits of Confidentiality

Students are encouraged to share prayer requests and life concerns with the professor in this class. Not only will the professor pray for and care for students, but can guide students to appropriate University resources if desired.

However, in the event of a student's disclosure, either verbally or in writing, of threat of serious or foreseeable harm to self or others, abuse or neglect of a minor, elderly or disabled person, victim or witness of a crime or sexual misconduct, or current involvement in criminal activity, the faculty, staff, administrator, or supervisor will take immediate action. This action may include, but is not limited to, immediate notification of appropriate state law enforcement or social services personnel, emergency contacts, notification of the appropriate program chair or online dean, or notification to other appropriate University officials. All reported information is treated with discretion and respect, and kept as private as possible.

Academic Misconduct

Academic misconduct includes: academic dishonesty, plagiarism, and falsification. See [policy] for specific definitions, penalties, and processes for reporting.

Disability Statement

Students with a documented disability may contact the Office of Disability Accommodation Support (ODAS) in [removed] to make arrangements for academic accommodations. You may email or call. For all disability testing accommodation requests (i.e. quieter environment, extended time, oral testing, etc.) Testing Services is the officially designated place for all tests administered outside of the regular classroom.

DROP/ADD POLICY

A Fall/Spring course may be dropped without a grade, tuition, and fee charges within the first five days of the semester. From the sixth day until the end of the tenth week (see academic calendar for exact date), a Fall/Spring course may be withdrawn with a grade of 'W'.

Classroom Policies

The inappropriate use of technology, such as cell phones, iPods, laptops, calculators, etc. in the classroom is not tolerated. Other disruptive behavior in the classroom is not tolerated. Students who engage in such misconduct will be subject to the penalties and processes as written in the [policy].

Expectations:

Always attend class. Arrive on time and stay for the entire class meeting.

Log in at least 3 hours each week in the classroom and the Math Emporium. Students will work in the Math Emporium at scheduled times and will complete the required 3 hours per week by working additional times of their choice.

Scheduled emporium hours are required. Work in the Math Emporium at your assigned time.

The first three weeks of the semester are crucial. Students who do not fully engage in the required activities the first three weeks of the semester have little chance of passing.

Bring a pencil, the Developmental Mathematics Notebook, and a notebook for working out homework problems.

Watch videos, take notes, read the Developmental Mathematics Notebook, and/or work examples before asking questions.

Use the Help Me Solve This and other helps in MyLabsPlus.

Work as many additional hours as it takes to complete the assignments for the week. Assignments may be submitted after the due date. Work may be done in the Math Emporium or any other location as long as the 3 required hours per week are completed in the Math Emporium.

Students who complete the weekly assignments early are encouraged to review previous homework and quizzes or start the next unit.

Students who are on track with the Course Chart and earn an A on the first attempt of Test 1 will be excused from Math Emporium hours (this does not include the weekly class meeting) through the scheduled time of Test 2. Students with an A on the first attempt of Test 2 and are on track with the Course Chart will be excused from Math Emporium hours (this does not include the weekly class meeting) through the scheduled time of Test 3.

Remember a final course grade of C or better is required before a student is allowed to take Math 110.

Keep a positive attitude.

Math Emporium Policies

Students are here to work on math.

The Math Emporium is a math classroom. Please be quiet during visits to the Emporium.

Only students registered in residential Math 100, Math 105, Math 106, Math 110, Math 114, Math 115, Math 116, Math 121, and Math 201 and BUSI 230 may use the Math Emporium.

Personal lap tops will only be permitted if there are no available computers in the Emporium.

The Emporium is used on a first come, first serve basis. There will be no reservations for normal course work. Reservations are required for Test 3 if taken during Final Exam week.

Each student must present his Flames Pass to the attendant when entering and leaving the Emporium.

All Math Emporium guests are expected to dress and act in accordance to the guidelines in {policy].

All personal belongings must be stored on the floor out of the walkway.

No food is allowed in the Emporium. No exceptions. Drinks with lids are permitted.

Activities such as surfing the web, checking e-mail, sleeping, or completing other course work will not be tolerated. Cell phones must be silenced and stored in the backpack or on top of the computer tower face down. Listening to music on the emporium computer, not on your phone or laptop, is permitted as long as neighbors cannot hear it.

Violations result in a 0 for emporium hours for the week and removal from the Emporium.

The expectation is that students will watch the video and/or read the book and attempt the homework question on their own. Be ready to show work for a problem when asking for help. To request help with homework, place the cup on top of the computer and wait patiently for assistance.

Students in Math 100 and Math 110 may use the calculator available on the computer or a blue emporium calculator. Other calculators are not permitted.

All tests must be taken in the Emporium. Homework and quizzes may be completed anywhere.

Please be courteous and respectful at all times. Students are here to work on math.

The Emporium will be closed when classes are cancelled or delayed. The Emporium is closed during convocation time even when convocation is cancelled.

Testing Policies

Consequences for cheating on a test will be a zero on the test. The student will be allowed a second attempt on the test to prove mastery and then the test grade changed to a zero. Cheating includes use of cell phones, smart watches, notes, videos, people, websites, and any unapproved calculator during the test.

All tests must be taken in the Math Emporium. No personal computers may be used.

ODAS students may test in the Testing Center in DH 1036 or the Math Emporium. The student must contact his instructor.

Flames Pass is required.

Absolutely NO ELECTRONIC DEVICES may be active in the testing area. All cell phones, smart watches, texting devices, iPods, MP3 players, etc. must be turned off and put away before seated for testing. Personal belongings will need to be placed on the floor out of the walkway.

Students are not allowed assistance of any kind. This includes faculty, staff, students, notes, formula sheets, or any other type of outside help. During testing, no access to other online materials including homework, quizzes, and online learning aids in MyLabsPlus is permitted.

The Math Emporium will provide testing paper. No other paper is allowed. All papers must be turned in to a test proctor before leaving the testing area.

Only the calculator on the computer or a Math Emporium issued calculator can be used.

Students will be allowed to review the test immediately after submitting. No information pertaining to the test may be written down or shared with other students. Violators will be charged with academic dishonesty as stated [policy].

Any student who works ahead may take the test early. Students who wish to test early must check in with the front desk and then the test proctor on duty. Seating for testing stops two hours prior to closing. However, if you have an ODAS accommodation you must allow for additional time before closing.

Reading Day is the last day to take Tests 1 and 2 with a 10% penalty and Test 3 without a reservation.

Test 3 after Reading Day

A minimum score is not required for Test 3 as long as the student earns 700 points overall.

Students must reserve a time to take Test 3 using the link in Blackboard or the Math Emporium Widget after Reading Day.

Students may only reserve one time slot.

The maximum time allowed for Test 3 is 120 minutes.

Do not schedule a time that conflicts with a Final Exam in another course. If the student misses another exam because he is taking Test 3, it is NOT an excused absence.

The last day to take Test 3 without a reservation is Reading Day.

Calendar for the Semester — See homework schedule in Blackboard. Below are other important dates to keep in mind.

Monday, August 27: Classes begin

Friday, August 31, 4 PM: Last day to add or drop a class

October 4 – 7: Fall Break, Math Emporium closed, no classes

Friday, October 12: Last day for Math 100 student to start Math 110

November 17 – 25: Thanksgiving Break, no classes, Math Emporium closed

Friday, November 30: Last day to withdraw from a class with a W

Tuesday, December 4: Last day of classes

Tuesday, December 4: Last day to do any homework or take a quiz

Wednesday, December 5: Reading Day; last day to take Test 1 and Test 2 with a 10% penalty; last day to take Test 3 without a reservation.

Thursday-Tuesday, Dec. 6 – 11: Test 3 with a reservation.

Math Emporium Web Page [removed]

APPENDIX B: MATH 110, Intermediate Algebra Syllabus

Math 110 – Intermediate Algebra

(3 credit hours)

Fall Semester 2018

I. 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.

II. 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.

III. Prerequisite statement

Math 100 or equivalent (e.g., Algebra I) with a grade of C or better, OR

Advised by a member of the mathematics faculty to take this course based upon the mathematics placement scores at University AND

Has not successfully completed a higher-level algebra or calculus course in college (a liberal arts math course such as Math 115 is specifically excluded from this restriction).

It is the student's responsibility to make up any prerequisite deficiencies, as stated in the University Catalog, which would prevent the successful completion of this course.

IV. Materials List

Purchase A or B not both.

Developmental Mathematics Notebook + Access Code by Squires & Wyrick, Second Edition (yellow cover), (ISBN 9781323118900). (Recommended)

Access to MyLabsPlus at [removed]. (ISBN 9780558927189) (Required)

A notebook to keep course documents and homework. (Highly Recommended)

Headphones or earbuds, pencils, paper, and thin dry-erase markers to use in class and in the Math Emporium. (Highly Recommended)

Learning Outcomes

The student will be able to…

A. Course Learning Outcomes

State and apply definitions, postulates, and theorems related to various concepts listed in the course description.

Apply the appropriate mathematical skills to problems and problem solving for the concepts listed in the course description.

Use mathematics to solve problems in the sciences, business and other fields of study.

B. Math Core Competency Learning Outcomes

Solve problems (including word problems) utilizing arithmetic concepts and algebraic equations.

Interpret information presented in various graphs and diagrams.

Solve problems using insight or logical reasoning.

Assignments/Requirements

Cognitive Growth

1. Demonstrate ability to apply the knowledge acquired through problem solving and/or graphing.

2. Demonstrate mathematical proficiency by simplifying expressions or solving equations that require applying the concepts listed in the course description.

Product

Class Meetings

Class meets once a week for 50 minutes at the scheduled time. The student's week starts on the day his class meets and ends on the day before the class meets the next time. Some exceptions apply to accommodate holidays. See the Course Chart for specific details.

Attendance is required. Students will receive a participation grade for each class meeting. Students must attend for 50 minutes, take notes, pay attention, stay awake, and follow the rules to earn the grade.

Class attendance counts toward the required 3 hours in the Math Emporium.

Any student who misses the first day of class may be dropped from the course. To re-enroll, go to the Math Emporium to appeal and watch a presentation.

All electronic devices must be turned off during class.

Homework

All homework assignments are in MyLabsPlus. Each assignment may be attempted an unlimited number of times before it is due, which is 11:59 PM periodically throughout the week. See the Course Chart for exact due dates. <u>Late assignments will receive a 10% per day penalty</u>. These late homework assignments must still be worked for a grade. The Help Me Solve This button is available on most of the exercises. Faculty and tutors are available in the Math Emporium to answer questions. A minimum grade of 80% is required on each assignment before the next one will open. Homework assignments will no longer be available on or after Reading Day.

Quizzes

There is one quiz each week due at 11:59 PM the night before the next class meeting. All quizzes are in MyLabsPlus. There are three attempts available for each quiz. <u>Late quizzes will receive a 10% per day penalty</u>. Quizzes will not have help buttons. Faculty and tutors will not answer questions on quizzes. After the first attempt a Post-Quiz Review will open, giving additional practice on the concepts missed. Once a 100% has been earned on the Post-Quiz Review, the second attempt will be available. Students who have not reached 80% on the quiz following three attempts will be required to complete a Quiz Review

Worksheet, which is available in the Math Emporium. Once the Quiz Review Worksheet is completed you will be required to review this with someone on duty in the Math Emporium. Afterwards another attempt on the quiz will be made available. The best score of the quiz attempts will be recorded. Quizzes will no longer be available on or after Reading Day.

Tests

There will be three tests in MyLabsPlus. Tests have a time limit. A password is required. Tests must be taken in the Math Emporium Testing Area. A prerequisite of 70% on the Practice Test is required before taking the test. There are two attempts on tests.

After the first attempt a Post-Test Review will open, giving additional practice on the questions missed. Once a 100% has been earned on the Post-Test Review and also 80% on the Test Review, the second attempt will be available.

Students who have not reached 70% on the test following two attempts will be required to schedule a meeting with their Developmental Math instructor to devise a plan to earn an additional attempt. The best score of the test attempts will be recorded. See additional information under Testing Policies.

Students who are on track with the Course Chart and earn an A on the first attempt of Test 1 will be excused from Math Emporium hours (this does not include the weekly class meeting) through the scheduled time of Test 2. Students with an A on the first attempt of Test 2 and are on track with the Course Chart will be excused from Math Emporium hours (this does not include the weekly class meeting) through the scheduled time of Test 3.

All test 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.

If a student does not take Test 1 or Test 2 by the due date, a penalty of 10% will be applied.

If a student does not take Test 3 by Reading Day, he will need an exam reservation to take it during Final Exam Week.

Process

Student attends class once a week.

Student works at least 3 hours in the Math Emporium viewing videos, working on homework and quizzes, and receiving assistance from faculty and tutors.

Student works in the Math Emporium at scheduled times.

Student completes his required 3 hours per week by working additional times of his choice.

Student works as many additional hours as necessary to complete the assignments due each week.

Student meets with instructor when necessary.

Grading Policies

Course grade will be determined by the following point system:

Participation	81
Class Meetings	
Emporium Hours	
Homework (45 x 3 points each)	135
Quizzes (11 x 7 points each)	77
Test 1	190
Test 2	212
Test 3	305
Total	1000

Letter grades will be assigned according to the following scale. A minimum of 700 points is required to pass Math 110.

A 900 – 1000 points

B 800 – 899 points

C 700 – 799 points

D 600 – 699 points

F Below 600 points

Failing to Complete the Course

A student will not pass the course if he does successfully complete all assignments through Unit K before Reading Day. The student will need to re-enroll the following semester in order to maintain progress in the course through the last test if eligible. If a student does not enroll in the course the following semester, the student must start at the beginning of the course.

Any student who has grades from the previous semester due to not completing a course must email the new instructor no later than the end of the day of the first class meeting to request the grades through the last test he passed be transferred to the new course. Grades may only be transferred one time. If a student starts a course in the spring, he must complete it in the following summer or fall semester. If he starts in the fall, he must complete it in the spring. If the course is not passed in the second semester, the student must start the course at the beginning the next time he enrolls. Beginning Spring 2017, grades will only be transferred for students with participation grades of 90% or higher in the previous semester.

Attendance Policies

For the good of the University student body, a consistent attendance policy is needed so that all students in all majors will understand the expectations of faculty in all their courses. In general, regular and punctual attendance in all classes is expected of all students. Though at times, students will miss classes.

Absences for 100-200 level courses fall into two categories:

University Approved Absences

University Approved Absences include University sponsored events, athletic competition, and other Provost-approved absences.

The student must provide written documentation in advance for University Approved Absences.

Work missed for University-approved absences may be made up.

Student Elective Absences

Student Elective Absences include, but are not limited to, illness and bereavement.

Work missed for Student Elective Absences may be made up at the discretion of the faculty member. Questions regarding missed work for Student Elective Absences must be addressed by the student with the professor within one week of returning to class. In cases where this is not possible, the student must notify the Professor in writing of the circumstances impacting his or her absence. The student may appeal the Professor's decision in writing to the respective Chair within one week. Final appeals may be made to the Dean in writing within one week of the Chair's decision and the Dean's decision is final.

When circumstances result in excessive absences (e.g., serious medical illness, family crisis), upon return to campus, the student shall communicate in writing with the Registrar's Office (Registrar@.edu) and provide an explanation of his or her situation with appropriate documentation. The Registrar will consult with the faculty member before making the final decision and will notify, in writing, the student and the faculty member.

Students who are more than 10 minutes late for class are considered absent.

Students who are late for class 10 minutes or less are considered tardy but present for the class. If a student misses in-class work due to tardiness, the faculty member may choose not to allow the student to make up this work. Three class tardies will be counted as one absence.

Number of Student Elective Absences Permitted:

For classes that meet three times per week, the student will be permitted four elective absences per semester.

For classes that meet twice per week, the student will be permitted three elective absences per semester.

For classes that meet once per week, the student will be permitted one elective absence per semester.

Penalties for each absence over the permitted number of elective absences per semester will be as follows:

50 points for classes that meet 3 times per week

75 points for classes that meet 2 times per week

100 points for classes that meet once per week

Other Policies

Dress Code

Students are expected to come to class dressed in a manner consistent with [policy].

Honor Code

We, the students, faculty, and staff of University, have a responsibility to uphold the moral and ethical standards of this institution and personally confront those who do not.

Limits of Confidentiality

Students are encouraged to share prayer requests and life concerns with the professor in this class. Not only will the professor pray for and care for students, but can guide students to appropriate University resources if desired.

However, in the event of a student's disclosure, either verbally or in writing, of threat of serious or foreseeable harm to self or others, abuse or neglect of a minor, elderly or disabled person, victim or witness of a crime or sexual misconduct, or current involvement in criminal activity, the faculty, staff, administrator, or supervisor will take immediate action. This action may include, but is not limited to, immediate notification of appropriate state law enforcement or social services personnel, emergency contacts, notification of the appropriate program chair or online dean, or notification to other appropriate University officials. All reported information is treated with discretion and respect, and kept as private as possible.

Academic Misconduct

Academic misconduct includes: academic dishonesty, plagiarism, and falsification. See [policy] for specific definitions, penalties, and processes for reporting.

Disability Statement

Students with a documented disability may contact the Office of Disability Accommodation Support (ODAS) in [removed] to make arrangements for academic accommodations. You may email them at [removed] or call. For all disability testing accommodation requests (i.e. quieter environment, extended time, oral testing, etc.) Testing Services is the officially designated place for all tests administered outside of the regular classroom.

DROP/ADD POLICY

A Fall/Spring course may be dropped without a grade, tuition, and fee charges within the first five days of the semester. From the sixth day until the end of the tenth week (see academic calendar for exact date), a Fall/Spring course may be withdrawn with a grade of 'W'.

Classroom Policies

The inappropriate use of technology, such as cell phones, iPods, laptops, calculators, etc. in the classroom is not tolerated. Other disruptive behavior in the classroom is not tolerated. Students who engage in such misconduct will be subject to the penalties and processes as written in the [policy].

Expectations:

Always attend class. Arrive on time and stay for the entire class meeting.

Log in at least 3 hours each week in the classroom and the Math Emporium. Students will work in the Math Emporium at scheduled times. Students will complete the required 3 hours per week by working additional times of their choice.

Scheduled emporium hours are required. Work in the Math Emporium at your assigned time.

The first three weeks of the semester are crucial. Students who do not fully engage in the required activities the first three weeks of the semester have little chance of passing.

Bring a pencil, the Developmental Mathematics Notebook, and a notebook for working out homework problems.

Watch videos, take notes, read the Developmental Mathematics Notebook, and/or work examples before asking questions.

Use the Help Me Solve This and other helps in MyLabsPlus.

Work as many additional hours as it takes to complete the assignments for the week. Assignments may be submitted after the due date. Work may be done in the Math Emporium or any other location as long as the 3 required hours per week are completed in the Math Emporium.

Students who complete the weekly assignments early are encouraged to review previous homework and quizzes or start the next unit.

Students who are on track with the Course Chart and earn an A on the first attempt of Test 1 will be excused from Math Emporium hours (this does not include the weekly class meeting) through the scheduled time of Test 2. Students with an A on the first attempt of Test 2 and are on track with the Course Chart will be excused from Math Emporium hours (this does not include the weekly class meeting) through the scheduled time of Test 3.

A final course grade of C or better is required before a student is allowed to take a higher level math course.

Keep a positive attitude.

Math Emporium Policies

Students are here to work on math.

The Math Emporium is a math classroom. Please be quiet during visits to the Emporium.

Only students registered in residential Math 100, Math 105, Math 106, Math 110, Math 114, Math 115, Math 116, Math 121, and Math 201 and BUSI 230 may use the Math Emporium.

Personal lap tops will only be permitted if there are no available computers in the Emporium.

The Emporium is used on a first come, first serve basis. There will be no reservations for normal course work. Reservations are required for Test 3 if taken during Final Exam week.

Each student must present his Flames Pass to the attendant when entering and leaving the Emporium.

All Math Emporium guests are expected to dress and act in accordance to the guidelines in policy.

All personal belongings must be stored on the floor out of the walkway.

No food is allowed in the Emporium. No exceptions. Drinks with lids are permitted.

Activities such as surfing the web, checking e-mail, sleeping, or completing other course work will not be tolerated. Cell phones must be silenced and stored in the backpack or on top of the computer tower face down. Listening to music on the emporium computer, not on your phone or laptop, is permitted as long as neighbors cannot hear it.

Violations result in a 0 for emporium hours for the week and removal from the Emporium.

The expectation is the students will watch the video and/or read the book and attempt the homework question on their own. Be ready to show work for a problem when asking for help. To request help with homework, place the cup on top of the computer and wait patiently for assistance.

Students in Math 100 and Math 110 may use the calculator available on the computer or a blue emporium calculator. Other calculators are not permitted.

All tests must be taken in the Emporium. Homework and quizzes may be completed anywhere, however, 3 hours per week in the Emporium are required.

Please be courteous and respectful at all times. Students are here to work on math.

The Emporium will be closed when classes are cancelled or delayed. The Emporium is closed during convocation time even when convocation is cancelled.

Testing Policies

Consequences for cheating on a test will be a zero on the test. The student will be allowed a second attempt on the test to prove mastery and then the test grade changed to a zero. Cheating includes use of cell phones, smart watches, notes, videos, people, websites, and any unapproved calculator during the test.

All tests must be taken in the Math Emporium. No personal computers may be used.

ODAS students may test in the Testing Center in [removed] or the Math Emporium. The student must contact his instructor.

Flames Pass is required.

Absolutely NO ELECTRONIC DEVICES may be active in the testing area. All cell phones, texting devices, iPods, MP3 players, etc. must be turned off and put away before entering the testing area. Personal belongings will need to be placed on the floor out of the walkway.

Students are not allowed assistance of any kind. This includes faculty, staff, students, notes, formula sheets, or any other type of outside help. During testing, no access to other online materials including homework, quizzes, and online learning aids in MyLabsPlus is permitted.

The Math Emporium will provide testing paper. No other paper is allowed. All papers must be turned in to a test proctor before leaving the testing area.

Only the calculator on the computer or a Math Emporium issued calculator can be used.

Students will be allowed to review the test immediately after submitting. No information pertaining to the test may be written down or shared with other students. Violators will be charged with academic dishonesty as stated in policy.

Any student who works ahead may take the test early. Students who wish to test early must check in with the front desk and then the test proctor on duty. Seating for testing stops two hours prior to closing. However, if you have an ODAS accommodation you must allow for additional time before closing.

Reading Day is the last day to take Tests 1 and 2 with a 10% penalty and Test 3 without a reservation.

Test 3 after Reading Day

A minimum score is not required for Test 3 as long as you pass the course.

Students must reserve a time to take Test 3 using the link in Blackboard or the Math Emporium Widget after Reading Day.

Students may only reserve one time slot.

The maximum time allowed for Test 3 is 120 minutes.

Do not schedule a time that conflicts with a Final Exam in another course. If the student misses another exam because he is taking Test 3, it is NOT an excused absence.

X. Calendar for the Semester — See course chart in Blackboard. Below are other important dates to keep in mind.

Monday, August 27:	Classes begin

Friday, August 31, 4 PM: Last day to add or drop a class

October 4 – 7: Fall Break, Math Emporium closed, no classes

November 17 – 25: Thanksgiving Break, no classes, Math Emporium closed

Friday, November 30: Last day to withdraw from a class with a W

Tuesday, December 4: Last day of classes

Tuesday, December 4: Last day to do any homework or take a quiz

Wednesday, December 5: Reading Day; last day to take Test 1 and Test 2 with a 10% penalty; last day to take Test 3 without a reservation.

Thursday-Tuesday, Dec. 6 – 11: Test 3 with a reservation.

XI. Math Emporium Web Page [removed]

APPENDIX C: Permission Emails and Exemption Letter

From: Perry, Cynthia Goodlet (College of General Studies Instruct)
Sent: Tuesday, October 16, 2018 4:24 PM
To: Sherman, George A (Professional/Continuing Education)
Subject: RE: Math: Doctoral Research Request

George,

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

Cindi Perry
Department Chair
College of Arts & Sciences

(434) 592-6150

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From: Sherman, George A (Professional/Continuing Education)
Sent: Tuesday, October 16, 2018 4:21 PM
To: Perry, Cynthia Goodlet (College of General Studies Instruct)
Subject: FW: Math: Doctoral Research Request

Hi, Cindi.

I'm completing IRB forms for my dissertation and must provide evidence that you—as the chair of the Math Emporium—approve my intended research. I aim to assess the accuracy of ACT/SAT scores, local math placement test scores, and high school GPAs as predictors of MATH 100 and MATH 110 final grades for residential students assigned to the two courses over the last several years—probably three to five years. If you're okay with this idea, will you please respond affirmatively?

Thank You!

George

George Sherman
Director
Center for Professional and Continuing Education

(434) 592-5961

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From: Sherman, George A (Professional/Continuing Education)
Sent: Tuesday, September 4, 2018 8:51 AM
To: Schultz, Roger D
Cc: Perry, Cynthia Goodlet (College of General Studies Instruct); Long, Scott
Subject: RE: Math: Doctoral Research Request

Dr. Schultz,

Thank you for supporting this research. I plan to assess the accuracy of the three placement criteria—ACT/SAT, unweighted high school GPA, and math test scores—as predictors of MATH 100 and MATH 110 grades for all residential students assigned to the two courses over the last three to five years.

Respectfully,

George

George Sherman
Director
Center for Professional and Continuing Education

(434) 592-5961

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From: Schultz, Roger D
Sent: Monday, September 3, 2018 4:04 PM
To: Sherman, George A (Professional/Continuing Education)
Cc: Perry, Cynthia Goodlet (College of General Studies Instruct); Long, Scott
Subject: Math: Doctoral Research Request

George,

I'd be happy to see work on this question. Will you be working with specific courses and specific placement scores. I'll copy Scott Long, the Math Chair, and Cindy Perry, the General Math and Science Chair, so that they are aware of your project.

Roger Schultz
Dean
College of Arts and Sciences

(434) 592-4031

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From: Sherman, George A (Professional/Continuing Education)
Sent: Monday, September 3, 2018 3:27 PM
To: Schultz, Roger D
Subject: Research Request

Good Afternoon, Dr. Schultz.

In addition to my continuing education work, I'm a Liberty University School of Education PhD candidate. I plan—for my dissertation research—to use archived data to evaluate math placement criteria as predictors of residential students' developmental math grades. Mike

Gibson expressed support for the idea and told me the data exists, but I understand I must have your permission to execute the study. Will you permit this research?

Thank You!

George

George Sherman
Director
Center for Professional and Continuing Education

(434) 592-5961

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